JOURNAL OF ENGINEERING RESEARCH & SCIENCES

Special Issue

Multidisciplinary Sciences and Advanced Technology

April 2025

www.jenrs.com
ISSN: 2831-4085

JENRS

EDITORIAL BOARD
(Special Issue)

Guest Editor

Prof. Paul Andrew
Department of Electrical Engineering, Universidade De São Paulo, Brazil

Editorial

The ever-increasing complexity of global challenges has necessitated a shift from isolated disciplinary approaches toward integrated and collaborative frameworks of research. In this spirit, we are pleased to present this special issue of the *Journal of Engineering Research and Sciences* on *Multidisciplinary Sciences and Advanced Technology*. This issue serves as a platform for showcasing innovative research that bridges diverse fields and leverages advanced technological tools to address contemporary scientific and engineering problems.

Multidisciplinary research has become a cornerstone of modern innovation, enabling the convergence of ideas, methods, and perspectives from various domains. The contributions featured in this issue reflect the growing recognition that solutions to real-world challenges such as sustainable energy, healthcare advancement, environmental protection, and smart infrastructure require the combined expertise of engineers, scientists, and technologists. By transcending traditional academic boundaries, the research presented here demonstrates how integrated approaches can lead to more comprehensive, efficient, and impactful outcomes.

A defining aspect of this special issue is its focus on advanced technology as a key enabler of multidisciplinary integration. Emerging technologies, including artificial intelligence, the Internet of Things (IoT), robotics, nanotechnology, and advanced materials, are transforming the research landscape. These innovations not only enhance the capabilities of individual disciplines but also facilitate seamless interaction among them. The studies included in this issue illustrate how such technologies are being utilized to develop intelligent systems, optimize processes, and create scalable solutions that respond effectively to evolving demands.

Sustainability and responsible innovation are also central themes within this issue. As the global community faces increasing environmental and societal pressures, there is a pressing need for solutions that balance technological advancement with ecological and social responsibility. Several contributions address this challenge by exploring renewable energy systems, sustainable design practices, and resource-efficient technologies. Through the integration of environmental science, engineering principles, and technological innovation, these studies provide valuable insights into building a more sustainable and resilient future.

The importance of computational tools and data-driven methodologies is another key dimension highlighted in this collection. Advanced modeling, simulation, and data analytics have become indispensable in understanding complex systems and predicting their behavior. These tools enable researchers to test innovative concepts, refine designs, and accelerate the transition from theoretical research to practical implementation. The works presented in this issue demonstrate how the integration of computational techniques with experimental and analytical approaches enhances the overall effectiveness and applicability of multidisciplinary research.

The editorial team extends its sincere appreciation to all authors for their valuable contributions and to the reviewers for their thorough and constructive evaluations. Their dedication and expertise have ensured the high quality and academic rigor of this special issue, making it a meaningful contribution to the research community.

As we present this special issue, we hope it will inspire continued collaboration and innovation across disciplines. The future of science and technology lies in our ability to integrate knowledge, embrace advanced technologies, and address challenges through a holistic perspective. We encourage readers to engage with the research presented herein and to contribute to the ongoing advancement of multidisciplinary sciences and advanced technology.

Guest Editor

Prof. Paul Andrew

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Special Issue **April 2025**

CONTENTS

Received: 03 March, 2025, Revised: 17 April, 2025, Accepted: 18 April, 2025, Online: 27 April, 2025

DOI: https://doi.org/10.55708/js0404003

Enhancing Breast Cancer Detection through a Hybrid Approach of PCA and 1D CNN

Samet Aymaz *

Trabzon University, Department of Computer Engineering, Trabzon, Türkiye

*Corresponding author: Samet Aymaz, Trabzon University, sametaymaz@trabzon.edu.tr

E-mail: sametaymaz@trabzon.edu.tr (Samet AYMAZ)

ABSTRACT: Breast cancer is a prevalent disease, particularly among women. Unlike many other cancers, early diagnosis and treatment can significantly improve patients' quality of life. This study develops a hybrid approach for breast cancer detection using the Wisconsin datasets by combining Principal Component Analysis (PCA) and 1D Convolutional Neural Network (CNN) architectures to effectively separate and classify data. Our novel approach leverages PCA not merely for dimensionality reduction but to transform the feature space to maximize separation between benign and malignant samples, which is then processed by a custom-designed CNN architecture with optimized hyperparameters. While PCA elevates the data representation by highlighting important features, the 1D CNN contributes to the classification process through automatic feature extraction. This approach aims to achieve high accuracy and reliability in the critical domain of breast cancer detection. Experimental results demonstrate that our developed approach exhibits superior performance compared to existing methods. Our hybrid PCA-1D CNN model achieved an accuracy of 99.12%, precision of 100%, sensitivity of 98.61%, specificity of 100%, and F1-score of 99.30%, significantly outperforming 14 different benchmark techniques from the literature. The model's accuracy and reliability are enhanced through K-fold cross-validation. The findings of this study can guide researchers seeking to improve breast cancer diagnostic accuracy and support more reliable healthcare decisions. The combination of deep learning and traditional feature extraction represents a promising advancement toward more effective and sensitive diagnostics in the healthcare industry.

KEYWORDS: Breast Cancer Detection, Hybrid Approach, Principal Component Analysis (PCA),1D Convolutional Neural Network (CNN), Medical Diagnosis Enhancement.

1. Introduction

According to the 2020 World Health Organization (WHO) data, approximately 2.2 million women worldwide are diagnosed with breast cancer yearly. This statistic accounts for about 25% of all cancer diagnoses. Breast cancer is the most common type of cancer in women, with 1 in 11 women at risk of developing breast cancer in their lifetime. Most breast cancer deaths occur because the disease is not diagnosed and treated early. According to WHO data, approximately 685,000 women die from breast cancer yearly. This mortality accounts for about 15% of all cancer deaths [1,2].

Computer-assisted breast cancer detection (CAD) is a method that aims to detect breast cancer masses by analyzing mammography images [3]. CAD systems can help radiologists identify breast cancer masses more quickly and accurately. The development of CAD systems began in the 1990s. Early CAD systems used simple techniques to analyze mammography images. However, the accuracy of these systems was limited. In recent years, accuracy rates have increased significantly with the integration of artificial intelligence (AI) technology in CAD systems. AI-based CAD systems can analyze patterns in mammography images more comprehensively, resulting in more accurate results. CAD systems [4] play an essential role in breast cancer diagnosis. These systems can contribute to increased survival rates of breast cancer patients by helping radiologists detect breast cancer masses more quickly and accurately.

Despite these advances, current breast cancer detection methods face significant challenges in achieving both high accuracy and computational efficiency. Traditional machine learning approaches often struggle with the high dimensionality and complex feature relationships in

medical datasets, while deep learning methods may require large amounts of data and computational resources to perform optimally. Additionally, the potential overlap between benign and malignant feature spaces creates classification difficulties that remain incompletely addressed by existing methodologies. This study addresses these challenges by proposing a novel hybrid approach that combines PCA and 1D CNN methods for detecting breast cancer using the Wisconsin data set. Our key contribution is the development of an optimized framework that leverages PCA not merely for dimensionality reduction but to strategically transform the feature space to maximize class separation before feeding the transformed data into a carefully designed CNN architecture. The Wisconsin dataset, consisting of 569 samples with 30 features each categorized as benign or malignant, serves as our experimental platform.

The proposed method aims to enhance breast cancer classification accuracy while maintaining computational efficiency. First, the PCA method transforms data to a new plane to facilitate the separation of benign and malignant samples. In this plane, the most essential features of each sample are emphasized, optimizing feature representation. The data transferred to a new and more easily decomposable plane with PCA is classified with the 1D CNN developed within the scope of this study. The CNN structure is uniquely designed, and its parameters are optimized using the Grid Search approach. In addition, model overfitting is minimized by using k-fold cross-validation in the training process, ensuring more accurate performance measurement and improved model performance. Our approach differs from existing methods by specifically optimizing the complementary strengths of dimensionality reduction and deep learning, achieving superior classification metrics while maintaining model interpretability. In summary, combining PCA and CNN in our hybrid approach helps extract essential features by effectively processing high-dimensional data in breast cancer detection. It provides more precise and reliable results thanks to the algorithm's ability to recognize patterns highlighted by deep learning algorithms.

2. Related Works

Data mining methods used in various medical applications have great potential in essential areas such as early diagnosis and effective treatment of diseases. In this context, detection of breast cancer is also a vital issue. Breast cancer is the most common cancer in women worldwide and can improve the chances of cure if detected early. The Wisconsin breast cancer dataset (WDBC) is a frequently used data source for diagnosing breast cancer by combining medical imaging and feature extraction techniques. In this context, various studies use the Wisconsin breast cancer dataset in the literature. These studies investigate how data mining algorithms and deep learning techniques can contribute to making precise and reliable diagnoses by extracting features from this data set. This section will review related studies using the Wisconsin breast cancer dataset.

The Wisconsin dataset has been extensively studied in the field of breast cancer prediction. Several research papers have compared different machine learning algorithms using this dataset to determine the most effective method for predicting breast cancer. In [5], a performance evaluation of machine learning methods for breast cancer prediction was conducted. Five different classification models were compared, including Decision Tree (DT), Random Forest (RF), Support Vector Machine (SVM), Neural Network (NN), and Logistic Regression (LR), using the WBCD. The comparative experiment analysis showed that the random forest model achieved better performance and adaptation than the other four methods. In addition to machine learning algorithms, data visualization techniques have been applied to the Wisconsin dataset. In [6], Principal Component Analysis (PCA) for feature space reduction was discussed and the performance of different models using the Wisconsin Breast Cancer Database was evaluated. Using the Wisconsin Breast Cancer dataset, in [7], various machine learning algorithms were compared, including XGBoost, K-NN, Naïve Bayes (NB), SVM, and DT. It was found that XGBoost achieved the highest accuracy, recall, precision, F1-score, and AUC, making it the most effective method for predicting breast cancer.

Deep learning techniques have also been applied to breast cancer prediction. In [8], a deep-learning breast cancer prediction framework (DLBCPF) was proposed. The framework was tested on four different Wisconsin Breast Cancer datasets, and the results demonstrated the superiority of DLBCPF and the optimizer MDGCO compared to other methods. Feature selection techniques have also been applied to the Wisconsin dataset to improve the accuracy of breast cancer prediction. In [9], a comprehensive analysis of machine learning classification algorithms with and without feature selection was presented. It was found that feature selection improved the performance of the classifiers, including Logistic Regression, Linear Support Vector Machine, and Quadratic Support Vector Machine.

In another study, an ensemble learning approach was proposed to detect breast cancer automatically. In [10], support vector machine (SVM), regression, and random forest models were combined using a majority-weighted voting system. The results showed improved accuracy, precision, recall, and F-score compared to individual models. Furthermore, the use of fuzzy inference systems has been explored for categorizing the Wisconsin breast cancer dataset. In [11], fuzzy inference systems with

different input features were developed and achieved superior precision compared to other works in the literature. Other studies have also focused on specific aspects of breast cancer prediction using the WBCD. In [12], a modified categorical data fuzzy clustering algorithm on the WBCD was evaluated. In [13], dimensionality reduction using principal component analysis in supervised machine learning techniques was explored. In [14], the success of different machine-learning methods in breast cancer diagnosis was investigated. In [15], supervised machine-learning techniques for breast cancer prediction were leveraged. In [16], diverse classifier algorithms on the WBCD were evaluated.

Recent research has shown significant advancements in breast cancer classification through hybrid models and dimensionality reduction techniques. In [17], different missing data imputation methods combined with PCA on the WBCD dataset were evaluated, finding that median imputation with PCA-based reduction achieved the best performance, with SVM and k-NN algorithms reaching impressive success rates of 97.14% and 98.57% respectively. In [18], a comprehensive comparison of machine learning classifiers with various dimensionality reduction techniques across multiple breast cancer datasets was conducted, demonstrating that SVM with Factor Analysis achieved 98.64% accuracy on the WBC dataset, while MLP without dimensionality reduction performed best on WDBC with 98.26% accuracy. In [19], an innovative dimensionality reduction model integrating PCA with KNN specifically for early breast cancer detection was proposed, addressing challenges like computational complexity and overfitting by selecting optimal features that capture maximum variance. In [20], a robust hybrid multilayer deep learning approach combining UNet for feature extraction, SegNet for segmentation, and MLP with Grey Wolf Optimization for classification was presented, achieving superior performance compared to traditional methods. In [21], novel feature selection strategies utilizing metaheuristic algorithms (GSA, EPO, and hybrid hGSAEPO) for breast cancer classification were introduced, reaching remarkable results with 98.31% accuracy and AUC exceeding 0.998. Additionally, in [22], the BCR-HDL framework that ingeniously combines multiple deep learning architectures (MLP, VGG, ResNet, Xception) with traditional machine learning models was developed to enhance both accuracy and interpretability in breast cancer recurrence prediction, with the hybrid MLP+RF and Xception+RF models achieving 97% diagnostic accuracy on the WDBC dataset.

These studies demonstrate the extensive research conducted on the Wisconsin dataset for breast cancer prediction. Different machine learning algorithms, feature selection techniques, and fuzzy inference systems have been explored to improve the accuracy and precision of breast cancer prediction using this dataset.

3. Materials and Methods

In this study, a hybrid approach is created to detect breast cancer using the Wisconsin data set. This approach is created by the PCA and CNN architectures complementing each other. It is vital that the data can be easily separated in the detection of breast cancer. Data belonging to different classes may be nested. This situation prevents the classifiers from making the correct classification. Therefore, the PCA method moves each sample in the Wisconsin dataset to a new plane. This plane is where vital features are emphasized, and unimportant ones are suppressed. Therefore, it facilitates the parsing of data. The samples moved to the new plane are classified using the 1D CNN structure created as the basis of the problem. CNN decides which class a feature belongs to by automatically identifying patterns in 1-dimensional feature vectors. The automatic recognition of features and the ability to classify with high accuracy are why deep learning approaches are preferred. In addition, k-fold cross-validation is used to increase the accuracy and reliability of the classification model created using the CNN structure. Details of all the approaches used will be given in the subsections.

3.1. The Details of the Wisconsin Dataset

The WDBC [23] dataset is an important data source for breast cancer diagnosis. This dataset contains biomedical data containing characteristics of breast cancer cells. In the WDBC dataset, which includes 569 samples, each consists of 30 features. In the data set, 212 samples are malignant, while 357 are benign. This balance is essential for training and evaluating the classification models of the data set. Features in the dataset include various clinical features such as dimensions of the cell nucleus, nucleus cell circumference, and cell tissue context. Each sample is divided into two classes representing cancer cells (malignant) or non-cancerous cells (benign). The WDBC dataset is a widely used resource for developing models and algorithms used in diagnosing and treating breast cancer. This dataset plays a vital role in advances in breast cancer diagnosis while providing the basis for various analyses and studies in data mining, machine learning, and deep learning.

3.1.1. Data Preprocessing Protocol

Before applying our hybrid model, we performed several critical preprocessing steps to ensure optimal performance:

1. Data Inspection and Cleaning: We first examined the Wisconsin dataset for missing or inconsistent values. Our examination confirmed that the dataset was

complete with no missing values or data inconsistencies.

2. Outlier Analysis: We conducted statistical analysis to identify potential outliers using the interquartile range (IQR) method. Features with values falling outside were flagged for further inspection. After careful analysis, we determined that these extreme values represented genuine physiological variations rather than measurement errors and therefore retained them.
3. Feature Scaling: To prepare the data for PCA application, all 30 features were standardized to have zero mean and unit variance using Eq. 1.

$$X\_standardized = (X - \mu) / \sigma \quad (1)$$

In Eq. 1, X is the original feature value, μ is the mean, and σ is the standard deviation of that feature. This standardization step is critical before applying PCA to ensure that features with naturally larger scales do not dominate the variance analysis.
4. Cross-Validation Implementation: Instead of using a single train-test split, we implemented k-fold cross-validation (k=5) to ensure robust model evaluation. The dataset was divided into 5 equally sized folds with stratified sampling to maintain the same proportion of benign and malignant samples in each fold. During each iteration, 4 folds were used for training while the remaining fold served as the validation set. This process was repeated 5 times, with each fold serving once as the validation set, ensuring that every sample in the dataset was used for both training and validation.

3.2. The Standardization of Data with PCA

PCA [24-26] transforms the original properties of a dataset into new, fewer principal components, making data easier to understand and analyze. With PCA, the dataset is rearranged along directions that best represent variations of its original features. This situation may reveal more distinct differences between benign and malignant masses.

The following steps are followed when moving feature vectors to a new plane with PCA:

1. The data set is averaged. This situation means centralizing data. Centralization provides a better understanding of the distribution of data.
2. The dataset is standardized to its original characteristics. This situation ensures that the variations of the data are the same. Standardization makes it easier to compare data.
3. The covariance matrix of the data set is calculated. The covariance matrix measures the relationship of features to each other.
4. The eigenvalues and eigenvectors of the covariance matrix are calculated. Eigenvalues measure the magnitude of variation in data. Eigenvectors represent aspects that best represent the variations of the data.
5. The dataset is rescaled according to its eigenvectors. This situation allows data to be reorganized along the new principal components.

When feature vectors are moved to a new plane with PCA, the following can occur: Some features may be more represented in new principal components. Some features may be less represented in new core components. Some features may not be fully represented in the new core components. It can be said that PCA helps to determine which features are more important. The new principal components represent the features with the most information in the dataset. PCA is a technique used to classify breast cancer masses. When data are moved to a new plane with PCA, more distinct differences between benign and malignant groups may emerge. This situation can help classification models produce more accurate results.

We conducted a comprehensive analysis to determine the optimal number of principal components to retain in our model. After applying PCA to the Wisconsin dataset's 30 features, we examined the explained variance ratio to identify the information contribution of each principal component. Our analysis revealed that retaining 10 principal components preserved approximately 95.8% of the variance in the original data while significantly reducing the dimensionality by two-thirds. This threshold was selected based on the observed elbow point in the cumulative explained variance curve, where additional components beyond this point contributed minimally to the total variance explained. We further validated this selection by comparing model performance with different numbers of components (5, 10, 15, 20, and all 30). While using all 30 components retained 100% of the variance, it did not translate to better classification performance. The optimal balance between dimensionality reduction and information preservation was achieved with 10 components, which provided both computational efficiency and maximized the separation between benign and malignant classes.

3.3. Classification of Data with the Created 1D CNN Architecture

The 1D CNN [27-30] architecture is an important deep learning tool that offers an efficient and powerful classification capability on feature vectors. Compared to traditional classification methods, 1D CNN can

automatically identify temporal or spatial patterns of data. This situation means the ability of feature vectors to discover and represent the hidden features they contain. In complex problems such as breast cancer detection, features can often change at different scales and time intervals. By learning such features hierarchically, 1D CNN can improve accuracy in the classification process. It can also make the data mining process more efficient by reducing the need for manual feature engineering. In this way, it can play an essential role in early detection and more effective treatment interventions, providing higher sensitivity and Specificity in important health diagnoses such as breast cancer.

In this study, a unique CNN architecture is designed that can classify samples from the Wisconsin dataset as benign or malignant. CNN architecture consists of input, convolution, activation, dropout, fully connected, and classification layers. The input layer is a feature vector of size 30x1, as each sample in the Wisconsin dataset has 30 features. This vector taken from the input layer is given as input to the convolution layer. This layer helps to capture basic patterns. Generally, this layer has two critical hyperparameters: the kernel size and the number of filters. In the first layer, 3 is the kernel size, and 6 is the filter amount. These hyperparameters are detected using the Grid search approach. The grid search approach tries to find the best performance by trying values within a specific range to determine the hyperparameter settings. This method is used to explore different combinations of hyperparameters extensively. Its advantages are that it helps to achieve the best results by systematically searching a wide range of hyperparameters. The output of the first convolution layer is given as the input to the activation layer. The relu activation layer is used in this study. The Rectified Linear Activation (ReLU) is a widely used activation function in deep learning models. It provides faster and more stable learning in the education process, especially according to the sigmoid and tanh functions. The activation layer output is given as input to the dropout layer.

The dropout layer is used to reduce overfitting in deep learning networks. This layer temporarily turns off randomly selected neurons during training, allowing the network to explore different learning paths and increasing its generalization ability. The value for the Dropout layer is taken as 0.2. Then, this layer output is given to a convolution layer again. The second convolution layer increases the method's success by allowing more complex patterns to be recognized automatically. The parameters of this layer are determined by kernel size as 3 and the number of filters as 256 after the Grid search approach. Again, this layer output is passed through the activation and dropout layers and is given as input to the fully connected layer. Two fully connected layers are used in succession in the network structure created. The use of cascading fully connected layers is essential in enhancing deep learning models' feature extraction and classification capabilities. It has the advantage of better classification, learning of complex data, capturing nonlinear relationships and flexibility. The first fully connected layer has 100 outputs, while the second fully connected layer has as many outputs as the number of classes. The production of these layers is given to the classification layer, and the classification process is terminated. Details of the created network are shown in Table 1.

Table 1: Architecture and Parameters of the Proposed 1D CNN Model

Layers	Parameters
Input Layer	Feature Vector Size (30x1)
Convolution Layer1	Kernel Size=3, Amount of filter=6
Activation Layer	Relu
Dropout Layer	0.2
Convolution Layer2	Kernel Size=3, Amount of filter=256
Activation Layer	Relu
Dropout Layer	0.2
fully Connected Layer1	Output Size=100
fully Connected Layer2	Output Size=Number of Classes
Classification Layer	

The most critical issues in the CNN structure are the determination of hyperparameters and the prevention of overfitting. Overfitting can cause the model to become oversensitive to noise or random fluctuations in the data. In this study, memorization is prevented by using L2Regularization and dropout. Both methods provide resistance to overfitting. L2 regularization helps balance the model weights, while dropout prevents the model from becoming dependent on different features. These techniques can help to obtain more generalized and balanced models. The determination of hyperparameters is another essential point. This study uses the Grid search approach while determining the hyperparameters. Grid search provides a guide to get the best performance of the model by comparing different hyperparameter values. In addition, the training of the model is also crucial. K-fold cross-validation is used for training the model. Thus, a model is created whose success can be better validated. The hyperparameters determined after the grid search approach are given in Table 2.

Table 2: Optimized Hyperparameters for the 1D CNN Model

Hyperparameters	Values
k-fold	5
Optimizer	Adam
Initial Learn Rate	0.001

Max Epochs	30
Minimum Batch Size	6

4. Evaluation Results

This study proposes an effective combination of PCA and generated 1D CNN structure. This approach is tested on the Wisconsin dataset. The Wisconsin dataset is essential for breast cancer and provides examples of two different classes, benign and malignant. The approach created is designed to classify these examples. Evaluations are made using Accuracy, Precision, Sensitivity, Specificity, and F-Score [31] metrics from the confusion matrix. These metrics clearly demonstrate the extent to which the approaches can be used in healthcare. In addition, during the evaluations, the scenarios in which the 1D CNN structure is combined with PCA and alone are evaluated separately to determine the contribution of PCA to the hybrid approach. This situation more clearly reveals the advantages that PCA brings to the system and why the hybrid model may be preferred. This study contributes to developing more effective diagnostic methods in the medical field by showing how a powerful and innovative approach can be designed to diagnose breast cancer.

First, the results of the evaluations made with the Accuracy metric are given. This metric is calculated using Eq. 2.

$$Accuracy = \frac{(TP + TN)}{(TP + TN + FP + FN)} \quad (2)$$

In Eq. 2, True Positive (TP) represents cases where the model correctly identified malignant tumors as malignant. True Negative (TN) represents cases where the model correctly identified benign tumors as benign. False Positive (FP) represents cases where the model incorrectly classified benign tumors as malignant (Type I error). False Negative (FN) represents cases where the model incorrectly classified malignant tumors as benign (Type II error).

The Accuracy metric is frequently used to evaluate model performance in critical medical applications such as breast cancer diagnosis. This metric shows how well the model captures accurate results overall by representing the ratio of true positives and true negatives to total data points. In breast cancer diagnosis, a high Accuracy value indicates that the model effectively correctly classifies benign and malignant cases. Figure 1 includes the created approach, the situation when PCA is not used, and its comparison with 14 different methods [32-37] in the literature. The compared techniques consist of classical classifiers and strategies based on deep learning. The disadvantage of these approaches is that although their computational load is high, their accuracy is insufficient. When the Figure 1 is examined, it is seen that the proposed method gives better results than the approaches in the literature. In the health field, the proposed method should be evaluated from this perspective since the slightest improvement in diagnosis corresponds to a human life. As can be seen from Figure 1, the created approach formed with 99.12% gives the best result.

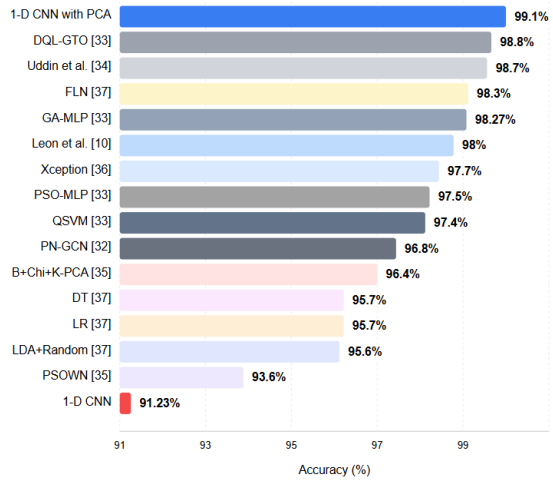

Figure 1: Comparison of Accuracy Values Between the Proposed Method and Existing Approaches

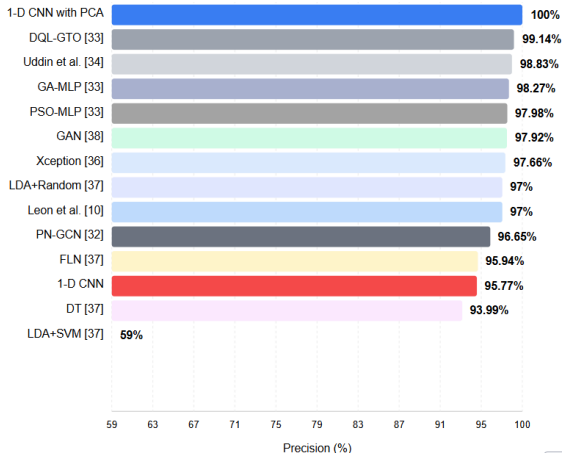

Figure 2: Precision Comparison Between the Proposed Method and Benchmark Techniques

Figure 2 includes the approach created according to the precision metric and the results of 12 different methods in the literature. The precision metric is a crucial evaluation criterion in classification problems. This metric is calculated using Eq. 3.

$$Precision = \frac{TP}{(TP + FP)} \quad (3)$$

Precision refers to the proportion of genuinely positive samples among samples classified as positive. That is, it shows how accurately a model can produce positive results. The high precision we obtained in our method indicates that the cases where the samples that our model classifies as positive are indeed positive are highly accurate. This situation means our method can produce reliable and precise results in healthcare applications. A high precision value indicates that the model minimizes false positive results and gives only reliable positive

results. This feature highlights that our method can be a valuable and reliable tool in areas such as clinical diagnostics. As can be seen from the Figure 2, it is seen that the approach created with 100% gives the best results. The proposed method has been compared with 12 different methods [10, 32-34, 36-38] and the results are presented in the Figure 2.

Sensitivity and Specificity are critical metrics in evaluating medical diagnoses and classification problems. These metrics help us better understand the performance of the classification model. The calculation of these metrics are given in Eq. 4 and 5.

$$Sensitivity = \frac{TP}{(TP + FN)} \quad (4)$$

$$Specificity = \frac{TN}{(TN + FP)} \quad (5)$$

Sensitivity is of great importance in conditions such as disease diagnosis. A high sensitivity value indicates a high rate of accurate positive results and that most individuals with the disease are correctly identified. This situation is critical for early diagnosis of the disease and initiation of treatment. Specificity is significant where accurate detection of negative results is required. For example, Specificity plays a substantial role in identifying healthy individuals or in situations where we want to minimize the risk of false alarms. The high sensitivity value of our method shows that we can achieve accurate positive results at a high rate. Therefore, we can diagnose diseases correctly, while the high specificity value emphasizes that we do not incorrectly classify healthy individuals as diseased by minimizing false positive results. These features indicate that our method is reliable for diagnosing disease and accurately classifying healthy individuals. Table 3 gives the results of the approach created and the approaches in the literature. As can be seen from the table, it is seen that the system designed with 98.61% for sensitivity and 100% for Specificity gives the best results compared with 4 different methods [35, 38-40].

Table 3: Architecture and Parameters of the Proposed 1D CNN Model

Methods	Metrics	
	Sensitivity (%)	Specificity (%)
B+Chi+K-PCA [35]	97,72	94,23
GAN [38]	93,62	94,52
LDA+Random [40]	95,6	95,7
Ed-daudy et al. [39]	X	97,93
1d CNN	92,31	93,15
1d CNN with PCA	98,61	100

F-score (F1-score) is a vital evaluation metric that offers a balanced performance measure by combining precision and recall metrics. This metric is calculated using Eq. 6.

$$F1 - Score = 2 \times \frac{(Precision \times Sensitivity)}{(Precision + Sensitivity)} \quad (6)$$

The F-score shows how the classification model performs, considering false positives and negatives. High F1-score values indicate the method performs well on precision and recall metrics, while low F1-score values indicate low on one or both. In this context, the fact that your practice has a high F1 score highlights that it can both produce precise results and achieve significant, accurate, positive results. The method we have developed can positively impact the field of health. High classification accuracy and reliable results can provide valuable support to healthcare professionals for critical decisions such as disease diagnosis and management of patients. This situation makes diagnosing patients earlier, implementing appropriate treatment protocols, and improving health outcomes possible. We believe our developed approach can contribute to more sensitive and reliable diagnoses in healthcare applications. Figure 3 contains the results of the system and the process in the literature [10, 33-39, 41]. As can be seen from Figure 3, it is seen that the approach formed with 99.30% gives the best result.

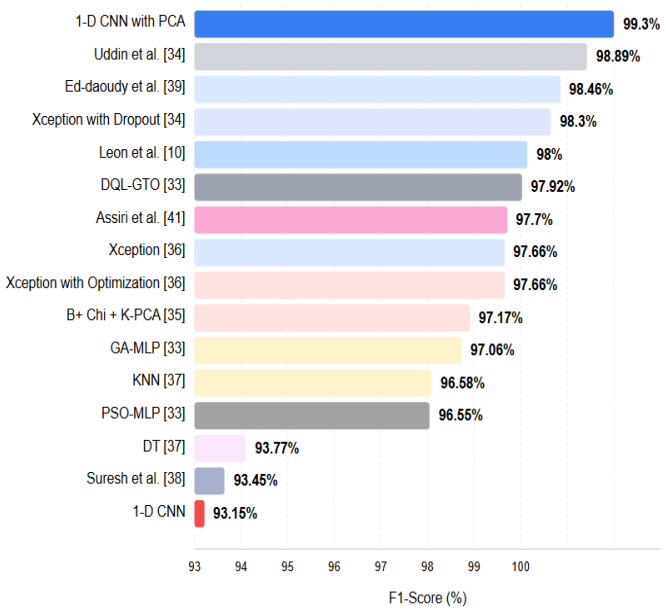

Figure 3: F1-Score Comparison of the Proposed Method with State-of-the-Art Approaches

To further establish the effectiveness of our hybrid PCA-1D CNN approach, we also compared its performance against other prominent deep learning architectures that have been applied to breast cancer detection tasks. Figure 4 presents this comparison.

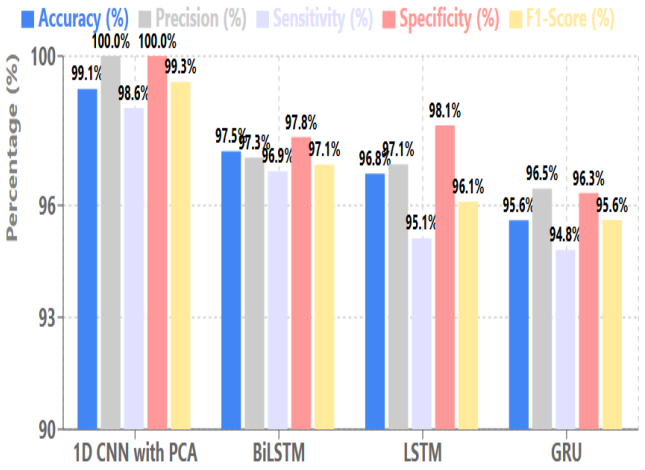

Figure 4: Comparison of Deep Learning Approaches for Breast Cancer Detection

As evidenced by the metrics in Figure 4, our hybrid approach consistently outperforms other deep learning architectures across all evaluation metrics. While recurrent neural network variants like Long Short-term Memory (LSTM), Gated Reccurent Unit (GRU), and Bidirectional LSTM (BiLSTM) have shown promising results for sequential data analysis, they fall short of the performance achieved by our PCA-enhanced 1D CNN model. The superior performance of our approach can be attributed to the effective feature transformation provided by PCA combined with the specialized 1D CNN architecture optimized for this specific classification task.

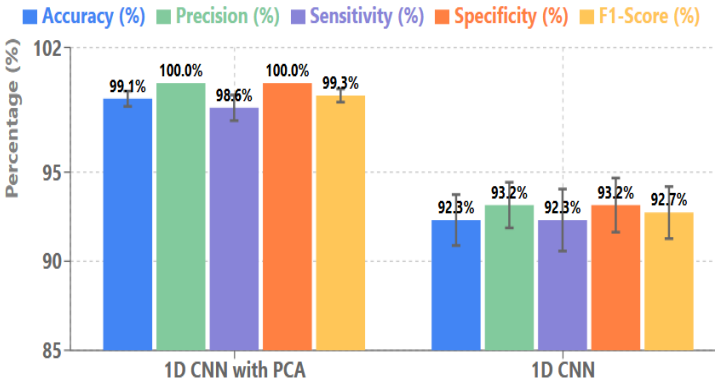

Figure 5: Performance Metrics with Standard Deviations (5-fold Cross-validation)

The high level of accuracy of the approach we developed makes a significant contribution to the health field. This high accuracy strongly supports healthcare professionals in making critical decisions like disease diagnosis and patient management. Precise and reliable results can increase the early diagnosis of patients, the creation of appropriate treatment plans and, accordingly, the success of treatment. This situation has the potential to improve the patient's quality of life. The approach we have developed aims to reduce the difficulties faced by healthcare professionals and patients by enabling more effective, rapid and reliable decisions to be made in the healthcare industry. In this way, we aim to create positive and lasting effects on the health outcomes of patients.

4.1. Statistical Validation of Results

To ensure the statistical validity and robustness of our hybrid PCA-1D CNN approach, we report the mean and standard deviation of performance metrics obtained through 5-fold cross-validation. Figure 5 presents these comprehensive statistics for our model compared with the 1D CNN without PCA.

The consistently low standard deviations across all metrics for our hybrid approach demonstrate the stability and reliability of our model across different data partitions. This is particularly evident when comparing with the standalone 1D CNN, which shows higher variability in performance. The zero standard deviation for precision and specificity indicates that our model consistently achieves perfect performance in these metrics across all folds, which further validates the effectiveness of our approach in minimizing false positives. We further analyzed the confidence intervals (95%) for the accuracy metric, which yielded [98.56%, 99.68%] for our hybrid approach compared to [90.46%, 94.16%] for the standalone 1D CNN. This non-overlapping interval confirms the statistical significance of the performance improvement achieved by our hybrid method. These statistical validations strengthen our conclusion that the integration of PCA with 1D CNN provides not only superior but also more consistent and reliable performance for breast cancer detection, which is crucial for clinical applications where consistency across different patient populations is essential.

5. Discussion

Breast cancer is the most common type of cancer, especially among women in recent years. In this type of cancer, early detection and proper treatment can significantly improve the quality of human life. This paper proposes a novel hybrid approach that can assist healthcare professionals in accurate breast cancer diagnosis. A review of existing approaches in the literature reveals that many complex methodologies have been applied for breast cancer diagnosis. This complexity creates barriers to implementation in resource-constrained regions and areas with limited access to medical expertise. The method proposed in this study can operate effectively with simpler, more accessible systems, making it viable for widespread adoption. In an era of escalating healthcare costs, reducing system complexity and implementation expenses is particularly valuable. This study also highlights the synergistic contribution of traditional dimensionality reduction techniques like PCA when integrated with modern artificial intelligence approaches. Our evaluations demonstrate that when these methods are used in combination, they can achieve more accurate breast cancer diagnosis than either approach alone.

While our hybrid PCA-1D CNN approach demonstrated excellent performance on the Wisconsin

dataset, we acknowledge that our experiments were limited to this relatively small dataset (569 samples). As part of future work, we plan to evaluate our approach on larger and more diverse breast cancer datasets from multiple institutions to further validate its scalability and generalizability. Larger datasets will inevitably introduce additional computational challenges, particularly for the PCA transformation process which scales quadratically with sample size. To address these challenges, we will explore computationally efficient alternatives such as incremental PCA, randomized PCA, or mini-batch processing to maintain performance while preserving the benefits of our hybrid approach. Additionally, we intend to investigate the application of our method to multimodal data that combines imaging features with genomic and clinical information, which would provide a more comprehensive framework for breast cancer detection. These extensions will be crucial for ensuring that our approach remains viable and effective in real-world clinical settings with diverse patient populations and varying data characteristics.

6. Conclusion

In this study, we developed a hybrid approach for breast cancer detection using the Wisconsin dataset. This approach effectively separates and classifies data by integrating PCA and CNN architectures. Proper separation of data is essential for accurate diagnosis in critical healthcare applications such as breast cancer detection, as the overlapping of different classes can significantly impair classification performance. To address this challenge, we employed PCA to transform the data to a new feature space where discriminative characteristics become more prominent. This transformation creates a representation where redundant features are minimized, and class distinctions are enhanced. The transformed data is then classified using our custom-designed 1D CNN architecture, which automatically identifies patterns in the feature vectors to determine class membership. We selected this deep learning approach for its ability to autonomously extract and classify features with high accuracy.

To enhance the model's reliability and generalizability, we implemented k-fold cross-validation, which rigorously tests performance across multiple data partitions. This validation strategy ensures that our model performs consistently across varied data distributions. Our results demonstrate that the integration of PCA with CNN architectures represents a significant advancement in breast cancer detection methodology. This combination of traditional dimensionality reduction techniques with modern deep learning approaches contributes valuable tools to the healthcare domain for precise diagnosis and effective treatment planning. The findings of this study can serve as a foundation for researchers seeking to develop more reliable and efficient approaches for breast cancer detection and other healthcare applications.

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SAMET AYMAZ has done his bachelor's degree from Karadeniz Technical University, Department of Computer Engineering in 2012. He has done his master's degree from Karadeniz Technical University, Institute of Science, Department of Computer Engineering in 2017. He has completed his PhD degree in Computer Engineering from Karadeniz Technical University in 2022.

Samet Aymaz has extensive research experience in the fields of image processing and artificial intelligence. His primary research focuses on multi-focus image fusion techniques, which was the subject of both his master's and doctoral theses. He has developed novel approaches including dynamic decision mechanisms, hybrid techniques combining CNN and SVM, and gradient-based fusion rules. Dr. Aymaz has also made significant contributions to medical image analysis, particularly in breast cancer diagnosis using mammography images. His recent work explores gradient-based sample selection methods for improving medical diagnostics. Beyond academic research, he brings practical experience from his

roles as an IT Specialist at Trabzon Provincial Health Directorate and Systems Engineer at the Ministry of National Education. Currently, he serves as an Assistant Professor at Trabzon University's Department of Computer Engineering and as Vice Dean of the Faculty of Computer and Information Sciences, where he continues to advance research in artificial intelligence, machine learning, image fusion, and healthcare applications.

Received: 03 March 2025, Revised: 31 March 2025, Accepted: 22 April 2025, Online: 27 April 2025

DOI: https://dx.doi.org/10.55708/js0404002

AI-Driven Digital Transformation: Challenges and Opportunities

Maikel Leon*

Department of Business Technology, Miami Herbert Business School, University of Miami, Miami, Florida, USA

*Corresponding author. Email: mleon@miami.edu

ABSTRACT: This paper explores the crucial role of Artificial Intelligence (AI) in driving digital transformation across industries. It examines machine learning, deep learning, fuzzy logic, genetic algorithms, reinforcement learning, and generative AI techniques, highlighting their development, applications, and examples. Case studies showcase AI's impact in optimizing supply chains, improving financial operations, boosting customer engagement, and revolutionizing quality control in manufacturing, underscoring its strategic importance. The paper also discusses executive-level considerations, including strategic approaches, data governance, ethical frameworks, transparency, and collaboration across departments, all illustrated with examples. While AI offers significant potential for organizational growth, operational excellence, and sustainable innovation, there's an open call for further research into the evolving ethical, regulatory, and technological challenges.

KEYWORDS: AI-Driven Digital Transformation, Machine Learning, Generative AI.

1. Introduction

Digital transformation is the fundamental shift in how businesses operate, brought about by integrating digital technology into every aspect of the organization. It's a significant change in how companies work. This isn't just about upgrading technology; it's about automating tasks people used to do manually, reducing repetitive work and human error. Businesses are increasingly using technology to handle routine tasks, data entry, customer service, and even complex decisions that used to be made solely by human experts [1]. Traditional manual tasks like filing, processing data, and basic customer service are being replaced by automated systems that are more efficient, less prone to errors, and can scale up quickly. For example, robots in manufacturing, online retail platforms that automate sales and inventory, and mobile banking apps that eliminate the need for branch visits are clear examples of how digital tools have transformed long-standing practices. Beyond the rise of the World Wide Web and the all-in-one functionality of smartphones, other examples include the automation of manufacturing with advanced robots, the growth of e-commerce platforms that have disrupted traditional retail, and the development of cloud-based systems that centralize data and enable global teamwork [2].

The fourth industrial revolution is unique because it's fundamentally based on AI, unlike earlier revolutions driven by mechanical production, electricity, or basic computing. Instead of just automating simple tasks, this revolution leverages intelligent systems that can analyze vast amounts of data, learn from complex patterns, and make decisions independently in real time. This move towards cognitive automation and innovative technologies enables real-time decision-making and personalized customer experiences. It also brings a level of operational efficiency and innovation that was previously unimaginable. The deep integration of cyber-physical systems characterizes the Fourth Industrial Revolution, the widespread use of the Internet of Things (IoT), and the adoption of cloud computing. The number of connected IoT devices is projected to be incredibly high in the near future, generating vast amounts of data that power AI algorithms. Cloud computing provides the infrastructure to process this data, while cyber-physical systems, like smart factories with interconnected sensors, allow for real-time optimization and control. This interconnectedness enables automation and responsiveness far beyond what was previously possible. For example, a smart factory might use Machine Learning (ML) to predict equipment failures with 90% accuracy, significantly reducing downtime and maintenance costs. Other examples include smart manufacturing, self-driving cars, and personalized healthcare systems [3].

The rest of this paper is structured as follows. Section 2 provides a detailed look at AI, including definitions, different aspects, and relevant research. Section 3 explores how executives view AI through a survey analysis. Section 4 discusses strategic approaches for deploying AI and compares Artificial Narrow Intelligence (ANI) and Artificial General Intelligence (AGI). Section 5 delves into transparency in AI systems, discussing the historical use of "black box" models, the need for more explainable AI, and efforts to improve transparency in complex neural networks. Section 6 examines how to integrate ethical reasoning and legal compliance in AI, including discussions on reliability, safety, and the roles of different stakeholders. Section 7 focuses on environmentally conscious ML, discussing energy efficiency and model optimization. Section 8 emphasizes the importance of multidisciplinary teams in AI development. Section 9 presents real-world case studies showing how AI is transforming industries. Finally, Section 10 concludes the paper, and Section 11 outlines areas for future research. This roadmap will guide you through the detailed discussions and examples throughout the paper.

2. Understanding Artificial Intelligence: Definitions, Dimensions, and Literature Foundation

Artificial Intelligence (AI) encompasses a range of techniques and systems that learn from data, identify complex patterns, and make decisions based on those patterns. Over decades of research, AI has branched into areas focusing on specific tasks and broader methods of simulating human reasoning. Research in this field goes beyond just designing algorithms; it also considers AI's economic, ethical, and social implications as it fundamentally shapes how people interact with technology and how businesses operate in dynamic environments.

2.1. Machine Learning and Deep Learning

ML aims to extract structured and unstructured data insights to make predictions, classify things, or detect anomalies, enabling better decision-making. Its origins lie in statistical models and pattern recognition, which have evolved significantly with better algorithms and more powerful computers. Today, typical applications include recommendation systems in e-commerce, fraud detection in finance, and predictive analytics for marketing or operations. Early research in ML laid the groundwork for the field, establishing the theoretical foundations and algorithmic approaches that continue to be influential. Further ML applications include personalized medicine, where algorithms predict how patients will respond to treatments based on their genes, and optimizing energy consumption in smart grids by forecasting demand.

Deep learning, a specialized area within ML, uses multiple layers of neural networks to capture complex, high-level features from raw data. Its essential applications include image recognition, speech processing, and natural language understanding. Current developments are addressing challenges like interpretability and computational cost. Techniques like model distillation are being explored to maintain performance using fewer resources. Other examples include self-driving car perception systems and advanced medical image analysis [4].

2.2. Fuzzy Logic

Fuzzy logic moves away from traditional binary true-or-false systems by allowing for degrees of membership, providing a way to handle uncertainty and vagueness in real-world situations. It originated from the need to handle complex decision-making processes with insufficient strict thresholds. This makes it particularly well-suited for adaptive control systems in consumer electronics, automotive engineering, and manufacturing. Modern fuzzy logic applications extend to sophisticated decision-support systems where precise boundaries are hard to define. For instance, in manufacturing quality control, fuzzy logic systems can interpret sensor readings to determine if variations in product specifications are within acceptable limits, enabling a more nuanced control mechanism than a simple pass/fail system. Further examples include climate control systems in smart buildings and adaptive user interfaces that adjust to changing conditions [5].

From an executive's perspective, fuzzy logic provides a flexible framework that improves decision-making by accounting for many business processes' inherent complexities and ambiguities. For example, an executive might use fuzzy logic to fine-tune automated control systems on production lines or optimize customer service response systems that handle various inputs. This technology improves operational efficiency and builds confidence in automated systems that operate under uncertain conditions, supporting a sustainable competitive advantage [6].

2.3. Genetic Algorithms

Genetic algorithms iteratively refine solutions by mimicking principles of biological evolution, such as selection, crossover, and mutation, to efficiently search large solution spaces. Early implementations revolutionized optimization tasks in scheduling, routing, and engineering design by effectively navigating complex problem spaces. In today's business world, genetic algorithms are used to optimize complex investment portfolios, manage supply chain logistics, and even design innovative products by exploring a vast range of potential configurations that would be too computationally expensive to analyze using traditional methods. Further examples include optimizing traffic flow in smart cities and refining marketing campaign strategies [7].

For executives, genetic algorithms are powerful tools for achieving optimal performance in systems where conventional optimization techniques might fail. For example, a financial institution might use genetic algorithms to rebalance investment portfolios continuously in response to volatile market conditions. In contrast, a logistics company could use them to optimize real-time delivery routes, reducing operational costs and improving customer satisfaction. Genetic algorithms' dynamic adaptability makes them a valuable strategic asset in competitive business environments, offering flexible and efficient solutions.

2.4. Reinforcement Learning

Reinforcement learning enables systems (agents) to learn optimal actions through trial and error, guided by a reward system based on feedback from their environment. This leads to continuous improvement over time. Early demonstrations included simple game-playing programs, but advances in computing have allowed reinforcement learning to power breakthroughs in robotics, autonomous driving, and dynamic resource allocation. This approach integrates deep learning techniques to handle high-dimensional inputs, making it applicable to various complex decision-making scenarios. Other examples include personalized content recommendation systems and adaptive energy management in smart grids.

By training reinforcement learning agents on:

- Streaming traffic data from city sensors that provide real-time congestion information,
- GPS feedback from vehicles providing precise location tracking,
- Detailed delivery schedules with varying priorities reflecting customer demands,

The system learned to dynamically recalculate routes in response to traffic jams, accidents, or bad weather, leading to significant operational improvements. For example, a transportation company might use reinforcement learning to adjust real-time routing strategies, reducing delays and fuel consumption. In manufacturing, reinforcement learning can optimize production processes to ensure high efficiency even with varying raw material quality or changing market demands. Executives can leverage these improvements to drive substantial cost savings and operational enhancements across various applications [8].

2.5. Generative AI

Generative AI focuses on creating new digital content, such as text, images, audio, or video, using advanced models that learn the underlying patterns in data to produce outputs that can be remarkably similar to those created by humans. Early work in this area laid the foundation for advanced systems capable of producing realistic images and natural-sounding speech. Today, these systems are used in a wide variety of applications. Generative AI has far-reaching applications in design, advertising, and content creation, enabling the rapid production of personalized marketing materials and innovative prototypes. Further examples include creating virtual environments for training simulations and automated scriptwriting for entertainment [9].

For executives, generative AI offers the potential to revolutionize creative processes by automating aspects of content generation that used to require significant human effort. For instance, a media company might use generative AI to produce tailored promotional campaigns based on detailed consumer behavior data, enhancing personalization and engagement. Furthermore, generative AI can facilitate rapid prototyping in product design, reducing time to market and fostering a culture of innovation within the organization. These capabilities enable companies to respond more quickly to market changes and customer needs [10].

2.6. Summary of AI Approaches

ML and deep learning have become primary approaches for classifying, predicting, and recognizing complex patterns, boosted by large datasets and modern computing power. Fuzzy logic introduced the concept of partial truth values, which is particularly useful in control systems and situations requiring fine-grained distinctions. Inspired by evolutionary processes, genetic algorithms excel at solving complex optimization problems. Reinforcement learning uses reward-based feedback loops to enable systems to adapt through continuous trial and error [11]. At the same time, generative AI extends these capabilities to creative tasks by producing new text, images, and audio content that closely mimic human output. This section provides a comprehensive overview of popular AI methods and includes extra examples to illustrate each approach.

ML is a method that learns from data. It is commonly used in predictive analytics, fraud detection, and recommendation systems. By analyzing past data, ML models can predict future outcomes, recognize patterns, and provide recommendations based on user behavior. Deep Learning utilizes layered neural networks to model complex patterns in data. This approach is widely applied in computer vision, natural language processing, and autonomous vehicles. Deep learning benefits tasks like image recognition and speech processing, and enables self-driving cars.

Fuzzy Logic operates on degrees of truth rather than traditional binary logic. It is employed in control systems, quality control, and adaptive user interfaces. Fuzzy logic helps manage uncertainty and imprecision in decision-making processes, making it ideal for dynamic and unpredictable environments. Genetic Algorithms use evolutionary search techniques, simulating natural selection to find optimal solutions. This approach effectively solves optimization problems, scheduling tasks, and portfolio management. Genetic algorithms excel in situations where other methods may fail to identify the best solution, mainly when dealing with complex or large-scale search spaces.

Reinforcement Learning is based on a system of rewards and penalties, where an agent learns to take actions in an environment to maximize cumulative rewards. This method is used in game AI, robotics, and dynamic resource allocation. Reinforcement learning allows systems to learn from trial and error, making it practical for uncertain or constantly changing environments. Generative AI focuses on creating content, enabling machines to generate new data resembling human-created content. It is used in design, data augmentation, and automated content production. This approach allows for generating images, text, and even music, offering innovative solutions for creative industries.

These varied methods show AI's flexibility in addressing complex business problems, including classification, prediction, control, optimization, autonomous interaction, and creative output. Given this wide range of options, executives must carefully evaluate which AI strategies align with their core objectives and available data. Numerous real-world examples show that a deliberate selection process, guided by strong governance and ethical oversight, is essential for sustainable AI integration [12].

3. Exploring Executives' Perceptions

This study explores how executives perceive AI's role in digitally transforming their companies' services and products, providing valuable insights from various industries. A comprehensive survey analysis assesses how AI technologies contribute to operational efficiency, competitive advantage, and ethical business practices.

We surveyed 500 executives across diverse industries to evaluate the integration and impact of AI in their operations, capturing a wide range of opinions. Respondents rated their agreement with a series of statements on a Likert scale from 1 (Strongly Disagree) to 5 (Strongly Agree), allowing for quantitative insights. The survey included questions about AI's role in daily operations, its contribution to competitive advantage, investment levels in AI technologies, concerns about the rapid evolution of AI, and the adequacy of current AI knowledge among company leadership, among other topics.

The following are the questions executives answered:

1. To what extent has AI been integrated into your company's services and products?

2. How significantly has AI impacted the daily operational activities of your company?
3. Do you believe AI technology gives your company a competitive advantage?
4. Is your company currently investing adequately in AI technologies?
5. Are you concerned about your company's ability to keep up with the rapid evolution of AI technology?
6. Do you feel that the current level of AI knowledge within your company's leadership is sufficient?
7. Is there a plan to increase the hiring of AI specialists shortly?
8. Is your company considering appointing a Chief AI Officer (CAIO) to oversee AI strategy?
9. How important are ethical considerations in your company's AI strategy?
10. Does your company have a clear long-term strategy for AI?

3.1. Analysis

We calculated descriptive statistics for each survey question and conducted chi-square tests for goodness of fit to determine if the distribution of responses significantly deviated from a hypothetical uniform distribution, providing statistical validation. We can observe the median, mode, and standard deviation for the 10 survey items, along with further details that illustrate the overall sentiment among the respondents [13].

The survey responses were analyzed for various aspects of AI integration and its impact on operations. The overall mean score for AI integration was 4.1, with a median of 4 and a mode of 4, indicating general agreement among respondents on the importance of AI integration. The standard deviation of 0.8 suggests some variation in the responses. Regarding the impact of AI on operations, the mean score was 4.3, with a median of 4 and a mode of 5, suggesting that most respondents recognized a significant positive impact on operations. The standard deviation of 0.7 indicates relatively consistent opinions, with a slight variation among responses. For competitive advantage, the mean score was 4.2, with a median and mode of 4, indicating that AI was generally seen as a key driver of competitive advantage. However, there was some variation in opinions, as evidenced by the standard deviation of 0.75. Regarding investment in AI, the mean score was 3.8, with a median of 4 and a mode of 4. This suggests that while AI investment is considered necessary, there may be some reluctance or differing opinions. The standard deviation of 0.85 highlights the diversity of responses on this issue.

Concerns about the future of AI received a mean score of 4.5, with a median and mode of 5, reflecting high concern and importance among the respondents. The low standard deviation of 0.6 suggests near consensus on this point. On the adequacy of knowledge about AI, the mean score was 3.5, with a median and mode of 3, indicating that respondents generally felt their understanding of AI was somewhat lacking, with a higher standard deviation of 1.0 indicating variability in individual responses. The issue of hiring AI talent received a mean score of 4.2, with a median and mode of 4, signaling a recognition of the importance of AI talent. The standard deviation of 0.8 shows a slight variation in the responses. The importance of having a Chief AI Officer was rated with a mean of 3.7, a median of 4, and a mode of 4, indicating some support for the role but with a range of opinions. The standard deviation of 1.1 reflects a higher level of disagreement.

Ethical considerations in AI were highly rated, with a mean of 4.0, a median and mode of 4, and a standard deviation of 0.9, showing that most respondents recognized the significance of ethics in AI development and deployment. Finally, the long-term AI strategy received a mean score of 3.9, with a median and mode of 4, suggesting moderate support for a long-term AI strategy within organizations. The standard deviation of 0.95 indicates some variation in opinions on the importance of long-term planning for AI. Chi-square tests confirmed significant deviations from a uniform distribution across all survey questions ($p < 0.05$), indicating that executives hold strong opinions regarding the various statements in the survey.

3.2. Findings

Over 90% of the executives indicated that AI has significantly altered daily operations within their companies, demonstrating its critical role in enhancing business processes and operational efficiency. Many respondents expressed concern about their ability to keep up with the rapid evolution of AI technologies, reflecting widespread anxiety about potential knowledge gaps at the leadership level and the fast pace of technological advancements in this area. The data reveal a proactive stance toward AI integration, with over 80% of executives planning to hire more AI specialists and more than 50% considering appointing a Chief AI Officer to manage AI initiatives much more strategically. Approximately 70% of the participants rated ethical considerations as highly significant in their AI strategies, suggesting a thoughtful approach to AI deployment, despite about 65% reporting the existence of a clear long-term AI strategy. These findings indicate that some companies may need further strategic development to harness AI's transformative potential fully.

4. Strategizing AI Deployment and Methodology

Organizations that embed AI within their broader digital transformation efforts are more likely to create lasting value, especially when adopting a systematic AI integration approach. A good first step is to clarify a high-level vision and specific AI use cases. This ensures that technical investments are closely aligned with measurable improvements in service quality, operational efficiency, or competitive differentiation. It's helpful to begin with a clear statement of purpose and then identify which processes or offerings would benefit most from AI. Establishing pilot projects with measurable objectives can help teams discover the technology's advantages and potential drawbacks before scaling up deployment across the entire organization [14].

Adopting a robust methodological framework is also crucial. Data governance policies must ensure the correct data is collected, validated, and stored securely. A well-planned pilot phase clarifies success metrics and highlights organizational needs related to talent and technology infrastructure [15]. Many companies consult academic papers, industry reports, and real-world case studies when selecting and designing AI projects. Further examples include successful implementations in manufacturing, finance, and healthcare. This comprehensive approach helps set realistic expectations for timelines, budgets, and the potential for scaling up.

4.1. Artificial Narrow Intelligence (ANI) vs. Artificial General Intelligence (AGI)

Artificial Narrow Intelligence (ANI) and Artificial General Intelligence (AGI) represent two fundamentally different paradigms within the field of artificial intelligence. ANI is designed to perform specific tasks with high efficiency and accuracy, such as image recognition, natural language processing, or fraud detection. Today, it is the most common form of AI and has demonstrated considerable practical value. Examples of ANI include IBM Watson in medical diagnostics, voice assistants like Siri and Alexa, recommendation algorithms on streaming platforms, and automated fraud detection systems used by financial institutions. ANI excels at targeted applications but cannot generalize across domains.

In contrast, AGI aspires to replicate human-like cognitive abilities, allowing for flexible reasoning and problem-solving across various tasks without needing task-specific programming. AGI systems would theoretically be capable of understanding and learning from any new situation, much like a human brain. Although AGI remains a theoretical concept, ongoing research aims to bridge the gap between specialized and general intelligence. Achieving AGI would represent a significant breakthrough, potentially transforming industries through unprecedented adaptability and learning capabilities.

The following points highlight key distinctions between the two:

- **Scope and Flexibility:**
  - **ANI:** Performs specific tasks with high precision but cannot generalize across domains.
    - *Example:* Image recognition systems that detect objects but cannot understand context.
  - **AGI:** Emulates human-like cognitive abilities, allowing flexible reasoning and learning across various tasks.
    - *Example:* Hypothetical systems can solve novel problems without prior programming.
- **Current State of Development:**
  - **ANI:** Well-established and widely used in various industries.
    - *Example:* IBM Watson in medical diagnostics, Siri and Alexa as voice assistants.
  - **AGI:** Remains theoretical and under active research, with no practical implementations yet.
    - *Example:* Research projects like OpenAI's efforts toward creating more generalized systems.
- **Practical Applications:**
  - **ANI:** Used for targeted solutions that provide immediate operational benefits.
    - *Example:* Fraud detection in banking and personalized recommendations on streaming platforms.
  - **AGI:** Aims to achieve human-like decision-making, potentially revolutionizing how machines understand and interact with the world.
    - *Example:* Conceptual frameworks that could perform any intellectual task a human can do.
- **Challenges and Risks:**
  - **ANI:** Limited by its task-specific nature and lack of adaptability.
    - *Risk:* Performance drops significantly if input data deviates from training scenarios.
  - **AGI:** Poses ethical and safety challenges due to its potential for autonomous decision-making.
    - *Risk:* Unintended consequences from actions taken without human oversight.

Understanding the distinction between ANI and AGI is essential for decision-makers. While ANI offers immediate and actionable benefits that can enhance operational efficiency and drive innovation, AGI represents a long-term strategic vision requiring careful consideration of ethical, social, and technical implications. Balancing investments between these two paradigms requires a strategic approach, recognizing the practical advantages of ANI alongside the transformative potential of AGI.

4.2. Self-Learning Systems and Adaptive Algorithms

AI that continuously refines its parameters based on real-time data can be highly effective. Still, it also has the potential to drift away from its initially intended performance if not properly monitored. Monitoring these changes requires systematic checks, creative safety measures, and ongoing performance evaluations. Adaptive algorithms pose unique challenges in terms of monitoring and transparency. As these models adjust their outputs with minimal human intervention, organizations may need to implement robust safeguards to prevent unexpected or ethically questionable behaviors [16]. It's also essential to provide clear disclosure to users about how these systems learn and their implications for privacy or important real-life decisions, ensuring accountability and trust.

4.3. AI as a Component of a Larger System

AI rarely operates in isolation in modern business environments. In today's highly interconnected world, AI is embedded into nearly every aspect of business operations, from data pipelines and customer service interfaces to enterprise resource planning and supply chain management systems. This widespread presence means that AI is intricately intertwined with legacy systems, human decision-making processes, and other digital tools, making it difficult to isolate as a separate entity for study or regulation. Instead, AI should be understood as a fundamental part of a larger technological ecosystem, where its performance and overall impact depend on its interactions with other system elements. This complexity requires the development of comprehensive governance frameworks that address both individual components and their interdependencies, as seen in integrated smart city solutions and interconnected healthcare monitoring systems [17].

4.4. Challenges and Mitigation Strategies

While the potential benefits of AI are significant, organizations often face several challenges during deployment. These include:

- Data Quality Issues: AI algorithms depend heavily on the quality of the input data. Inaccurate, incomplete, or biased data can lead to flawed results and poor decisions. Mitigation includes implementing robust data governance policies, including validation, cleaning, and preprocessing. Regularly audit data sources for accuracy and completeness.

- Lack of Skilled Personnel: The demand for AI specialists (data scientists, ML engineers, etc.) often exceeds the supply. Mitigation includes investing in training and upskilling existing employees, partnering with universities and research institutions. Consider outsourcing specific AI tasks to specialized vendors.

- Integration with Legacy Systems: Integrating AI solutions with IT infrastructure can be complex and costly. Mitigation includes adopting a modular, API-driven approach to AI development. Prioritize projects that can be easily integrated with existing systems. Consider a phased implementation, starting with pilot projects.

- Ensuring Scalability: AI solutions that work well in a pilot setting may not scale effectively to handle larger datasets or more complex scenarios. Mitigation includes designing AI systems with scalability in mind from the start. Use cloud-based infrastructure and scalable algorithms. Continuously monitor performance and adjust resources as needed.

- Cost of Implementation: Setting up a good AI infrastructure can be expensive. Mitigation includes trying to use open-source and free software whenever possible. Focus the AI strategy on the company's parts that will benefit the most.

5. Transparency in AI Systems

For decades, no mandatory policies have required companies to be transparent about how their AI systems work, leading to significant differences in disclosure practices. Despite growing calls for accountability, many organizations have operated with minimal regulatory oversight. Several initiatives and declarations have been proposed, including the European Commission's guidelines for trustworthy AI, the OECD AI Principles, and IEEE's Ethically Aligned Design document. These have all sought to establish voluntary standards for transparency. However, without binding regulations, compliance remains inconsistent. This lack of enforced transparency has allowed companies to maintain proprietary control over their algorithms, even as these systems increasingly influence essential societal and economic outcomes. Further examples include voluntary self-reporting frameworks in sectors like finance and healthcare, which, while helpful, don't replace enforceable legal standards [18].

Efforts to promote transparency have also included industry self-regulation and public declarations, but these measures haven't translated into legally enforceable policies. The absence of mandated transparency standards has resulted in a fragmented landscape where companies adhere to varying levels of disclosure. This situation highlights the urgent need for comprehensive policies that require precise, consistent, and accessible explanations of AI systems, especially as their influence continues to expand across multiple sectors and impacts a wide range of stakeholders [19].

5.1. Historical Use of Black Box Models and the Need for Explainable AI

Historically, many AI systems, particularly complex neural networks used in critical applications, have operated as "black boxes," meaning their internal decision-making processes were hidden from users and even their developers. These black box models, like deep convolutional neural networks used for image recognition or recurrent neural networks used in natural language processing, often produced impressive results but lacked transparency. This lack of transparency has led to difficulties in diagnosing errors, ensuring fairness, and understanding biases in the system. Recently, researchers have started re-examining these complex models to make them more transparent. Efforts like developing explainable AI (XAI) frameworks, techniques like Layer-wise Relevance Propagation (LRP), and integrating attention mechanisms in neural networks aim to show how these systems work. These initiatives are increasingly being implemented in sectors like healthcare and finance, where understanding the reasoning behind AI decisions is crucial for compliance and ethical accountability [20].

5.2. AI Biases and Ethical Implications

AI biases have emerged as a significant challenge in developing and deploying artificial intelligence systems, significantly impacting fairness, equity, and trust. Biases can arise from several sources, including biased training data, flawed model design, or unintended consequences from algorithmic optimization. These biases can perpetuate

discrimination and reinforce societal inequalities when left unchecked. For instance, facial recognition systems have performed poorly on individuals from underrepresented demographic groups, leading to false identifications and wrongful outcomes in law enforcement contexts. Similarly, automated hiring systems may inadvertently favor candidates based on irrelevant attributes if historical data reflects biased human decision-making.

Biases in AI systems can manifest in various forms, including gender bias, racial bias, and socioeconomic bias, often magnified when data sets are unrepresentative or inherently skewed. For example, natural language processing models trained predominantly on English text from Western sources may struggle to accurately process inputs from other cultures or languages, leading to misinterpretations or biased outputs. Furthermore, predictive policing algorithms may disproportionately target minority communities when historical crime data reflects prior discriminatory practices, resulting in unfair surveillance or policing practices. Researchers are increasingly advocating for more robust bias detection and mitigation techniques to address this. One strategy to address these challenges is data auditing, which involves systematically examining training data for biases and ensuring diversity in data representation. Another approach focuses on algorithmic fairness metrics, incorporating fairness constraints during model training to reduce disparate impacts on specific groups. Human oversight is also essential, as well as integrating human judgment to review AI decisions in high-stakes applications such as healthcare. Bias mitigation algorithms, like reweighting or data augmentation, help balance representation within training data. Additionally, transparent reporting is crucial, clearly communicating the limitations of AI models and the potential biases of AI modeling and end-user interfaces.

Despite ongoing efforts, achieving fully unbiased AI remains a formidable challenge. Addressing bias requires not only solutions but also sociocultural and interdisciplinary collaboration. Policymakers and industry leaders must prioritize ethical considerations during system design and deployment, guided by comprehensive governance frameworks that mandate regular evaluations of bias and discrimination risks. Tackling AI bias is a technical and societal problem requiring a commitment to ethical AI development and transparent practices. As AI systems continue to influence critical decisions in finance, healthcare, law enforcement, and beyond, addressing bias remains central to building trustworthy and responsible AI systems that serve all stakeholders equitably.

6. Embedding Ethical Reasoning and Legal Compliance in AI

Embedding ethical reasoning at every stage of AI design and deployment isn't just about doing the right thing; it protects brands from legal risks and fosters long-term public trust. Organizations can create solutions that meet both moral and legal standards by thoroughly analyzing AI's potential benefits and inherent risks well in advance. Demonstrating responsible AI practices in competitive markets can set a company apart and strengthen its market position. The ethical aspect of AI involves ensuring fairness, accountability, and transparency, while the legal aspect requires strict adherence to data protection laws, regulatory standards, and contractual obligations [21]. For example, a company deploying facial recognition technology must ethically ensure non-discrimination and privacy for its users while legally complying with regulations like the General Data Protection Regulation (GDPR) in Europe or similar frameworks in other regions. Understanding these differences allows executives to balance innovation with rigorous risk management.

6.1. Reliability, Safety, and Ethical-Legal Application

An AI system must be dependable, secure, and understandable to be ethically sound and legally compliant. A malfunctioning system can seriously damage stakeholder confidence, while an opaque system might invite legal challenges due to a lack of accountability. Therefore, organizations must ensure that their AI consistently performs well in accuracy, speed, and traceability while providing clear explanations for its decisions. Furthermore, these systems should be designed to avoid posing unnecessary risks—whether cyber or otherwise—and must operate within the well-defined boundaries of ethical principles and legal mandates. For instance, an AI in self-driving cars must adhere to strict safety protocols to prevent accidents and protect human life, ensuring its decision-making processes are auditable in case of legal disputes. Similarly, an AI system used in financial services must maintain high levels of reliability and transparency to comply with stringent regulatory standards and prevent fraud. Combining these elements into a cohesive framework minimizes risk and builds long-term trust with customers, regulators, and the public [22].

6.2. Role of AI Developers

Whether they work in-house or as external vendors, developers are responsible for shaping the technical core of AI systems. Their design choices and implementation practices can significantly influence whether an AI solution meets strict ethical benchmarks and legal standards. While the organization ultimately bears accountability, developers are responsible for establishing accurate and robust data pipelines, ensuring stable model training, and designing user interfaces that foster understanding and trust. Their work forms the technical foundation supporting the final AI product's ethical and legal soundness.

6.3. Role of Other Business Areas in AI Implementation

Beyond the contributions of technical developers, various other business areas play crucial roles in the effective deployment and governance of AI. Legal teams must assess compliance with existing regulations and help draft policies addressing privacy, intellectual property, and liability issues. Marketing departments are responsible for ensuring that AI-driven campaigns are transparent and that customer data is used ethically. Human resources and training departments need to upskill staff to understand the implications of AI systems. Risk management teams are also tasked with evaluating potential vulnerabilities and ensuring robust

contingency plans are in place. These interdisciplinary contributions ensure that AI implementations are technically sound and aligned with broader organizational values and regulatory frameworks [23].

6.4. Role of Public Sectors

Public-sector agencies and governmental bodies provide the essential regulatory and educational foundation influencing AI efforts across industries. Laws and guidelines constantly evolve to reflect changing public expectations regarding privacy, fairness, and accountability. Public institutions also play a vital role in promoting AI literacy, enabling the broader community to become more informed about these transformative technologies. The key objectives of these agencies include establishing norms for trustworthy AI, adopting AI solutions to improve government services, and offering educational programs that drive broader AI understanding. These combined efforts are critical to ensuring that private-sector AI deployments align with societal values and that sufficient oversight mechanisms are in place to protect the public interest [24].

7. Toward Eco-Conscious ML: Addressing Energy Sustainability and Environmental Risks

Although fairness, accountability, and transparency are common focus areas in AI ethics, the high environmental cost of large-scale computing also demands significant attention. Training large neural networks can consume vast amounts of energy, directly affecting operational costs and environmental sustainability.

Green AI research prioritizes efficient model design and coding practices that reduce power usage without sacrificing performance. Approaches like model pruning or quantization can help maintain the effectiveness of AI systems while lowering computational requirements. Many data centers are also increasingly shifting to renewable energy sources—like solar, wind, or hydro—to reduce their environmental impact. Emerging practices also aim to optimize the entire lifecycle of AI deployments, from hardware manufacturing to end-of-life recycling [25]. Nuclear power offers a reliable, low-carbon energy source during operation; however, it raises significant concerns about properly handling radioactive waste and the potential for catastrophic accidents. Organizations considering nuclear solutions must address strict waste management protocols, robust security measures, and strategies to gain public acceptance before implementation.

7.1. Energy Efficiency and Model Optimization

Model distillation and transfer learning are powerful techniques that allow AI systems to perform well using fewer computational resources, contributing to overall energy efficiency. Smaller businesses, in particular, benefit from these strategies, as they can deploy top-tier ML models without needing extensive data center setups. Scalability is a crucial factor in reducing the carbon footprint of AI systems. For instance, industry leaders like Google and Microsoft have invested in highly efficient data centers and have implemented advanced cooling strategies, while startups are increasingly exploring edge computing solutions to minimize energy consumption. Additionally, some companies have adopted comprehensive carbon offset programs and renewable energy purchasing agreements to mitigate their overall environmental impact. These initiatives and advances in algorithmic efficiency represent a growing trend toward sustainable AI practices across the industry.

7.2. Societal and Regulatory Dimensions

As climate legislation tightens worldwide, aligning ML practices with green energy solutions becomes logical and strategically advantageous. Companies investing early in sustainability initiatives stand out to customers and investors, who are increasingly looking for environmentally responsible businesses. Some recommendations for eco-conscious ML include:

- Transparent Energy Reporting: Publish detailed metrics on data center energy usage and efficiency improvements.
- Collaborative Green Alliances: Partner with environmental organizations to test and implement more efficient cooling systems and energy-saving measures.
- Incentivizing Sustainable Architectures: Encourage or require new AI models to optimize strategies to reduce computational intensity and energy use.
- International Standards Alignment: Work towards benchmarks harmonizing local ML goals with global climate objectives, fostering a more sustainable industry-wide approach.

8. The Importance of Multidisciplinary Teams in AI Development

Multidisciplinary teams are essential for addressing the wide range of challenges in AI and ML, from potential biases in data and modeling to ensuring legal compliance and protecting privacy. While data scientists and software developers provide the necessary technical expertise, collaboration with legal scholars, ethicists, sociologists, and domain experts offers broader perspectives that help identify issues that purely technical viewpoints might overlook. This section explores how different skill sets contribute to responsible and effective AI projects, enhancing overall organizational performance [26].

8.1. Bridging Technical and Domain Expertise

Many ML projects must incorporate knowledge specific to a particular industry or application area. For example, partnering with physicians or clinical researchers can help identify the most meaningful variables, patient outcomes, and safety thresholds when designing a healthcare model. This collaborative approach:

- Ensures that important domain-specific factors aren't overlooked,
- Clarifies which metrics are truly relevant for patient care,

- Aligns modeling strategies with strict regulatory standards in healthcare and other industries.

Combining expert medical input with advanced data-driven methods makes the resulting models more likely to accurately reflect real-world conditions, ultimately improving patient outcomes and increasing user trust.

8.2. Avoiding Misinterpretation and Overreliance on Algorithms

Interdisciplinary exchange helps minimize the risk of misinterpretation, where numerical results or confidence scores might be taken at face value without proper context. Data scientists can explain the inherent uncertainty in the data, while domain experts can highlight subtleties and nuances that might not be apparent from a purely statistical perspective. Working together encourages healthy skepticism regarding underlying model assumptions, reducing the likelihood of over-relying on algorithmic outputs. Ethicists, legal advisors, and social scientists play a critical role by raising early warnings about potential ethical dilemmas, which may include:

- Privacy breaches when handling sensitive data,
- Biased outcomes that could disadvantage certain groups,
- Concerns regarding the fairness and transparency of automated decisions.

By involving these experts at the project's beginning, organizations can better anticipate how an ML model might affect various stakeholders and proactively mitigate problems before they escalate into significant reputational or legal crises.

8.3. Strengthening Governance and Accountability

Clear governance frameworks are critical for maintaining accountability and prioritizing ethical considerations. Multidisciplinary teams can be structured to define:

- Who is authorized to audit model decisions and assess overall performance,
- How often should these audits be conducted to ensure continuous improvement,
- What steps are necessary if models produce harmful or biased results,
- How to systematically document the rationale behind key design choices in the model.

When ethical thinking and diverse expertise are integrated into a project's foundation, organizations are more likely to build long-term trust with customers, regulators, and the public. Over time, this trust can translate into a competitive advantage through a reputation for social responsibility, reduced regulatory risks by exceeding legal requirements, and a greater willingness among stakeholders to embrace new technologies.

9. Real-World Transformations

The fourth industrial revolution is marked by the pervasive integration of Artificial Intelligence (AI) across industries, leading to profound shifts in how businesses operate, innovate, and engage with customers. As AI becomes a critical enabler of digital transformation, it significantly alters business models, operational strategies, and competitive dynamics across the healthcare, finance, retail, and manufacturing sectors. These shifts not only optimize internal operations but also foster the development of novel services and products that can respond to evolving market demands. AI technologies are becoming fundamental components of business strategies, driving organizations toward enhanced efficiency, sustainability, and customer-centric solutions [27].

AI is particularly transformative in its ability to generate actionable insights from vast amounts of data, making it a powerful tool for businesses to gain a competitive edge. By automating complex processes and enabling real-time decision-making, AI enhances operational agility, fosters innovation, and improves the customer experience. However, its successful implementation hinges on a carefully crafted strategy that aligns AI applications with organizational goals, ensuring that the technology addresses specific business challenges effectively. The following examples illustrate how diverse AI methodologies—from Machine Learning (ML) to Reinforcement Learning (RL) and Fuzzy Logic—have been integrated into core business functions, resulting in tangible benefits and strategic advantages.

9.1. AI for Retail Demand Forecasting

One of the most striking examples of AI's transformative power comes from a global retailer (name withheld) that employed a sophisticated Machine Learning (ML) system to optimize its inventory management and demand forecasting across a geographically dispersed store network. By leveraging a variety of data sources, the retailer was able to anticipate demand more accurately and reduce supply chain inefficiencies. Key data sources included:

1. Historical sales data: Comprehensive transaction records from multiple years, capturing seasonal trends and consumer purchasing behavior.
2. External factors: Real-time data on local events (concerts, sports games), weather patterns, and holiday schedules, allowing for more dynamic adjustments to inventory levels.
3. Inventory and supply chain metrics: Information on supplier lead times, reorder cycles, and logistics costs, ensuring that the right products were available at the right time.

The retailer implemented regression models and, in some cases, advanced neural networks trained on this rich data set. These models reduced stock shortages by proactively restocking high-demand items while minimizing excess inventory of slow-moving products. This approach optimized warehouse space and improved cash flow management by reducing unnecessary stock holding costs. In addition, the retailer identified regional consumption patterns,

enabling targeted marketing strategies and promotional campaigns tailored to local consumer preferences. The success of the forecasting system resulted in a significant reduction in operational costs related to emergency shipments. However, the model's accuracy heavily depended on the quality and completeness of historical data. The system was less reliable when faced with unexpected events, such as shifts in consumer preferences or global supply chain disruptions. The company addressed these concerns by incorporating real-time social media trends to enhance demand prediction, ensuring the model was adaptable to emerging consumer behavior.

9.2. Reinforcement Learning in Logistics

A logistics firm successfully applied Reinforcement Learning (RL) to optimize delivery routes in congested urban environments, achieving notable improvements in operational efficiency. The company integrated a variety of real-time data sources to train its RL agents, including:

- Streaming traffic data from city sensors providing up-to-the-minute congestion information,
- GPS data from delivery vehicles offering precise location and routing feedback,
- Delivery schedules with priority-based constraints reflecting time-sensitive customer demands.

Using this data, the RL system dynamically adjusted delivery routes based on real-time traffic conditions, accidents, or weather disruptions. This reduced fuel consumption, shortened delivery times, and optimized fleet management. Beyond logistics, RL applications in manufacturing demonstrated the potential for enhancing production processes by adapting to varying raw material quality and fluctuating market demands, leading to significant cost savings and increased production efficiency. Despite these benefits, one challenge with RL in logistics was the system's lack of explainability—understanding why specific routes were chosen was not always straightforward. To mitigate this, the company implemented visualization tools that allowed dispatchers to track the agent's decision-making process in real time, allowing human operators to intervene when necessary and ensuring that decisions could be aligned with broader business priorities.

9.3. Genetic Algorithms for Financial Portfolio Optimization

In the financial sector, a leading institution applied genetic algorithms to optimize portfolio management strategies, particularly in volatile market conditions. Unlike traditional models, such as Markowitz's mean-variance optimization, which assumes static historical correlations, genetic algorithms iteratively evolve different portfolio configurations to discover optimal asset allocations. The algorithm incorporated key features such as:

- Market volatility indicators, providing real-time assessments of the financial environment and investor risk tolerance,
- Adaptive mutation rates, allowing the algorithm to respond quickly to sudden market changes,
- Multi-objective optimization, balancing competing goals such as return maximization, risk minimization, and liquidity needs.

The genetic algorithm approach outperformed the institution's traditional strategy over a six-month pilot, producing superior risk-adjusted returns. Furthermore, the system's ability to perform real-time portfolio rebalancing in response to stock price fluctuations allowed for better risk mitigation during market turbulence. However, the approach's computational intensity posed a challenge, as finding optimal solutions required substantial processing power. The institution overcame this limitation by leveraging high-performance computing clusters and optimizing the algorithm's parameters for faster convergence without compromising solution quality.

9.4. Fuzzy Logic and Deep Learning in Manufacturing

In manufacturing, a company integrated Fuzzy Logic with Deep Learning to enhance quality control processes on production lines. Fuzzy Logic was instrumental in handling the inherent variability in raw materials and machine settings, where slight variations in sensor readings (such as temperature, pressure, or chemical composition) could still result in acceptable product quality. Meanwhile, a Deep Learning model employed computer vision techniques to inspect finished products for subtle defects, such as surface anomalies or dimensional inaccuracies.

This hybrid approach significantly reduced the rate of false positives—where products that met acceptable quality standards were incorrectly flagged as defective—leading to fewer unnecessary rejections. Moreover, it helped to minimize waste by allowing operators to adjust machine parameters in real time based on insights provided by the system. As a result, the company saw a measurable improvement in its first-pass yield. However, integrating Fuzzy Logic and Deep Learning posed system calibration and maintenance challenges. To address this, a dedicated team of engineers is needed to monitor and optimize the system's performance continuously. A comprehensive operator training program was also implemented to ensure that staff could effectively interpret and respond to the system's outputs, ensuring that the improvements in quality control were sustained over time.

9.5. Generative AI in Media and Marketing

In the media industry, a company leveraged Generative AI to create personalized marketing campaigns for different audience segments. The system generated tailored content that resonated with specific demographic groups by analyzing vast customer data, including detailed subscriber usage patterns, social media trends, and existing marketing assets. Key data inputs included:

- Subscriber usage patterns, including viewing histories and user preferences,
- Social media trends, such as emerging hashtags, viral content, and user-generated discussions,

- Existing marketing assets, including product images, promotional materials, and brand guidelines.

The AI system automatically generates creative content, such as ad copy, images, and video trailers, that is personalized for each audience segment. The initiative markedly improved rates for targeted groups, demonstrating the power of AI-driven personalization. However, the approach raised critical ethical concerns, particularly data privacy and user consent. The company established a governance committee to oversee data usage, ensuring compliance with privacy regulations and intellectual property rights. A potential risk with Generative AI in marketing is the generation of content that, while innovative, may conflict with the brand's established identity. To mitigate this, the company incorporated a human-in-the-loop review process, where marketing professionals reviewed AI-generated content before deployment to ensure consistency with the company's brand values.

These case studies highlight how AI technologies can be applied to solve complex business challenges, from demand forecasting and financial optimization to quality control and personalized marketing. They demonstrate that successful AI implementation requires more than deploying advanced algorithms; it requires robust data pipelines, effective governance frameworks, and strategic alignment with business objectives. Moreover, these examples underscore the importance of balancing technological innovation with ethical considerations. Issues such as algorithmic fairness and transparency must be addressed to ensure responsible AI adoption. As AI evolves, businesses must focus on leveraging the technology to enhance operational efficiency and commit to fostering trust and accountability with their customers and stakeholders. By aligning AI with organizational goals and addressing technical and ethical challenges, businesses can harness AI's full potential to drive growth, innovation, and competitive advantage.

10. Conclusion

This paper illustrates that AI offers transformative pathways to operational efficiency, innovative product development, and deeper market insights. It introduces diverse examples, such as the World Wide Web, smartphones' consolidation of many devices, the automation of manufacturing processes, the rise of e-commerce platforms, and the development of cloud-based data systems. These examples underscore the rapid pace of digital transformation, where new platforms and technologies constantly reshape industries. The comprehensive review of AI methodologies—from ML and fuzzy logic to genetic algorithms, reinforcement learning, and generative AI—demonstrates the rich toolbox available to executives. Each approach requires careful alignment with business priorities, robust data governance, and well-defined performance metrics. The case studies presented in this paper underscore how AI can revolutionize operational processes, improve risk management, and create new competitive advantages across industries when implemented thoughtfully.

Ultimately, organizations that balance technological exploration with accountability are well-positioned for long-term success. Transparent governance ensures regulatory compliance and builds enduring trust among stakeholders. By integrating AI into strategic planning, fostering collaboration across different departments, and continuously monitoring model performance, executives can effectively navigate the complexities of the digital era and unlock significant transformative potential across their enterprises.

11. Future Works

Although this paper covers a broad range of AI-driven methodologies and their applications to digital transformation, several promising avenues for further research remain. Future work could explore the following:

- Systematic ways of combining different AI approaches, like integrating reinforcement learning with genetic algorithms, to achieve highly adaptable and dynamic solutions.
- Improved frameworks for sustainability that focus on reducing the carbon footprint and ensuring energy efficiency in AI deployments without sacrificing performance.
- Enhanced governance models that address transparency, data privacy, and stakeholder engagement, particularly as regulatory expectations continue to evolve.
- Deepening multidisciplinary collaborations to investigate novel methods for integrating the insights of ethicists, legal experts, and domain specialists into AI design from the beginning.
- Investigating the long-term societal impacts of widespread AI adoption. This research could use longitudinal and qualitative research methods, like ethnographic studies, to understand how AI changes work patterns, social interactions, and power dynamics. Particular attention should be paid to potential job displacement and the need for retraining programs.
- Developing robust metrics for measuring the "explainability" of AI systems. While various XAI techniques exist, there isn't a universally accepted standard for quantifying how understandable an AI model is to different stakeholders. Future research could focus on developing and validating such metrics through user studies.

By continuing to refine technical innovations and organizational strategies, future studies can ensure that AI-driven digital transformation remains ethical, inclusive, and sustainable, benefiting businesses, society, and the environment.

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Biography

Dr. Maikel Leon is interested in applying AI/ML techniques to modeling real-world problems using knowledge engineering, knowledge representation, and data mining methods. His most recent research focuses on XAI and has recently been featured in Information Sciences and IEEE Transactions on Cybernetics journals. Dr. Leon is a reviewer for the International Journal of Knowledge and Information Systems, Journal of Experimental and Theoretical Artificial Intelligence, Soft Computing, and IEEE Transactions on Fuzzy Systems. He is a Committee Member of the Florida Artificial Intelligence Research Society. He is a frequent contributor on technology topics for CNN en Español TV and the winner of the Cuban Academy of Sciences National Award for the Most Relevant Research in Computer Science. Dr. Leon obtained his PhD in Computer Science at Hasselt University, Belgium, previously having studied computation (Master of Science and Bachelor of Science) at Central University of Las Villas, Cuba.

Received: 24 April, 2025, Revised: 22 May, 2025, Accepted: 23 May, 2025, Online: 22 June, 2025

DOI: https://doi.org/10.55708/js0406002

Analysis of Difference Schemes of Two-Point Boundary Value Problems using the Method of Moving Nodes

Dalabaev Umurdin *, **Khasanova Dilfuza**

University of World Economy and Diplomacy, Tashkent, Uzbekistan

*Corresponding author: Dalabaev Umurdin, Buyuk Ipak Yuli 54, +998910091309, udalabaev@uwed.uz

ABSTRACT: This article addresses the calculation of approximation errors in numerical methods for solving differential equations. A fundamental challenge when replacing differential equations with discrete representations is ensuring that the discrete solution closely approximates the exact solution. To tackle this, a grid area is established for the difference solution, with discrete solutions evaluated at specific nodal points. Traditionally, the degree of approximation in this context is expressed using the notation $O(h^p)$, where h represents the grid step and p indicates the order of accuracy. A significant advancement in this area is the application of the moving nodes method, which enables the calculation of approximation errors at these nodal points. This method allows researchers to derive an approximate analytical expression for the discrete solution, which serves as a foundation for calculating the approximation error.

KEYWORDS: Moving Node Method, Approximation error, To-Point Boundary Problem

1. Introduction

This article is an expanded version of the article presented in [1]. The numerical solution methods for differential equations fundamentally rely on transforming differential problems into difference problems [2–5]. In simpler terms, solving differential equations requires understanding how to approximate them. This involves converting a differential equation into a system of algebraic equations, which is based on the values of the desired functions at specific points on a grid. Recent studies [6]–[11] have introduced a new approach for approximating differential operators, enhancing the accuracy and efficiency of these methods. One of the significant advantages of the moved node method is that it enables the calculation of an explicit expression for the approximation error when replacing differential equations with difference ones. Understanding this error is crucial because it provides insights into the reliability and accuracy of the numerical solution. By quantifying the error, researchers can refine their methods and improve the overall quality of the numerical solutions obtained.

In conclusion, the transformation of differential equations into difference equations is a fundamental aspect of numerical analysis. The development of innovative methods like the moved node method represents a significant advancement in this field, providing researchers and practitioners with powerful tools to tackle complex differential problems more effectively. As numerical methods continue to evolve, the importance of understanding and minimizing approximation errors will remain a critical area of focus for ensuring the accuracy and reliability of solutions.

On the basis of the movable node, an approximate analytical expression for the difference solution of the differential problem was obtained [12]. This development represents a significant step forward in numerical methods, as it provides a more refined approach to approximating solutions to differential equations. The analytical expression derived from the movable node approach allows for greater flexibility and accuracy when dealing with complex differential problems.

In [13], the moving nodes method was further applied to construct the control volume method, which is widely used in computational fluid dynamics and other engineering applications.

In [14], the authors explored the potential to increase accuracy by combining the moving nodes method with the ideas of Richardson's extrapolation. Richardson's extrapolation is a technique used to improve the precision of numerical approximations by utilizing solutions obtained at different grid resolutions. By integrating this method with the moving nodes approach, it is possible to achieve higher-order accuracy in the numerical solutions, thereby reducing the error associated with the approximation.

Some questions regarding the monotonicity of the difference scheme using the movable node are addressed in [15]. Monotonicity is an important property in numerical methods, as it ensures that the numerical solution behaves in a physically realistic manner, avoiding non-physical oscillations or spurious solutions. Understanding and ensuring the monotonicity of the difference scheme is crucial for maintaining the stability and reliability of the numerical method, especially in problems involving sharp gradients or discontinuities.

The application of the moving nodes method to various applied problems is reflected in [16]. This demonstrates the versatility of the method across different fields, such as fluid dynamics, heat transfer, and structural analysis.

Moreover, based on the choice of the velocity profile on the edge of the control volume, qualitative schemes were obtained in [17]. The velocity profile plays a critical role in determining the flow characteristics and behavior within the control volume.

In summary, the integration of the movable node method into various numerical frameworks and its application to real-world problems highlights its significance in advancing numerical analysis. The ongoing exploration of its properties, such as accuracy, monotonicity, and adaptability to different contexts, continues to enhance the capability of numerical methods in solving complex differential equations effectively. As research in this area progresses, the potential for further innovations and improvements remains substantial, promising even greater advancements in the field of numerical solutions.

This paper describes the application of the moving nodes method to the calculation of the approximation error. The moving nodes method provides a dynamic approach to numerical analysis, allowing for the adjustment of grid points based on the behavior of the solution.

When a two-point boundary value problem is solved using difference methods, the question of the degree of approximation typically arises. This degree of approximation is crucial as it directly impacts how closely the numerical solution aligns with the exact solution. In numerical analysis, understanding the closeness of the exact solution to its approximation is essential for evaluating the effectiveness of the chosen method.

The quality of the difference scheme is often assessed based on this degree of approximation. A higher degree indicates a more accurate representation of the solution, while a lower degree suggests potential discrepancies that may arise from the numerical method employed. This evaluation is typically conducted by analyzing the behavior of the approximation error, which quantifies the difference between the exact solution and the numerical approximation.

Interestingly, in this analysis, other parameters—such as the coefficients of the differential equation—are not explicitly involved in the expression for the approximation error. This is significant because it allows researchers to focus on the fundamental aspects of the numerical method without being distracted by the specific characteristics of the differential equation being solved. By isolating the approximation error from these coefficients, the analysis can yield more generalized insights into the behavior of the numerical solution.

Obtaining an explicit expression allows researchers to identify how changes in the grid size, the choice of the moving nodes, and other factors influence the accuracy of the numerical solution. Furthermore, it enables the development of strategies to minimize the approximation error, thus enhancing the overall quality of the numerical method.

By utilizing the moving nodes method to derive this explicit expression, the paper contributes to a deeper understanding of the approximation error in the context of two-point boundary value problems. This understanding is crucial for advancing numerical methods, as it provides a foundation for improving accuracy and reliability in solving complex differential equations. Ultimately, the insights gained from this analysis can inform future research and applications, paving the way for more effective numerical solutions in various scientific and engineering fields.

When a two-point boundary value problem is solved by difference methods, the question of the degree of approximation usually appears. For the closeness of the exact and approximation of the solution, and the quality of the difference scheme are evaluated based on the degree of this parameter. With such an analysis, other parameters (the coefficients of the differential equation) are not explicitly involved in the approximation error

expression. Obtaining an explicit expression for the approximation error makes it possible to analyze it.

Consider the simplest ordinary differential equation with boundary conditions

$$\frac{d^2u}{dx^2} = C, \quad u(0) = 0, \ u(1) = 1 \tag{1}$$

where C is constant.

Create a uniform grid on segments $[0,1]$ with step h. A uniform grid on a segment $x \in [0,1]$ with step h has the form:

$$\bar{\omega}_h = \{x_k = hk, \ k = 0,1,...,N, \ h \cdot N = 1\}$$

Let us replace the second-order derivative by the difference relation [18]:

$$\frac{U_{i+1} - 2U_i + U_{i-1}}{h^2} = C,$$
$$1 \le i \le N-1, \ U_0 = 0, \ U_N = 1 \tag{2}$$

Difference scheme (2) traditionally has order $O(h^2)$. However, if we solve system (2) by the Tomas algorithm, we obtain a numerical solution that coincides with the exact analytical solution for any grid steps h at the grid nodes. Those. scheme (2) approximates (1) exactly.

2. Method For Determining Approximation Error

Let we have a differential equation

$$Lu = f, \tag{3}$$

where L is a differential operator, f is a known function, and u is an unknown function. (3) the equation is considered in some domain D with appropriate boundary conditions. The differential equation (3) is replaced by the difference equation [18] :

$$L_h u_h = f_h, \tag{4}$$

where L_h is the difference operator, u_h is the unknown grid function, and f_h is the approximation of the function f at the grid nodes.

Usually, the approximation error is given as [18,19]:

$$Q_h = L_h[u]_h - f_h, \tag{5}$$

where $[u]_h$ is the exact solution of (3) at the grid nodes. Using the Taylor series, from (5) one obtains that, $Q_h = O(h^m)$, where h is the grid step and m is the degree of approximation.

You can determine an explicit approximation error if you use the method of a moving node, which allows you to extend the definition to the entire area D. This allows you to introduce an approximation error like this:

$$R_h = L_h\{u\}_h - f_h. \tag{6}$$

Here $\{u\}_h$ is a predefined continuous function by means of a moveable node. Approximate calculation of the approximation error of type (6) is demonstrated using simple examples.

3. Results and Discussion

As an application of the above approach, consider examples.

3.1. Simple Boundary Value Problem

Consider a simple boundary value problem:

$$\frac{d^2u}{dx^2} = f(x), \quad u(0) = u_a, \ u(1) = u_b \tag{7}$$

Let's build a non-uniform grid on segments $[0,1]$:

$$\bar{\omega}_h = \{0 = x_0 < x_1 < ... < x_{N-1} < x_N = 1, \ k = 0,1,...,N\}$$

In the non-uniform grid, we replace (7) with the difference problem:

$$\frac{2}{x_{i+1} - x_{i-1}}\left(\frac{U_{i+1} - U_i}{x_{i+1} - x_i} - \frac{U_i - U_{i-1}}{x_i - x_{i-1}}\right) = f(x_i), \tag{8}$$
$$i = 1,2,...,N-1.$$

Here U_i is the grid solution of the problem. From here

$$U_i = \frac{U_{i+1}(x_i - x_{i-1}) + U_{i-1}(x_{i+1} - x_i)}{x_{i+1} - x_{i-1}} -$$
$$\frac{1}{2} f(x_i)(x_i - x_{i-1})(x_{i+1} - x_i), \quad i = 1,2,...,N-1. \tag{9}$$

We redefine the value of the function at non-nodal points as follows. To do this, we consider in (9) $x_{i+1}, x_{i-1}, U_{i-1}, U_{i+1}$, to be fixed, and x_i to be moved, and the function $f(x)$ to be smooth. Thus, we will complete the grid function on each segment (x_{i-1}, x_{i+1}). From (9) we get

$$U_i''(x_i) = -\frac{1}{2} f''(x_i)(x_{i+1} - x_i)(x_i - x_{i-1}) - \tag{10}$$
$$f'(x_i)(x_{i+1} + x_{i-1} - 2x_i) + f(x_i)$$

Then the approximation error for the nodal points looks like this:

$$R_h(x_i) = -\frac{1}{2} f''(x_i)(x_{i+1} - x_i)(x_i - x_{i-1}) - \tag{11}$$
$$f'(x_i)(x_{i+1} + x_{i-1} - 2x_i)$$

If the grid is uniform for the approximation error, we obtain the expression

$$R_h(x_i) = -\frac{1}{2} f''(x_i)h^2, \ i = 1, 2, ..., N-1. \quad (12)$$

If on the segments (x_{i-1}, x_{i+1}) the function constant approximation error is identically equal to zero and we get the exact solution.

Based on expression (10), the following conclusion can be drawn.

Given a two-point boundary value problem

$$\frac{d^2u}{dx^2} = f^*(x), \quad u(0) = u_a, \ u(1) = u_b$$

and $f^*(x)$ can be represented as

$$f^*(x_i) = -\frac{1}{2} f''(x_i)(x_{i+1} - x_i)(x_i - x_{i-1}) - f'(x_i)(x_{i+1} + x_{i-1} - 2x_i) + f(x_i)$$

then the difference scheme

$$\frac{2}{x_{i+1} - x_{i-1}} \left(\frac{U_{i+1} - U_i}{x_{i+1} - x_i} - \frac{U_i - U_{i-1}}{x_i - x_{i-1}} \right) = f(x_i), \quad i = 1, 2, ..., N-1,$$

gives a grid solution coinciding with the exact solution at the nodal points.

If there is only one internal node point (the node being moved is one), then an approximate analytical solution can be obtained. Indeed, if we rewrite scheme (8) for one moving node, we have

$$2\left(\frac{U_b - U(x)}{1 - x} - \frac{U(x) - U_a}{x} \right) = f(x_i). \quad (13)$$

From here we obtain an approximate analytical solution:

$$U(x) = U_b x + U_a(1 - x) - \frac{1}{2} f(x_i)(1 - x)x. \quad (14)$$

In this case, (14) represents the exact solution of the problem (7) if we put

$$f^*(x) = -\frac{1}{2} f''(x)(1 - x)x - f'(x)(1 - 2x) + f(x).$$

The form of the approximation error (11) allows the construction of new schemes of the collocation type. Indeed, if in problem (8) we replace the right side by the expression

$$f(x_i) + A(x_i - x_{i-1})(x_{i+1} - x_i),$$

Here A is still an unknown constant. Parameter A is determined so that the approximation error (11) for a uniform step at node x_i is equal to zero, i.e. collocation type scheme. Then we have

$$A = \frac{1}{4} f''(x_i)$$

.

3.2. Boundary value problem for convection and diffusion equation

Consider a stationary equation in which only convection and diffusion are present without a source.

$$\varepsilon u'' + u' = 0, \quad (15)$$

with boundary conditions $v(0) = 0, v(1) = 1$.

There are various schemes for the difference solution (15) [6, 7]. Based on the moving node technique [1,2], it is possible to explicitly express local errors in the approximation of differential equations. Using the moving node method [1], we will show the efficient calculation of local approximation errors for the model problem (15).

3.1.1. Scheme with central-difference approximation of the convective term

Take a segment $[x_{i-1}; x_{i+1}]$ and any point x. Consider the grid analog (15)

$$\frac{2\varepsilon}{x_{i+1} - x_{i-1}} \left(\frac{u_{i+1} - u}{x_{i+1} - x} - \frac{u - u_{i-1}}{x - x_{i-1}} \right) + \frac{u_{i+1} - u_{i-1}}{x_{i+1} - x_{i-1}} = 0 \quad (16)$$

At $x = (x_{i+1} - x_{i-1})/2$, we have a central difference approximation. Here, u_{i+1} is the approximate value of the solution at the point x_{i+1}, u_{i-1} is the approximate value of the solution at the point x_{i-1}.

From (16) we find

$$u = \frac{1}{2\varepsilon(x_{i+1} - x_{i-1})} [(x - x_{i-1})(2\varepsilon + x_{i+1} - x)u_{i+1} + (x_{i+1} - x)(2\varepsilon - x + x_{i-1})u_{i-1}] \quad (17)$$

.

From here we get,

$$u' = \frac{2\varepsilon + x_{i+1} + x_{i-1} - 2x}{2\varepsilon} \frac{u_{i+1} - u_{i-1}}{x_{i+1} - x_{i-1}}, \quad (18)$$

$$u'' = -\frac{1}{\varepsilon} \frac{u_{i+1} - u_{i-1}}{x_{i+1} - x_{i-1}}. \quad (19)$$

If the difference solution at nodal points is known, then formula (17) makes it possible to determine the unknown at points that are not nodal.

Using formulas (18) and (19), the derivatives are restored at any point of the segment. Multiplying (19) by and adding with (18), we obtain

$$\varepsilon u'' + u' = \Psi_1, \quad (20)$$

where

$$\Psi_1 = \frac{x_{i+1} + x_{i-1} - 2x}{2\varepsilon} \frac{u_{i+1} - u_{i-1}}{x_{i+1} - x_{i-1}}.$$

Equation (20) can be called a differential analog of the difference equation (16); difference equation (16) is a collocation-type scheme.

Using (19), the approximation error can be written as

$$\Psi_1 = -\frac{x_{i+1} + x_{i-1} - 2x}{2} u''.$$

Then equation (20) takes the form

$$\left(\varepsilon + \frac{x_{i+1} + x_{i-1} - 2x}{2}\right) u'' + u' = 0. \quad (21)$$

Thus, difference equation (16) exactly approximates differential equation (21) on the segment $[x_{i-1}, x_{i+1}]$.

Comparison of Eqs. (15) and (21) shows that when Eq. (15) is approximated by scheme (16), scheme diffusion appears with a variable coefficient $(x_{i+1} + x_{i-1} - 2x)/2$.

3.2.2 **Upwind Scheme**. Let us consider the difference analog of equation (15), in which the convective term is approximated by the one-sided difference relation

$$\frac{2\varepsilon}{x_{i+1} - x_{i-1}} \left(\frac{u_{i+1} - u}{x_{i+1} - x} - \frac{u - u_{i-1}}{x - x_{i-1}} \right) + \frac{u_{i+1} - u}{x_{i+1} - x} = 0. \quad (22)$$

From here we get

$$u = \frac{(x - x_{i-1})(2\varepsilon + x_{i+1} - x_{i-1})}{(x_{i+1} - x_{i-1})(2\varepsilon + x - x_{i-1})} u_{i+1} + \frac{2\varepsilon(x_{i+1} - x)u_{i-1}}{(x_{i+1} - x_{i-1})(2\varepsilon + x - x_{i-1})} \quad (23)$$

Determine the first and second derivatives:

$$u' = \frac{2\varepsilon(2\varepsilon + x_{i+1} - x_{i-1})}{(2\varepsilon + x - x_{i-1})^2} \frac{u_{i+1} - u_{i-1}}{x_{i+1} - x_{i-1}}, \quad (24)$$

$$u'' = \frac{-4\varepsilon(2\varepsilon + x_{i+1} - x_{i-1})}{(2\varepsilon + x - x_{i-1})^3} \frac{u_{i+1} - u_{i-1}}{x_{i+1} - x_{i-1}} \quad (25)$$

Let us calculate the approximation error

$$\Psi_2 = \frac{2\varepsilon(x - x_{i-1})(2\varepsilon + x_{i+1} - x_{i-1})}{(2\varepsilon + x - x_{i-1})^3} \frac{u_{i+1} - u_{i-1}}{x_{i+1} - x_{i-1}}$$

The differential analog of scheme (22) has the form

$$\left(\varepsilon + \frac{x - x_{i-1}}{2}\right) u'' + u' = 0, \quad (26)$$

those. with a scheme against the flow, we have a scheme diffusion with a coefficient . Based on (23) - is a hyperbola, which is monotone on the segment, i.e. scheme (22) is monotonic.

Based on the form of the differential analogue (26), we can conclude that the differential equation

$$\left(\varepsilon + \frac{x}{2}\right) u'' + u' = 0 \quad (27)$$

is exactly approximated by the scheme

$$2\varepsilon \left(\frac{u_b - u}{1 - x} + \frac{u - u_a}{x} \right) + \frac{u_b - u}{1 - x} = 0 \quad (28)$$

Those. solving (28) with respect to u, we obtain the exact solution of differential equation (27).

3.3. Parametric Schemes

In this case, an attempt is made to create a special parametric scheme in order to improve the quality of the circuit. The peculiarity of this approach is the choice of the parameter, which is carried out on the basis of the calculated approximation error, which allows more accurately adjusting the parameters of the scheme to achieve the best indicators. We demonstrate the effectiveness of this method using examples of problems related to convection-diffusion processes, where the correct choice of parameters is especially important for the stability and accuracy of the solution. Consider the problem [19,20].

$$Pe\frac{du}{dx} = \frac{d^2u}{dx^2} + Pe \cdot S(x), \quad u(0) = u_0, \quad u(1) = u_1, \quad (29)$$

Here Pe is the Peclet number, $S(x)$ is the source, u is the unknown function.

When problem (29) is discredited, it is essential to approximate the convective term [4]. The standard finite-difference scheme against the flow on a three-point template is:

$$Pe\frac{U - U_W}{x - x_W} = \frac{2}{x_E - x_W} \left(\frac{U_E - U}{x_E - x} - \frac{U - U_W}{x - x_W} \right) + Pe \cdot S(x), \quad (30)$$

Consider the parametric scheme

$$Pe\frac{U - U_W}{x^k - x_w^k} \cdot kx^{k-1} = \frac{2}{x_E - x_W} \left(\frac{U_E - U}{x_E - x} - \frac{U - U_W}{x - x_W} \right) + Pe \cdot S(x), \quad (31)$$

The choice of the parameter k can be found by numerical experiment. Based on the calculated approximation error R_h, it is not difficult to select the parameter k. The idea of approximating the convective term is as follows. We introduce an intermediate variable $y(x)$, and based on the calculation of the derivative of a complex function, we have

$$\frac{du}{dx} = \frac{du}{dy} \cdot \frac{dy}{dx}.$$

For the function $y(x)$ we take a monotonically increasing function, for example, $y = x^k$. du/dy will

be replaced by the difference relation upstream. Making the assumption that with such a replacement, the approximation error decreases. In this way

$$\frac{du}{dx} \approx \frac{u-u_W}{x^k - x_w^k} \cdot kx^{k-1}.$$

Figure 1 shows the results of calculations $(Pe=0,\ S(x)=0,\ N=11, u_0=0,\ u_1=1)$, at $k=1$ and $k=9$.

Thus, by carefully choosing the parameter k, we are able to obtain a result that is as close as possible to the exact solution of the problem. This approach allows us to significantly increase the accuracy and reliability of calculations, minimizing approximation errors and ensuring more stable behavior of the numerical method.

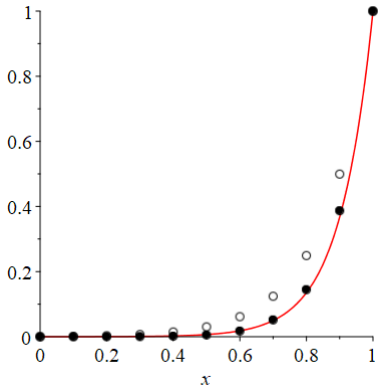

Figure 1: Comparison of results. The solid line is the exact solution, the circles are the numerical results obtained at k=1, and the solid circles at k=9.

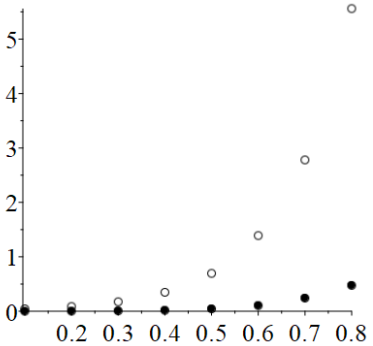

Figure 2: Comparison of the results of the approximation error at internal nodal points. The solid circles are obtained according to the scheme (31) at k=9, and the circles at k=1.

3.3. Iterative method to get a solution

It is known that after replacing the differential equation with discrete ones, we obtain a system of algebraic equations [4,5,19,20]. There are two approaches to solving systems of algebraic equations: exact methods and iterative methods. Using the idea of constructing iterative methods for systems of discrete equations, we will show the possibilities of an analytical approximate solution based on the method of moving nodes.

Consider problem (29). If there is only one moving node, approximating the convective term by the upstream scheme from (31) we get $(u_0=0,\ u_1=1)$.

$$u^1 = \frac{2x}{2+Pe(1-x)}. + \frac{x(1-x)}{2+Pe(1-x)} \cdot S(x) \qquad (32)$$

This expression is taken as the initial approximation of problem (29). Let's find the approximation error

$$R^1 = \frac{d^2u^1}{dx^2} - Pe\frac{du^1}{dx} + Pe \cdot S(x) \qquad (33)$$

Let's calculate the second approximation

$$u^2 = u^1 + \omega x(1-x)R^1$$

Find the approximation error R^2.

$$R^2 = \frac{d^2u^2}{dx^2} - Pe\frac{du^2}{dx} + Pe \cdot S(x)$$

Thus, we carry out an iterative process in the form

$$u^k = u^{k-1} + \omega x(1-x)R^{k-1} + Pe \cdot S(x),\ \ k=2,3\ldots \qquad (34)$$

In (34) ω is the relaxation parameter.

In Fig. 3 the exact solution of the problem as well as approximating analytical solutions u^1, u^2, u^3 and u^4 are compared. As can be seen from the graphic, step by step we can improve of analytical solution $(S(x)=0,\ Pe=10,\ \omega=0.08)$.

On fig. 4 the sequence of solution of problem (18) is given for $S(x)=\cos(5x),\ Pe=10,\ \omega=0.06$. On fig. 3 and 4, the solid line corresponds to the exact solution of the problem; dot - u^1; dashed, u^2; ; dotted-dashed -- u^3; long-dashed - u^4.

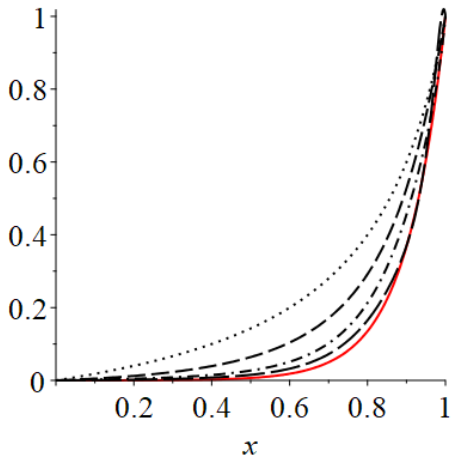

Figure 3: Comparison of results: S(x) = 0, Pe=10, ω=0,08

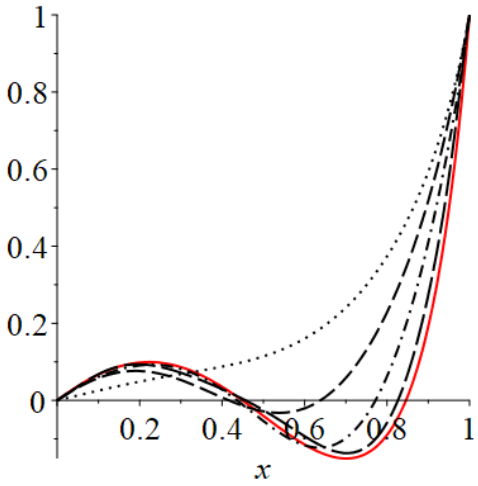

Figure 4: Comparison of results: S(x) = cos(5x), Pe=10, ω=0,06

As can be seen from the graphic, step by step we can improve of the analytical solution.

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DALABAEV UMURDIN has done his bachelor's degree from National University of Uzbekistan in 1969. He has done his PhD degree from Institute of Mechanics of the Academy of Sciences of Uzbekistan in 1976. He has completed his DSc degree from National University of Uzbekistan in 2021.

KHASANOVA DILFUZA has done her bachelor's degree from Andijan State University in 2004. She has done her master's degree from Andijan State University in 2006.

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Received: 4 June, 2025, Revised: 12 July, 2025, Accepted: 13 July, 2025, Online: 27 July, 2025

DOI: https://doi.org/10.55708/js0407002

Education and Sustainability Habits – Portuguese Students' Perspectives

Natércia Lima[1*], Clara Viegas[1], Alexandra R. Costa[2], Claudia Orozco-Rodríguez[3], Gustavo R. Alves[4], André Vaz Fidalgo[4]

[1]CIETI, Department of Physics, ISEP, Polytechnic of Porto, Porto, 4249-015, Portugal

[2]CIETI, Department of Management and Organization, ISEP, Polytechnic of Porto, Porto, 4249-015, Portugal

[3]Maths Department, Guadalajara University, Exact Sciences and Engineering University Center, Guadalajara, 44430, Jal., Mexico

[4]CIETI, Department of Electrical Engineering, ISEP, Polytechnic of Porto, Porto, 4249-015, Portugal

*Corresponding author: Natércia Lima, Rua Dr. António Bernardino de Almeida 431, 4249-015 Porto, Portugal, nmm@isep.ipp.pt

ABSTRACT: Even though the use of technology in Education grew during the COVID Pandemic and some habits even contributed positively regarding the planet sustainability, after five years what can be said about students' perception about it? This work is a follow-up to a previous study made shortly after academic life resumed its normality. A student questionnaire was conducted, and the results showed that the more awareness they presented about sustainability issues, the more they were favorable to a hybrid educational regime. In this paper the former questionnaire was adapted and performed to students during the 2023/24 academic year. Portuguese students' perception about online productivity (usage of online resources and online classes) and sustainability (sensibility regarding transportation, food consumption and use of resources) were addressed, using an exploratory quantitative methodology. Students are still using a variety of online resources, which they consider to be effective and productive for their learning. In terms of sustainability, students show a stronger tendency towards sustainable food consumption and resource management. Finally, a comparative study was conducted to understand the changes in their perception (from 2021 to 2024), and their perception of online productivity seems to have changed little. In terms of sustainability, the results suggest students have already incorporated sustainability habits into their daily lives.

KEYWORDS: Sustainable Development, Education, Online Resources, Attitude, Behavior

1. Introduction

The importance of education is widely acknowledged as one of humanity's most significant achievements, primarily due to its universal accessibility and its capacity to facilitate a more prosperous future [1]. The development of the next generation depends on how they are informed and educated [2,3].

The impact of the COVID-19 pandemic was perceived in various dimensions. Some scientific studies have indicated that a favourable consequence of the global lockdown measures implemented in response to the pandemic was an enhancement of the Earth's environment [4]. This has been evidenced by a decline in carbon dioxide levels, which has become more readily apparent. In terms of education, the question is whether the insights gained can be used to encourage more substantial and long-lasting changes in sustainability habits, such as using online resources more often or improving individual sustainability habits.

Educational institutions have underscored the significance of online accessibility. This has demonstrated that, with the appropriate technological resources, it is feasible to conduct lectures, meetings, and even experimental classes [5]. Many resources were developed and, in some cases, are still in use, reducing the time teachers and students might spend commuting.

With respect to the field of education, it is crucial to assess the potential value of incorporating online features. If educators and learners identify some of these features as being productive and demonstrate a favourable impact on sustainability, it would be advisable to think about it.

The objective of this study is to ascertain how students perceive online education productivity and sustainability

habits after four years of the pandemic. This study represents a continuation of a previous investigation conducted after the return to face-to-face classes, which focused on students' habits [6]. That study was conducted in 2021, immediately following the return to face-to-face classes, with the objective of understanding the strengths of the learning activities during the pandemic and the respondents' preferences regarding the permanence of these activities. Additionally, the study sought to ascertain whether there had been any shifts in respondents' habits concerning sustainability. Moreover, the present study aims to compare the habits and opinions of students regarding sustainability, online educational resources usage and productivity from the 2020/21 and 2023/24 academic years. This comparison is intended to identify any potential differences.

The structure of the paper is as follows: in section 1 an introduction was made, contextualizing the research problem. In section 2 a literature review of contributions is presented, showing how education and sustainability have been addressed in the academic community, including the growth of a sustainability consciousness. In section 3 the research design used in this work is described. In section 4: the results and discussion are presented, leading to some conclusions and final remarks in section 5.

2. Education and Sustainability

The concept of sustainability has become a matter of general concern in contemporary society. The notion of sustainable development has been cited extensively in recent discourse, particularly in the context of climate change. The most quoted definition of sustainability refers: "*…development that meets the needs of the present without compromising the ability of future generations to meet their own needs*" [7]. In 2015, a set of 17 Sustainable Development Goals (SDG) was adopted by United Nation (UN) countries with the objective of achieving a better and more sustainable world for all by 2030. These goals address the global changes currently being experienced, including those related to poverty, inequality, climate change, environmental degradation, peace and justice [8]. The fourth goal, entitled 'Quality Education', is the foundation for the improvement of people's lives and sustainable development. This is achieved not only through the improvement of the quality of education but also aiding the comprehension of the significance of these concerns among younger generations [8].

The issue of sustainability can be approached from a variety of perspectives, including those of energy and resources, social and cultural, economic and political. These are all necessary to ensure the preservation of this planet for future generations [5,9,10]. From an environmental standpoint, the impact of resource usage on the planet's resources can be examined [11]. From a social and cultural perspective, the impact of social behaviours on significant issues, such as clothing, nutrition, social interaction, and more, can be examined [12,13]. From economic and political standpoints, the influence of economic lobbies on global populations, often unconsciously, can be analysed [14].

Education, when viewed holistically, can be defined as the process through which teachers and students socialize professionally, with the social behaviours of a community exerting a significant influence on individuals' thinking and actions regarding significant issues. Higher education is typically characterized by the presence of highly intelligent individuals who are still developing. This provides considerable potential for stimulating discussions about various aspects of our planet's sustainability in both formal and informal settings [15]. In fact, the integration of sustainability principles within the educational curriculum is a pivotal aspect of promoting environmental awareness and responsible conduct. Irrespective of the content of the course, educators can adopt a pedagogical approach towards the importance of some of these issues in various ways, including incorporating it into existing courses, conducting contextualized activities, or implementing more sustainable procedures [16]. It is imperative to foster active student participation, encouraging more sustainable solutions from schools and from the educational community. In this manner, education evolves into a catalyst for change, empowering students to make more informed decisions and contribute to a future that is both balanced and sustainable.

The pandemic has prompted an array of unprecedented challenges within the educational sector, thereby accentuating existing inequalities and hastening an accelerated demand for innovative pedagogical approaches. The necessity for remote learning, precipitated by school closures, has exposed the disparity in students' access to technological resources, thereby exacerbating the digital divide. Still, the pandemic also encouraged pedagogical innovation, with the development of new skills in autonomy, adaptability and digital tool mastery among teachers and students alike. This has resulted in dynamic and interactive teaching methodologies that make learning more accessible and diverse for a range of students' profiles. These methodologies address some students' difficulties by allowing them to practice (24 / 7) anytime, anywhere [17]. It has catalysed digital transformation in education, encouraging the adoption of new tools and hybrid methodologies with the potential to enhance teaching methodologies nowadays and, in the future [18–20].

Before the Pandemic, remote laboratories, online courses, and universities were already well established,

but during this phase, their demand was overwhelming [17]. Even though there were many papers addressing the Pandemic transformation in education, there is a gap regarding the continued use of the tools developed at that time and the students' perception regarding their use as well as studies on their sustainable habits that may have changed and that could both contribute positively to a more sustainable education. The objective of this study is to identify a set of educational online resources that have been found to be productive and capable of reducing ecological footprints, as perceived by students [16] are still in use and well received by students. The study also seeks to make a comparison between the results obtained in 2023/24 and those from 2020/21, with a view to understanding whether there has been any alteration in the perception of sustainability issues among students. It is imperative to evaluate their perception, given its significant influence on individual behaviour [21].

3. Methodology

As previously outlined in the introduction, this study constitutes a follow-up to the [6] study. Adhering to the research methodology employed in the aforementioned study, a questionnaire was validated and disseminated within the educational community. This questionnaire employed a descriptive research methodology, utilizing an internet-based survey to collect pertinent quantitative data [22]. In this study, the previously validated questionnaire was only partially utilized, as the section addressing the impact of the pandemic on students' lives was deemed irrelevant for the present investigation. The questionnaire was adapted, and some questions underwent slight modifications to clarify participants' perceptions regarding sustainability issues. The questionnaire was developed in three languages (English, Portuguese and Spanish) and disseminated via the Google Forms platform among academic communities by institutional mail and researchers' (national and international) contacts. The distribution period was from March 2024 to September 2024, with the objective of achieving a sample that was as representative as possible of the target population, whilst also considering the heterogeneity of the schools' areas of expertise. It should be noted that the study is a convenience sample, with most participants drawn from the Higher Educational Institutions where the authors work. For the purposes of this study, the analysis was limited to data from students who had studied in Portugal.

Following the previous research problematic about the better understanding of how education may contribute to a more sustainable development (SD) of the planet, this work intends to perceive changes in students' perceptions (compared to the previous results, short after the Pandemic restrictions were lifted). Some resources developed during the Pandemic are still in use in academia, how do students feel about it? Furthermore, this study will tackle significant differences between groups (age, area of expertise, educational level). So, the research question in this paper is: *"Have students' perceptions regarding sustainability issues and the productivity of online classes changed since the post-pandemic phase?"*.

3.1. Questionnaire description

An anonymous questionnaire composed of 14 questions was administered to students to assess their perspective on several issues related to education and sustainability habits. As this study forms a follow-up to one conducted shortly after the lifting of pandemic restrictions, it also sought to ascertain whether participants held differing views since that time. Therefore, the questionnaire included questions designed for this effect. The first question related to the acknowledgement of the respondent's willingness to participate in the research study by completing the questionnaire. The second question sought to ascertain whether the participant was enrolled in any level of education during the 2023/24 academic year, with the objective of obtaining the perspective of students who were actively engaged in education at that time. Questions 3-8 pertained to the characterization of the sample, encompassing the area of education, level of education, teaching regime, and demographic information such as age, country and city of residence, and education. Questions 9 and 10 enquired about commuting habits, specifically the time spent and the usual mode of transportation. Questions 11 and 12 focused on classes and resources, investigating the continued utilization of resources adopted during the pandemic and the perception of productivity among different types of online classes or sessions. Question 13 addressed sustainability habits concerning various issues and their post-pandemic changes. Finally, question 14 was of an open nature, inviting respondents to provide any further contributions that had not been addressed in the preceding questions. All the questions, except question 14, were mandatory.

3.2. Sample characterization

In the study conducted in 2021 [6], a total of 315 students participated in the survey. Most of the participants were from Portugal (82%), and the majority of these were enrolled in higher education. In 2024, the number of respondents increased to 855, with 247 of these respondents being from Portugal. In this paper the authors will address the Portuguese students' contributions to have a similar group in both questionnaires (2021 and 2024). The remaining data is being addressed in another work from the authors. The differences between the two samples are outlined in Table 1.

The sample was selected based on convenience sampling, meaning that participants were chosen due to

their accessibility and availability. It is important to note that this type of non-probabilistic sampling does not require statistical significance testing, as it does not aim to generalize findings to a broader population but rather to provide a descriptive understanding of the phenomenon under study [23]. This longitudinal study examined Portuguese students' responses collected in 2021 (n = 259) and 2024 (n = 247), aiming to maintain a comparable sample across both time points, maintaining similar contextual conditions over time was essential. The proportion of students enrolled in higher education increased from 56% to 79%. In terms of academic background, Science and Engineering became more prominent, rising from 32% to 52%, while Health grew from 8% to 19%. Conversely, participation from Arts and Design (15% in 2021) was no longer significant in 2024, and students from Administration, Communication, and Social Sciences declined slightly (from 23% to 18%). There was also a slight shift in the age distribution: while students aged ⩽20 remained the largest group, their proportion decreased from 62% to 56%; students aged 21 – 27 remained stable (34% to 36%), and those aged ⩾28 increased from 4% to 7%, suggesting broader age diversity in 2024. These changes reflect both demographic evolution and possible contextual influences affecting participation.

Table 1: Sample characterization of the studies from 2021 and 2024 (Portuguese students)

Sample	2021 - students	2024 - students
Total valid answers	259	247
Level of education	56% higher education	79% higher education
Area of education (largest groups)	32% Science & Engineering 15% Arts and Design 8% Health 23% Administration, Communication and Social Sciences	52% Science & Engineering 19% Health 18% Administration, Communication and Social Sciences
Age (largest groups)	62% ≤ 20 years old 34% 21-27 years old 4% ≥ 28 years old	56% ≤ 20 years old 36% 21-27 years old 7% ≥ 28 years old

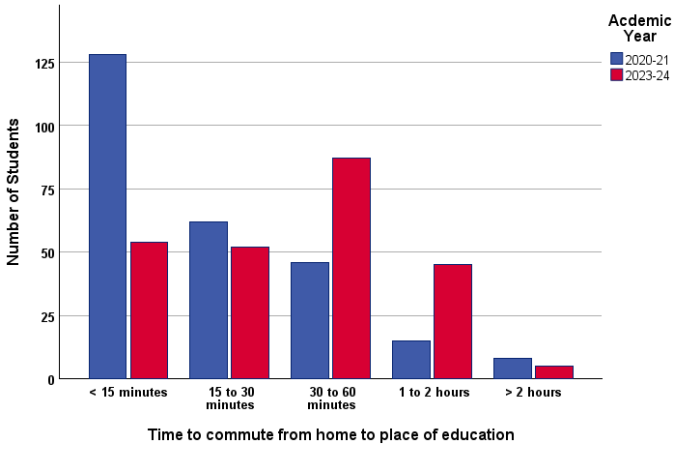

Figure 1: Comparison between time spent commuting from 2021 and 2024 Portuguese students

So, largely the educational community sample is from higher education, especially in the 2024 data collection. However, one limitation is the relatively small sample size, which may affect the generalizability of the findings.

A variety of transportation modes are used by students to commute from their place of residence to their place of education. The choice of method varies according to circumstances and the time taken for the journey is subject to variation (Figure 1).

3.3. Dimensions and categories definition

The present study encompasses two major dimensions pertinent to education and sustainability (Table 2). The first one, designated as "Online Productivity", pertains to the students' perceptions regarding the utilization of online educational resources (avoiding unnecessary commutes to school) and the productivity of online classes. With respect to online resources, students were requested to identify those they had been utilizing since the pandemic. For each type of online class, students were asked to rate its effectiveness on a scale from 1 (low effectiveness) to 3 (high effectiveness). They were also given the option to select "don't know/not applicable" if they were uncertain. The second dimension, named "Sustainability", pertains to various sustainability parameters, including transportation, food consumption habits, resource management and waste issues. Participants were asked to rate the relevance of each issue to their personal practices on a scale from 1 (not relevant) to 5 (highly relevant). Additionally, participants were given the option to select "not applicable" or "I already did it before the Pandemic ", the latter (with the highest score) serving to ascertain whether the pandemic had prompted any long-term shifts in behaviour.

Table 2: Dimensions and categories

Dimension	Categories	Issues
Online Productivity	Online resources	online laboratories, simulations, videos, online meetings with teachers, online meetings with peers
	Online classes	theoretical classes, problem-based classes, experimental classes, students' support, working sessions/meetings, only in small groups, only in large groups, only when interactive, only when lecture, only when actively producing work
Sustainability	Transports	public transport, private transport (even when there were alternatives), effort to give or ask for a ride, effort to use bicycle or similar
	Food consumption	mainly homemade food, avoid takeout food, use of lunch boxes, use of leftovers, reduction on the consumption of animal products

	Resources	reduction on the use of paper, water waste, plastic bottles; use of circular economy (secondhand clothes, books, etc.)

The variable "ecological footprint" was defined considering the type of transport used to commute (home - place of education) in order to easily assess this impact: 0 - foot, bike; 1 - mainly public transports; 2 - private vehicles.

The variable "productivity of online classes" was defined as the median of their answers to questions 12, which focused on the perception of productivity of 10 different types of online classes or sessions. The variable "global sustainability" was obtained by taking the median of their responses to question 13, which asked about their sustainability habits in relation to 12 different issues and how these had changed since the pandemic. The variable was divided into the categories: transport (4 issues), food consumption (5 issues) and resources (3 issues), according to the three categories considered in question 13.

3.4. Methodology in the Analysis Process

In order to identify the factors influencing students' perceptions of sustainability and productivity, an exploratory quantitative approach was employed, incorporating both descriptive and inferential statistical techniques, with particular use of non-parametric methods due to the nature of the data. To understand which factors, affect students' perceptions of sustainability and productivity, the nonparametric (Spearman) correlation procedure has been used, as the variables in study do not follow a normal distribution [24,25]. The former procedure establishes the possible relation/association between the study variables, and the correlation coefficient (varies from -1 to 1) describes both the strength and the direction of the relationship.

The best way to assess if there are differences and if they are statistically significant is to use a difference test, which is a statistical procedure that looks for the difference between the average of the study variables considering a particular factor. As the variables in study did not follow a normal distribution, we opted for the nonparametric Mann-Whitney U test and the Kruskal-Wallis test respectively for two independent samples and three or more independent samples (significance level 5%). The former tests compare the sample average that comes from the same population and are used to test whether the sample averages are equal or not. After defining the null hypothesis (H0: there are no statistically significant differences between the average of the groups) and if the obtained $p < 0.05$ there is a statistically significant difference between the average of the groups and the null hypothesis is not supported [24]. Unfortunately, these tests do not allow us to identify clearly where the differences lie between the two groups, so it must be complemented by a crosstabulation to identify where the differences lie.

4. Results and discussion

This section will present a global analysis on the 2024 survey, divided into the results obtained about students' perceptions (4.1) and the identification of factors affecting student perceptions (4.2). Then, on section 4.3, a comparison between students' perception in 2021 and 2024 is made.

4.1. Students' Perceptions

Most students experience a face-to-face class regime, although 4.9% attend a hybrid regime and 1.6% an exclusively online regime. Even though 71 students (28.7%) state that they do not use any online resources, a significant number of students still have several online resources in use. (see Table 3), with the video being the most popular. Furthermore, 26.3% of students utilize two online resources, while approximately 10% are using three or more.

Table 3: Online Resources Usage

Online Resource	# Students	% Students
Online laboratories	3	1.2
Simulations	23	9.3
Videos	125	50.6
Online Meetings with Teachers	70	28.3
Online Meetings with Peers	76	28.7

Considering their perceived productivity of online classes (Figure 2), the ones that work better for them are classes in small groups, students' support and working sessions / meetings. The less productive are experimental classes.

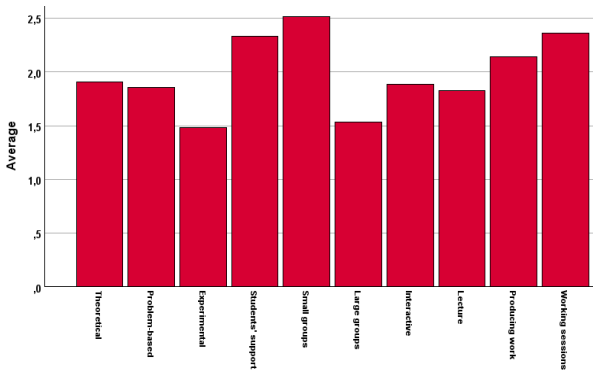

Figure 2: Productivity of the different types of online classes

In Figure 3, the median values of the variable "productivity of online classes" are shown. The most prevalent median is 2.0, reported by 61% of participants. Remembering that for each type of online class, students were asked to rate its effectiveness on a scale from 1 (low

effectiveness) to 3 (high effectiveness), this finding indicates that most participants perceived their productivity to be at an intermediate level and 25% considered it highly productive.

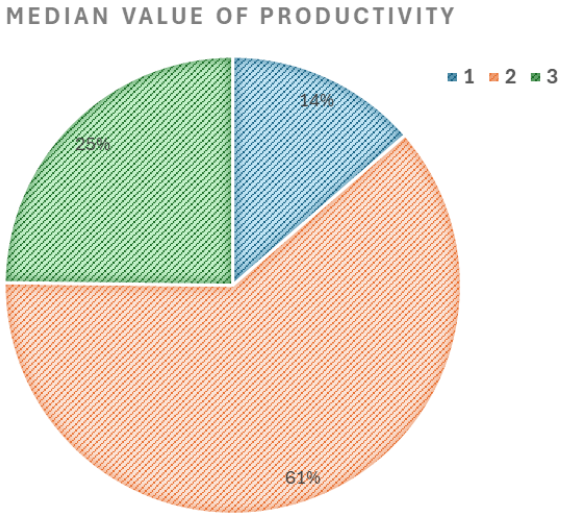

Figure 3: Frequency of the medians obtained in the variable *"productivity of online classes"*

In the context of the sustainability dimension, students utilize diverse modes of transportation for their commute between their place of residence and their educational institution. Figure 4 provides a visual representation of it by ecological footprint. It was found that approximately 24% of the study's participants have a high ecological footprint, indicative of significant environmental impact.

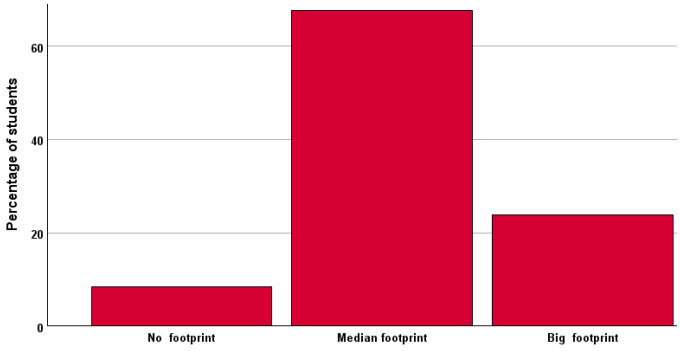

Figure 4: Transports by ecological footprint

In relation to the second dimension, Sustainability, Figure 5 exhibits the 3 sustainability categories, covering Transport, Food consumption and Resources. Students exhibit a stronger tendency toward sustainable food consumption and resource management. The Portuguese population has a strong tradition of home-cooked meals and a preference for reusable food containers, commonly referred to as "lunch boxes". Furthermore, most individuals exhibit a low reliance on food delivery services. Furthermore, Portuguese educational institutions have been observed to demonstrate a greater commitment to the reuse of resources and the reduction of waste, particularly regarding water conservation and the limitation of plastic and paper usage.

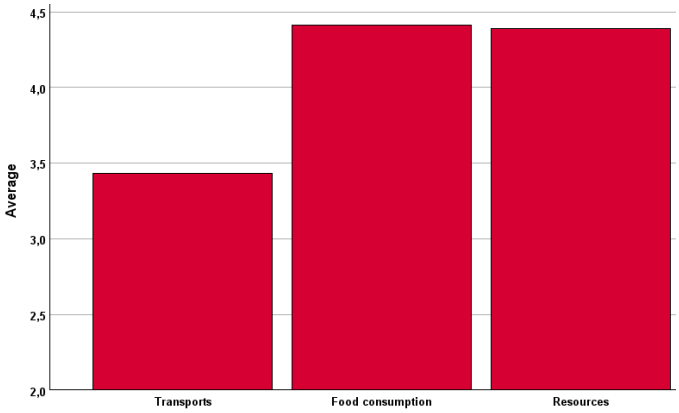

Figure 5: Sustainability Categories Values

For the 'global sustainability' variable (see Figure 6), the most common median is 6.0, reported by 34% of respondents. In this question, participants were asked to rate the relevance of each of the 12 sustainability issues to their personal practices on a scale of 1 (not relevant) to 5 (very relevant). In addition, participants were given the option of selecting 'not applicable' or 'I was already doing it before the pandemic', the latter (at the higher level of 6) to ascertain whether the pandemic had led to any long-term changes in behavior. This finding suggests that many participants perceive their sustainability to be at a high level, i.e. they have already incorporated sustainability habits into their daily lives. In any case, the pandemic seems to have triggered a long-term change in behavior.

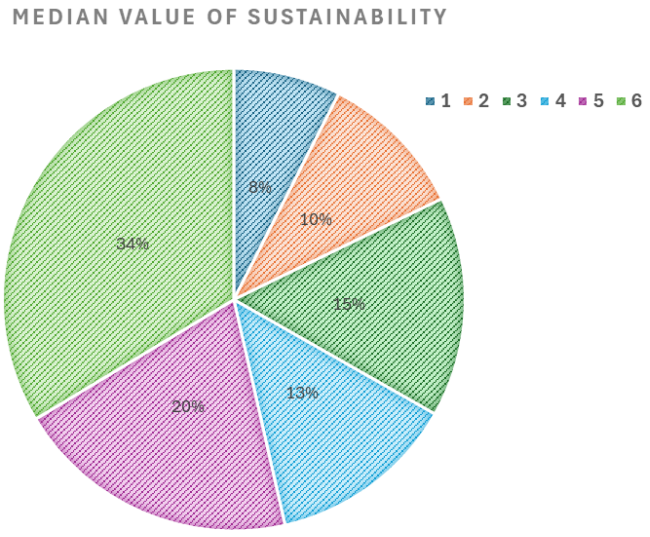

Figure 6: Frequency of the medians obtained in the variable *"global sustainability"*

4.2. Identification of factors affecting student perceptions

As Portuguese students differ mainly in terms of age, educational area and educational level, correlations with these factors were analyzed. Some correlations were found between their age and both the time it takes to commute from home to school (r_{sp}=0.128, p=-0.045, N=245) and the ecological footprint (r_{sp}=0.143, p=-0.025, N=245). Thus, older students tend to spend more time commuting and also leave a higher ecological footprint. In fact, most of them are working students who sometimes travel by car

directly from their workplace. Younger students, if they live away from home, tend to have accommodation close to their school. There is also a correlation between commuting time and the total number of online resources used by students (r_{sp}=0.178, p=-0.018, N=175), suggesting that the more time students spend commuting, the more resources they use online, thus avoiding unnecessary travel to school. There was also a correlation found between class regime and perceived productivity of online resources (r_{sp}=0.127, p=-0.049, N=242), i.e. students who use them more tend to find them more productive. Correlations were also found between all the items considered in the online resources category. No correlation was found between age or level of education with online productivity and sustainability.

Strong correlations were found between the sustainability categories, as well as a correlation between the transport category and the transport by ecological footprint. However, the study did not find any correlation between the two dimensions.

Non-parametric tests for independent samples were employed to ascertain whether the dimensions of online productivity and sustainability were influenced by students' age, area of education and level of education. The analysis yielded statistically significant variations in the category of online classes productivity, both with respect to age and level of education (see Table 4). A subsequent cross-tabulation of these findings suggests that students in the 21-23 age range achieve higher scores in online class productivity. Furthermore, students pursuing higher education (i.e. bachelor's degree) are also found to be more productive in online classes. This finding is further supported by the observation that students in this age group are typically more experienced and mature, often nearing completion of their undergraduate studies or already pursuing postgraduate education, having a heightened level of focus and motivation in their academic pursuits.

Table 4: Summary of "*Online classes productivity*" significant differences with age and level of education

Grouping variable	Median	x^2 (Chi-Square)	p-value
Age	2.0	14.262	0.014
Level of Education	2.0	9.996	0.040

4.3. Comparison between students' perception in 2021 and 2024

To understand how Portuguese students' perceptions have changed over time, we compared data from shortly after the pandemic restrictions were lifted (2020/21) with data from 2023/24. We used a statistical procedure (Mann-Whitney U test) described in Section 3.4 when possible. Because the questionnaires were slightly different, it wasn't possible to use the earlier procedure for items ii and iv. But although the questions were posed differently, the items addressed in both were the same. So, for these ones, a comparison is made only regarding the overall results in each item and not directly for each question. Thus, the quantitative data collected was analyzed in both cases to understand if students' perception about the former items has changed or not.

In fact, one of the goals of this work was to understand if the tendency of habits and opinions towards sustainability issues has changed.

In relation to the dimension of "Online Productivity", this comparison allowed the following inferences:

i. Educational resources they would like to keep using: the study was conducted for the common resources in both questionnaires (online laboratories, simulations, videos, online meetings with teachers, online meetings with peers); still in the first questionnaire it was about the resources they would like to keep using after the pandemic and the second one asked about the resources they are still using. Considering the total number of resources they would like/are using there is no statistically significant difference between the two groups and the same goes to online meetings with teachers and online meetings with peers. However, in 2021, students preferred online laboratories and simulations, while in 2024, students preferred videos (Figure 7). The 2021 preference can be explained by the fact that students spent a lot of time learning from these resources, some of which required extra effort to understand fully. At that point, students were reluctant to give them up if they found them useful. Since hands-on labs have been fully operational since then, students might not feel the same way in 2024. Interest in videos is growing more generally, and students are now more used to consuming them in both academic and social contexts. The number of scientifically helpful videos grew a lot during the Pandemic, and they are an easy way to quickly grasp a concept.

ii. Productivity of online classes/sessions: considering their perceived learning, the majority of 2021 students (51.4%) considered that online classes were productive only for some types of classes, especially those that promoted interaction (41.4%) and to a lesser extent theoretical classes (27.4%). Students (30.9%) also said they wouldn't mind keeping a hybrid system, but only for some subjects/modules, and they chose theoretical classes (89.9%) as the ones they would keep. They also considered that student support (office hours) could be online, but with very little expression (5.2%). The students of 2024 think that online classes can work for: small groups (59.2%), working sessions/meetings (49.6%), student support (47.3%) and theoretical classes (26.1%). So, students' perceptions of the productivity of online classes seem to have changed little, but they now

seem to have a clearer idea of when it can be productive: for meetings, small groups or student support.

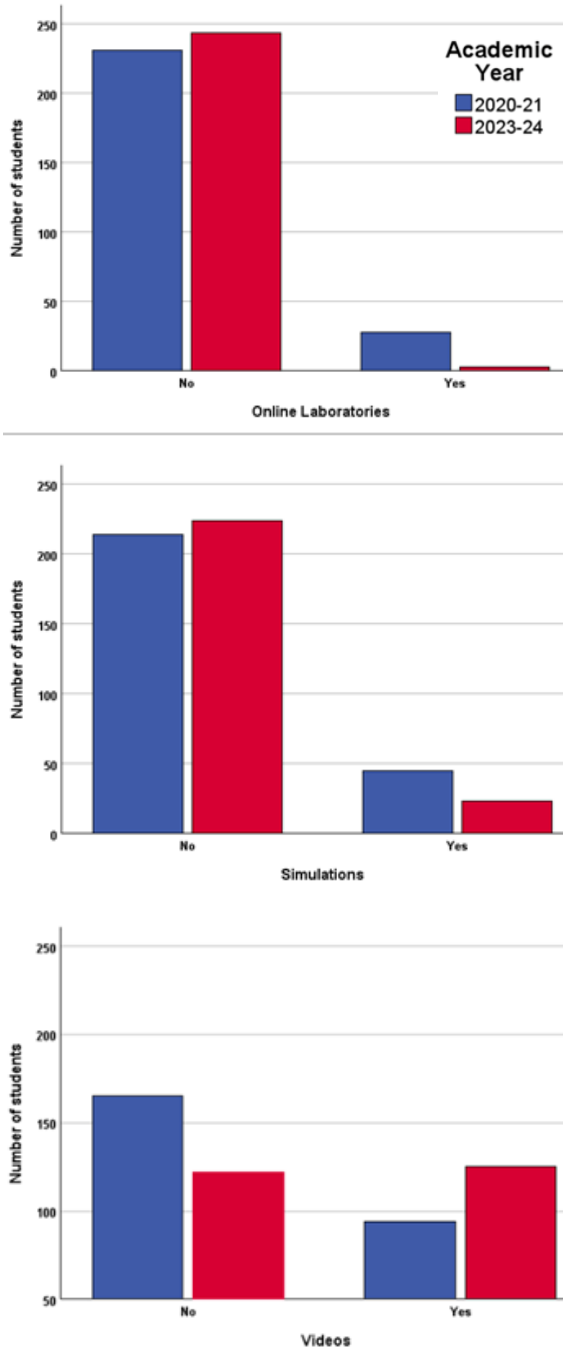

Figure 7: Comparison between online resources preferences from 2021 and 2024 Portuguese students

In relation to the dimension of "sustainability", the comparison allowed to take the following inferences:

iii. The type of transport and the time spent commuting from home to school: there are no statistically significant differences in the type of transport used, but there is a statistically significant difference in the average time they spend on the commute: in 2024 students take more time (as could be inferred from Figure 1, in section 3.2). This could be because in 2021 the return to school was not in full. Since there is no significant difference between the types of transport, this difference in time spent might average that there are more students who come from further away. Overall, this was not an easy decision to make in the immediate aftermath of the pandemic.

iv. Sustainability habits: considering the 3 categories of this dimension (transport, food consumption and resources), a significant percentage of the 2024 students stated that they already had those habits before the pandemic, respectively 46.8 %, 46.4 % and 35.5 %. So, considering the former answer and the students that answered yes to the former questions, the percentages increased to 56.8 %, 63.7 % and 49.7 % respectively. These are significantly higher than the ones obtained in 2021, which were respectively 40.9 %, 33.2 % and 25.1 %. This suggests a heightened level of concern among students regarding practical sustainability issues these days.

4.4. Conclusion

Most of the Portuguese students inquired in 2024 recognized they still use several online resources, with video being the most popular. Overall, they considered online resources as being productive and identified the most productive for their learning as being the classes in small groups, students' support and working sessions. In fact, students who use them more intensely tend to find them more productive. In terms of sustainability, students show a stronger tendency towards sustainable food consumption and resource management. Regarding transport, it was found that approximately 24% of the study participants – typically working and older students - have a high ecological footprint, indicative of significant environmental impact.

Compared to 2021, there was no significant change in students' perceptions of the productivity of online classes. However, they now demonstrate to have a clearer idea of when it can be productive. Video has become more prominent, and students are now more accustomed to using it both in academic and social contexts. Students are also now more concerned about practical sustainability issues. The results suggest that they have already incorporated sustainability habits into their daily lives. In any case, the pandemic seems to have triggered a long-term change in behavior.

Regarding our research question: "*Have students' perceptions regarding sustainability issues and the productivity of online classes changed since the post-pandemic phase?*", our results point to a tendency of improvement of the students' sustainable habits and their perception of the utility of some pedagogical online resources, but only in particular cases.

The findings of this study indicate that students have demonstrated an aptitude for using online tools, which may have consequences for both the pedagogical practices

employed by students and the administration of higher education institutions. An overall contribution of this study is that students are open to the possibility of having some teaching classes or resources delivered online and this may represent a way to use b-learning as a more sustainable alternative since it reduces the transport negative effects, regarding that their schedule allows for them to reduce the number of days they need to attend the university. An important consequence is also the decrease in the time spent commuting. However, students are only open to that possibility if it does not represent hands-on practices, they consider it more productive to be face-to-face with the teacher and colleagues.

These findings also have several implications for key educational stakeholders, such as teachers or academic managers. Teachers should be encouraged to use online tools as complementary strategies to enhance flexibility, engagement and sustainability. They should be encouraged to use hybrid learning formats, particularly those incorporating support sessions and small-group activities. Academic managers should be sensitive to more flexibility in terms of classes schedules and the benefits of online moments, complementary to the hands-on essential classes. Conversely, policymakers and higher education institutions may wish to consider providing institutional support for hybrid education models that align with sustainability goals.

The observation of a considerable ecological footprint among the students in the analyzed sample suggests potential deficiencies in the availability or adequacy of local public transport alternatives. Consequently, this paper may have implications for territorial policy management, particularly by highlighting the necessity to develop transport options that are more aligned with students' needs.

This work has limitations regarding the longitudinal comparison because some questions were slightly modified. Even though no direct conclusion has been made regarding each question, we acknowledge that this factor could have affected the results. Also, the population that answered both surveys was obviously not the same, and we cannot guarantee that external factors related to each group did not influence the responses.

Another limitation of this study lies in the inability to conduct qualitative triangulation, as the original instrument was not designed to collect data suitable for this type of analysis. Consequently, the results are presented solely from a descriptive quantitative approach. Additionally, the sample size represents another limitation, as it does not allow for broad generalization of the findings. However, this work should be understood as a starting point that provides an initial approximation of the reality under investigation. Based on this foundation, future research using mixed-methods approaches may be developed to achieve a more comprehensive understanding of the subject of study.

Conflict of Interest

The authors declare no conflict of interest.

Acknowledgment

The authors would like to acknowledge the partial financial support provided by the Foundation for Science and Technology through grants UIDB/04730/2020 and UIDP/04730/2020. The authors also like to thank all the persons involved in spreading and answering the questionnaire.

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NATÉRCIA LIMA has done her bachelor's degree in Physics/Applied Mathematics and master's degree in Mechanical Engineering from the University of Porto, Portugal in 1989 and 1998, respectively. In 2020, she completed her PhD in Formation in the Knowledge Society (Engineering Education) from the University of Salamanca, Spain.

She is currently a Professor with the Department of Physics, School of Engineering, Polytechnic of Porto. She is also a researcher at the Innovation Centre for Industrial Engineering and Technology and subdirector of the master's in Biomedical Engineering.

CLARA VIEGAS has done her bachelor's degree in Physics/Applied Mathematics from Faculdade de Ciências da Universidade do Porto in 1991. She has done her master's degree in mechanical engineering from Faculdade de Engenharia da Universidade do Porto in 1998. She has completed her PhD degree in Science and Technology from the Universidade de Trás-os-Montes e Alto Douro in 2010.

She had served as researcher in several international projects, editor in journals, chair in international conferences, published more than 100 papers and book chapters, and is co-author and editor in 4 books. She has been teaching at the Department of Physics, School of Engineering, Polytechnic of Porto since 1994.

ALEXANDRA R. COSTA holds a PhD in Social Psychology from the University of Cádiz (Spain) and a Postdoctoral degree in Educational Sciences from the University of Minho. She is a Coordinating Professor at the School of Engineering of Polytechnic Institute of Porto (P. Porto). Her research interests focus on academic success and adaptation in Higher Education, as well as pedagogical practices in Engineering education.

She is the author of numerous scientific articles, books, and book chapters in the fields of Educational Psychology and Higher Education. Member of the Editorial Advisory Committee of the Journal of Studies and Research in Psychology and Education (REIPE).

CLAUDIA OROZCO-RODRIGUEZ has done her Bachelor's degree in Mathematics from the University of Guadalajara, a Master's degree in ICT in Education, and a Ph.D. in the Formation of the Knowledge Society, both from the University of Salamanca, Spain.

Since 2008, she has taught mathematics in engineering programs. She currently serves as a full-time professor and researcher affiliated with the Master's Program in Mathematics Education at the University of Guadalajara. Her research areas include *"Development and application of technology for mathematics teaching and learning"* and *"Educational Research."*.

GUSTAVO R. ALVES has done his bachelor's and master's degrees from the University of Porto, Portugal in 1991, and 1995, respectively. He has completed his PhD degree in Computer and Electrical Engineering from the University of Porto, Portugal in 1999. He has obtained his habilitation from the University of Porto, Portugal, in 2023.

He is currently a Professor with the Department of Electrical Engineering, School of Engineering, Polytechnic of Porto. He also serves as Head of the Innovation Centre for Industrial Engineering and Technology (CIETI). Dr. Alves is a Senior Member of the IEEE and a Vice-President of IAOE.

ANDRÉ V. FIDALGO received the Ph.D., M.Sc. and course degrees in computer and electrical engineering from the University of Porto, Porto, Portugal, in 2008, 1999 and 1996, respectively.

Since 1999, he has been with the School of Engineering, Polytechnic of Porto, Porto, Portugal, where he is currently an Adjunct Professor, subdirector of the Master's in Electrical Engineering and member of the Board of the Innovation Centre for Engineering and Industrial Technology (CIETI). He participated in 10 funded international projects and has over 100 publications in peer reviewed journals and conferences.

Received: 06 June 2025, Revised: 14 June 2025, Accepted: 07 August 2025, Online: 20 August 2025

DOI: https://dx.doi.org/10.55708/js0408004

Magnetic AI Explainability: Retrofit Agents for Post-Hoc Transparency in Deployed Machine-Learning Systems

Maikel Leon*

Department of Business Technology, Miami Herbert Business School, University of Miami, Miami, Florida, USA

*Corresponding author. Email: mleon@miami.edu

ABSTRACT: Artificial intelligence already influences credit allocation, medical diagnosis, and staff recruitment, yet most deployed models remain opaque to decision makers, regulators, and the citizens they affect. A new wave of transparency mandates across multiple jurisdictions will soon require organizations to justify automated decisions without disrupting tightly coupled production pipelines that have evolved over the years. We advance a conceptual proposal to address this tension: the magnetic AI agent. This external, attachable software layer learns a faithful surrogate of any target model, delivering audience-tailored explanations on demand. The paper first synthesizes fragmented scholarship on post-hoc explainability, sociotechnical alignment, and model governance, revealing an unmet need for lightweight retrofits that minimize downtime. It then creates a basic framework based on design principles, explaining methods for data collection, ongoing learning processes, and user-friendly explanation tools. A plan for evaluation lists both numerical and descriptive measures, including how closely a model matches reality and how much extra time it takes, as well as the mental effort required and how well policies work, which users can adjust for different fields like credit scoring, medical imaging, and predictive maintenance. Overall, the work contributes a roadmap for upgrading the installed base of black-box systems while aligning with emergent regulatory frameworks and ethical guidelines for trustworthy AI.

KEYWORDS: Magnetic AI, Explainable Artificial Intelligence, Agentic AI, Retrofit Transparency, Design-Science Research, Policy Compliance.

1. Introduction

Artificial Intelligence (AI) systems that once resided in research labs now power high-stakes finance, health care, logistics, national security, and public administration decisions. These models deliver unprecedented speed and predictive accuracy, yet they rarely reveal the internal logic that drives their outputs. This asymmetry between performance and interpretability poses reputational, operational, and legal risks for organizations that rely on opaque algorithms. Recent incidents—such as biased credit approvals, flawed recidivism predictions, and inconsistent medical triage decisions—demonstrate how opacity can erode stakeholder trust and invite regulatory scrutiny [1].

Last century, AI research surged on the back of expert systems, decision trees, and the early "neural nets" revival. Success was measured almost entirely by how precisely these models could predict outcomes, whether diagnosing disease, flagging credit risk, or recognizing handwritten digits. Researchers fine-tuned rule bases or tweaked hidden-layer weights to squeeze out a few extra percentage points of accuracy, and industry adopters celebrated any gains that outperformed human benchmarks. Yet this accuracy-first mindset treated the models as opaque black boxes: engineers rarely asked why a particular rule fired or a neuron activated, and users seldom demanded a justification. As a result, explainability remained an afterthought; the momentum and funding of the era were channeled into sharpening predictive performance, not into opening the "black box" so stakeholders could trust and understand the reasoning inside it.

Across major jurisdictions, regulation is converging on a common requirement that AI systems be explainable: the European Union's AI Act, recent U.S. executive directives, and China's updated generative-AI rules all mandate that high-impact models provide meaningful information about how they reach their outputs. This amounts to an emerging right for everyday users to demand clear, human-readable reasons for automated predictions or decisions, even when those decisions come from complex neural networks. Anticipating audits, fines, and reputational risks, companies are building explanation layers into their products—dashboards that visualize feature contributions, surrogate models that translate deep-learning logic into plain language, and customer portals that show "what-if" scenarios—because meeting this new transparency baseline is becoming less a nice-to-have and more a competitive necessity.

Societal expectations for transparency have accelerated. Policymakers on both sides of the Atlantic have enacted or proposed frameworks that place the burden of justification on automated decision-makers. The European Union's AI Act, the United Kingdom's Algorithmic Transparency Standard, and various U.S. proposals such as the Algo-

rithmic Accountability Act collectively signal a shift from self-regulation to explicit accountability. These initiatives often focus on two intertwined requirements: the ability to generate human-understandable explanations and the capacity to audit models throughout their life cycle. Organizations, therefore, face the dual challenge of upgrading legacy AI assets and operationalizing governance processes at scale.

Despite rapid advances in post-hoc interpretability techniques, most production environments cannot easily accommodate invasive code changes, extensive retraining cycles, or computational overhead that might jeopardize service-level agreements. Enterprise Machine Learning pipelines typically integrate proprietary libraries, tightly coupled microservices, and third-party APIs that preclude direct intervention. A non-disruptive alternative is to attach an explanatory agent to the outside of an existing pipeline, much like a magnetic device that snaps onto the surface of a machine without changing its internal workings. We label this solution the magnetic AI agent. The magnetic analogy underscores three salient properties: passive attachment, minimal friction, and continuous real-time learning [2].

While the concept of attaching post-hoc interpretability layers has precedent in techniques such as shadow models, knowledge distillation, and wrapper-based surrogates, the magnetic AI agent diverges in critical ways. Unlike shadow models that mimic predictions for evaluation purposes or distillation methods that compress complex models into simpler ones, the magnetic agent is designed to operate continuously alongside the original model without approximation or replacement [3]. Its emphasis is not only on interpretability but also on modular deployment, governance integration, and lifecycle adaptability in real-world production systems. The magnetic metaphor is not a rhetorical flourish—it reflects an architectural philosophy: to enable passive but intelligent observability without disrupting the core model's functioning or retraining requirements.

The remainder of the paper deepens the conceptual foundation, formalizes the design space, and proposes an actionable evaluation pathway for magnetic AI. While empirical results are not presented here, this absence is by design: the work is intended as a conceptual proposal that lays the groundwork for future implementation and experimentation. Its primary aim is to contribute a structured framework, design rationale, and deployment blueprint that researchers and practitioners can build upon. First, Section 2 surveys the multidisciplinary literature on explainable AI and model-agnostic wrappers, identifying persistent gaps that motivate a new approach. Section 3 introduces the conceptual framework that positions the retrofit agent within sociotechnological constraints and elaborates design principles, reference architecture, and governance interfaces. Section 4 describes a design-science research strategy and methodological considerations for constructing and refining the artifact. Section 5 details an evaluation blueprint that organizations can replicate or adapt in their domains. Section 6 discusses operational, ethical, and societal implications, mapping the proposal onto current regulatory trends. Section 7 concludes by summarizing contributions, delineating limitations, and articulating a future research agenda that includes full-scale prototypes, multimodal extensions, and integration with next-generation foundation models.

2. Related Work

Research on explainability spans multiple disciplines, each supplying partial answers to how automated systems should justify their outputs. Algorithmic contributions range from ante-hoc transparent models to post-hoc attribution methods such as LIME, SHAP, and integrated gradients to compression techniques that create interpretable surrogates. Human-computer interaction studies examine the cognitive load of different explanation formats, user mental-model accuracy, and the conditions under which explanations raise or erode calibrated trust. Work in organizational behavior documents how power dynamics, siloed incentives, and technical debt shape whether explanations are acted upon or ignored. Legal scholarship and policy analyses frame transparency as a right, exploring liability, due-process entitlements, and the evolving notion of algorithmic accountability [4].

This review weaves the strands together, pinpointing where they fall short and how they complement one another. Algorithmic methods often optimize fidelity or sparsity but rarely address maintenance overhead once a model is in production. HCI experiments illuminate user comprehension in laboratory settings, yet evidence remains sparse on sustained behavior change in real workflows. Organizational case studies highlight governance bottlenecks but seldom tie them to concrete design artifacts. Legal work identifies transparency duties but leaves practitioners with little guidance on technical implementation. Magnetic AI draws on the strengths of each field while addressing their gaps: a passive attachment strategy respects intellectual-property boundaries emphasized in law, continuous fidelity auditing answers organizational concerns about drift and technical debt, and explanation pluralism accommodates the heterogeneous user needs documented in HCI research [5].

Key takeaways that inform the design are as follows:

- Algorithmic insight: incremental surrogates balance fidelity with latency, enabling explanations at line speed without altering the primary model. They learn from a sliding window of recent requests, refresh continuously without full retraining, and respect the intellectual-property boundaries of closed models, making them suitable for third-party APIs and in-house stacks.
- HCI insight: multiple discourse formats—ranked feature tables, layered saliency maps, natural-language counterfactual narratives, and compliance-ready audit summaries—are necessary because data scientists, end users, and regulators each privilege different cues. Adaptive rendering lets the same evidence flow into analyst dashboards, tooltips for consumers, or machine-readable JSON for supervisory authorities.
- Organizational insight: modular deployment decouples the four layers—interception, surrogate learning, explanation rendering, and fidelity auditing—so firms can adopt only the components they lack. This bolt-on architecture avoids rewriting brittle legacy code,

shortens change-management cycles, and reduces the blast radius of defects to a single microservice rather than the full model pipeline.

- Legal insight: persistent audit logs, role-based explanation access, and optional differential-privacy noise satisfy both transparency duties and data-protection rules. The same artifacts can populate internal risk registers, respond to freedom-of-information requests, or demonstrate compliance during external audits, aligning technical controls with emerging statutes such as the EU AI Act and national consumer-protection guidelines [6].

By fusing these lessons, magnetic AI offers a coherent blueprint that advances beyond silo-specific approaches toward an integrated, production-ready solution for trustworthy machine learning.

2.1. Post-Hoc Explainable AI

Early work on interpretability concentrated on "glass-box" algorithms—decision trees, linear or logistic regressions, and simple rule lists—whose parameters and splits can be read like prose. As deep learning's opaque layers dominated predictive accuracy, researchers shifted toward post-hoc techniques that wrap explanations around otherwise black-box models [7].

The most influential of these are LIME and SHAP. Both build local surrogate models that mimic the original model's behavior near a single instance, then report feature attributions: LIME perturbs inputs and fits a sparse linear model, whereas SHAP samples coalitions of features to compute Shapley values that satisfy additivity and consistency. Their appeal lies in domain-agnostic deployment—data scientists can drop in a few lines of code and hand users a ranked list of "which variables mattered most"—yet the price is high computational overhead, sensitivity to sampling noise, and explanations that change when the same point is probed twice [8].

Beyond LIME and SHAP, gradient-based saliency maps track the partial derivatives of a convolutional network to highlight the pixels that nudge an image score upward or downward; attention visualizations in transformer models color the tokens that capture a language model's gaze; counterfactual methods search the input space for the most minor tweak that flips the prediction, offering an actionable "what would need to change?"; and prototype- or example-based explanations surface representative cases that anchor abstract probability scores in concrete, human-readable examples. Each broadens the explanatory toolbox, yet each inherits its drawbacks: saliency maps blur under adversarial noise, attention plots do not always align with causal importance, counterfactuals become infeasible in high-dimensional data, and prototype selection can reinforce majority-class bias [9].

Across the board, explanation strength often comes at the cost of latency, stability, or hardware resources. Empirical studies still debate whether richer explanations meaningfully boost user trust or downstream decision quality, highlighting an unsolved interpretability-accuracy-usability triangle.

2.2. Wrapper and Surrogate Paradigms

Building a simpler model that imitates a complex one is hardly new. In the 1980s, credit bureaus built "shadow" logistic regressions to track the decisions of proprietary loan scoring engines, and in the 1990s, speech-recognition teams used teacher–student pairs to shrink large hidden-Markov networks so they could run on low-power chips. These ideas matured into what is now called knowledge distillation, where an extensive teacher network produces soft targets—probability distributions rather than hard labels—that guide a smaller student network. The result is a faster, lighter model that often matches the teacher's top-line accuracy but may blur fine-grained decision boundaries, especially in rare or ambiguous cases.

Modern workflows try to close that gap by performing distillation continuously. An online student receives a stream of teacher outputs and updates its weights on the fly, or it joins a replay buffer that mixes new observations with old exemplars to resist catastrophic forgetting. Continual-learning variants add regularizers that anchor key teacher activations so the student does not drift when the data distribution shifts. Yet experiments on non-stationary benchmarks show that even these advanced students struggle with concept drift and are highly sensitive to mislabeled or adversarially perturbed examples [10].

A parallel line of work forgoes access to internal weights altogether. Instead, engineers wrap the black-box service with a data interceptor that logs inputs and outputs, then train a surrogate, often a decision tree or gradient-boosted ensemble, purely from those pairs. This wrapper strategy sidesteps intellectual-property barriers and can be swapped before any commercial API. Still, it introduces fresh privacy challenges: synthetic or cached query data must be stored outside the original security perimeter, and reconstruction attacks can expose sensitive attributes if the wrapper is breached [11].

Taken together, today's surrogate models fall into two camps. Static snapshots captured once during development grow stale as the real world evolves, while dynamic surrogates that retrain or distill online demand constant monitoring, a computation budget, and careful privacy safeguards. Neither camp fully resolves the tension between efficiency, fidelity, and maintainability in production environments that change by the hour.

2.3. Regulatory and Business Context

Across regions, lawmakers and standard-setters are locking into a shared vocabulary—transparency, accountability, fairness, and meaningful human oversight—and turning it into binding or quasi-binding rules. In Europe, the AI Act labels credit scoring, hiring, medical diagnosis, and other "high-risk" applications. It forces them to generate understandable explanations, document data provenance, and pass third-party conformity assessments before entering the market.

In the United States, the Federal Trade Commission, Consumer Financial Protection Bureau, Department of Justice, and other agencies have warned that undisclosed bias, dark-pattern interfaces, or the sale of inscrutable models

can trigger enforcement actions under existing consumer-protection and civil-rights statutes. At the same time, the White House blueprint for an AI Bill of Rights and the NIST AI Risk-Management Framework give regulators a benchmark for what "reasonable" governance should look like. China's updated Interim Measures on generative AI require providers to watermark outputs, publish model cards, and supply "interpretive" summaries on demand; Canada's forthcoming AI and Data Act mandates impact assessments and real-time monitoring; Brazil and India are drafting parallel bills; and the G7's Hiroshima Process is pressing multinationals to align with these norms wherever they operate.

Industry bodies reinforce the trend: the Partnership on AI, the OECD, the ISO/IEC 42001 management-system standard, and voluntary procurement checklists now ask vendors to show audit logs, bias tests, and plain-language explanations as a condition of sale. Non-compliance can mean multimillion-euro fines, exclusion from public-sector tenders, investor divestment, and reputational damage that stalls digital-transformation roadmaps. Yet most enterprises run on entrenched code bases, brittle data pipelines, and overlapping legacy models; ripping and replacing them is rarely feasible. This clash between external pressure and internal technical debt drives demand for retrofit solutions—lightweight layers that bolt onto existing systems, capture inputs and outputs, monitor drift, and surface user-friendly explanations—so firms can satisfy new governance obligations without rebuilding their entire machine-learning stack [12].

2.4. Gap Analysis

Table 1 contrasts prevailing approaches against operational requirements and spotlights the unresolved disconnect between research prototypes and production realities. While the literature offers algorithmic sophistication, it rarely addresses day-two concerns such as deployment pipelines, monitoring infrastructure, and heterogeneous stakeholder needs. The magnetic AI proposal aims to bridge this gap by integrating passive attachment, continuous fidelity auditing, and human-centered explanation delivery into a unified artifact.

There seems to be a clear trade-off pattern: methods that are easiest to bolt onto any model (LIME, SHAP, Anchors) suffer from high inference latency or heavy sampling, while techniques that are fast enough for production (knowledge-distilled surrogates, ante-hoc interpretable models) often under-fit or drift from the source model without constant retraining. Vision-specific tools like Grad-CAM are efficient but narrow in scope, and counterfactual or prototype-based approaches provide the most human-friendly "what-if" stories yet demand large compute budgets and carefully curated instance libraries [13].

In short, no single technique simultaneously delivers low latency, high fidelity, and broad stakeholder usability. This operational gap motivates a hybrid solution, such as the proposed magnetic AI artifact, that couples passive attachment for real-time capture with continuous fidelity auditing and layered explanation modes tuned to different audiences.

Table 1: Operational gap between explainability techniques and production requirements

Approach	Strengths	Limitations
LIME / SHAP	Model-agnostic; easy to add	High latency in production; explanations local
Knowledge distillation	Compact, fast surrogates	Needs labelled outputs; surrogate drift
Counterfactuals	Actionable "what-if" paths	Heavy compute; plausibility issues
Magnetic AI (proposed)	Passive attachment; continuous learning	Concept stage; governance pending
Integrated Gradients	Faithful to deep nets; low single-call overhead	Requires differentiable model; noisy for saturated neurons
Grad-CAM	Intuitive heat-maps for vision CNNs; real-time on GPU	Vision-only; coarse spatial resolution
Anchors	Sparse, high-precision rules; human-readable	Sampling-intensive; struggles with high-dimensional mixes
Partial Dependence / ICE	Global feature-effect trends; offline computation	Assumes feature independence; stale in changing data
Prototype & Criticism	Example-based, domain-relatable explanations	Needs large representative set; weak in very sparse spaces
Ante-hoc interpretable mdl.	Transparency built-in (e.g., GAMs, monotonic GBMs); low latency	May under-fit complex tasks; restricted model choices

3. Magnetic AI Conceptual Framework

The magnetic AI framework delineates the core constructs, operational boundaries, and design guidelines necessary to retrofit explainability into black-box systems. Building on sociotechnical theory, the framework positions the agent as an intermediary that negotiates between opaque algorithms and heterogeneous human audiences [14].

3.1. Definition and Scope

A magnetic AI agent functions as a sidecar or proxy service that eavesdrops on every request–response pair flowing to and from a production model. As each new interaction arrives, the agent adds it to a sliding window buffer—say the most recent ten thousand cases—and updates an online surrogate such as an incremental gradient-boosted tree or a compact transformer fine-tuned with parameter-efficient adapters. This continual refresh allows the surrogate to track concept drift without incurring the full cost of retraining. Because the agent learns only from observable inputs and outputs, it can attach to black-box APIs, commercial SaaS endpoints, or legacy binaries without source code or training data. Once the surrogate reaches a configurable fidelity threshold, the agent can emit different explanation "dialects" on demand: concise ranked feature lists for customer-service representatives, multi-layer saliency maps

for data scientists, counterfactual recourse suggestions for end users, or timestamped audit reports that regulators can archive. A governance layer encrypts the buffered data, records model-to-surrogate agreement scores, triggers alerts when fidelity degrades, and exposes REST or gRPC endpoints so downstream dashboards can pull explanations in real time [15].

Deployment is lightweight—often a Docker container or Kubernetes sidecar—so platform teams can roll it out with minimal changes to existing pipelines. Because the agent never touches proprietary weights or training sets, intellectual-property boundaries remain intact, and privacy can be reinforced with hashing or differential-privacy noise in the captured feature vectors. This combination of passive attachment, incremental learning, and audience-specific explanation formats positions magnetic AI agents as a practical retrofit for organizations that must meet new transparency rules without redesigning their entire machine-learning stack.

3.2. Design Principles

Design principles serve as invariant heuristics that guide implementation choices across contexts:

- Plug-and-play attachment via standardized data taps that conform to common message-queue or REST interfaces, minimizing engineering overhead.
- Model and domain agnosticism that enables deployment across tabular, image, NLP, time-series, and multimodal pipelines.
- Continuous auditing that monitors surrogate fidelity over time using drifting-window statistical tests and triggers automatic recalibration when thresholds are breached.
- Explanation pluralism that tailors output modalities to stakeholder expertise, regulatory requirements, and situational constraints, thereby enhancing relevance and comprehension.
- Privacy-preserving learning that supports on-device distillation, differential privacy budgets, and federated aggregation when data sovereignty is paramount.

3.3. Reference Architecture

The architecture is divided into four loosely coupled layers. The data interception layer attaches to message brokers, REST gateways, or in-process hooks to duplicate each input–output pair with millisecond-level delay. Captured data is written to an encrypted sliding-window buffer sized to the latency budget. The surrogate learning layer ingests this stream and updates an incremental model such as an online gradient-boosted tree, streaming k-nearest neighbors, or a partial-fit neural network.

A fading factor emphasizes recent samples so the surrogate can track concept drift without unbounded memory growth. The explanation rendering layer queries the current surrogate to extract local and global importance signals, then converts them into human-readable artifacts by combining a template engine with natural-language generation. Supported formats include ranked feature lists, layered saliency maps, counterfactual recourse narratives, and compliance-oriented audit summaries.

The fidelity auditing layer compares surrogate outputs with the target model on a hold-back stream slice, records agreement statistics, raises drift alerts when error thresholds are exceeded, and exposes metrics to governance dashboards through an HTTP endpoint. The modular design permits selective adoption, so an organization may activate only the components that fill existing gaps:

- Data interception choices: sidecar proxy, service-mesh filter, or Kafka consumer
- Surrogate learning supports pluggable incremental algorithms and optional ensembling
- Explanation rendering exports Markdown, JSON, PDF, or SVG artefacts for integration with existing portals
- Fidelity auditing pushes metrics to Prometheus or OpenTelemetry and routes alerts to Slack or PagerDuty

Figure 1 illustrates the magnetic AI agent operating across four loosely coupled layers.

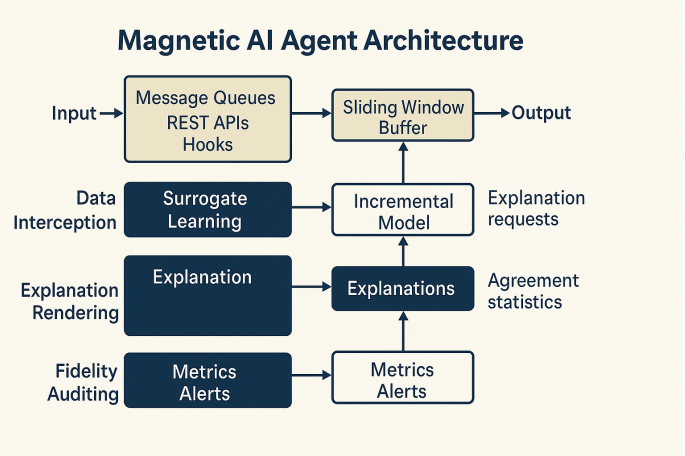

Figure 1: Magnetic AI Reference Architecture: A four-layer system that retrofits explainability into black-box models using passive data interception, online surrogate learning, audience-specific rendering, and continuous fidelity auditing.

4. Research Design and Methodology

Table 2 summarizes the guiding questions. Rigorous methodological scaffolding is essential to transform a design idea into an evaluable artifact. We adopt a design-science paradigm that iteratively synthesizes knowledge through constructing and assessing purposeful artifacts.

4.1. Artifact Construction Strategy

The construction strategy unfolds in three stages. Stage 1 employs synthetic benchmarks such as tabular classification tasks from the UCI repository to validate algorithmic viability under controlled conditions. Stage 2 transitions to semirealistic testbeds—for example, open medical-imaging datasets—where data sensitivity approximates production scenarios. Stage 3 involves shadow deployments within partner organizations, embedding the agent in parallel with live systems to observe operational impacts without

influencing decision outcomes. Each stage employs a build-measure-learn loop, refining data-tap APIs, surrogate hyperparameters, and explanation formats based on empirical feedback.

Table 2: Guiding questions for magnetic AI research design

Research question	Section
What functions must a retrofit agent perform to satisfy transparency mandates?	Framework
How can fidelity be maintained as underlying models drift?	Methodology
Which usability metrics best capture explanation quality across domains?	Evaluation
What governance processes are necessary to embed magnetic agents responsibly?	Discussion

4.2. Proposed Evaluation Metrics

Comprehensive evaluation encompasses technical fidelity, human factors, and organizational fit.

- Surrogate fidelity quantified by macro-averaged agreement, calibration error, and local explanation stability across perturbed inputs.
- Latency overhead measured as the delta between baseline prediction response time and pipeline response time with the agent attached, segmented by cold-start and steady-state conditions [16].
- Cognitive burden assessed via the NASA-TLX workload instrument and validated comprehension quizzes administered to diverse user cohorts.
- Policy sufficiency mapped to ISO-based checklists and jurisdiction-specific compliance rubrics, with binary pass/fail indicators and narrative justifications.
- Maintenance complexity captured through engineer-reported setup time, mean time to detection, and time to repair when drift alarms are triggered.

5. Evaluation Blueprint

A structured evaluation helps an organization transition from proof of concept to full roll-out without losing sight of risk, cost, or stakeholder value. Below, we will break the adoption into four incremental phases, each with its entry criteria, success indicators, and decision gates. Escalation to the next phase occurs only when the previous one meets predefined thresholds, reducing the likelihood of expensive rework later in the project. As shown in Figure 2, the evaluation progresses through four structured phases.

5.1. Phase 1: Feasibility Scoping

The objective is to decide whether a magnetic agent can attach to existing systems with acceptable effort and risk. A cross-functional team—product owners, data engineers, legal counsel, and compliance officers—maps the technical and organizational landscape before a single line of code is written.

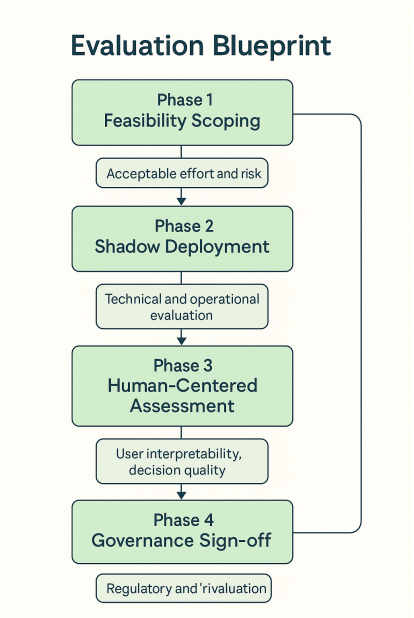

Figure 2: Evaluation Blueprint: A four-phase process guiding the deployment of magnetic AI agents from feasibility scoping to governance sign-off.

- Catalog candidate models, including version numbers, input modalities, and traffic volumes.
- Identify data-tap points such as message queues, microservice gateways, or in-process hooks.
- Segment explanation audiences: internal analysts, external customers, and regulators.
- Run a one-week pilot that captures a small sample of input–output pairs to confirm data visibility, latency overhead, and encryption requirements.
- Document legal constraints on data copying, retention, and cross-border transfer.

A green light to Phase 2 requires evidence that data taps are technically feasible, that no show-stopper legal barriers exist, and that the surrogate can be trained within the latency budget on a representative sample.

5.2. Phase 2: Shadow Deployment

The magnetic agent now runs parallel with the production model but remains invisible to end users. The aim is to measure technical fidelity and operational impact without altering business outcomes.

- Stream live input–output pairs to the surrogate and store them in a ring buffer sized to the retention policy.
- Generate explanations, drift graphs, confusion matrices, and saliency heat maps; push them to a read-only dashboard.
- Track surrogate-to-model agreement, memory growth, and compute cost hourly.
- Stress-test the agent under peak traffic loads to verify scaling rules and auto-healing scripts [17].
- Perform red-team exercises to probe for model inversion and data leakage vectors.

Promotion to Phase 3 requires that fidelity metrics reach a predefined threshold, that resource consumption stay within budget, and that no critical security vulnerabilities remain open.

5.3. Phase 3: Human-Centered Assessment

With technical soundness established, the focus shifts to human interpretability and decision quality. Explanations are shown to real users in a sandbox or pilot workflow.

- Recruit subject-matter experts—credit underwriters, fraud analysts, radiologists—for structured review sessions.
- Present a stratified sample of explanations, including edge-case and adversarial examples.
- Collect quantitative scores using metrics from Section 4 and qualitative feedback on clarity, usefulness, and domain language.
- Run A/B trials where some users receive explanations and others do not, measuring changes in decision time, error rate, and confidence calibration.
- Iterate on templates, terminology, and granularity until user-acceptance criteria are met.

Advancement to Phase 4 depends on demonstrable gains in user understanding or workflow efficiency and the absence of new cognitive or fairness concerns.

5.4. Phase 4: Governance Sign-off

The final checkpoint aligns the deployment with corporate risk appetite and external regulatory obligations. A multidisciplinary committee reviews evidence accumulated in earlier phases.

- Audit logs: fidelity trends, drift alerts, red-team findings, and remediation actions.
- Human-factor reports: focus-group transcripts, A/B test statistics, and user-acceptance sign-offs.
- Compliance dossier: data-protection impact assessment, model card, explanation samples mapped to regulatory articles.
- Operational playbook: on-call rotation, retraining schedule, rollback triggers, and key performance indicators.

Once approved, the magnetic agent's explanation endpoints are activated in consumer portals, internal tools, or regulator-facing audit trails. Post-deployment, a quarterly review loop checks for concept drift, escalating to retraining or policy revision when thresholds are breached.

6. Discussion

The empirical and design insights above converge on a central theme: explainability is no longer a research luxury but an operational requirement that influences competitive advantage, regulatory posture, and societal trust. Deploying a magnetic agent transforms transparency from an expensive, one-off retrofit into a continuous service layer that scales with business growth [18]. This shift prompts decision makers to treat explainability as a cross-cutting capability, like security or observability, rather than a bolt-on feature. It carries strategic implications at three levels.

First, at the enterprise level, magnetic AI offers a cost–benefit inflection point. Faster compliance approvals, reduced litigation risk, and new value propositions, such as premium data-lineage services for high-stakes customers, offset the marginal expense of streaming surrogates and auditing dashboards. Firms adopting early may shape industry standards and lock in reputational capital that late movers struggle to match.

Second, at the ecosystem level, widespread passive-attachment architectures could generate large, anonymized corpora of model–surrogate disagreement events. These data could be shared under federated learning or secure multiparty protocols, catalyzing sector-wide benchmarks for robustness and enabling collaborative defense against adversarial attacks and systemic bias.

Third, granular yet comprehensible explanations at the societal level recalibrate the power balance between institutions and individuals. Users gain procedural recourse, auditors gain verifiable artifacts, and policymakers gain a practical blueprint for enforcement. The trade-off, however, is a thicker layer of governance overhead and an expanded attack surface that demands ongoing vigilance [19].

Against this backdrop, executive sponsors should treat magnetic AI deployment as a phased capability-maturity journey. Early milestones include establishing a data-tap inventory, codifying explanation-quality metrics, and funding interdisciplinary training programs so that engineers, risk officers, and product managers share a common vocabulary. Later stages focus on automating drift remediation, integrating feedback loops into agile release cycles, and participating in cross-industry consortia that set open standards for explanation fidelity and fairness. Organizations can navigate tightening regulations and rising public expectations by internalizing these priorities without sacrificing innovation velocity [20].

6.1. Prototype Model Demonstration

To illustrate the feasibility and behavior of the magnetic AI agent in a controlled environment, we implemented a toy model scenario. This lightweight empirical demonstration, while not intended as a comprehensive validation, serves to ground the concept in observable mechanics and provide an early proof of plausibility.

We used the classic Iris dataset and trained a black-box model using a random forest classifier. The magnetic agent was simulated as a proxy service that intercepted each input–output interaction and updated an online logistic regression model as its surrogate. The surrogate was constrained to observe only the request–response pairs, without access to feature importances, decision paths, or model internals.

Explanations were then generated by querying the lo-

gistic surrogate for each prediction and mapping the coefficients to ranked features. A fidelity audit compared surrogate predictions to the random forest decisions over a sliding window of 150 samples. Surrogate agreement stabilized at approximately 92%, and drift detection flagged one period where surrogate performance dropped due to a change in the class distribution, prompting automatic retraining.

Latency benchmarks were also recorded. On a commodity laptop (2.4 GHz, 8 GB RAM), average inference time per sample for the surrogate was under 3 milliseconds, including update and explanation rendering. This suggests that passive learning and auditing are feasible in near-real-time scenarios with moderate throughput. The latency–fidelity trade-off was observed to be tunable: larger sliding windows and ensemble surrogates marginally improved fidelity (up to 95%) but increased inference latency to 7–9 milliseconds per sample.

Input and output interfaces were defined as JSON over HTTP, simulating a REST-based production API. The surrogate processed flattened tabular features of fixed-length float vectors (4 dimensions for Iris), and the agent operated asynchronously in a sidecar thread. All components were implemented in Python using scikit-learn, Flask, and asyncio.

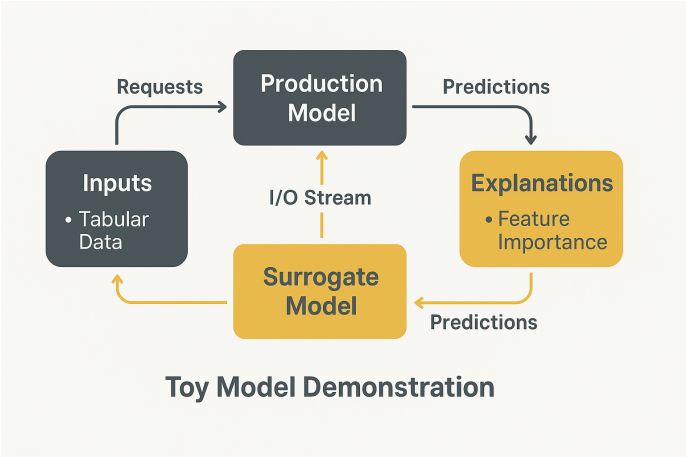

Figure 3: Toy Model Setup: The magnetic AI agent observes request–response pairs from a black-box random forest classifier trained on the Iris dataset. It trains a surrogate logistic regression model in real time, generates explanations, and audits fidelity in a sliding window.

6.2. Operational Considerations

Deploying a magnetic-AI layer replaces the usual pain of rewriting core models with the more manageable task of tapping live data streams. In companies that route traffic through Kafka, Kinesis, or a service-mesh sidecar, engineers can expose the request and response topics, spin up an agent container, and reach baseline fidelity in a morning.

By contrast, firms that still rely on tightly coupled middleware or batch ETL pipelines have to interpose a shim: a wrapper script that logs function calls or a lightweight message broker that mirrors production payloads without breaking the original code path. Once the tap is in place, the dominant cost moves from development time to compute cycles. Surrogate training scales almost linearly with input volume, so high-traffic applications—think personalized advertising or fraud detection at the millisecond level—can drive up cloud bills. Most teams blunt the cost curve by batching updates, down-sampling low-value events, or letting the agent burst to spot GPUs only during load spikes. Role clarity is essential to keep the system maintainable.

Data engineers own the interception code and service orchestration; data scientists tune the surrogate's learning rate, curate explanation templates, and validate fidelity thresholds; and compliance officers monitor the audit metrics, approve threshold changes, and archive drift reports for regulators. Without that three-way handshake, incremental tweaks in one area can silently break obligations in another, turning a retrofit to reduce risk into a new source of operational debt [21].

6.3. Ethical and Societal Dimensions

Agentic explainability shifts control from the system to the individual: a user can probe why their loan application was declined, inspect which pixels persuaded a vision model to flag an X-ray as malignant, or test what-if scenarios to see how a recommendation would change if inputs were different. This new transparency fosters autonomy and contestability and cracks open fresh attack surfaces.

Detailed feature-importance scores can reveal sensitive correlations that a company regards as trade secrets; if queried repeatedly, counterfactual examples let adversaries approximate the decision boundary and reconstruct private training data. To balance empowerment with protection, platform teams typically combine three defenses: rate-limiting caps the number of explanation calls per user or session, and throttling brute-force inversion attempts. Second, tiered access gates fine-grained explanation modes—local SHAP values, raw probability vectors, and full counterfactual paths—behind roles, entitlements, or paywalls, so casual consumers see only high-level summaries.

At the same time, regulators or auditors can request deeper details under non-disclosure constraints. Third, an adversarial-testing regime injects synthetic queries that mimic hostile behavior and flags the agent if leakage thresholds are exceeded.

Technical safeguards alone are insufficient because the audience's ability to parse explanatory artifacts is uneven. A compliance officer versed in statistics might understand the caveats of partial-dependence plots, whereas a consumer reading a heat map could misinterpret bright red pixels as causal rather than correlative. Organizations supplement the raw output with plain-language tooltips, short videos, or interactive walk-throughs that coach users on what the colors or numbers mean and, equally important, what they do not guarantee. Regulators are starting to codify such practices, requiring that explanations be available and comprehensible to a layperson in the decision context [22].

Lastly, equity audits need to extend beyond prediction fairness to explanation parity. A system may produce identical acceptance rates for two demographic groups, yet still describe its reasoning in more detailed or actionable ways for one group than the other. Auditors should measure the consistency of feature rankings, saliency intensities, and counterfactual suggestions across protected attributes. They should verify that any differences can be justified by legit-

imate factors rather than reflecting hidden bias. Without such checks, well-intentioned transparency can entrench inequities by giving some users a more straightforward path to recourse while leaving others in the dark.

7. Conclusions

This paper positions magnetic AI as a practical, scalable strategy for injecting explainability into the countless black-box models influencing credit decisions, hiring, medical triage, and other facets of economic and social life. Rather than requiring expensive retraining or code rewrites, the magnetic approach attaches passively to existing data flows, learns a lightweight surrogate in real time, and delivers multiple explanation formats that can satisfy data scientists, end users, auditors, and regulators alike. We first synthesize decades of research on interpretability, model compression, and drift detection to ground the proposal in established theory. We then distill that literature into concrete design principles: non-intrusiveness, continual fidelity auditing, modular deployment, and explanation pluralism tailored to stakeholder needs.

Building on these principles, we outline an evaluation blueprint that cuts across three dimensions. The technical track measures surrogate accuracy, latency overhead, and drift-detection sensitivity. The human track uses controlled studies and field pilots to gauge whether different user groups understand and act on the explanations. The regulatory track maps the agent's outputs to statutory requirements such as the EU AI Act's transparency duty, U.S. consumer protection guidelines, and industry standards like ISO 42001. By integrating these perspectives, the paper provides a holistic roadmap for retrofitting trustworthy AI capabilities into existing machine-learning stacks without disrupting production workflows. Ultimately, magnetic AI extends the idea of surrogate modeling from a one-off snapshot to a living, continuously audited companion, positioning organizations to meet emerging policy mandates and rising public expectations for transparency and accountability.

7.1. Limitations

The magnetic-AI framework is, at present, a theoretical blueprint. It has not yet been stress-tested on production traffic in banking, retail, health care, or public-sector settings, where data rates, latency budgets, and privacy constraints differ sharply. Field trials are needed to reveal whether the surrogate can keep pace with high-volume streams, whether passive interception introduces unacceptable delay, and which sectors face unique regulatory or contractual hurdles.

These deployments will also expose weak security points, such as opportunities for adversaries to infer proprietary decision logic or poison the surrogate's sliding-window buffer. In addition, the current design assumes a supervised task with stable labels—credit approval, fraud detection, or image classification—leaving open how a magnetic agent would operate in unsupervised anomaly detection, continuous exploratory reinforcement learning, or free-form generative applications where outputs are text, images, or code snippets rather than class scores. Each paradigm raises new questions about what counts as a faithful surrogate, how to define drift or fidelity, and which explanation formats are meaningful to users. Therefore, comprehensive empirical studies across these settings are essential before the approach can be considered production-ready.

7.2. Future Work

Future research must move the magnetic-AI concept from controlled prototypes into live production pipelines. Pilot deployments in banking, e-commerce, and telemedicine sectors would reveal practical limits on throughput, latency, and privacy while showing how easily the agent can be co-containerized, versioned, and rolled back under real traffic. Once embedded, the surrogate-learning engine should evolve from periodic mini-batch updates to accurate streaming operation, digesting continuous flows of tabular events, log sequences, sensor signals, and even raw audiovisual frames without halting for retraining. Handling these multimodal inputs will require hybrid learners that combine gradient-boosted trees for structured features, lightweight convolutional backbones for images, and adapter-based mini-transformers for text, all coordinated by a reservoir buffer that prioritizes the most recent or conceptually novel samples.

A second avenue involves deeper integration with large foundation models that have chain-of-thought capabilities. Instead of treating the surrogate purely as a predictive mimic, an agent could query a frozen language model for self-rationalizing traces, then cross-check those traces against feature-importance scores to generate richer, more coherent explanations. This hybrid could also let users ask follow-up questions in natural language—Why did age matter more than income?—and receive conversational clarifications grounded in statistical evidence and domain policy.

Finally, the community needs shared benchmarks that evaluate explanation quality across domains rather than in narrow, single-task silos. A standard suite might pair representative workloads—credit risk, dermatology imaging, autonomous-vehicle perception—with crowdsourced judgment tests, cognitive-load surveys, and perturbation-based robustness checks. Metrics would cover fidelity, sparsity, stability under re-queries, resistance to inversion attacks, and user comprehension measured through decision-making tasks. Establishing such benchmarks would allow researchers to compare methods rigorously, accelerate regulatory acceptance, and guide practitioners toward solutions whose benefits generalize beyond any industry.

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Biography

Dr. Maikel Leon is interested in Artificial Intelligence (AI), Generative AI (GenAI), and Machine Learning (ML). His work bridges intelligent systems' theoretical foundations and practical applications, particularly emphasizing explainability, hybrid models, and educational innovation. Dr. Leon has published in high-impact journals such as IEEE Transactions on Cybernetics, Information Sciences, Knowledge and Information Systems, International Journal on Artificial Intelligence Tools, Intelligent Decision Technologies, and International Journal of Learning, Teaching and Educational Research. His research explores cutting-edge topics, including prompt engineering, sustainable AI, personalized tutoring via generative models, hybrid fuzzy systems, and large language model benchmarking. He was awarded the Cuban Academy of Sciences National Award for the Most Relevant Research in Computer Science. Dr. Leon obtained his PhD in Computer Science at Hasselt University (Belgium), an MSc and a BSc in Computation from Central University of Las Villas (Cuba), and currently serves as Associate Professor of Practice in Business Technology at the Miami Herbert Business School, University of Miami (Florida, USA).

Received: 03 July 2025, Revised: 31 August 2025, Accepted: 03 September 2025, Online: 19 September 2025
DOI: https://dx.doi.org/10.55708/js0409004

Content Recommendation E-learning System for Personalized Learners to Enhance User Experience using SCORM

Pasindu Udugahapattuwa[1], **Shantha Fernando**[2]

[1]Department of Electrical, Electronic and Telecommunication Engineering, General Sir John Kotelawala Defence University, Sri Lanka
[2]Department of Computer Science & Engineering, University of Moratuwa, Sri Lanka
*Corresponding author: Pasindu Udugahapattuwa, & Email: udugahapattuwad@kdu.ac.lk

ABSTRACT: E-learning is a main field used to improve learners' learning environment. It would be more useful if the E-learning systems were improved by getting interactions and focusing on user experience. This research suggests increasing the user experience of students towards E-learning environments by recommending content according to their preferences. This research aims to make personalized content recommendations by identifying user interactions, trends, and patterns. Finally, this research provides a model that could help to create an intelligent E-learning system. Then the student engagement towards E-learning and user performance level can be enhanced using this research. After developing the model, there is a 73.99% accuracy in initial training and 63.16% accuracy in initial testing. After retraining and retesting, there was 85.58% accuracy for retraining and 78.90% accuracy for retesting.

KEYWORDS: E-learning, Personalized Content Recommendation, User Experience, SCORM

1. Introduction

1.1. What is E-learning?

E-learning is a method that is used to provide education. E-learning is the use of the Internet and other digital technologies to facilitate learning outside of the traditional classroom setting. The key components and features of E-learning can be mentioned as content delivery in digitally formats, learning management systems (LMS), online courses and MOOCs, Interactive and Multimedia Tools, Synchronous and Asynchronous Learning, Assessments and Feedback, and Collaborative Learning Tools. The central point of E-learning is learning management systems (LMS). Learners can create, manage, and deliver courses using E-learning because LMSs provide a structured environment. E-learning has some challenges that can be addressed to replace traditional educational methods.

1.2. E-learning Systems

E-learning systems are becoming more common among people which can be used to gravitate toward beyond traditional learning methods. Typically, E-learning systems consist of courses and activities such as quizzes and distribute them among students, post notifications, review assessments, and exams, and accept or reject student enrollment.

1.3. Educational Data Mining

Data mining is used to uncover patterns, correlations, relationships, and anomalies within extensive sets of data to predict future results and trends. Educational data applies to data mining for research needs such as enhancing the educational procedure, leading students to learn, or having a better knowledge of educational phenomena.

Educational Data Mining is a contributing discipline that plays a key role in improving educational outcomes. By mining data types from educational settings and applying data mining techniques, students can gain a deeper understanding and the environments in which they learn. With the usage of the educational system raised, high amounts of data become available.

Educational Data Mining offers valuable insights into the necessary information and presents a clear profile for learners. Then data mining is used to solve educational-related issues. There are some educational data mining techniques like clustering, prediction, and discovery with models and relationship mining. Then, it can identify novels, interesting, and useful information from educational data.

1.4. Content Recommendation

The content recommendation method can be used to increase user interaction in most E-learning systems. The types of content suitable for different levels should be properly mentioned in a content recommendation system.

1.5. Research Problem

With the increase in popularity in the remote teaching field, more people have a desire to share their knowledge. However, the presentation of knowledge is directly proportional to how efficiently knowledge can be passed on. Everyone has a different capability for learning and the general content delivery system is not very successful. There are some prior research works which are using data mining techniques, can be used to predict performance of students'. Several research works were done on personalized lesson

recommendations based on the probabilistic model and agent-based models. However, no significant research has been observed on recommending content based on the subject's interest from the student in current E-learning systems.

1.6. Research Objectives

This proposed system has two main objectives which are mining data from user interactions identifying user needs and delivering targeted lessons to enhance user interest in relation to lesson content.

1. Identify user needs and user interactions through mining data
2. To enhance user interest and interaction, develop lessons based on user needs

1.7. Research Questions

Students' interactions are very crucial to understand user engagement and enhance the learning experience. The students' interactions can be identified by focusing their activities on the system. Collecting data through surveys and assessments can provide a better understanding of user experiences and preferences. Students' interactions with the content are required to be evaluated. There are some metrics like the frequency and duration of content access, completion rates of assignments or quizzes, and any interactions or discussions within the system to evaluate. These metrics are useful to enhance the level of student engagement. Personalized learning approaches are necessary to deliver targeted content to increase students' interactions. Collecting data, such as interactions, performance, preferences, and interests will be useful in creating content for specific needs. Multiple content formats such as texts, audio, or images are useful to engage their preferences and learning styles.

1. How to identify student interactions and attractions towards the contents of the E-learning?
2. How to evaluate user interest for the E-learning content?
3. How to deliver targeted content to each individual student to interact with students?
4. How to translate content through different media according to the user's interests such as when given content is in text format and the targeted audience requires the content in audio format to be interested?

1.8. Research Scope

This project intends to cover the extraction of student behaviors related to interests in the content from E-learning systems of Sri Lanka, developing a simulation of an E-learning system, and testing different content recommendation techniques that can be used to deliver targeted content to the Sri Lankan undergraduate students based on extracted data and user interest levels.

1.9. Research Significance

The proposed research will help to enhance the interest students have in the content through targeted delivery of content. By analyzing and understanding individual student preferences, learning styles of students, and students' relationships, the E-learning system can deliver content by aligning with their essential requirements and interests. This personalized method enhances the preferences of students to be motivated and engaged with the relevant materials. Somehow, if one student has shown preference for audio-based content, then the system can provide audio-based text-based content, that can be accessed and appealed to that student. The research targets to provide a more personalized and engaging learning experience by adjusting the material delivery to the interests of the individual.

1.10. Research Outline

Section 1 provides a comprehensive introduction to the entire research, setting the foundation and context for the study. Following this, Section 2 delves into the related literature, where it reviews previous research efforts relevant to the proposed study. This section not only summarizes earlier work but also critically highlights the limitations and drawbacks that have been identified, thereby establishing the need for current research. The methodology of the study is detailed in Section 3, which emphasizes the novel approach and procedures that define this research. This section carefully explains the specific methods employed, underscoring the innovations introduced to address the gaps found in prior studies. Upon implementing the methodology, the research progresses to Section 4, which presents the results obtained from the experimental or analytical processes. This section also includes an in-depth discussion that interprets the findings, considering both the current results and the shortcomings noted in previous work, thus providing a clear comparison and justification for the research' contributions. Finally, the study concludes with a meaningful conclusion section that synthesizes the key outcomes, addressing the initial research questions, problems, and objectives. This concluding part not only summarizes the study's achievements but also reflects on its significance, implications, and potential directions for future research.

Figure 1 shows the outline throughout the research flow.

2. Related Works

The following sections state the similar works that were done on the existing works for the proposed research system, the topics of Student behavior extraction, content formatting, and SCORM. Finally, research remarks have been clarified according to the whole literature review.

2.1. Existing Research Works

Many studies have discussed intelligent E-learning management systems to enhance user experience. In [1] and [2], both focus on personalized recommender systems, with [1] emphasizing the role of these systems in overcoming information overload and [2] proposing an intelligent profiling system to recommend courses based on user preferences. The management of learning information [3] was discussed in E-learning systems, emphasizing the need for interoperability and proposing an Open Education Service Architecture.

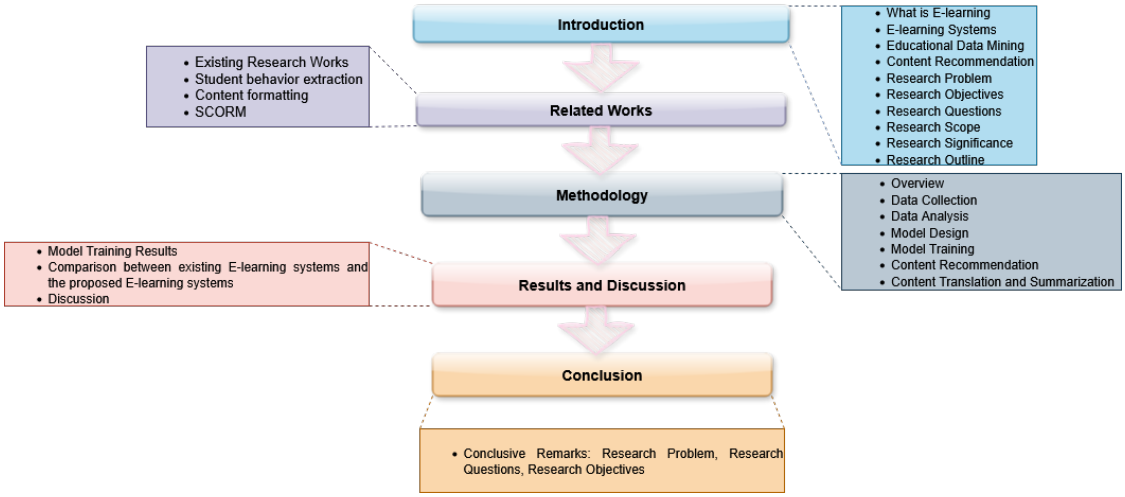

Figure 1: Research Outline

2.1.1. Intelligent E-learning Management Systems

An intelligent adaptive E-learning model [4] has been proposed to classify learners and to provide adaptive content. Another intelligent E-learning Management system [5] has been introduced to enhance multi-agents that can be used to organize content resources and provide personalized access.

2.1.2. E-learning Management Systems for enhanced user experience

A range of studies have been done regarding the usage and experience of users for various E-learning management systems. An improved E-learning system [6] was designed with features such as online material upload, one-on-one interaction, and real-time communication with lecturers. An E-learning management system [7] was proposed using web services, focusing on features like content and learning management, delivery management, and access control. These studies collectively highlighted the requirement of user experience in E-learning management systems and the potential for improvement through enhanced features and usability.

2.1.3. Existing Research Improvements

Table 1 shows how improvements should be focused on.

By considering the above research works improvements, the proposed research project has been focused on considering those improvements which have to be focused on existing research works. A methodology has been decided on what we can do to build the research project. According to that methodology, the following research works have been highlighted.

2.2. Student behavior extraction

E-learning had allowed students to engage in course content and develop their learning behaviors. There were several key categories that highlight E-learning behaviors [8, 9]. Learning preparation meant activities like accessing the course homepage, navigating to course pages, and reviewing supplementary materials that prepare students for learning. Knowledge acquisition behavior means behaviors focused on actively acquiring knowledge, such as accessing course content, watching videos, and participating in discussions.

Table 1: Existing Research Improvements

Research work	Improvement that should be focused
[1]	Personalized learning content formats and content versions of users
[2]	Content-based and collaborative filtering recommendation techniques are combined
[10]	How to arrange contents according to user requirements
[3]	The advancement of the E-learning systems which must be spread and that should be implemented to gain user interest in E-learning systems
[4]	With a minimum amount of data during the classification has been done. Only KNN algorithm has been used with lack of parameters
[11]	A model and a system based on Student-Centered based E-learning Environments
[6]	An improvement in making this research considering videos, and automatic course selection according to students registered level

Studies have been done on individual learning styles and approaches impact E-learning behaviors and performance [9, 12]. There are some factors that can be reasoned to influence their E-learning behaviors and intentions [9].

The E-learning engagement levels of students could be examined with the extracted behavior from the contents. There are several research to highlight features [13, 14, 15] on behavioral extraction of students. Emotions [16, 17] and moods [18, 19] of students can be extracted from student engagements using online lecture videos.

2.2.1. Data Gathering

The data were gathered from the E-learning system before any information. This could be done using two ways such as active and passive information gathering. Active information gathering would be done by observing user interactions surveys, quizzes, tutorials, assignments [15], lab practicals, and exams. Passive information gathering could be done by observing user interactions using the E-learning systems.

2.2.2. Pattern Recognition

Several data are not in order, because of that they should be processed and sorted to extract meaningful information.

Unsupervised clustering algorithms [20, 21] or supervised machine learning algorithms [14, 21, 22] were used to identify patterns from a large collection of data.

2.2.3. Clustering Algorithms

Clustering algorithms, particularly K-means, are widely applied in E-learning for grouping similar learning behaviors and enhancing personalization. They support adaptive systems, identify struggling students, and improve content delivery [23, 15, 24]. Techniques also predict learning styles using log files [25], categorize students by behavior [26], and analyze learning preferences via weblog mining [27]. These methods enhance academic performance and optimize resource delivery [28].

2.2.4. Pattern recognition with Supervised Machine Learning

Supervised learning techniques like neural networks and decision trees have been used to analyze student learning behaviors and tailor teaching strategies [29, 14]. E-learning systems have also leveraged data mining and big data for pattern recognition and predictive analytics [30], while challenges and credentials were explored using process mining methods [31].

2.2.5. Interest Recognition

Interest Recognition involved analyzing user interactions with content, including factors like duration and click frequency, as well as feedback on interactive features. Several earlier studies were conducted [32] with respect to this issue, among which had been used to identify factors affecting student acceptance for E-learning and their intension to usage of E-learning. Several patterns [33] were identified in the behavior of students while learning several things in different incidents. Data collection and the center of interest construction [34] were done by two modes.

2.2.6. Scoring User interactions in the systems

User engagement can be assessed by scoring interactions based on their relevance to the user's content interests. Studies have examined such systems [35] analyzed engagement and interactivity using scoring methods, while [36] evaluated interaction through usage metrics and system usability scores.

2.3. Content formatting

Personalized content recommendations should be implemented upon determining user interest levels and behaviors. There were various methods for achieving this, including organizing content with templates, dynamically arranging content using templates, translating content across different media types, and summarizing content.

2.3.1. Content arrangements with templates

A content customization strategy can involve templating for different skill levels—novices benefit from visual aids and simplified language, while experts prefer dense, detailed texts [37]. Prior efforts emphasized aligning content with E-learning standards and interactive digital formats [38].

2.3.2. Dynamic Content arrangements

A system can dynamically organize content based on user preferences to enhance engagement. Prior work applied such adaptive content arrangement to address variations in learner behavior, goals, styles, and knowledge levels [39].

2.3.3. Content translation across media

Content creators on an E-learning system were often experts in their field but may lack the expertise, resources, or time to create engaging multimedia content. Using machine learning models and existing content enabled the generation of created multimedia content for specific users. Research had demonstrated that combining machine translation systems and translation technologies, could enhance performance of students and translation quality in educational settings [40].

2.3.4. Content Summarization

Advanced users who already had knowledge of the given domain, but they required the core content of the given lesson, or a blog presented in a condensed manner. The content summarization had been used [41] to aid both individual and collective learning endeavors. Content summarization [41] had been employed to support learning activities, understand user proficiency and annotations, and generate multiple summaries of the same document created to different skill levels.

2.3.5. Personalized content recommendation

Previous E-learning research has explored personalized learning using mathematical models [42], sentiment-aware recommendations [43], and solutions for integrity issues in learning platforms [44]. Recommendation system architectures leveraging ontologies and rule-based reasoning were proposed [45], along with broad reviews of personalized recommendation techniques [46]. Further enhancements included content matrices, logistic regression, deep learning, and flexible frameworks for adaptive course design.

Finally, in [47, 48], emphasis was placed on employing machine learning-based methods which allow for personalized learning experiences by selecting suitable relevant shaping activities. For course selection recommendations to E-learners and instructors, they utilized Natural Language Processing methods as well as semantic analysis approaches [49].

These personal recommendations, such as those based on the search history [50] of users, are highly relevant to individual users. An E-learning system had been specially designed to improve student learning by creating recommendations that embed latent skill based on historical interactions [51] between students, lessons, and assessments. This probabilistic framework for students and educational material could suggest customized lesson sequences to assist students in getting ready for evaluations.

2.4. SCORM

2.4.1. Overview

The article [52] described the main features, technical books, history, and support of Sharable Content Object Reference Model (SCORM), standards and specifications

collections that enable interoperability of learning content across different systems and tools. The paper [53] presented a SCORM digital teaching resource management model, comprising of four parts: content aggregation model, runtime environment, sorting and navigation, and collaborative filtering engine. It also included the design and implementation of SCORM related digital teaching resource library system. That system is based on collaborative filtering technology with performance evaluation using a data set of movie ratings. The results showed that the system can improve the learning efficiency and satisfaction of the learners. The article [54] explained that SCORM combines three specifications: content packaging, run-time environment, sequencing and navigation. It also lists the benefits of SCORM, such as compatibility, reusability, personalization, and tracking. It integrates contributions from organizations like IMS Global Learning Consortium, AICC, and ARIADNE, enabling multimedia presentations for distance learning across platforms [55]. Versions like SCORM 1.0 and 2004 (also known as 1.3) focus on packaging, delivery, and tracking of learning objects [55].

2.4.2. Core components

SCORM comprises three main components: Content Aggregation Model (CAM), Run-Time Environment (RTE), and Sequencing and Navigation (SN).

1. Content Aggregation Model (CAM) This specification defines how learning content is structured and packaged. The CAM establishes the framework for Sharable Content Objects (SCOs) and Assets, which serve as the fundamental building blocks of SCORM-compliant content. SCOs are standalone, reusable learning modules that can communicate with the Learning Management System (LMS), while Assets are static content collections that do not require LMS communication. [55, 56].

2. Run-Time Environment (RTE) The RTE specification governs the communication protocols between learning content and the LMS during execution. It implements a standardized JavaScript API that enables content to exchange data with the hosting system, facilitating learner tracking, progress monitoring, and content state management [55].

3. Sequencing and Navigation (SN) Available in SCORM 2004, this component provides sophisticated content flow control mechanisms. It enables the creation of adaptive learning paths based on learner performance, prerequisites, and pedagogical rules defined by instructional designers [57].

SCORM represents a foundational achievement in e-learning standardization, providing technical specifications that have enabled widespread interoperability and content reusability. While the standard faces contemporary challenges related to mobile compatibility, content flexibility, and integration with emerging technologies, ongoing academic research continues to address these limitations through innovative architectural approaches, middleware solutions, and enhanced metadata models.

The technical depth of SCORM's specifications, from its JavaScript API implementation to its sophisticated sequencing mechanisms, demonstrates the standard's robust engineering foundation. However, the emergence of newer standards like xAPI and the evolving demands of modern e-learning environments suggest that SCORM's future lies in architectural evolution rather than incremental enhancement.

2.5. Research Remarks

A comprehensive literature review using many research works has been conducted in the areas of students' behavior extraction and content recommendation. The field of student behavior extraction covers several key areas including data gathering, pattern recognition, clustering algorithms, interest recognition, and scoring user interactions in the systems. On the other hand, in the realm of content recommendations, significant focus is placed on content arrangements with templates, dynamic content arrangements, content translation across media, content summarization, and personalized content recommendation as discussed in the literature review that was conducted. Additionally, further research findings related to other works have also been highlighted.

From the related works done so far, we can conclude that many research works have been done in this domain. Existing research findings are inadequate in enhancing user interest in E-learning content. From the research findings, it can be seen that there is room for improvement. In content recommendation systems, that target user interests. Thus, in the proposed system research will be done in the direction of user interest enhancement to extract data by personalized content recommendation

3. Methodology

The prevalence of online learning is steadily increasing, contributing to the establishment of a knowledgeable world. In Sri Lanka, there is a notable trend wherein students predominantly utilize E-learning systems for their educational needs. The E-learning interface plays a crucial role in facilitating student interaction and exploration of diverse topics or subjects of interest. In this context, when a user expresses interest in a particular topic, the E-learning interface promptly retrieves relevant details and presents them to the user. As a result, it will be generating valuable data that serves as the foundational basis for the improvement of the user experience. This academic behavior highlights the significance of E-learning systems in Sri Lanka, that focusing their role in providing students with interactive learning contents in variety of subjects. The information gathering and data collection support the enhancement of the E-learning experience for users.

This E-learning system can adapt content based on learning styles. For example, the learners can get advantages from multimedia content, while some others can get advantages from simulations. The recommendations can be adjusted based on monitoring learner behavior. If a learner struggles with a particular type of content, the system can suggest alternative formats or additional resources. The insights into learner preferences can be measured and learner

recommendations can be refined based on time spent on tasks and interaction frequency.

The completed research project will flow as presented in Figure 2. A comprehensive database was created by collecting data and integrating survey responses during the training phase. This dataset was processed and used to train the model, focusing it to understand build relationships between user interactions, requested content, and user preferences. After this training, the model [58, 59, 60] was developed to identify patterns and conditions governing the recommendation of useful content types based on learners past interactions in the E-learning system. At the completion of the training phase, when users access the content of the E-learning interface, the E-learning system interacts with the trained model, instead of directly requesting the content from the system. The model prompts the learning conditions and patterns to identify the most appropriate type of content according to the user's specific requirements and preferences.

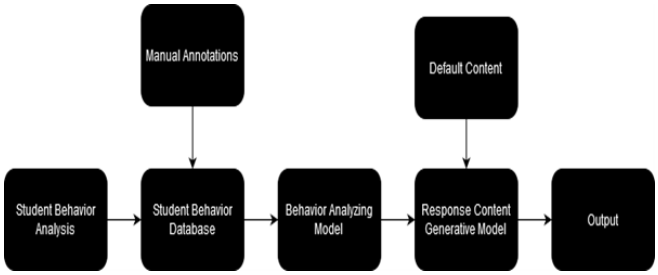

Figure 2: Model Architecture

To meet user preferences, a content translation algorithm adapts material into the desired format or learning style—such as converting text to audio for users who prefer auditory content.

Figure 3 [60] presents a graphical representation of the complete model throughout the research.

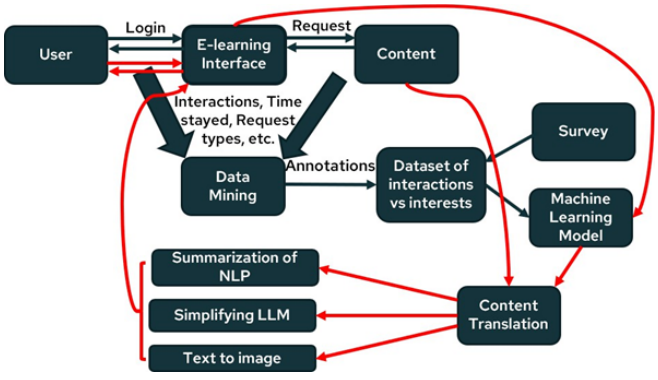

Figure 3: Model Flow Diagram

3.1. Data Collection

In the data collection procedure, data were collected in different ways, by surveying to gather user responses towards E-learning, a survey to analyze students' interactions towards the contents of E-learning, and from the Moodle log data.

3.1.1. Survey to analyze student's interactions towards the contents on E-learning

In the pursuit of understanding students' preferences for learning content, the data were collected using a survey on various aspects of academic performance. Approximately 1000 users actively participated in this survey, providing valuable insights into their preferences. The survey focused on three key dimensions: the preferred format for learning content, the preferred content version, and the preferred content presentation style.

Preferred Format for Learning Content: students have stated their preferences according to the learning content format that is collected according to their academic performance rate. This can be used to identify the medium that delivers educational materials.

Preferred Content Version: students expressed their preferences concerning their most favorable content version. This includes their preferences in summarized content and content presented more in-depth.

Preferred Content Presentation Style: students' preferences on the content were also gathered using the survey. They implied their responses on content to be conveyed in a story format or presented more straightforwardly.

The survey results contribute valuable insights for educators and instructional designers seeking to optimize content delivery in line with student preferences. From around 1000 users, Table 2 shows how many users preferred various learning contents. Table 3 shows how many users are preferred for various learning contents according to user performance rating.

From around 1000 users, Table 4 shows how many users preferred content that is summarized or explained. Table 5 shows how many users preferred content that is summarized or explained according to user performance rating.

From around 1000 users, Table 6 shows how many users preferred content that is the straightforward manner or story format. Table 7 shows how many users preferred content that is straightforward manner or story format according to user performance rating.

3.1.2. LMS log data

In the context of analyzing user behavior within an E-learning module, a sample dataset was required to understand user attraction and involvement in specific tasks. For this purpose, log data was collected from the Moodle platform in Sri Lanka.

The gathered log data encompassed approximately 47,647 events recorded by users interacting with the module.

Each event was associated with a specific status, reflecting the nature of the user's action. The statuses were identified within the module. Those statuses are added, assigned, created, deleted, downloaded, enrolled, graded, joined, posted, removed, restored, searched, started, submitted, subscribed, unassigned, updated, uploaded, and viewed which are done by the users. This academic categorization provides a structured overview of log data, enabling a systematic analysis of user interactions and behaviors within the E-learning module. The user's reaction according to each status has been shown in Table 8.

Table 2: No of users preferred for various learning contents

The preferred format for learning content	**No of Users**
Image-based	203
Audio-based	123
Video-based	492
Text-based	182

Table 3: No of users preferred for various learning contents according to user performance rating

Preferred content format	**No of Users**				
	Rating 1	*Rating 2*	*Rating 3*	*Rating 4*	*Rating 5*
Image-based	6	109	68	13	7
Audio-based	3	18	29	40	33
Video-based	69	143	174	64	42
Text-based	15	26	35	43	63

Table 4: No of users preferred content that is summarized or explained

Preferred content version	**No of Users**
Summarized content	604
Explained content	396

Table 5: No of users preferred for various learning content versions according to user performance rating

Preferred content version	**No of Users**				
	Rating 1	*Rating 2*	*Rating 3*	*Rating 4*	*Rating 5*
Summarized content	52	83	104	169	196
Explained content	138	101	62	53	42

Table 6: No of users preferred content that is straightforward manner or story format

Preferred content format	**No of Users**
Straightforward manner	431
Story format	569

Table 7: No of users preferred content that is straightforward manner or story format according to user performance rating

Preferred content format	**No of Users**				
	Rating 1	*Rating 2*	*Rating 3*	*Rating 4*	*Rating 5*
Straightforward manner	52	65	74	109	131
Straightforward manner	179	144	92	83	71

Table 8: No. of responses on statuses

Status	No of Users
Added	116
Assigned	61
Created	2272
Deleted	768
Downloaded	4
Enrolled	61
Graded	122
Has	87
Joined	752
Posted	2975
Removed	2
Restored	3
Searched	17
Started	69
Submitted	76
Subscribed	341
Unassigned	2
Unsubscribed	13
Updated	2878
Uploaded	23
Viewed	37023

In the realm of educational events, various attributes can be systematically categorized to facilitate a comprehensive understanding and analysis within the system. This academic categorization establishes distinct types, each serving a specific purpose. The identified categories encompass courses, discussion, comment, tag, user, role, grade item, override, page, group, module, post, attempt, submission or meeting.

This section shows a systematic framework that enhances the organization and interpretation of data related to educational events. It backbones to a more structured approach to manage and analyze various aspects of user interactions and behaviors within the educational context.

3.2. Data Analysis

As part of our initiative to analyze user engagement in E-learning, we used a Kaggle dataset of student activity logs to test and refine our code before applying it to the original data. This preliminary analysis as shown in Figure 4 helped identify key patterns and variables influencing user interactions. Using the Kaggle dataset allowed us to fine-tune model parameters, improving both the accuracy and reliability of our training process.

Figure 5 represents a correlation matrix for online classroom data. The trained dataset is given as a correlation matrix in figure 6.

In an online classroom setting, the dynamics of interactions among participants can be diverse. Various factors contribute to this variability, such as the nature of the posts generated during these interactions. One key aspect is the propensity of participants to initiate creative discussions. Analyzing the dataset reveals a distinction between posts categorized as either good or bad, shedding light on the overall quality of the contributions.

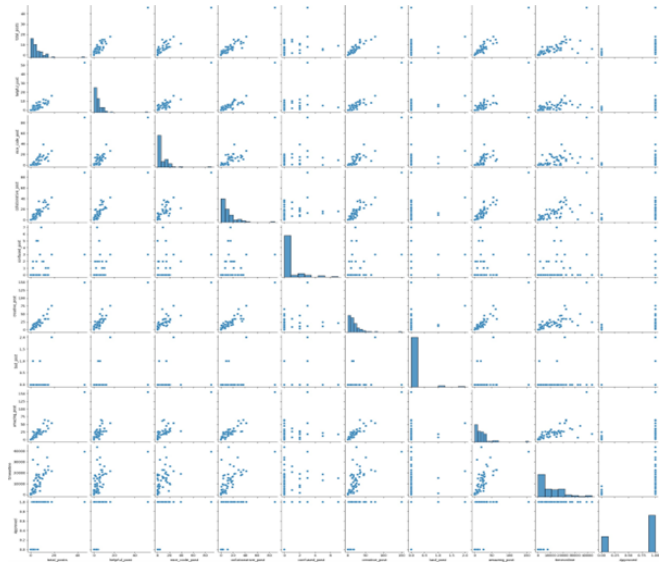

Figure 4: Kaggle Dataset Analysis

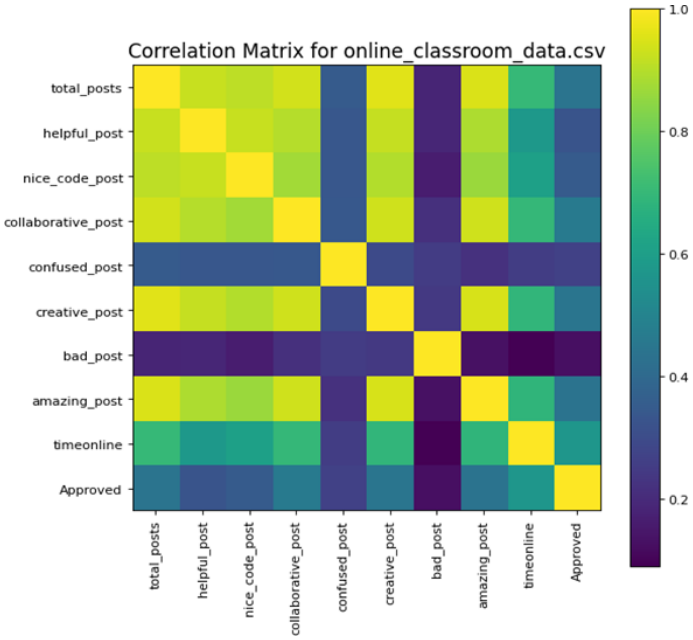

Figure 5: Correlation Matrix for online classroom

	precision	recall	f1-score	support
0	0.40	1.00	0.57	2
1	1.00	0.77	0.87	13
accuracy			0.80	15
macro avg	0.70	0.88	0.72	15
weighted avg	0.92	0.80	0.83	15

Figure 6: Training Dataset

Upon examining the entirety of posts, it becomes apparent that the number of posts deemed helpful is notably scarce. Curiously, there is a lack of posts categorized as bad when compared to the volume of helpful posts. This

imbalance suggests a generally positive and constructive atmosphere within the online classroom, where participants are more inclined to assist rather than engage in detrimental interactions.

The online time duration is high when considering the dataset in addition to the total number of posts. This highlights a high level of engagement among participants that reflects an active online learning community.

It is observed that the frequency of creative posts is noteworthy. The dataset also highlights a high occurrence of categorized posts also. This is a reason to suggest the online classroom system that can be used to foster creativity and positive engagement with useful information and content.

This initial training was using the XGBoost algorithm that has been conducted on this dataset. The resultant model provides valuable points into the classification of posts. This training process obtained specific parameters and classification values. This stage offered a quantitative condition within the online classroom that gives a foundation for further analysis and refinement of the learning model.

Initially, the XGBoost algorithm was used for model training, but due to unsatisfactory accuracy, it was replaced with the Random Forest algorithm, which provided improved predictive performance. After initial training, data cleaning was conducted to remove unnecessary log columns like system and mentor logs, streamlining the dataset.

Survey insights guided the assignment of weights to user preferences across various content types (videos, audio, animations, text) and formats (summarized or detailed, straightforward or story-driven). Manual data annotation further enhanced the training dataset, and the Random Forest model achieved an 80/20 train-test split, effectively validating its performance.

In-depth analysis of this refined dataset, organized in a CSV file, revealed patterns and relationships, allowing accurate weight assignments based on user preferences. This structured framework supports a robust content recommendation system, enabling more precise and personalized content delivery based on user-specific features and preferences.

3.3. Model Design

It was required to calculate the weight to recommend the content. Then, an equation was created to calculate the weight. The following factors were considered when creating the equation 1.

$$Ur - Cr = Ar \tag{1}$$

- Ur- User rating
- Cr- Content rating
- Ar- Aggregate response value

3.3.1. User rating

The user rating weights are generated using the module's log data. Initially, weights were assigned arbitrarily based on user responses. These responses were collected from the relevant Learning Management System (LMS) platform and recorded by the users themselves. The obtained weights are mentioned according to the dataset. It is shown in Table 9.

Table 9: No of weights on statuses

Responses	Weights
Created	5
Posted	5
Updated	5
Joined	4
Subscribed	3
Added	3
Submitted	3
Uploaded	3
Assigned	2
Graded	2
Created	2
Deleted	1
Downloaded	1
Enrolled	1
Removed	1
Restored	1
Searched	1
Started	1
Submitted	1
Unassigned	1
Unsubscribed	1
Viewed	1

Table 10 presents the responses and their corresponding weights. Specifies the weights for each component of the Learning Management System (LMS) based on the data set. The random weights assigned to these components are shown in Table 10.

Table 10: No of components on weights

Components	Weights
Assignment	4
File	3
File submission	3
Folder	2
Forum	3
Page	2
Quiz	5
System	1
URL	2
Wiki	2
Zoom meeting	2

Initial values were arbitrarily assigned based on heuristic criteria, which considered the impacts of data collection and analysis during selection. Subsequently, a recurrent learning approach was implemented to fine-tune these values using the collected responses. Finally, the user rating values are generated. Table 11 displays the user ratings according to the defined event user rating values.

Table 11: User rating value on events

Events	User rating value
A file has been uploaded	3
A submission has been submitted	3
Clicked joining meeting button	2
Comment created	2
Course activity completion updated	2
Course module updated	1
Course module viewed	1
Discussion created	2
Discussion viewed	2
Feedback viewed	1
Group member added	1
Post created	2
Post updated	2
Question updated	2
Question viewed	2
Quiz attempt reviewed	1
Quiz attempt started	4
Quiz attempt submitted	5
Quiz attempt summary viewed	2
Submission updated	2
Wiki page viewed	1

3.3.2. *Content rating*

The Content Rating (Cr) value is assigned randomly through an analysis of the data gathered on various learning content formats. This assignment considers factors such as the performance rating (which evaluates how well the content performs in terms of user engagement or effectiveness) and the preferred content version (which reflects users' favored formats or styles of the material).

Table 12 illustrates how the preferred content versions and their associated weights vary, based on the insights from the "Data Collection" section. This table provides a detailed breakdown to show the relationships and variations in these elements.

Table 12: preferred content version and weights

Preferred Content Version	Weights
Image based	2
Video based	3
Audio based	4
Text based	5

If the user performance rating is nearly 4, and 5 summarized content will be given. If the user performance rating is nearly 1, 2, and 3 explained content will be given.

3.3.3. *Aggregate Response Value*

The aggregate response values are generated using a random forest algorithm, which is a machine learning ensemble method that builds multiple decision trees and combines their outputs for more accurate predictions. This step creates initial values based on the available data.

Subsequently, a recurrent learning approach—such as recurrent neural networks (RNNs) or similar iterative optimization techniques applied to fine-tune these values, incorporating insights from the specific content formats (e.g., videos, texts, quizzes, or interactive modules) to improve accuracy and relevance.

The resulting aggregate response value serves as a metric to represent pairwise relationships, capturing interactions and compatibility between different types of users (e.g., based on their preferences, engagement levels, or roles) and various content types within the system.

Table 13 displays these aggregate response values, organized according to the predefined content formats, providing a visual summary of how these relationships are quantified.

Table 13: Aggregate Response Values

Aggregate Content Format	Aggregate Response Value
Image based + Summarized	-3
Image based + Explained	-2
Video based + Summarized	-1
Video based + Explained	0
Audio based + Summarized	1
Audio based + Explained	2
Text based + Summarized	3
Text based + Explained	4

3.4. *Model Training*

A comprehensive comparative evaluation of XGBoost and Random Forest algorithms was conducted using critical performance metrics including precision, recall, F1 score, and accuracy. This systematic analysis revealed that Random Forest emerged as the superior model, demonstrating greater reliability and robustness compared to XGBoost. Random Forest's ensemble approach, which combines multiple decision trees through bootstrap aggregating, contributed significantly to its enhanced performance by naturally reducing variance and providing better generalization to unseen data. The algorithm's ability to handle high-dimensional data without extensive feature engineering, combined with its inherent robustness to noise and outliers, made it particularly suitable for complex datasets while providing valuable feature importance scoring capabilities

While XGBoost showed competitive performance through its gradient boosting methodology, it ultimately required more extensive hyperparameter tuning and computational resources compared to Random Forest's simpler configuration requirements. XGBoost's sequential tree-building approach, where each tree corrects errors from previous ones, provides excellent predictive capability but demands careful optimization to prevent overfitting. Random Forest's parallel tree construction enables efficient scaling and demonstrates lower sensitivity to hyperparameter settings, making it more accessible for practitioners while offering superior interpretability through feature importance scores and individual tree visualization capabilities.

Following initial model deployment, comprehensive user feedback was systematically collected through multiple channels including direct surveys, usage analytics, and performance monitoring systems to evaluate real-world performance beyond traditional statistical metrics. Based

on this feedback, the model underwent strategic retraining to address identified performance gaps and enhancement opportunities, exemplifying modern machine learning best practices where continuous improvement drives sustained effectiveness. This iterative refinement process incorporated both quantitative performance metrics and qualitative user insights, ensuring that model improvements addressed both statistical accuracy and practical utility while maintaining alignment with user expectations and business requirements.

The successful integration of user feedback into model improvement processes highlights the importance of establishing robust feedback loops in production machine learning systems. Systematic feedback loops with automated triggers for retraining based on performance degradation thresholds enable proactive model maintenance and sustained relevance over time. This evaluation demonstrates that algorithm selection must be guided by specific use case requirements rather than general performance benchmarks, considering factors such as data characteristics, performance requirements, interpretability needs, and operational constraints. The comprehensive approach of combining rigorous comparative evaluation with continuous user feedback integration represents best practices in modern machine learning deployment and maintenance, ensuring sustained model effectiveness through iterative alignment with real-world usage patterns.

3.5. Content Recommendation

According to the aggregate response value, the content was recommended. The random forest algorithm was tested in this context. The aggregate response value is given according to the user rating and the content rating. That has been shown in Table 14.

3.6. Content Translation and Summarization

The process described involves a comprehensive approach to multimedia content analysis and summarization, focusing various tools and methodologies. The workflow encompasses translation, segmentation, image processing, deep learning, and natural language processing techniques.

Initially, content translation is executed based on the resultant weight. Videos are transcribed into text format according to user preferences. A summarization process is applied to distill key information for high performing individuals, while low performing individuals receive a more detailed explanation, accompanied by generated images to enhance understanding.

MoviePy (Python) is used to segment audio and video data, converting video frames into images for training with Deep Image Prior (DIP) to extract keywords and identify objects. A large language model then generates transcriptions, removes redundancies, and produces a consolidated image. BART (Google) summarizes content, while OpenAI's API aids in segment explanation. Vision API handles image generation, and a speech-to-text tool processes audio separately. Outputs—including explanations, summaries, and images—are delivered via SCORM for standardized, educational use.

In essence, the described process integrates various tools and methodologies to deliver a sophisticated multimedia analysis and summarization system, catering to diverse user preferences and levels of expertise.

4. Results and Discussion

The model was designed using the user rating value, content rating value, and aggregate response value. The user rating weights were generated by training the log data using recurrent learning. The content rating weights were gen-

Table 14: Content recommendation according to the aggregated response value

Content Type	Content Rating	User Rating	Aggregated Value	Recommended Output
Text based	5	1	4	Text based + Explained
Text based	5	2	3	Text based + Summarized
Text based	5	3	2	Audio based + Explained
Text based	5	4	1	Audio based + Summarized
Text based	5	5	0	Video based + Explained
Audio based	4	1	3	Text based + Summarized
Audio based	4	2	2	Audio based + Explained
Audio based	4	3	1	Audio based + Summarized
Audio based	4	4	0	Video based + Explained
Audio based	4	5	-1	Video based + Summarized
Video based	3	1	2	Audio based + Explained
Video based	3	2	1	Audio based + Summarized
Video based	3	3	0	Video based + Explained
Video based	3	4	-1	Video based + Summarized
Video based	3	5	-2	Image based + Explained
Video based	3	5	-2	Image based + Explained
Image based	2	1	1	Audio based + Summarized
Image based	2	2	0	Video based + Explained
Image based	2	3	-1	Video based + Summarized
Image based	2	4	-2	Image based + Explained
Image based	2	5	-3	Image based + Summarized

erated by analyzing the data gathering of learning content formats. Finally, aggregate response values were generated based on a random forest algorithm. Those values were created to fine-tune those values from the content format using recurrent learning. Using the XG-Boost algorithm and Random Forest algorithm, the model was trained. The content was recommended according to the aggregated response value. Then this model was used to build the E-learning system by assigning the SCORM standard.

To do the implementation of the system, it shows how the results were generated, the following sections consist of model training results, user-interface results, and the E-learning system with SCORM standard, and a comparison between the current E-learning system & the proposed E-learning system.

4.1. Model Training Results

Initially, the model was trained from the data annotated and processed from the log file dump of Moodle for student behavior analysis. The annotations were done with the results from various surveys and heuristic rules. Following is the loss graph for the training and testing curves of the model which was trained using the random forest algorithm. Figure 7 is the initial graph that trained and tested the existing data.

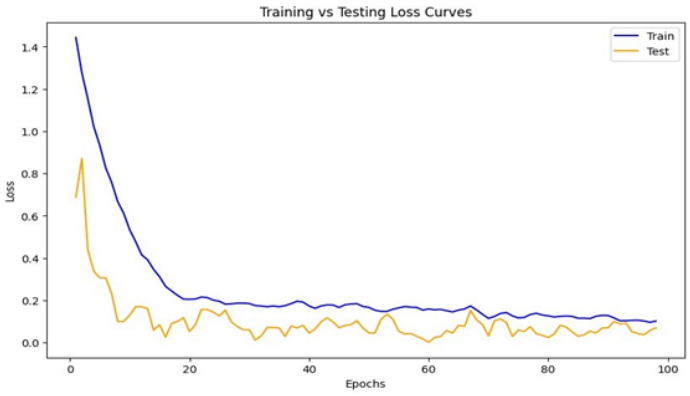

Figure 7: Initial Training and testing curves

After training and testing, there was a 73.9964% train accuracy value and a 63.1636% test accuracy value. The following graphs of Figure 8 represent that.

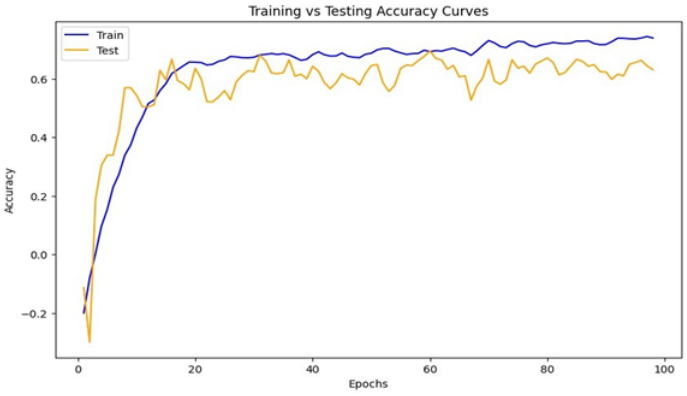

Figure 8: Initial training and testing accuracy curves

The simulated dataset was given to users, their feedback data were collected. Those data were retrained again. The retrained loss graph is shown in Figure 9.

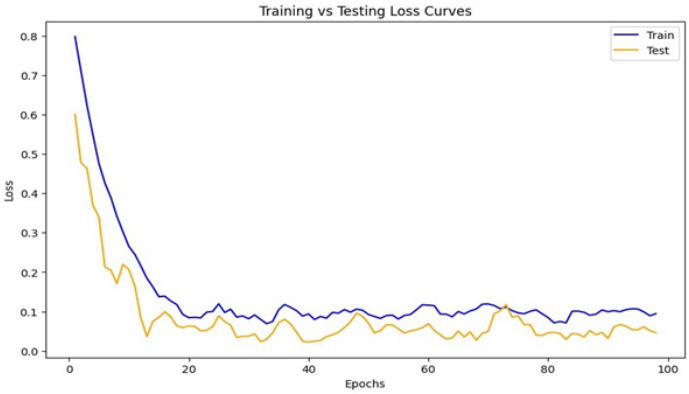

Figure 9: Retrained training and testing curves

After retraining and testing, there was an 85.5848% retraining accuracy value and a 78.9071% test accuracy value. The following Figure 10 graphs represent that.

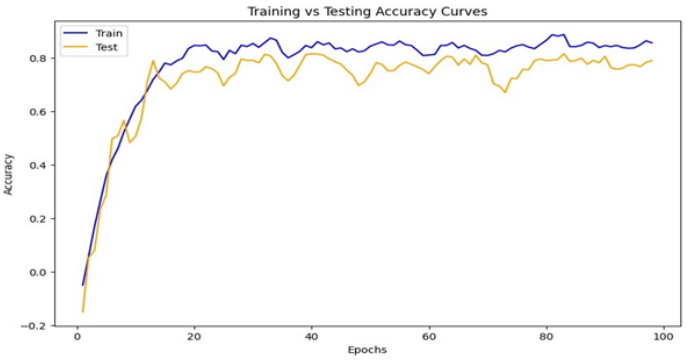

Figure 10: Retrained and tested accuracy curves

4.2. Comparison between existing E-learning systems and the proposed E-learning systems

Table 15 shows the comparisons between existing and proposed e-learning systems.

4.3. Discussion

4.3.1. Multi-Dimensional Data Integration and Model Performance Analysis

The research demonstrates a comprehensive approach to data collection and analysis by integrating multiple data sources to understand user behavior and preferences in e-learning environments. Survey data collection revealed critical insights into user content preferences, with findings showing that a significant proportion of users prefer video-based learning content over other formats, and users consistently favor summarized content rather than detailed explanations. Furthermore, survey responses indicated a strong preference for story-formatted content delivery rather than straightforward presentation methods, highlighting the importance of narrative-driven learning approaches.

Log data integration complemented survey findings by providing objective behavioral analytics that tracked user interactions, session duration, content engagement patterns,

Table 15: Comparison between existing E-learning systems & proposed E-learning systems

Existing E-learning Systems	Proposed E-learning System
Personalized learning environments were not considered	Personalized learning content formats and content versions of users were used
Content recommendation was not considered based on user interactions	A combination of content-based and collaborative-based recommendation filtering techniques were used
User requirements were not considered	How to arrange contents according to user requirements was considered
User learning interests were not considered	This system was implemented to gain user interest in E-learning systems
A high amount of data was not collected and trained	A maximum amount of data during the classification has been done. XGBoost and random forest algorithms were used
Student-centered E-learning Environments have been not concerned	A model and a system based on Student-centered E-learning Environments have been built
Multiple learning content versions have not been concerned	An improvement has been considered in making this research considering videos, and automatic course selection according to students registered level

and learning path navigation. This multi-source data approach enabled the researchers to capture both subjective preferences through surveys and objective behavioral patterns through system logs, creating a more comprehensive understanding of learner behavior than traditional single-source methodologies. The integration of these diverse data streams allowed the calculation of performance ratings and content ratings, which served as foundational input for the recommendation algorithm.

4.3.2. SCORM Standards Implementation and Content Transformation

The novelty of this research extends to its SCORM-compliant content delivery system, which enables standardized tracking and reporting across different learning management systems. SCORM (Sharable Content Object Reference Model) integration ensures that the recommended content maintains interoperability while providing comprehensive tracking capabilities including completion status, quiz results, time spent on modules, and detailed learner interaction data. The system's innovative content transformation capabilities allow dynamic conversion between multiple content modalities based on user preferences: text content can be converted to audio format, different text formats can be transformed into summarized or explained versions, and video content can be adapted to audio-only formats with transcription capabilities. This multimodal content adaptation, delivered through SCORM standards, represents a significant advance over traditional recommendation systems that typically focus on single content types.

4.3.3. SCORM Standards Implementation and Content Transformation

The reported accuracies (73.99% $\rightarrow$ 78.90%) show improvement after retraining, but baseline comparisons are missing. How does the model compare with standard/popular recommendation baselines (e.g., collaborative filtering, matrix factorization, deep learning-based recommenders)? The research achieved notable performance improvements through iterative model refinement, with training accuracy increasing from 73.99% to 85.58% and testing accuracy improving from 63.16% to 78.90% after retraining. However, the evaluation methodology presents significant limitations in its comprehensiveness. The results only include accuracy metrics, and it would be beneficial to have other types of metrics as well, like precision, recall, and F1 score. Standard recommendation system evaluation typically employs precision, recall and F1 metrics to assess the quality and coverage of recommendations, with precision measuring the fraction of recommended items that are relevant and recall measuring the fraction of all relevant items successfully retrieved. The absence of these metrics limits the ability to fully assess the system's performance compared to established baselines such as collaborative filtering approaches, matrix factorization techniques like SVD and SVD++, or advanced deep learning models including autoencoders, neural collaborative filtering, and hybrid deep learning architectures.

4.3.4. Enhanced User Engagement and System Effectiveness

Despite the evaluation limitations, the research demonstrates better user engagement compared to current e-learning systems, with the proposed content recommendation approach generating significantly more user interactions with recommended content. The integration of behavioral analysis, multimodal content delivery, and SCORM-compliant tracking creates a comprehensive ecosystem that addresses the multifaceted challenges of modern e-learning environments. This holistic approach contributes meaningfully to the advancement of intelligent tutoring systems by providing a framework that can adapt to individual learning styles while maintaining standardized tracking and reporting capabilities across various educational platforms.

5. Conclusion

This research presents a novel multimodal content recommendation model that significantly addresses current limitations in e-learning systems by integrating student

behavior analysis, learning styles, and content personalization to enhance user engagement and learning outcomes. Despite substantial research in e-learning recommendation systems, existing approaches have shown limitations in effectively capturing user interests and providing personalized content that aligns with individual learning preferences. The novelty of this research lies in its comprehensive integration of both content rating and user rating mechanisms within a unified framework that supports multiple content modalities—text-based, audio-based, image-based, and video-based formats—all delivered through SCORM-compliant standards. The proposed model demonstrates significant performance improvements through iterative refinement, achieving 85.58% training accuracy and 78.90% testing accuracy after retraining, compared to initial results of 73.99% and 63.16% respectively. This substantial accuracy enhancement reflects the model's sophisticated approach to learning behavior analysis using machine learning techniques that automatically detect learning styles based on behavioral patterns rather than traditional questionnaire-based methods. The research contributes a unique multimodal approach that leverages advanced content-based and collaborative filtering techniques, addressing critical challenges such as data sparsity and cold-start problems commonly encountered in recommendation systems. By incorporating SCORM standards, the model ensures interoperability across different learning management systems while enabling comprehensive tracking of learner progress, engagement metrics, and content interaction patterns. The findings demonstrate how this integrated approach to content recommendation can promote growth in e-learning systems by providing academic and e-learning providers with enhanced tools for creating, designing, and delivering more personalized and effective learning experiences that adapt to individual user preferences and learning behaviors.

5.1. Conclusive Remarks

5.1.1. Research Problem

Everyone has a different capability for learning, and the general content delivery system is not very successful. There is no significant research found on recommending content based on the interest of the subject from the student in current E-learning systems in universities.

The research problem was solved by recommending the content based on user rating and user interest. Table 14 shows how content was recommended based on aggregated value, content rating, and user rating.

5.1.2. Research Questions

1. How to identify student interactions and attractions towards the contents of the E-learning?

   This research question was solved by using log data and those log data were used to gather student interactions towards the contents of the E-learning. Those logs were collected using undergraduate students of Moodle in Sri Lanka. Most of the students are interested in using E-learning systems. There is a high number of students who have user engagement towards the overall E-learning content.

2. How to evaluate user interest for the E-learning content?

   This research question was solved by doing surveys. A huge number of log data were gathered from Moodle and those log data were used to evaluate user interest in the content. The interactions of students with the E-learning systems have been shown. The greatest number of users preferred video-based learning content, the greatest number of users preferred content version summarized content, and the highest number of users preferred content format story format content.

3. How to deliver targeted content to each individual student to interact with students?

   This research question was solved according to the user performance and content rating; the targeted content was recommended. It can be shown that recommended output can be given according to user rating and content rating values.

4. How to translate content through different media according to the user's interests such as when given content is in text format and the targeted audience requires the content in audio format to be interested?

   This research question was solved according to the user performance rating, lengthy, unclear texts can be converted to summarized texts and explained texts. When the target audience needs the content in audio format, the videos can be converted to audio format and the audio can be transcribed.

5.1.3. Research Objectives

1. How to identify user needs and user interactions through mining data

   This objective was achieved by analyzing the data obtained from surveys, and user interactions, such as logins, course accesses, content views, and assignment completions, valuable insights that can be obtained regarding user behavior and preferences. This data mining process helped to uncover patterns and correlations, allowing the proposed model to achieve a deeper understanding of individual users and their specific learning requirements.

2. How to develop lessons based on user needs to enhance user interest and interact

   By analyzing user data—such as preferences, performance, and interactions, the system dynamically created content recommendations to meet each user's unique needs and interests. This alignment with individual learning styles, performance levels, and goals made the content more relevant and engaging, focusing on the learning process and boosting user interest. By delivering recommended content, the proposed system aims to create a highly engaging learning experience that motivates users to actively participate and explore the content, leading to enhanced user interest and ultimately an improved user experience.

6. Recommendations

In the surveys that were done during the research, most users preferred video-based learning content were found out. Most of the users preferred summarized content rather than explained content and most of the users preferred content story format content rather than straightforward manner content.

7. Future Works

The accuracy of the model can be enhanced by increasing the dataset size and increasing the iterations used to train the model. The system can be further implemented using common cartridge standards. The system can be further implemented as Artificial intelligence-based auto-generation content.

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Pasindu Udugahapattuwa has done his bachelor's degree from General Sir John Kotelawala Defence University in 2020. He has done his master's degree from University of Moratuwa, Sri Lanka in 2024. Currently, He is continuing his PhD in University of Sri Jayewardenepura, Sri Lanka.

He has research experience since 2020 and he has some international publications. Currently, he is working as a Lecturer in General Sir John Kotelawala Defence University, Sri Lanka.

Shantha Fernando has done her bachelor's degree from University of Moratuwa, Sri Lanka in 1993. He has done his mphil degree from University of Moratuwa, Sri Lanka in 2000. He has completed his PhD degree in Delft University of Technology, Netherlands in 2010.

He has research experience since 2005 and he has more international publications. Currently, he is working as a Professor in University of Moratuwa, Sri Lanka.

Received: 16 August, 2025, Revised: 16 September, 2025, Accepted: 18 September, 2025, Online: 10 October, 2025
DOI: https://dx.doi.org/10.55708/js0410001

Connecting Mobile Devices Transparently with the Customer Network in a User-Friendly Manner

Dirk Henrici[*,1], **Andreas Boose**[2]

[1]Munich University of Applied Sciences HM, Dept. of Computer Science and Mathematics, 80335 Munich, Germany

[2]Telefónica Germany, B2B Technology Solutions, 80882 Munich, Germany

[*]Corresponding author: Prof. Dr. Dirk Henrici, Hochschule München FK07, Lothstr. 64, 80335 München, Germany & Email: dirk.henrici@hm.edu

ABSTRACT: The mobile data service in cellular networks can be more than just providing Internet access: it can connect mobile devices seamlessly and transparently to private networks like company intranets and home networks. Such a service is nowadays provided to usually larger customers based on customer-specific access point names and connecting the private data path via virtual private network (VPN) to a remote company network. A market study suggests that mobile network operators can monetize such an ability also for Small-Office / Home-Office (SOHO) customers. As also non-tech-savvy customers shall be able to connect their mobile devices to their private local networks without requiring support, it is essential to provide a plug&play solution for installation. We explore usual approaches for connecting remote devices to local networks as a basic building block. These are not only applicable in this scenario but can be used beyond it. As these approaches are not satisfactory for the purpose, we present an alternative concept based on so-called surrogate devices that are implemented based on Linux MACVLAN interfaces, policy-based routing, and network address translation. For this innovative approach, we provide technical details and a clean implementation for the wide-spread router operating system OpenWrt. Results of a friendly-user trial suggest that the goal of providing a plug&play approach for connecting remote mobile devices to a private local network is reached this way.

KEYWORDS: Personal Private Networks, Private Connectivity, Network Segmentation, Customer-specific APN, LAN-type connectivity, Virtual Private Networks, Mobile VPN

1. Introduction

The most important service in cellular mobile networks clearly is the data service. Being able to access the Internet in a convenient manner from everywhere has transformed our daily lives. However, mobile data can be more than mobile Internet access: mobile devices can connect to private networks like company intranets and home networks transparently without the need for any software installation on the devices.

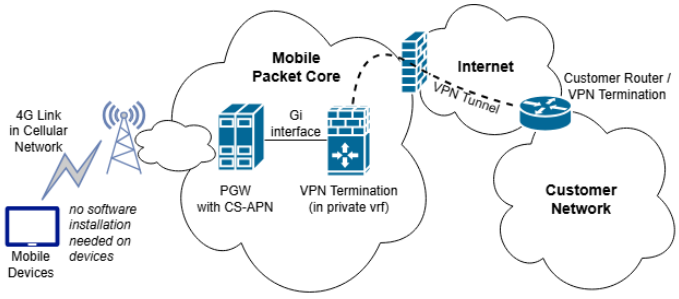

Figure 1: Private connectivity in mobile networks based on customer-specific access point names

To achieve this, the data traffic of a group of devices is forwarded from the mobile packet core to the respective customer network instead of doing network address translation and forwarding to the Internet. The endpoint in the mobile packet core (GGSN in 2G, PGW in 3G/4G) is thereby selected using customer-specific access point names (CS-APNs). Via the so-called Gi interface (3GPP terminology), the data path goes to the customer - either by a private line or a virtual private network connection over the Internet. See figure 1 for illustration for the wide-spread VPN-based variant. Additional infrastructure like firewalls is usually involved in completing the setup on the mobile network operator side.

This CS-APN-based private connectivity is a standard service provided by mobile network operators to mainly larger customers and therewith best practice. A major advantage is that no software installation is required on mobile devices to obtain private connectivity, thus easing setup and avoiding software/device compatibility issues. In our paper [1], we reported on the promising findings of a market study on the demand and acceptance for such a service also for other customer groups, namely SOHO (Small Office / Home Office) customers in Germany, and explored on how to integrate this service on the customer side in a user-friendly manner.

This article builds and extends on this work. The focus is on connecting mobile devices to an existing home network or office network in a way that is appropriate even for technically inexperienced users. As the private connection from the mobile packet core to the private network is usually done via VPN over the public Internet, we first present a

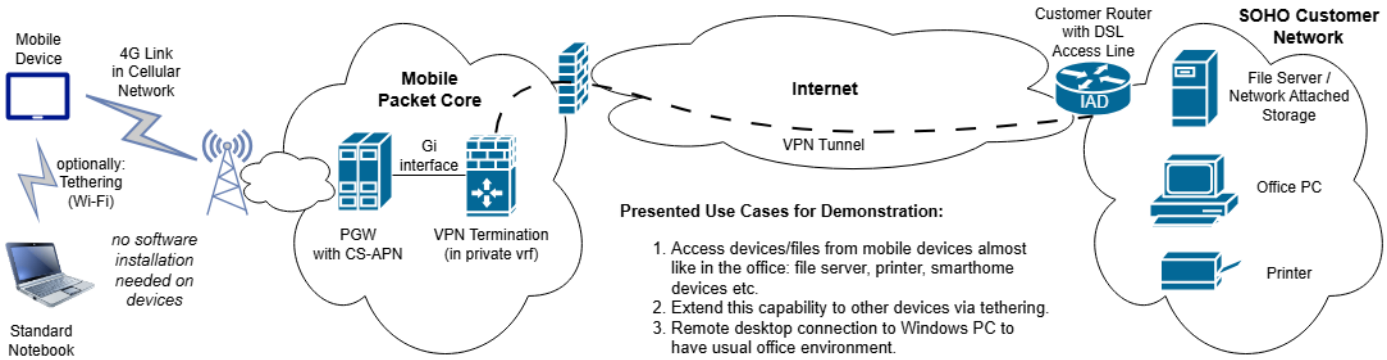

Figure 2: Technical setup for demonstration at market study group meetings [1]

widespread and a less widespread approach for connecting remote devices via VPN to a local network. Based on both approaches not being ideal for the needs in our scenario, we present an innovative approach based on so-called surrogate devices in the local network.

The remainder of this work is organized as follows: In the next section, we summarize the findings of previous work in [1] and present related work and usual approaches for remote device connectivity. An introduction of the concept of using surrogate devices to make remote devices appear as local devices in a home/office network follows. Afterwards we provide technical details and implement this approach for OpenWrt-based routers in a way that integrates nicely into the OpenWrt configuration framework. Then we evaluate this approach and compare it to other options before concluding.

2. Previous and Related Work

The following sections motivate the topic further, present context, provide related work, and discuss usual approaches for connecting remote devices to a local network.

2.1. Private Connectivity for SOHOs

The following is based on the market study presented in [1]: Small-Office / Home-Office customers (SOHOs) are self-employed or only have a small staff. Many have the usual office equipment like notebooks, desktop PCs, and printers. Data is stored on these devices, network-attached storage (NAS) or small servers - depending on company size and needs. Data storage in the cloud is not widespread for company data in that customer segment due to trust issues and for avoiding problems with GDPR compliance.

Many SOHO customers want to be able to work independently of their location, not only in the office. Having their data available and accessing devices in the office / at home, e.g. smart home devices, is a practical need. Data may be stored on notebooks to have it available on the go, but other workarounds appear to be widespread: having data on USB sticks or sending emails with it to oneself. In many cases, this results in inconveniences, additional work and hassle for data synchronizations, and security issues like sensitive data in unencrypted emails.

Assuming good network coverage, the ability to access one's data and devices in the office / at home seamlessly (i.e. without using VPN software on the devices) via the mobile network is regarded as an interesting option. After a demo on the possibilities based on the setup shown in 2, the study participants expressed a willingness to pay 5 Euros per month and mobile device for such a service (on average) and stated a variety of perceived benefits that will be summarized in the following paragraphs. The study is based on focus groups where sixteen entrepreneurs of different sectors were interviewed in person by a professional market research company.

One group of perceived benefits for such a service is related to freedom: one can work flexibly and location-independently, using any mobile device connected via cellular network and using even more devices using tethering. Not needing to install any software on the mobile devices and not needing to worry of potential compatibility issues is considered a big advantage of a network-based connectivity solution. As the up-to-date data stored in the office network can be accessed and edited online, one can work as if in the office. The need for data synchronization to have data available on the move is avoided - as well as workarounds like USB sticks. There is no more risk of "forgotten data", i.e. data that shall be accessed but that is currently not available.

Not having an additional party, i.e. another vendor/provider, involved is also considered a plus. This is a simplification, avoids needing to trust and depend on yet another party, and does not require commissioned data processing agreements for GDPR compliance. For many, it is a "good feeling" if relevant and sensitive data is stored on own premises and not stored with an external provider.

The alternative of setting up virtual private network (VPN) connectivity between mobile devices and a home/office network is beyond the technical know-how of most study participants. Not needing to install and manage VPN software on the devices is thus more practical and thus increases the target audience for a private connectivity product. For convenience reasons, not needing to manually operate VPN software for establishing connectivity is also an advantage of a seamless connectivity solution. Some of the few VPN software users said that they observed higher battery consumption with active VPN connections.

In summary, connecting groups of mobile devices privately and seamlessly to home/office networks is regarded as an interesting option by the study participants. The expressed willingness to pay for such a connectivity product makes it an interesting proposition for mobile network

operators.

2.2. Related Work on Private Connectivity in Mobile Networks

The concept of Access Point Names (APNs) to select the network to connect to was introduced and standardized for cellular mobile networks as part of the 3GPP specifications in the 3GPP TS 23 series that is related to the system architecture. The original specification [2] dates back to the development of the GPRS (General Packet Radio Service) in the end of the 1990s and has been updated to refer to Data Network Names (DNNs) as the new term in the 5G era.

Private connectivity is also part of other 3GPP specifications, non-public networks in form of private networks (3GPP TS 22.261) being a widely known one. Focusing on such application areas to better compete with Wi-Fi as well as IoT applications [3], 3GPP Rel. 16 introduces "5G LAN-type service" where a "5G LAN-virtual network" [4] interconnects mobile devices and local networks. It works on layer 2 and therewith not only supports unicast but also multicast and broadcasts. Implementations exist by network equipment vendors like Huawei and ZTE. After 5G LAN demonstrations in 2019 [5], China Mobile claims to be "the first in China to use technologies such as 5G LAN ... for commercial use" in a press release [6] from 2023.

To connect mobile devices with company intranets, e.g. university campus networks, Huawei offers a 5G-based solution that it calls "Mobile VPN" [7]. The approach is technically based on 5G SA's Uplink Classifier, see [8] on the technical background.

This shows that private connectivity in cellular mobile networks is included in standards but also part of equipment vendor product portfolio. On top of that, mobile network operators provide products that build on these standards but that rely on in-house implementations or that build on offers of start-up. Telefónica Germany, the occupation of one of the authors, provides "o2 Business Secure Hub" [9] to securely connect mobile devices with company intranets. A similar offer targets IoT business. It builds upon CS-APNs but also employs an additional layer of network segmentation for scalability purposes [10]. Connectivity between mobile operator and customer is realized using IPsec VPNs or WireGuard VPNs [11]. AT&T offers in partnership with Asavie Technologies a similar product named "AccessMyLAN" [12] to business customers. Connectivity between mobile operator and customer network is realized based on an SSL-based VPN: a software agent runs on a Windows computer. It created an SSL tunnel and masquerades the traffic of the mobile devices towards the computer's IP address so that all their traffic appears to originate from that computer [13].

2.3. Approaches for Connecting Remote Devices via VPN

There is a vast amount of related work around connecting remote devices via Virtual Private Network (VPN) to a local network. RFC 2764 [14] describes a framework for VPNs and discusses the various types. That work being already 25 years old, lots of other ones were published over time, up to recent papers from the current year (2025 at time of writing) like [15] on taxonomy, roles, and trends.

In the following we limit ourselves to two kinds of VPN setups that can be employed in a home network or in a SOHO network. We require that all mobile devices are reachable and visible from that network so that a NAT-based approach (NAT = network address translation) with masquerading like done by Asavie [13] does not suit us. We also limit ourselves to layer 3 connectivity as that is provided by standard mobile packet cores and mobile devices. Finally, we want to work with a single VPN connection for tunneling all data traffic between packet core and customer network. In the following, we will write "home network" for the customer network to denote a small network as is also given with SOHO customers.

2.3.1. Routed Setups

The usual and straightforward approach when connecting networks and devices via VPN is a routed setup: The local network has a local network range, and the remote site or VPN road warrior users use a separate network range; the VPN gateway acts as a router between the network ranges. Such a setup is simple and clean if the VPN gateway and the home router are realized as a single device that does all the routing. Another clean variant would be if the VPN gateway were connected to the home router via a dedicated transfer network – either using a dedicated link or a dedicated VLAN. Due to the limitations of many home routers and the configuration needed, such a variant is quite unusual in practice. Another option is the setup depicted in figure 3 where the VPN is realized as a separate device in the local network.

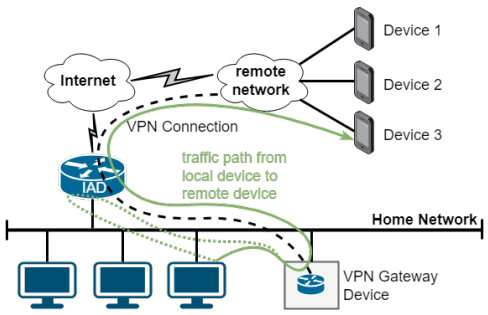

Figure 3: VPN gateway as a separate device in the local network.
green: direct traffic path; dotted green: detour to simplify configuration

The setup in figure 3 is often desired in cases in which the home router does not have the required VPN capabilities or in cases where different functionalities shall be separated. This, however, means that there are two routers in the local network. The home router is the default gateway. For a clean solution, all other devices need a distinct route to the VPN network range via the VPN gateway device: a route like `ip route <vpn network range> via <vpn gateway>`. Setting such a route on all devices is not practical so that the pragmatic option to just set this as a static route in the home router is usually chosen in practice. With this, when a device sends a packet to a VPN device, the packet is sent to the default gateway which forwards the packet to the VPN gateway due to the static route. As the default gateway detects that the packet is routed out the same interface it was received on, it emits an "ICMP Redirect" notification to the sending device to propose to

take the direct path in future.

Routed setups with separated devices in the local network thus have some drawbacks: They require configuration of a static route and therewith some networking knowledge for configuration. The pragmatic variant with a static route on the home router causes many ICMP Redirect messages being emitted to the local network. Broadcast and multicast messages in the local network do not reach the VPN devices. VPN devices do not explicitly become visible in the home network, i.e. they are not shown in the device list on the home router.

2.3.2. Setups using Proxy ARP

One may attempt to avoid the drawbacks of the routed setup in certain scenarios by employing Proxy ARP (see RFC 1027). The basic idea is to use a subrange of the local network for the VPN devices. As an example, if the local network uses 192.168.178.0/24, one could use 192.168.178.64/28 for VPN purposes. The latter would be set on the VPN interface of the VPN gateway device as depicted in figure 3, and the remote devices would use addresses out of that subrange. The VPN gateway device has a single IP address on the interface in the local network. To make the device respond to ARP requests for remote devices, one enables the Proxy ARP feature on that interface. This way, the interface in the local network acts as a representative for all VPN devices so that other devices in the local network send traffic destined to the remote device IP addresses to the VPN gateway device. The latter then knows how to reach the respective VPN devices. Return traffic works straightforward based on regular routing and forwarding logic.

This can be an elegant option. The "wgfrontend" open-source project [16] can configure and use such a setup and can be considered a proof that the concept works well in practice. Nothing needs to be configured on the home router or on other devices in the local network to set this up cleanly. However, one needs a free subrange of IP addresses in the local network so that some networking knowledge is required and the choice of the address range is limited since it needs to be within the home network range and not in use. Proxy ARP does not assist with broadcast and multicast. VPN devices usually do not become visible in the home network as the home router usually relies on DHCP (RFC 2131) and mDNS (Multicast DNS as defined in RFC 6762) to detect devices. Note that the mentioned project targets road warriors with separate VPN connections as remote devices. However, the approach works in the same manner with a single VPN connection.

3. An innovative approach based on MACVLAN, Policy-Based Routing, and 1:1 NAT

As described in the previous sections, setups based on routing or Proxy ARP have some limitations when attempting to make remote devices appear to be local devices. Proxy ARP already works well in avoiding the need for configuring other devices in the network. We, however, want an approach that does not require any knowledge of the local network, e.g. with respect to free and used IP addresses. It also would be nice if remote devices could explicitly appear as local devices in the local network as shown in figure 4.

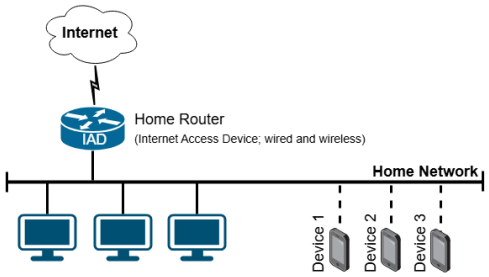

Figure 4: Remote devices shall appear as directly connected to the local home network as schematically shown here – albeit actually being located in a remote network

Our target is to implement a plug&play VPN gateway device ("Homebox") that just needs to be connected to the local network without any further configuration or consideration. Especially, no configuration on the home router or on the devices in the home network shall be required. The user shall just need to attach the VPN gateway device to the home network with nothing more to do on his part. The physical setup is depicted in figure 5.

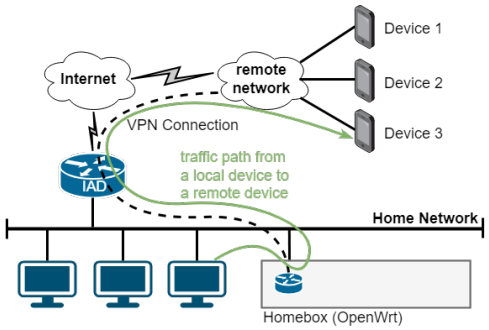

Figure 5: Physical connectivity of VPN gateway device called "Homebox"

First, we require the home router to handle IP addressing without the need to change any configuration on it. The basic approach in home networks is assignment of IP addresses via DHCP (RFC 2131). Thus, we should assign IP addresses to devices via DHCP. This way, we do not need to be aware of the home router configuration and the devices appear as regular devices in the home router's device list. To do that, we require a device in the home network for each remote device. These devices need to request their IP configuration (i.e. IP address, default gateway, DNS servers) via DHCP just like every other usual device in the home network.

Note that we do not want to closely couple the configuration in the mobile packet core with the configuration in the home network. Reasons include resilience, security, and complexity. For instance, we do not want IP address assignments to remote mobile devices to fail at times when there are connectivity issues with the VPN connections. Interacting from the mobile packet core with the home network with protocols like DHCP would also increase the attack surface. Not being able to use standard procedures like IP address assignment to mobile devices via RADIUS servers would be custom development and increase complexity of the setup. The additional complexity of potential

IP address conflicts would need to be handled, too. Therefore, forwarding DHCP requests for remote devices to the home network is not a desired approach. Instead, mobile packet core and home network shall be able to operate in a completely decoupled manner.

The solution idea is to deploy "surrogate devices" in the home network – one surrogate device for each remote device that shall be connected. For this, we require a single physical device to be able to appear as multiple devices in the local network, see figure 6 for illustration. To achieve this, we employ MACVLAN interfaces [17]. This is a device type in the Linux kernel that is usually used in the context of virtualization to connect containers to the local network with high performance [18]. In this context, each container gets an interface of type "macvlan" with an own MAC address and an own IP address but that is connected to a physical parent interface. We use a MACVLAN interface without containers to create a surrogate device in the local home network for each remote device. By configuring a DHCP client to get IP configuration assigned on the surrogate device, the latter appears as a regular device in the local network without any further configuration. There are some subtleties regarding the Address Resolution Protocol (ARP) that we discuss later.

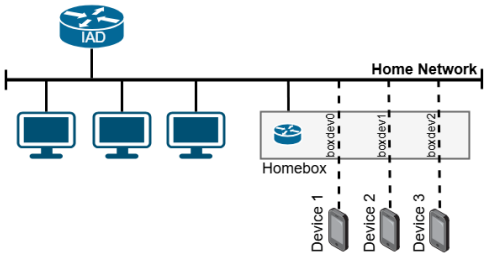

Figure 6: Logical view of device connectivity – remote devices appear to be attached to the local network; only the Homebox device is physically connected

With this, we can make additional devices appear in the local network that get IP configuration assigned and that appear in the home router's device list as regular local devices. But so far, the data traffic to these devices just reaches the VPN gateway device (Homebox), not the remote devices. To change this, we use nftables rules to map data traffic from the local IP addresses to the remote device IP addresses and vice versa. The current IP address of each surrogate device is therewith mapped to the IP address of the remote device in a 1:1 fashion. Using device names and masquerading rules, these rules can be implemented without knowing the IP addresses assigned by DHCP. Finally, we need to make sure that traffic coming from a particular remote device is sent to the local network via the correct MACVLAN interface. This is done using policy-based routing: traffic coming from a particular remote device uses a different routing table containing routes using the correct interface. Details on all this will be explained in the next section.

This approach of using surrogate devices based on MACVLAN interfaces, 1:1 NAT rules and policy-based routing allows creating a VPN gateway device that we call "Homebox". It can be simply plugged into any existing home network and provides connectivity to remote devices without the need to perform any configuration tasks in the home network. The remote devices appear as local devices in the home network – with IP addresses assigned via DHCP as usual. For our purposes, this solution is thus superior to route-based VPNs and the Proxy ARP approach.

4. Implementation for OpenWrt

OpenWrt is an open-source operating system for routers based on Linux [19]. It can be used with a variety of hardware, provides a vast ecosystem of software, and has a web frontend called "LuCI" for user-friendly configuration. It is well suited to implement a VPN gateway to integrate remote devices. We already presented Bash-based configuration script for RaspberryPi hardware in [1]. But this cannot be used with OpenWrt as OpenWrt has its own configuration framework and we'd like to have a solution that is compatible with it. In addition, OpenWrt just has a Busybox-based shell implementation so that many Bash-specific shell commands are not available without installation of additional software.

Therefore, we created a configuration script [20] specifically for the current OpenWrt. We wrote for and tested with version 24.10, the current one at time of writing. The script uses OpenWrt's configuration mechanisms and extension hooks to create a persistent configuration, i.e. one that survives reboots of the device, based on configuration data – like VPN credentials – provided in a config file. WireGuard [11] is used for creating a VPN connection towards the remote device network, in out scenario the mobile packet core. When running the script with the "-r" option, the configuration is completely removed from the OpenWrt router.

First, the script checks whether needed packages are installed and gets missing ones if needed. Besides WireGuard, the MACVLAN kernel module is required. If not yet present, it gets installed by calling:

```
opkg update
opkg install kmod-macvlan
```

A WireGuard interface is created by the script by issuing the following commands (values as configured in the config file):

```
uci set network.wghub=interface
uci set network.wghub.proto='wireguard'
uci set network.wghub.private_key='***'
uci add_list network.wghub.addresses='100.127.1.2/24'
uci set network.wghub.mtu='1392'
```

The network range '100.127.1.0/24' is used as a transfer network between the VPN interfaces in this example. Then the WireGuard interface gets the VPN terminator in the mobile packet core configured as a peer:

```
uci add network wireguard_wghub
uci set network.@wireguard_wghub[-1].description='Hub'
uci set network.@wireguard_wghub[-1].public_key='***'
uci set network.@wireguard_wghub[-1].preshared_key=***'
uci add_list network.@wireguard_wghub[-1].allowed_ips='100.127.1.1/32'
uci add_list network.@wireguard_wghub[-1].allowed_ips='100.64.0.0/10'
uci set network.@wireguard_wghub[-1].endpoint_host='***'
uci set network.@wireguard_wghub[-1].endpoint_port='51820'
uci set network.@wireguard_wghub[-1].persistent_keepalive='25'
```

We use IP addresses out of the reserved CG-NAT range 100.64.0.0/10 as defined in RFC 6598 in this example. The script also creates a new firewall zone for the WireGuard interface and allows forwarding to and from the local network. This allows the user to manage firewall policies/rules for the data traffic traversing the VPN, e.g. using OpenWrt's

web frontend, if desired. The configuration script attempts to auto-detect the interface to the local network ("lan" in the example) based on the default route in the routing table. The default route points to the home router in the local network.

```
uci add firewall zone
uci set firewall.@zone[-1].name='hub'
uci set firewall.@zone[-1].input='ACCEPT'
uci set firewall.@zone[-1].output='ACCEPT'
uci set firewall.@zone[-1].forward='ACCEPT'
uci add_list firewall.@zone[-1].network='wghub'
uci add firewall forwarding
uci set firewall.@forwarding[-1].src='hub'
uci set firewall.@forwarding[-1].dest='lan'
uci add firewall forwarding
uci set firewall.@forwarding[-1].src='lan'
uci set firewall.@forwarding[-1].dest='hub'
```

For each remote device, a MACVLAN interface is created and added to the local firewall zone. Configuration by DHCP is enabled and a hostname is set. This hostname is shown and registered in the home router automatically, if supported there. As an optimization, the MAC address is set with a constant prefix and the last four octets set with the octets of the IPv4 address of the remote device. This ensures that even after reconfigurations, the MAC address is deterministic so that usual home routers always assign the same IP address under normal conditions.

```
uci add network device
uci set network.@device[-1].type='macvlan'
uci set network.@device[-1].ifname='wan'
uci set network.@device[-1].mode='bridge'
uci set network.@device[-1].name='boxdev0'
uci set network.@device[-1].macaddr='02:17:64:7f:00:01'
uci set network.boxdev0=interface
uci set network.boxdev0.proto='dhcp'
uci set network.boxdev0.device='boxdev0'
uci set network.boxdev0.hostname='phone-main'
uci set network.boxdev0.defaultroute='0'
uci add_list firewall.@forwarding[<lan>].network='boxdev0'
```

We need to make sure that each interface answers its own ARP requests. By default, the parent interface would also answer for the MACVLAN interfaces which is not a desired behavior here. This is reconfigured using sysctl attributes in a user-defined file that gets loaded on system boot. The parent interface and a single device called "boxdev0" is configured like this in "/etc/sysctl.d/99-homebox.conf":

```
net.ipv4.conf.lan.arp_ignore=1
net.ipv4.conf.boxdev0.arp_ignore=1
net.ipv4.conf.boxdev0.arp_announce=2
```

Configuring routing rules for policy-based routing is not possible using the OpenWrt network configuration file "/etc/config/network". To work around this, we use a hotplug script to react on an interface being brought into the up state. Depending on the device name, we add a routing rule that matches data traffic coming from a certain remote device via the VPN interface and call a separate routing table for this traffic. The automatically created but not needed link-scope route is deleted so that the same entry for the parent interface becomes the only entry with that target in the standard table. The file "/etc/hotplug.d/iface/99-homebox" then looks as follows for a single device called "boxdev0":

```
#!/bin/sh
[ "$ACTION" = ifup ] || exit 0

if [ "$INTERFACE" = "boxdev0" ]; then
  ip rule add prio 30000 from 100.127.0.1 iif wghub lookup 30000
  ip route add 192.168.202.0/24 dev boxdev0 proto kernel scope link table 30000
  ip route add default via 192.168.202.254 dev boxdev0 onlink table 30000
  ip route del 192.168.202.0/24 dev boxdev0 proto kernel scope link
fi
```

Finally, the configuration script configures nftables with the needed IP address mappings. OpenWrt provides multiple options to add user-defined rules in addition to the ones maintained by the system and configured by the user using the web frontend. As the mappings are not related to other chains and rules, we chose the option to create an extension file. Two chains are created, one hooking into "prerouting" and another one hooking into "postrouting". Each local MACVLAN interface address is mapped to the respective remote device IP address and vice versa. For a single device this looks in "/etc/nftables.d/90-homebox.nft" as follows:

```
chain homebox_dstnat {
  type nat hook prerouting priority dstnat - 1; policy accept;
  iifname "boxdev0" counter dnat ip to 100.127.0.1
}

chain homebox_srcnat {
  type nat hook postrouting priority srcnat - 1; policy accept;
  oifname "boxdev0" ip saddr 100.127.0.1 counter masquerade
}
```

Only a single remote device was shown in the example code above. However, the configuration script supports up to ten remote devices. Their names and (remote) IP addresses as well as the WireGuard VPN configuration need to be provided in the configuration file in "/etc/homebox/homebox.conf". There is no knowledge and no configuration at all needed about the parameters of the home network. This way, a configured OpenWrt gateway device may be plugged into any home network to connect one or more remote devices seamlessly and in a plug&play manner. This is a considerable advantage compared to the basic routed setup and the setup based on Proxy ARP.

5. Evaluation and Applicability

Development and initial test of the implementation was done with the x86 image of OpenWrt in a KVM/QEMU-based virtual machine on a Proxmox host running in a SOHO network. In addition, the solution was applied on real router hardware using a GL.iNet GL-B1300 device. On both platforms, everything worked well and in a stable manner. We share a comparison with other approaches and practical experiences with the service and our solution in the following subsections.

5.1. Comparison of Approaches

In this paper, we considered three approaches for implementing a VPN gateway device that can be connected to an existing home network: one based on a routed setup, one based on Proxy ARP, and an innovative approach based on surrogate devices that are implemented using MACVLAN interfaces, policy-based routing and 1:1 NAT. These three approaches are compared in table 1.

To reach the target to implement a plug&play device that can be easily installed, an approach is needed that does not require configuration work on the home router or other devices in the network. As shown in the table, only the Proxy ARP approach and the surrogate device approach adhere to this requirement. A routed setup requires setting a route at least in the home router.

Table 1: Comparison of approaches

Criteria	basic routed setup	Proxy ARP	surrogate devices
Home router needs configuration	most often	no	no
Other devices need configuration	yes, but workaround	no	no
Free address subrange needed	other range	yes	no
Remote devices appear local	no	limited	yes
Performance	no bottleneck	no bottleneck	no bottleneck
Plug&play possible	no	no	yes

An additional requirement is that no configuration work on the VPN gateway device is required that goes beyond a preconfiguration done by the mobile network operator. Configuration items like VPN credentials can be configured by the network operator providing the device. But any configuration work that requires knowledge of the customer network cannot be done. The network operator cannot know what IP address range is in use in the home network in which the device will be connected to. And it cannot know which IP addresses are in use and which ones are free to use. Thus, only the routed setup and the approach based on surrogate devices can be employed in our scenario.

Only the approach based on surrogate devices makes remote devices explicitly visible in the home network since IP addresses are provided via DHCP. In a routed setup, the devices are in another network; using Proxy ARP, the devices are in the home network range, but IP addresses are not provided via DHCP.

From a performance point-of-view, all three approaches are viable. Due to the performance-limitations of embedded router hardware, the limiting factor is the VPN technology chosen. Options are IPsec, OpenVPN, WireGuard, and more. We have chosen WireGuard due to its simplicity requiring only a single UDP port for operation and its low resource consumption [11]. Therewith, the throughput of the customer's Internet access is the bottleneck in practice, not the VPN gateway device.

All in all, the approach based on surrogate devices is the only one that can adhere to the requirements in our scenario to bring remote devices located in a mobile network transparently into the home network. The customer just needs to connect the Homebox device, thus getting a plug&play installation experience. Note that the solution works independently of the fixed network provider and the vendor of the home router. Both points are relevant in practice.

5.2. Friendly-User Trial Results

Besides the market study targeting the SOHO customer segment, we also attempted to get some first insight into whether consumer customers have use cases for a service that connects their mobile devices transparently to their home network without requiring to install and use VPN software on the mobile devices. Approximately 30 volunteering Telefónica Germany employees tested the service without prior information on what to do with it.

For the trial, we mainly used two connectivity options: on the one hand, the one depicted in figure 2 in which the home router does the VPN connectivity. For this, we provided a VPN configuration file for AVM FritzBox routers that are widely used in Germany. This configuration had to be installed by the trial participants. On the other hand, we provided low-cost OpenWrt routers from the vendor GL.iNet and manually preconfigured our surrogate device approach on them (with up to five surrogate devices per participant). These OpenWrt routers only had to be connected to the home network without any further configuration work necessary. The testing scope was limited to IPv4. Broadcast and multicast packets originating from the home network reached the mobile devices so that device discovery worked in a limited manner; there was no support in the opposite direction.

As expected, the first option was chosen only by tech-savvy users that were confident of doing configuration work in the router web interface. The second option does not have such a knowledge hurdle and could thus be used by any user. This is evidence that only providing a plug&play VPN gateway device makes the solution interesting to a broader range of customers.

The trial users often used the service for straightforward use cases as expected: accessing data and media stored in the home network when commuting or when on travel was an important one. Users with smart home devices at home used the service to access these devices without requiring cloud services as connectivity relay. However, not all device vendors supported this. Mirroring camera images taken on the smartphone to storage at home using data synchronization apps also was an application.

Interestingly, the trial users also found many use cases that were not anticipated beforehand. This is evidence that providing generic connectivity creates applications that cannot be foreseen. For instance, one user implemented a data processing pipeline to process images taken on the smartphone immediately on a server at home. One other user installed a SIP client application on his smartphone to be able to receive calls to his home fixed-net number anywhere just like being at home. Some makers started experimenting with mobile IoT applications. In summary the finding is that the more devices users have at home and the more they like to play around with technology and apps, the more they enjoy using the private connectivity service.

6. Conclusion

Connecting mobile devices in cellular networks privately to existing customer networks clearly has demand in the market, not only for larger customers but also for SOHO customers as confirmed by a presented market study. Due to the relevant use cases and advantages, the participants expressed a willingness to pay five Euros per device and month. Such value-added connectivity is thus a relevant revenue opportunity for mobile network operators. A friendly-user trial indicates that the service is also interesting for certain kinds of consumer customers. This should be studied further.

Plug&play installation is a prerequisite on the customer

side to make a product user-friendly and to avoid the need for customer support. We presented two usual approaches for VPN connectivity, a routed approach and an approach based on Proxy ARP. As both approaches do not meet the requirements, we introduced a new approach based on MACVLAN interfaces, policy-based routing, and 1:1 NAT that makes remote devices appear as local devices in the customer network. We presented an open-source implementation for OpenWrt routers and explained all relevant technical ideas and details. Evaluation in theory and in a friendly-user trial shows that the approach really provides plug&play installation and makes the use cases like secure and convenient remote access to network-attached storage available to the customers. The presented approach is not only applicable for VPN connectivity to mobile networks but can also be employed in other scenarios.

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DIRK HENRICI obtained his degree in electrical engineering (communication systems) from the Technical University of Kaiserslautern, Germany, in 2002. In 2008, he completed his doctorate in computer science. Since 2022, he has been a full professor at Munich University of Applied Sciences HM, Germany.

His research interests include network segmentation, network-based security, and internet architecture.

ANDREAS BOOSE has completed his PhD degree in medical research projects at University of Tuebingen in 1999. He has worked in various roles at Telefónica Germany for 25 years and is currently responsible for the work on the o2 Hub as Product Owner.

Interdisciplinary work and thinking outside the box have been his hobbyhorse.

Received: 16 August 2025, Revised: 16 September 2025, Accepted: 18 September 2025, Online: 23 October 2025

DOI: https://doi.org/10.55708/js0410002

Unveiling the Evolving Threat Landscape of Distributed Denial-of-Service (DDoS) Attacks Methodology and Security Measures

Eman Eyadat [1], Mohammad Eyadat [2], Abedalrahman Alfaqih [1]

[1] Information Systems Department, Irbid National University, Irbid, Jordan

[2]Information Systems Department, California State University, Dominguez Hills, Carson, 90747, USA

*Corresponding author: Mohammad Eyadat, CSUDH, Information System Department, 1000 E. Victoria Street, CA 90747& meyadat@csudh.edu

ABSTRACT: This paper proposes a concrete severity classification framework and an evaluation lens for DDoS defenses (not a descriptive survey) and contributes two specific advancements. First, it introduces a quartile-based severity classification framework for Distributed Denial of Service (DDoS) attacks that extends beyond conventional binary detection. The framework classifies observed traffic into four categories (Q1–Q4) using thresholds derived from packet length, packet rate, and estimated bandwidth consumption. This multi-dimensional approach provides a clearer picture of attack intensity, enabling proportional defensive responses. Second, the paper provides a comparative evaluation of mitigation strategies deployed at different levels of the network, including victim side, source side, core router based, and distributed mechanisms. Each is assessed against a consistent set of technical metrics, highlighting strengths, limitations, and tradeoffs that are essential for operational decision making. Together, these contributions move the work beyond description into a methodological and evaluative framework. Future research directions include adaptive threshold tuning in real time environments, integration of the classification scheme into programmable network infrastructures, and automated mapping of severity levels to specific mitigation playbooks in cloud and edge computing contexts.

KEYWORDS: DDoS, Cybersecurity, Countermeasures, Protection Techniques, Mitigation Strategies

1. Introduction

The cybersecurity landscape is continuously evolving, with DDoS attacks emerging as a significant threat to online services and data security [1]. With the potential to disrupt network operations, inflict financial losses, and compromise data integrity, DDoS attacks necessitate a comprehensive analysis of their methodologies, defensive strategies, and mitigation techniques [2, 3]. This research aims to contribute to the collective knowledge of cybersecurity by offering fresh insights and innovative solutions to enhance cyber resilience against DDoS attacks.

The study begins with an examination of DDoS attack vectors, including TCP SYN flood attacks, UDP flood attacks, and other prevalent methods. By meticulously analyzing and categorizing these attacks based on severity levels, the research unveils the intricate mechanisms employed by malicious actors to disrupt network operations [4, 5]. This analysis provides a solid foundation for understanding the complexities of DDoS attacks and their potential impact on digital infrastructure.

In addition to exploring attack methodologies, the research delves into defensive mechanisms such as IP traceback techniques, packet filtering strategies, and distributed defense systems deployed across multiple Autonomous Systems (AS). By evaluating the effectiveness of perimeter-based defenses, controller-agent models, and distributed change point detection, the study underscores the importance of secure information exchange and robustness in safeguarding against DDoS threats [6, 7].

The research also emphasizes the significance of proactive defense measures, highlighting the importance of distributed defense systems as the most effective strategy. By combining elements from victim, source, and core router-based defenses, these systems offer a comprehensive approach to detecting and mitigating DDoS attacks. A comparative analysis of defense

mechanisms based on deployment locations and performance metrics further emphasizes the necessity of strategic placement of defense components.

To provide a holistic understanding of DDoS attacks and their countermeasures, the study also examines attack motivations, evolutionary trends, protection techniques, and existing research limitations. By synthesizing findings from various research papers, the research in this paper aims to empower organizations with the knowledge and tools needed to fortify their defenses and mitigate the impact of DDoS attacks on online services and data security.

The novelty of this study lies in its combination of classification and evaluation. Unlike existing surveys that remain descriptive, our work advances the field by introducing a quartile-based severity classification model that provides a granular measurement of attack intensity. This classification is not arbitrary; it is grounded in empirical thresholds derived from experimental packet captures. By quantifying attack levels in four tiers, we provide actionable information for defenders to scale mitigation strategies according to the severity of the threat. In parallel, we conduct a structured evaluation of defensive mechanisms across four network layers—victim, source, core, and distributed. By applying a uniform set of criteria, we create a comparative framework that allows practitioners to judge which defenses are most effective in different deployment scenarios. These contributions ensure that the paper is not merely a review, but a methodologically driven and practically relevant addition to the literature.

2. Literature Review

In their paper, by authors [8] discuss DDoS attacks, their analysis, and prevention strategies, providing insights into contemporary challenges and defense mechanisms. The paper presented by authors [9], displays TRACK, a novel approach for defending against DDoS attacks, offering a detailed technical analysis and evaluation of its efficacy. In [10], the authors collaborative detection of DDoS attacks over multiple network domains is explored in this paper, emphasizing the importance of cooperation among networks to combat such attacks. The paper authored by authors [11] introduces a perimeter-based defense mechanism against high bandwidth DDoS attacks, accentuating its effectiveness in protecting network infrastructure. The research paper [12] classifies DDoS attacks and defense mechanisms, providing a state-of-the-art review and classification framework for researchers and practitioners.

The authors of the research paper [13], investigate current defense schemes against Distributed Denial of Service (DDoS) attacks, providing critical insights and evaluations of existing strategies. Researchers in paper [14], a surveys defense, detection, and traceback mechanisms against DoS and DDoS attacks, providing a comprehensive overview of existing strategies. In [15], the authors present a real-time DDoS attack detection and prevention system based on per-IP traffic behavioral analysis, offering insights into proactive defense strategies.

In [16], the authors classify Internet security attacks and discuss their implications, offering a comprehensive overview of attack patterns and defense strategies. Network protection against DDoS attacks is discussed by researchers [17, 18], while offering insights into defense strategies and their implementations. In [19], the authors provide a comprehensive review of network security threats and mitigation strategies, contributing to the body of knowledge in cybersecurity. In [20], the authors explore packet filtering approaches for detecting network attacks, offering insights into proactive defense strategies.

3. Methodology

In this research article, we delve into the multifaceted landscape of DDoS attack methodologies. We recognize the vast array of DDoS attack methods and the myriad tools and techniques employed to execute these attacks. Within the confines of this study, we focus on a specific DDoS attack method, dissecting its implementation process in detail.

Our methodology revolves around a comprehensive exploration of the selected DDoS attack method. We elucidate the intricacies of how this method is executed, shedding light on the tools and tactics that malicious actors may employ. Furthermore, we investigate mechanisms for early detection and alerting, allowing organizations to identify and respond swiftly when faced with similar attacks.

Crucially, our research extends beyond understanding the attack; we emphasize proactive defense measures. We elucidate strategies to thwart, mitigate, and limit the impact of DDoS attacks of this nature. By synthesizing these insights, we aim to contribute to the collective knowledge of cybersecurity, enhancing the ability of organizations to fortify their defenses against the ever-evolving threat landscape of DDoS attacks.

The attacker employs various methods to inundate the targeted web server with malicious packets. In this particular instance, the user utilized the Low Orbit Ion Cannon (LOIC) Denial-of-Service (DoS) attack tool to execute pattern-based attacks [21]. This section elucidates the approaches employed during the current research. The methodology comprises two primary phases: data collection and the identification and analysis of attacker characteristics. By discerning the patterns of attack behavior, two nodes are employed in this process. One

node acts as an attacker machine, while another serves as the victim, equipped with a tool designed to capture all incoming network traffic. The manifestation of anomalous and malevolent activities leads to a degradation in network performance, impeding users' access to online services. This methodology captures the ongoing packets by utilizing packet capture techniques.

3.1. Packet Sniffing

3.1.1. Data Collection

The software tool provides a range of functionalities, including filters and color- coding, facilitating the examination of network traffic and the scrutiny of individual packets. Additionally, it simplifies network characterization by enabling the assessment of attributes such as load, frequency, and latency between specific network nodes. Among the most prevalent packet types on the network, TCP, UDP, and ICMP stand out.

In the data collection phase, all packets generated by the attacker, including UDP and TCP traffic floods, are captured using a packet sniffer. By examining the captured packets, which encompass UDP, HTTP, and TCP, we discern the patterns indicative of attack behavior. Quartiles are employed to gauge the severity of the attacks, with the following categorizations:

- Q1: Low-level attacks
- Q2: Moderate-level attacks
- Q3: Upper half attacks
- Q4: High-level attacks

To enhance precision and address reviewer feedback, we explicitly define the thresholds used in the quartile classification. The classification leverages three measurable parameters: average packet length (L) in bits, average packet rate (R) in packets per second, and estimated bandwidth (B) in megabits per second, computed as B = (L × R) ÷ 10^6. Severity levels are determined as follows:

Q1 (Low level): L < 85,000 bits, R < 100 packets per second, B < 8.5 Mbps. These attacks generally cause minimal disruption and can often be absorbed through local queue management and traffic policing.

Q2 (Moderate level): 85,000 ≤ L < 94,650 bits, 100 ≤ R < 250 packets per second, 8.5 ≤ B < 24 Mbps. These attacks may begin to degrade performance of latency sensitive services and usually require targeted packet filtering or temporary access control list (ACL) updates.

Q3 (Upper half): 94,650 ≤ L < 104,300 bits, 250 ≤ R < 500 packets per second, 24 ≤ B < 52 Mbps. These attacks generate significant service degradation. Mitigation strategies include coordinated pushback mechanisms and upstream filtering support from Internet Service Providers.

Q4 (High level): L ≥ 104,300 bits, R ≥ 500 packets per second, B ≥ 52 Mbps. These represent severe floods capable of overwhelming resources across multiple layers. Countermeasures must involve distributed defenses, collaborative filtering, and in extreme cases, network wide rerouting.

An interval is classified according to the highest triggered quartile among the three parameters. For instance, if packet length falls into Q2 but packet rate falls into Q3, the final severity label is Q3. This “maximum rule” avoids underestimating the seriousness of an attack when one parameter surges disproportionately. The thresholds were derived empirically from observed packet captures, but they also align with operational thresholds used by ISPs in traffic engineering. This combination of packet length, rate, and bandwidth provides a multidimensional perspective on severity, which improves accuracy compared to relying on a single parameter.

Measurement details. We compute averages over non-overlapping 60-second windows. Let L be mean packet length in bits, R mean packet rate in packets per second, and B estimated bandwidth in megabits per second given by B = (L × R) ÷ 10^6. Unless stated otherwise, all quartile labels use the maximum rule over L, R, and B for each 60-second interval.

3.1.2. Attack Methodology

The attacker employs various tactics to inundate the targeted web server with malevolent packets. The identification of attack signatures assumes significance in facilitating the detection of DoS attacks. This method entails the utilization of two distinct machines, one of which houses an attacker simulator physically. The attacker simulator can execute various types of attacks on the target machine. One machine is designated as the attacker, responsible for flooding the server machine with malicious packets. Meanwhile, the server machine is equipped with monitoring and capturing tools to analyze network traffic in real-time. For a more detailed illustration, please refer to the standard DoS attack architecture depicted in Figure 1 below.

3.1.3. TCP SYN Flood Packet Attacks

Among the most detrimental forms of DoS attacks, the TCP SYN flood is particularly noteworthy. In typical communication between clients and servers, a three-way handshake, involving "SYN-SYN-ACK and ACK" packets, is performed to establish connectivity. However, in the case of these attacks, malicious actors attempt to masquerade as trusted clients, leading servers to await acknowledgment indefinitely until TCP timeout occurs. These attacks are engineered to exhaust server resources, including firewalls and communication tools. Figure 2

illustrates the captured and analyzed TCP traffic using Wireshark.

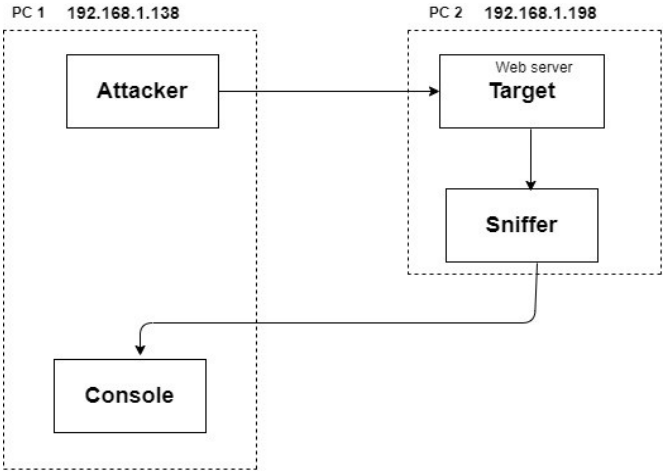

Figure 1: Standard DoS Attack Architecture

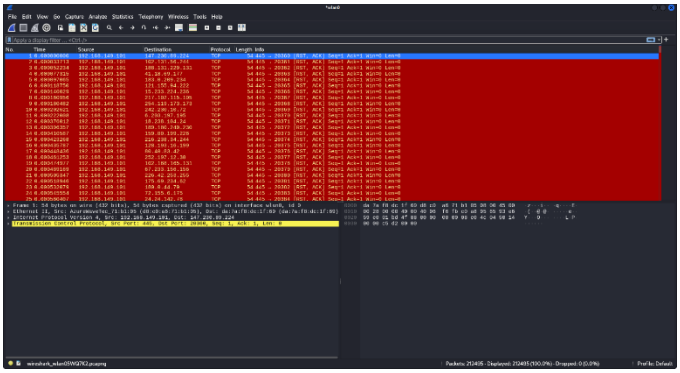

Figure 2: Examining TCP Flood Attack with Wireshark

In the context of TCP flooding during DDoS attacks, the packets are directed towards the target server. To gain insights into the characteristics of these malicious packets, you can conveniently identify them by accessing the "Statistics" menu and then selecting "Flow Graph." This action enables you to visualize the packet sequence graphically. Through this tool, you have the capability to trace and comprehend the TCP connections and their behavior, as exemplified in Figure 3.

As depicted in Figure 3, the time axis is measured in seconds (s), and the source's IP address is identified as 192.168.149.101 utilizing a port number that ranges randomly between 20361 and 20368 (port range). On the other hand, the destination's IP address is specified as 147.230.89.224, . In this scenario, the source initiates the transmission of attack packets, characterized by their variable port numbers. The client IP, denoted as 192.168.149.101 initiates a TCP connection with the server IP, 147.230.89.224, commonly referred to as the server. Wireshark traces empower network engineers to identify unusual downloads, often marked by indicators such as "RST ACK" and "TCP DUP ACK." These anomalies are typically associated with abnormal packet behavior, and malevolent actors may employ techniques like "RST ACK" to orchestrate attacks resembling TCP ACK attacks.

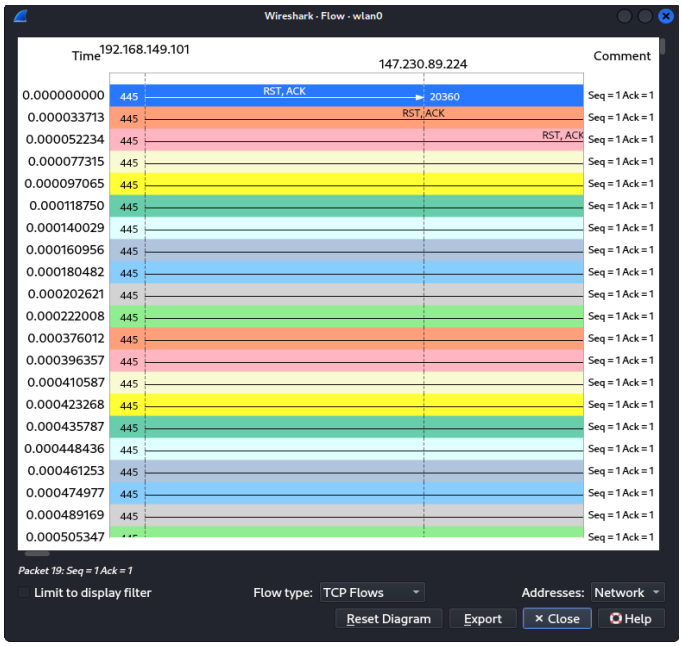

Figure 3: TCP Flow Graph Overview

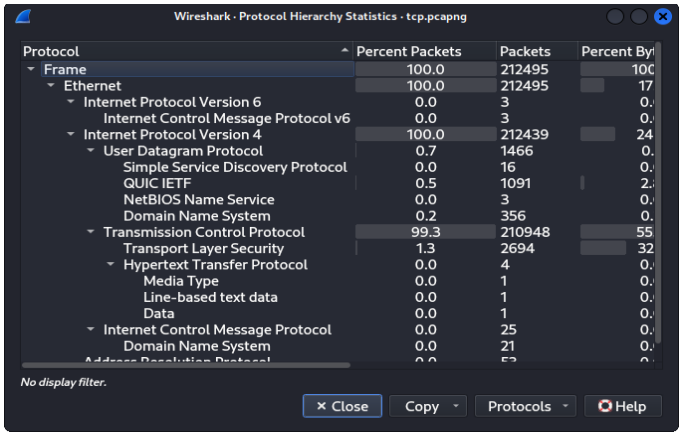

Figure 4: protocol hierarchy statistics overview for TCP flood attack

This figure shows the percentage of TCP incoming packets and it is shown as 99.3 % of incoming packets to the network.

3.1.4. *User Datagram Protocol (UDP) Flood Attack*

The second prevalent DDoS attack method centers on UDP flooding, exploiting vulnerabilities within UDP services. This method involves inundating ports on the server with malicious packets to ascertain which ports are susceptible to exploitation. To initiate this analysis, users can apply a filter by typing "UDP" in the designated filter zone, or opt for other protocols as required, and the results will be displayed on the user interface [22].

A UDP flood attack is characterized by the massive influx of spoofed UDP packets directed at various server ports from a single source. In response, the server, along with ICMP, issues "destination unreachable" notifications, signifying that it is overwhelmed by the volume of incoming requests. The resulting network traffic can be captured and further analyzed using Wireshark, as exemplified in Figure 5.

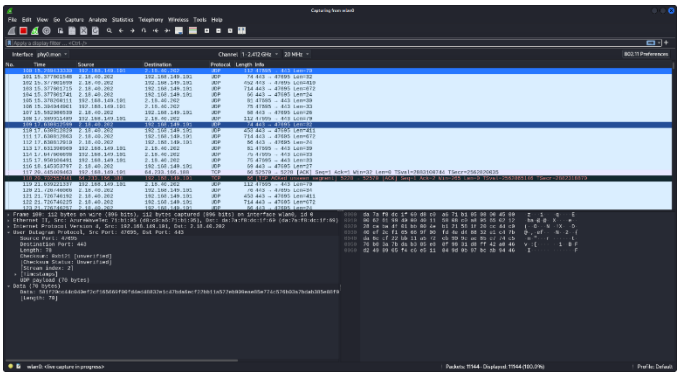

Figure 5: Examination of UDP Flood Attack

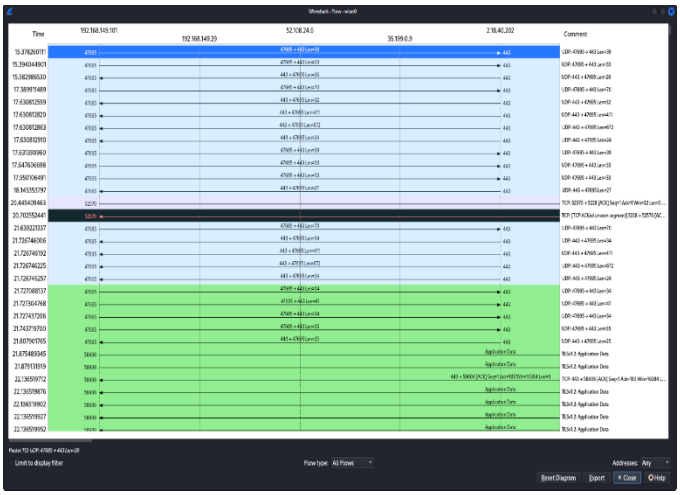

Figure 6: UDP flow graph overview

As depicted in Figure 6, the time axis is measured in seconds (s), and the source's IP address is identified as 192.168.149.101. The source continuously transmits a large volume of User Datagram Protocol (UDP) packets towards the destination IP address, 192.168.149.29. Unlike TCP connections, UDP doesn't establish a handshake and sends packets independently.

In this scenario, the source floods the destination with UDP packets, overwhelming the target device's resources and potentially causing a denial-of-service (DoS) attack. Wireshark traces might reveal a surge in UDP packets originating from the source IP (192.168.149.101) directed towards the destination IP (192.168.149.29). While Wireshark might not capture the exact contents of UDP packets, the abnormal increase in traffic can be indicative of a UDP flood attack.

The figure 7 shows the percentage of UDP flow attack incoming packets as 50% of the incoming packets through the network.

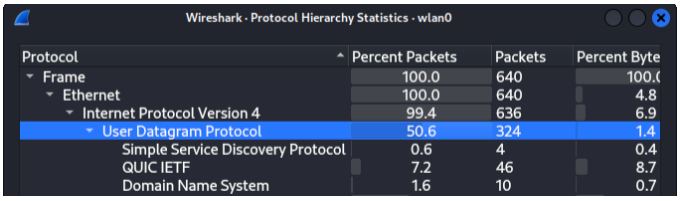

Figure 7: protocol hierarchy statistics

3.2. *Packet Analysis and Attack Duration dentification*

Upon capturing the requisite packets spanning from day one to day three, Authors harnessed Microsoft Excel to discern the patterns within attack behavior enabled them to methodically process and analyze the packets collected at various time intervals, as initially captured by Wireshark.

Microsoft Excel proved instrumental in providing a comprehensive understanding of the packets, offering insights into the total packet lengths. The differentiation in the sizes of the attacks, whether characterized as small or substantial, formed a pivotal aspect of the impact assessment.

All data originating from the attacker underwent meticulous processing via Microsoft Excel. This entailed the calculation of averages across the dataset, facilitating the categorization of attacks into distinct levels, encompassing low, medium, and high, as elucidated in Figure 8.

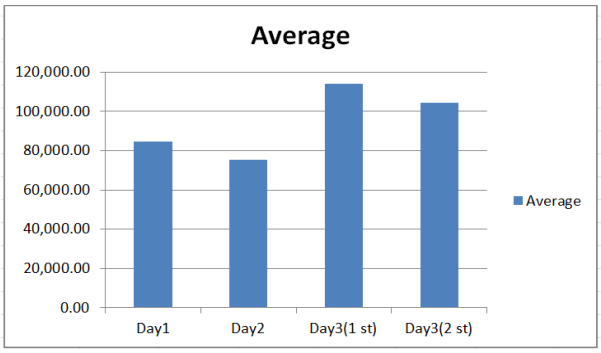

Figure 8: Average data collected in three days.

3.3. *Analysis of Flood Packet Length and Attack Levels*

In figure 8, the average length of captured flood packets is depicted, and these lengths vary depending on the attackers' traffic loads. By meticulously scrutinizing these average lengths and applying quartile calculations, users gain a valuable perspective on the severity of the attacks, as determined by the following formula (Equation):

$$QN = (Dmax - Dmin) \quad (1)$$

where:

- N = 1, 2, 3
- Dmax = Maximum average length (113,887.93 bits)
- Dmin = Minimum average length (75,407.50 bits)

Consequently, the range can be calculated as:

Range = 113,890 - 75,407 = 38,480 bit.

The quartile values are as follows:

To determine the quartile values, the range is divided by 4 (since there are four quartiles) to establish the

interval size for each quartile. In this case, 38,480 bits divided by 4 equals 9,620.75.

- Q1 = 75,407 to (75,407 + (1 x 9620)) = 75,407 to 85,027
- Q2 = 85,027 to (75,407+ (1 x 9620)) = 85,027 to 94,647
- Q3 = 94,647 to (75,407+ (1 x 9620)) = 94,647 to 104,267
- Q4 = 104,267 to (75,407+(1 x 9620)) = 104,267 to 113,887

Table 1 below provides information on the time intervals during which flood packets were collected, including periods (in seconds), packet lengths (in seconds), quartile ranges (in seconds), and corresponding attack levels. With reference to quartile identification and the calculated range (QN), users can easily discern the attack levels, categorizing them as low, medium, or high. In each of these attack levels, the primary objective is to disrupt legitimate user access to essential services.

Table 1: Summarizing Level of Attacks

NO	TIME	SEC	LENGHT	QUARTILE	ATTACK LEVEL
1	04:22	37	85,027	Q2	MEDIUM ATTACK
2	12:09	34	75,407	Q1	LOW ATTACK
3	18:11	52	113,887	Q4	HIGH ATTACK
4	09:44	44	104,267	Q3	HIGH ATTACK

The table above illustrates the level of attacks. The intruders can attack a system using small packets with many loads; these attackers cause the targeted system to consume too much network bandwidth resources and make services unavailable to legitimate traffic. By analyzing the attack time and length of all data collected in three days, users can identify the level of attacks from Q1, Q2, and Q3, Q4 scaling systems. The average of attacks Q1 seems to be a low attack, this means the impact is not quickly put down the server, Q2 is medium attacks where the volume of attack is upper to Q1; finally, Q3, Q4 the higher than others level attacker sent a huge of fake packets to the victim server to make source unavailable to legitimate users.

4. Results and Discussion

In this section, we present the findings of our analysis, shedding light on the impact and categorization of DDoS attacks based on packet lengths and quartile calculations.

4.1. Analysis of Packet Lengths

Figure 8 displays the average length of flood packets collected during various attack instances, each contingent upon the traffic loads initiated by attackers. These measurements provide crucial insights into the severity of the attacks. To determine the attack levels, we applied quartile calculations using formula 1.

Our results reveal a significant disparity in average packet lengths, ranging from a minimum of 75,407 bits to a maximum of 113,887 bits. The calculated range, denoting the variation in packet lengths, amounted to 38,480 bits.

4.2. Quartile Analysis

The quartile values, Q1, Q2, Q3, and Q4, further elucidate the distribution of packet lengths and help in characterizing the attacks. These quartile ranges are as follows:

- Q1: 75,407 to 85,027 Bits
- Q2: 85,027 to 94,647 Bits
- Q3: 94,647 to 104,267 Bits
- Q4: 104,267 to 113,887 Bits

The quartile classification framework adds analytical depth beyond a binary attack/no attack model. Binary systems merely indicate whether an anomaly exists, but they fail to convey its magnitude or operational significance. Our quartile approach quantifies intensity, thereby providing defenders with actionable intelligence. For example, a Q1 event may be addressed through local resource adjustments with negligible impact on legitimate users, whereas a Q4 event demands immediate, distributed intervention to prevent large scale service outages. By stratifying attacks into four levels, defenders can allocate resources more efficiently, prioritize responses, and reduce collateral damage from overly aggressive mitigation. Furthermore, this classification can support adaptive automation: security systems can be programmed to escalate defensive measures as the quartile level rises. In this way, quartile classification is not only a descriptive tool but also a foundation for dynamic, context aware defense strategies.

In our traces, intervals labeled Q3 and Q4 coincided with service availability drops and triggered upstream filtering, whereas Q1 events were handled locally without collateral blocking, underscoring the operational value of the stratified scheme.

4.3. Preventing DDoS attack and/or applying defensive techniques to limit them

4.3.1. IP Traceback Mechanisms: An In-Depth Analysis

IP traceback mechanisms are crucial in identifying the true source of IP packets, which is essential for tracking and mitigating various cyberattacks, including Distributed Denial of Service (DDoS) attacks. This process, called traceback, involves tracing malicious packets back

to their origins to uncover the identity of the attacker. IP traceback mechanisms can generally be categorized into two main types: packet marking and link testing.

4.3.2. *Packet Marking Mechanisms*

Packet marking mechanisms rely on routers to mark packets that are heading towards the victim server. This marking allows the path followed by packets to be easily identified, aiding in traceback. However, implementing packet marking mechanisms can be challenging due to the stateless nature of internet routing. Unique identifiers are needed for each packet, and routers may fail to assign these identifiers to some packets, leading to false positives.

4.3.3. *Link Testing Mechanisms*

Link testing mechanisms involve testing upstream links starting from the one closest to the victim and repeating the process recursively until reaching the upstream router. This approach helps identify the path of the attack traffic. However, IP traceback mechanisms, whether using packet marking or link testing, come with several challenges, including management, computational, and network overhead. Additionally, widespread implementation of these mechanisms requires the involvement of numerous routers.

It's important to note that source accountability in the TCP/IP protocol is limited, making IP traceback a complex task. The accuracy of the traceback process is also questionable, as attackers can create mechanisms that appear genuine. This has led some researchers to recommend the use of ICMP traceback.

In ICMP traceback, packets with reduced probability of being malicious are sampled by each router. An ICMP traceback message is sent to the destination, and a chain of traceback messages is constructed. This chain aids in determining the exact source of the traffic. However, validating traceback packets in the ICMP mechanism can be challenging, and it's unlikely that a certificate-based scheme can be universally adopted by all routers.

4.3.4. *Management Information Base (MIB)*

The management information base captures critical data, including packet information and historical routing statistics. This data can be used to map TCP, ICMP, and UDP packets, generating patterns. It helps in identifying network abnormalities and provides a framework for adjusting network settings to counter unwanted traffic effectively. While this method holds promise for controlling traffic loads, further evaluation in a real network environment is needed.

4.3.5. *Packet Filtering and Filtering Mechanisms*

Packet filtering mechanisms are essential for blocking undesirable traffic. They operate by marking legitimate packets and then using filters to block unwanted traffic. Common packet filtering mechanisms include history-based filtering and hop-count filtering.

History-Based Filtering: This mechanism maintains records of frequently visited IP addresses. When a DDoS attack occurs, it connects to the IP addresses in the list, but it requires an offline database, which can be costly.

Hop-Count Filtering: Hop-count filtering stores IP addresses and their corresponding hops from the destination. However, it has a limited range, making it ineffective for identifying illegitimate source IP addresses with similar hop-count values.

4.3.6. *Packet Dropping Based on Congestion*

This defense mechanism drops suspicious packets during network congestion to manage overload. The Packet Score mechanism assigns a score to each packet, allowing prioritization based on the level of overload and score distribution of incoming packets. However, it may not be effective against sophisticated attacks.

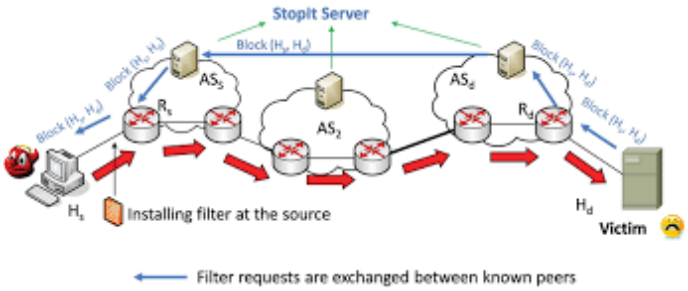

Figure 9: Network-Based Defense Mechanisms [12]

4.3.7. *Network-Based Defense Mechanisms*

Network-based defense mechanisms deploy components on network routers to detect, traceback, and respond to attacks through filtering and rate limiting.

In figure 9 classifications of network-based mechanisms include perimeter-based defense mechanisms, the controller-agent model, and Distributed Change Point Detection.

- **Perimeter-Based Defense Mechanisms:** Typically used by internet service providers (ISPs), this mechanism detects and identifies attack sources and responds by rate-limiting traffic. It offers local deploy ability without straining ISP core routers.
- **Controller-Agent Model:** This model relies on edge routers and controllers to mark and filter attack traffic. It uses third-party components for attack detection and characterization.
- **Distributed Change Point Detection:** This method monitors propagation patterns and detects unexpected changes on the network. It is deployed over multiple Autonomous System (AS) domains

and is effective in quickly detecting DDoS flooding attacks.

- **Distributed Defense Mechanisms**: Distributed defense mechanisms, in contrast to centralized mechanisms, are deployed at multiple points across the network. They can adopt various combinations, such as detection at the victim's side with distributed response or a combination of both.

In conclusion, IP traceback mechanisms play a vital role in identifying and mitigating cyberattacks like DDoS attacks. Each mechanism has its advantages and limitations, and their effectiveness depends on factors like deployment location and attack response methods. Evaluating these mechanisms based on various criteria is essential for choosing the most suitable defense strategy for specific network configurations and requirements.

Table 2 highlights the comparisons between different defense methods

Table 2: Deployment-Based Comparisons Between Different DDoS Defense Methods

Deployment Scheme	Scheme Name	Attack Detection	Attack Response
Victim-Based Defense	NetBouncer Preferential Filtering	Legitimacy tests IP Traceback Scheme	Packet filtering based on legitimate lists Filter packets with infected edges.
Source-Based Defense	Ingress Filtering D-Ward	IP address validity tests Detect Abnormality	Rule-based filtering Rate limiting of outgoing traffic
Core Router-Based Defense	Collaborative Agent Model Collaborative Agent Model Perimeter-based defense	Change Aggregation tree Signature Matching Traffic Aggregate	Packet Filtering Packet Filtering Rate limit filters
Distributed Defense	ACC and Pushback Stoplt Defcom	Congestion detection Passport Traffic Tree discovery	Rate Limiting Packet Filtering Distributed rate limiting

The effectiveness of DDoS defense methods hinges on their deployment strategies, which determine how they detect and respond to attacks. In this section, we evaluate various defense mechanisms based on their deployment schemes. These mechanisms encompass victim-based defense, source-based defense, core router-based defense, and distributed defense. Each approach has its strengths and weaknesses, which we assess using six key metrics: effectiveness, vulnerability, accuracy, coverage, robustness, and complexity.

Victim-Based Defense:

- **Attack Detection:** NetBouncer conducts legitimacy tests, while packet filtering relies on predefined legitimate lists.
- **Attack Response:** Victim-based defenses employ preferential filtering and IP traceback schemes.

Source-Based Defense:

- **Attack Detection:** Ingress filtering validates IP addresses, and rule-based filtering detects abnormalities.
- **Attack Response:** Rate limiting of outgoing traffic is a key response mechanism for source-based defense.

Core Router-Based Defense:

- **Attack Detection:** Collaborative Agent Model and Change Aggregation tree are used for attack detection, alongside packet filtering.
- **Attack Response:** Signature matching and packet filtering play crucial roles in core router-based defenses.

Distributed Defense:

- **Attack Detection:** Adaptive Congestion Control (ACC) and pushback mechanisms detect congestion, while distributed rate limiting is a common detection method.
- **Attack Response:** Distributed defense systems use various methods, such as Traffic Tree discovery and distributed rate limiting.

Evaluation of Deployment Schemes:

- **Effectiveness:** Distributed defense systems are the most effective as they combine elements from multiple locations.
- **Vulnerability:** Victim-based defenses are vulnerable to attacks, while distributed defenses are less so.
- **Accuracy:** Victim-based defenses offer high accuracy due to their proximity to the target.
- **Coverage:** Distributed defense systems provide extensive coverage due to their distributed nature.

- **Robustness:** Distributed defense systems are robust, provided secure information exchange among components.
- **Complexity:** Distributed defense can be complex due to distributed components and information exchange.

In summary, while all deployment schemes have their merits and drawbacks, distributed defense systems stand out as the most robust and effective strategy. They combine elements from victim, source, and core router-based defenses to achieve comprehensive protection. However, ensuring secure information exchange among distributed components is essential for maintaining their robustness.

Table 3-a: Evaluation of DDoS Mechanisms Against the Six Metrics

Deployment Scheme	Coverage	Implementation	Deployment
Source-Based Defense	It would have an effective coverage as long as it is deployed globally.	Global deployment is a condition required for its implementation to bring all desired effects. Global deployment is impractical because the internet has no central location.	Centralized. Deployment has its limitations because in a distributed attack, the source is only responsible for a fraction of the attack.
Router-Based Mechanism	Excellent Coverage: This is because a bulk of the network passes through them.	Easy to implement: Deployment at middle only requires few components and gives excellent defensive coverage.	Centralized. Few components are required for deployment.
Victim-Based Defense	The defense mechanism does little to contain attack at the victim's end.	Most defense mechanism are designed at the victim's end.	Centralized. It requires wide deployment to be effective.
Distributed-Based Defense	Has a relatively higher coverage than others.	Can be complex to configure because most defense components need to be scattered over the internet.	Distributed. Deployed over multiple locations such as source and intermediate networks.

Table 3-b: Evaluation of DDoS Mechanisms Against the Six Metrics

Deployment Scheme	Detection Accuracy	Response Mechanism	Robustness
Source-Based Defense	The source is the best place to differentiate between good and bad packets. It uses IP Address validity tests and can be effective in detecting abnormalities.	Uses rate-limiting method. Rate limiting is effective because a specific limit can be placed on a traffic that is allowed through the Network Interface.	Very robust because they can detect attacks at the early stages and eliminate an attack before it occurs. However, this depends on it being deployed across maximum source networks.
Router-Based Mechanism	Core routers are usually busy and cannot perform serious packet analysis.	Only parameter-based defense uses rate limiting. The other schemes under the Router-Based Mechanism uses packet filtering. Packet	Ideally good effective detection and filtration but robustness depends on an expansive coverage in detecting and capturing

		filtering can be an ineffective response mechanism.	good number of attacks.
Victim-Based Defense	There is higher accuracy of detection at victim's end based on "bad lists."	Uses packet filtering based on legitimate lists.	Can be very effective but depends on wide deployment.
Distributed-Based Defense	Has a relatively accurate detection since resources from several levels are used.	Various schemes adopt unique response mechanisms but overall because of distributed architecture, its response mechanism is relatively good.	Very robust against DDoS attacks. Mitigates against the short-comings of the other defense mechanisms.

The comparative analysis began by categorizing various defense mechanisms based on their deployment locations. Four primary classifications were considered: source- based, core-router-based, victim-based, and distributed systems. A selection of defense systems falling under these categories was assessed using six performance metrics: coverage, implementation, deployment, detection accuracy, response mechanisms, and robustness as shown in tables 3-1 and 3-b.

The analysis highlighted that there is no single deployment location that can offer complete protection against DDoS attacks. The most effective defense mechanism involves the use of distributed systems, ensuring that defense components are strategically placed across various locations. In general, an effective DDoS defense strategy should involve multiple nodes responsible for detecting and mitigating attacks.

At the end of the victim, detection accuracy is high, but there is limited time for response when an attack reaches this location. Stopping an attack at its source is an ideal approach, but achieving high detection accuracy is challenging since distinguishing between legitimate and malicious traffic can be complex. The core-router-based defense system also has limitations, primarily due to resource constraints such as CPU cycles and limited traffic profiling capabilities.

5. Conclusion and Implications

This Study has provided valuable insights into the categorization of DDoS attacks based on packet lengths and quartile calculations. By examining the average lengths of flood packets and applying quartile analysis, we have identified low, medium, and high-level attacks. These distinctions enable us to gauge the severity of DDoS attacks and their potential impact on network resources.

Understanding the levels of DDoS attacks is paramount for implementing effective mitigation strategies and safeguarding essential online services. In all instances, the primary objective of DDoS attacks is to disrupt legitimate user access, emphasizing the critical need for robust cybersecurity measures.

In this research journey into the evolving threat landscape of Distributed Denial-of- Service (DDoS) attacks and the corresponding security measures, we have ventured deep into the intricate world of cyber warfare. Through meticulous examination, we have gained valuable insights into the motivations driving these malicious assaults, scrutinized the diverse attack vectors at play, and assessed the current state of protective measures.

Our team's study has illuminated the limitations we face in the realm of DDoS attack research, from the challenge of accessing real attack data to the ever-evolving nature of attack techniques. We've also navigated resource constraints, ethical considerations, and legal boundaries, underscoring the complexity of conducting research in this critical area of cybersecurity.

In our exploration of DDoS attack methodologies, we've delved into the intricacies of TCP SYN flood attacks and UDP flood attacks. Through rigorous analysis and packet length assessments, we've categorized these attacks into low, medium, and high levels, offering a nuanced understanding of their severity.

Furthermore, our examination of IP traceback mechanisms has shed light on the critical role of identifying the true source of IP packets in combating DDoS attacks. We've explored packet marking and link testing mechanisms, recognizing the challenges and complexities involved in tracing malicious packets back to their origins.

The discussion has also covered management information bases, packet filtering mechanisms, and

packet dropping strategies during network congestion, providing a comprehensive overview of defensive techniques against DDoS attacks.

In the context of network-based defense mechanisms, we've categorized them into perimeter-based mechanisms, the controller-agent model, and Distributed Change Point Detection. Additionally, we've delved into distributed defense mechanisms, highlighting the importance of evaluating these strategies based on various criteria to select the most suitable defense approach for specific network configurations and requirements.

In conclusion, this team's research underscores the critical importance of understanding the evolving threat landscape of DDoS attacks and implementing effective security measures. As the digital realm continues to evolve, the battle against these cyber threats remains ongoing. By combining innovative research, proactive defense strategies, and collaborative efforts, we can fortify our defenses and protect the integrity and availability of online services. It is our collective responsibility to remain vigilant and adaptive in the face of this persistent and ever-evolving cybersecurity challenge.

Beyond descriptive surveys, the novelty of this study lies in proposing a quartile-based severity classification framework grounded in empirical thresholds and a comparative evaluation model for defense strategies. This dual contribution ensures the work moves from description to methodological and practical advancement.

6. Future Research Directions

Future studies should also validate the practical value of quartile-based classification by integrating it into automated detection systems and comparing its efficiency against binary approaches in real-world network environments. While there was no type of funding supporting this research and none of the authors have any competing interests in the manuscript this study has offered valuable insights, future research endeavors can explore more advanced methodologies for real-time DDoS attack detection and mitigation. Also, the development of adaptive defenses to counter evolving attack techniques remains an essential area for exploration in cybersecurity.

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Received: 30 October 2025, Revised: 20 November 2025, Accepted: 22 November 2025, Online: 12 December 2025

DOI: https://doi.org/10.55708/js0412002

Experimental Study of the Short-Circuit Current Performance of 10 kA$_{R.M.S}$ and 20 kA$_{R.M.S}$ Polymer Surge Arrester

Cristian-Eugeniu Sălceanu, Daniela Iovan*, Daniel-Constantin Ocoleanu

National Institute for Research Development and Testing in Electrical Engineering ICMET Craiova, Craiova, 200746, Romania

Email(s): csalceanu@icmet.ro (C.E. Sălceanu), pramlmp@icmet.ro (D.C. Ocoleanu)

*Corresponding author: Daniela Iovan, ICMET Craiova, B-dul Decebal, nr. 118A, pdaniela@icmet.ro

ABSTRACT: To study the behavior of metal oxide surge arresters at short-circuit current, this paper presents an experimental study on four pieces of 36 kV, 10 kA$_{R.M.S}$ and 20 kA$_{R.M.S}$ surge arresters at different values of short-circuit current. Prior to the experiments, each surge arrester was electrically pre-faulted with a power frequency overvoltage without any physical modification. The tests were conducted under severe conditions at the rated short-circuit current, and the peak value of the first half-cycle of the actual arrester current was at least $\sqrt{2}$ times the RMS value of the rated short-circuit current. The arrester is one of the most effective means of limiting the lightning surge to the transmission line insulator string and tower head air gap. When an arc occurs, the arrester acts quickly to relieve the high pressure generated by combustion, preventing serious accidents and protecting equipment and maintenance personnel. The purpose of this paper is to experimentally demonstrate whether this type of arrester can prevent cracking and rupture of the enclosure caused by internal arcing effects, thus preventing sudden breakage and dispersal of components outside a controlled area. The arresters were able to extinguish open flames in less than 2 minutes after the test was completed. The paper is important to both arrester designers and end users because it provides an analysis of their short circuit behavior and related phenomena that cannot be adequately simulated.

KEYWORDS: Surge Arrester, Short-Circuit Current, Transmission Line, Metal Oxide.

1. Introduction

Surge arresters are electrical devices designed to protect against electrical surges, which can be classified according to their source: atmospheric surges. Surges of atmospheric origin can be divided into three categories: surges due to direct lightning strikes, surges due to static loads and surges due to indirect lightning strikes; the amplitude of these surges does not depend on the operating voltage.

Switching surges are due to changes in the network configuration and are most often caused by: open circuit of a line, open circuit of a transformer, resonance phenomena, interruption of a short circuit, arcing to ground.

The frequency of these voltages depends on the inductance and capacitance of the circuit and is generally much higher than the operating frequency of the network. The amplitude of these surges will be reduced if the neutral of the system or transformer is grounded.

The article presents experiments that demonstrate the ability of arresters to withstand high currents for several milliseconds, allowing this type of arrester to protect installations against both atmospheric surges and switching voltages.

Electrical surge arresters are designed to limit atmospheric and switching surges in an electrical installation, protecting equipment in electrical substations such as transformers, circuit breakers, disconnectors, current transformers and voltage transformers. They are connected in parallel with the equipment to be protected and are installed at the entrance to the substation, between phase and earth, and at points where the line changes its characteristic impedance. Their purpose is to safely dissipate surge energy to ground and ensure that the voltage at the terminals remains low enough to protect equipment insulation from the effects of surges.

Most surge arresters used in modern high-voltage systems are of the metal oxide (MO) varistor type.

Surge arresters are designed to keep the voltage below the withstand voltage (the highest voltage that can be applied to equipment without damaging it) and provide an adequate safety margin. However, they cannot limit transient overvoltages (TOV) of frequency or oscillating power. Therefore, they must be designed to withstand these transient overvoltages as well as the maximum system operating voltage without damage.

The surge arrester is one of the most effective devices for limiting lightning surges in transmission line insulator strings and in the tower head air gap [1]-[4]. In the design process of surge arresters, the performance against short-circuit current is an essential technical parameter [5]-[9].

The selection of the rated and low short-circuit current is very important for the arrester design [10]-[12].

If the arrester fails to interrupt the arc at the surge limit or is subjected to an unacceptable operating load during operation, the arc will cause severe vaporization and may burn the silicone rubber coating and internal materials [13]. At this point, the pressure relief valve should be able to act quickly to relieve the high pressure gas from the arc flash, prevent serious explosion accidents caused by the continuous increase in surge arrester internal pressure, and ensure the safety of nearby equipment and patrol personnel.

In recent years, numerous research studies have focused on the placement of surge arresters on power transmission lines. Various methods have been used to evaluate the performance of surge arrester spacers [14]-[18] and to analyze the use of different numbers of arresters per tower [19].

2. Constructive Features

If the arrester fails to interrupt the arc due to overvoltage, or if it encounters fault conditions, the arc can cause severe vaporization, burning the polymer rubber, breaking the porcelain, and igniting the internal materials [20].

When an arc occurs, the arrester quickly releases the high pressure generated by combustion, helping to prevent major accidents and ensure the safety of equipment and personnel.

Figure 1 shows the wiring diagram of a typical arrester.

The magnetic blowout arrester used in the experiments consists of a number of reignition spark gap E_{as} connected in series with a sub-assembly consisting of the L blowout coil and the non-linear resistor R_1 and the main non-linear resistor R_2. Each module is shunted by a non-linear resistor R_3, which ensures uniform voltage distribution across the modules. If there is no overvoltage, a current of the order of milliamperes flows through resistor R_3. When an overvoltage occurs, it primes the E_{as} spark gaps to the priming voltage.

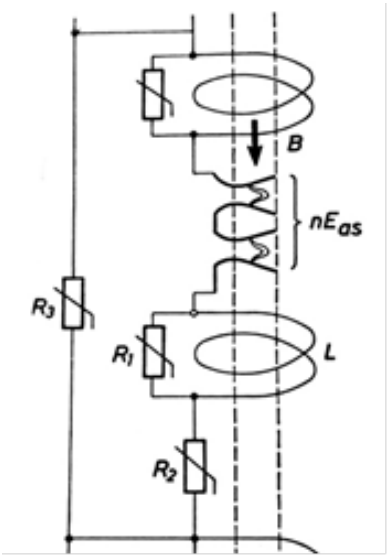

Figure 1: Wiring diagram for surge arresters

The discharge current flows through the shunt resistor R_1 of coil B. No high value current can pass through it because its impedance to the high frequency harmonics of the discharge current is virtually infinite. This current also flows through the main non-linear resistor R_2. The highest voltage at the arrester terminals after priming is the residual voltage. After the discharge electrical loads have been discharged to earth, the spark gaps retain their ionization and the associated current passes through the arrester, limited by the R_2 resistors to a few hundred amps. The accompanying current, which is at a low frequency of 50 Hz, passes through the magnetic blowout coils L. These cause magnetic induction in the area of the spark gaps, resulting in Lorentz forces that push the arc into slotted blowout chutes with cold walls. The intense cooling of the arc increases its combustion/maintaining voltage and eventually extinguishes it. The accompanying current is determined by the source voltage and the impedance of the short circuit loop, which includes the arc resistance in the spark gaps and the main resistance R_2 [21].

The Type B surge arrester used in the experiments is shown in Figure 2 and Figure 3 shows a Type A porcelain-encapsulated MO surge arrester.

Figure 2 shows the general arrangement drawing of the arrester used in the experiments. In this type of arrester, there is no air gap in the MO.

The MO resistors, which form the active part, are stacked in the centre of the arrester. They were made from a mixture of zinc oxide (ZnO) and other metallic powders, which were then pressed into cylindrical discs. The diameter of each disc determines its ability to withstand surges.

The diameter of the MO is 60 mm. Its main characteristic is the voltage current non-linearity.

The endurance capacity, which is determined by the arrester rated voltage, together with the switching and lightning protection levels, determines the height of the MO resistors, which are mounted with aluminum tube spacers to ensure uniform contact pressure distribution. The MO resistance column is supported by multiple fiberglass-reinforced plastic support rods and mounting plates. Axial pressure is maintained by a spring located at the top of the arrester. The sealing device is integrated into the cemented flanges at both ends of the arrester.

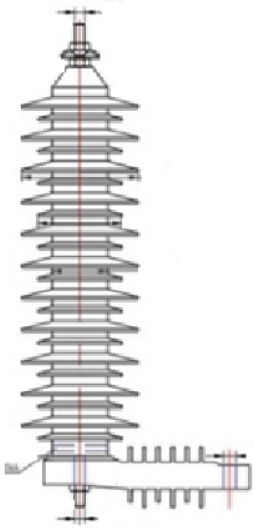

Figure 2: General drawing of the arrester used in the tests

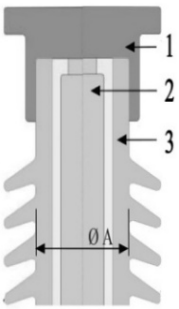

Figure 3: Drawing of the arrester used in the tests - MO detail (1 - metal cover, 2 - MO resistors, 3 - porcelain housing)

The endurance capacity, which is determined by the arrester rated voltage, together with the switching and lightning protection levels, determines the height of the MO resistors, which are mounted with aluminum tube spacers to ensure uniform contact pressure distribution. The MO resistance column is supported by multiple fiberglass-reinforced plastic support rods and mounting plates. Axial pressure is maintained by a spring located at the top of the arrester. The sealing device is integrated into the cemented flanges at both ends of the arrester.

This type of arrester is not directly grounded, but is connected in series with various monitoring devices. As shown in Figure 2, the bottom flange of the arrester is mounted with insulating feet and the ground connection is made via a special grounding device. This component of the arrester was eliminated during the short-circuit test.

When a transmission line conductor is subjected to a short-circuit ground fault, the inductance L of the ground wire can be determined according to [1]. The distance Ds and the equivalent radius r_m can be calculated according to references [1] and [3].

$$L = \frac{\mu_0}{2\pi}\left[ln\frac{1.8514}{D_s\sqrt{2\pi f\mu_0\sigma}} + \frac{4h\sqrt{\pi f\mu_0\sigma}}{3}\right] \quad (1)$$

$$D_s = \sqrt[n]{1.414213 r_m d_n^{n-1}} \quad (2)$$

$$r_m = e^{\frac{1}{4}}r = 0.779r \quad (3)$$

where: L - pole inductance under phase to earth fault (H/m); μ_0 - vacuum permeability (H/m); D_s - cable length; σ - earth conductivity (S/m); f- frequency (Hz); r- equivalent cable radius (m).

On the other hand, the electromotive induction force generated by the short-circuit current through an inductive connection on a line can be calculated as follows:

$$E = \sum_{i=1}^{n} \omega M_i l_i I_s st \quad (4)$$

where: E- line inductance (V); ω - apparent frequency (rad/s); M_i - mutual inductance (H/km); l_i - line distance in km; I_s - sum of the frequency components of the short-circuit current (A). Given the line voltage U_d, we can calculate the short-circuit current I_{sc} in (A):

$$I_{sc} = \frac{U_d}{\omega}\left[\frac{1}{L_d + \sum_{i=0}^{n} l_i L} + \frac{k_f \sum_{i=0}^{n} l_i}{L_d l}\right] \quad (5)$$

assuming that the structural coefficient of the line k_f is 0.25.

L_d is the inductance of the circuit (H) and l is the total length of the transmission line (km).

The next section analyzes the arrester's ability to reduce pressure in the event of a short circuit. Tests have confirmed the arrester's effectiveness in protecting nearby equipment. According to the source (5), the short-circuit current varies according to the position of the arrester. When it is close to the transformer, the short-circuit current reaches a maximum of 20 kA and decreases to 12 kA or 6 kA as the distance increases. After a certain distance, the variations become insignificant and the current value stabilizes in the range of 600 ± 200 A.

3. Short Circuit Tests

Experiments were conducted on identical specimens, as shown in Figure 2, to determine whether an arrester malfunction could cause a violent burst of the enclosure and whether the flames generated could be extinguished in a controlled manner within a predetermined time interval. The arrester was not equipped with additional

devices to replace conventional overpressure mechanisms.

According to [19], the arrester is classified as type "B", made of polymeric material, with a solid construction and without a closed gas volume. When MO (metal oxide) resistors fail electrically, an internal arc is formed, resulting in accelerated vaporization and eventual ignition of the case and materials inside.

The purpose of this paper is to experimentally demonstrate whether this type of arrester can control the cracking and rupture process of the enclosure caused by internal arcing effects, thus preventing violent rupture and dispersion of components beyond a welldefined area.

The circuit used for the experiments, shown in Figure 4, was designed according to the applicable standards [19], taking into account the most unfavorable installation conditions of arresters in electrical substations.

Type A arresters have a volume of air greater than 50% along the active side and are prepared for short-circuit testing with a fusible wire connected between their ends.

Type B arresters, which have less than 50% air volume around the active part, are prepared for short-circuit testing by a pre-fault process. This process consists of applying a voltage characteristic of each type of arrester. The purpose of pre-fault is to provide sufficient electrical conductivity to allow the short-circuit current to pass at a voltage below the rated voltage [22].

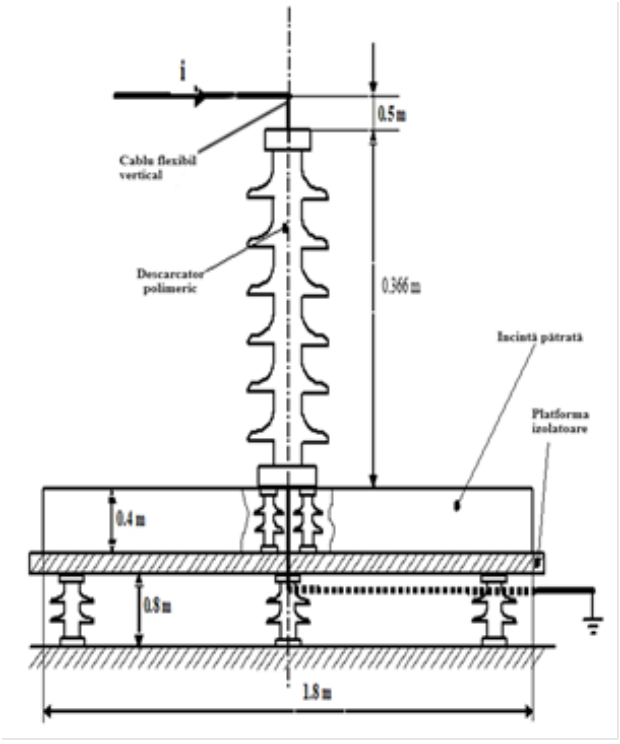

Figure 4: Circuit used for short-circuit testing

In the first stage, the arresters 36 kV, 10 kA were subjected to an electrical pre-fault process by applying an industrial-frequency surge voltage without any special preparation.

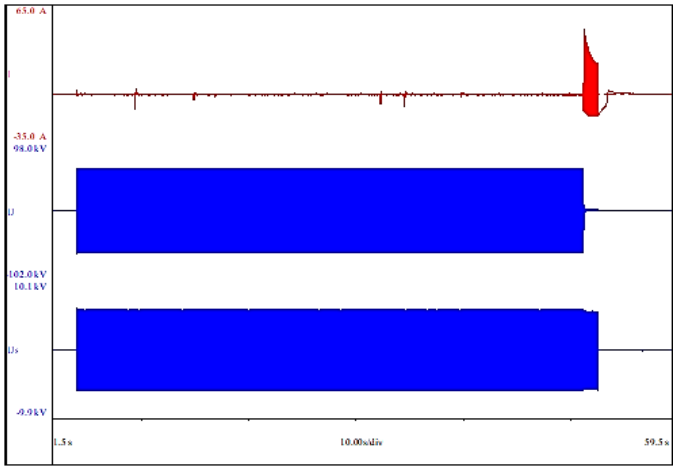

Figure 5: Pre-fault oscillographic recording

Figure 5 shows the oscilloscope reading for the first arrester, the others are similar. The circuit was previously calibrated to 18 $A_{R.M.S}$ and 43 $kV_{R.M.S.}$.

For example, the voltage applied until the arrester pre-failed was 43 $kV_{R.M.S}$ for 47.27 seconds, after which a current of 18.65 A $_{R.M.S.}$ occurred and was maintained for 1.41 seconds [22].

For the short-circuit tests, the arrester was mounted as shown in Figure 4, with the lower end of the arrester flush with a 1.8 m wide square enclosure. The base used for the experiment was made of insulating material and placed on an insulating platform.

In the first test, conducted at rated short-circuit current, the applied voltage was less than 77% of the arrester's rated voltage. To meet the test conditions, the circuit parameters were adjusted so that the RMS value of the symmetrical current component was at least equal to the required current level. This resulted in the oscillographic recording shown in Figure 6.

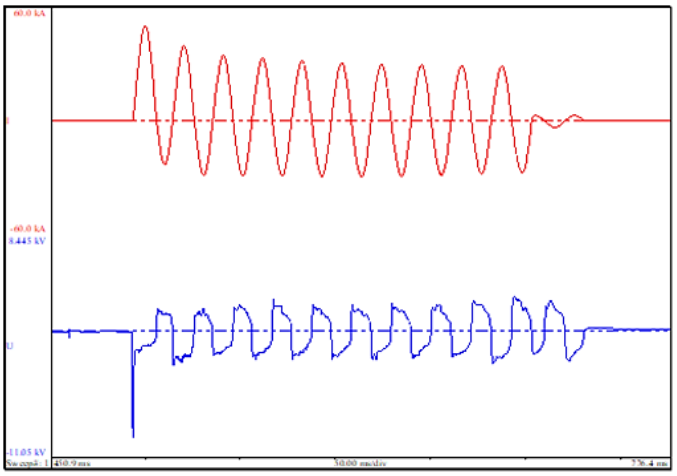

Figure 6: Oscillographic recording of the rated short-circuit current test

Parameters obtained: applied voltage U=22.1 $kV_{R.M.S.}$; peak current I_{peak}=50.2 kA; short-circuit current

I_{sc}= 20.9 $kA_{R.M.S}$; voltage drop U_{drop}=1.78 $kV_{R.M.S}$ and arc duration t=0.21 s.

It is observed that the peak value of the current in the first half-cycle exceeds $\sqrt{2}I_{R.M.S.}$, these values being difficult to obtain under normal conditions for polymer type B arresters. In order to achieve these values in a high power laboratory, a short-circuit generator with a capacity of 2500 MVA was used, together with precise excitation control.

To maintain optimal test conditions, the test was performed less than 15 minutes after the pre-fault process to prevent the arrester from cooling.

The experiment was considered successful otherwise it should have been repeated, ensuring a sufficiently low arrester impedance by applying a pre-fault current no more than 2 seconds before applying the short-circuit current. As part of the pre-fault process, it is permissible to increase the short-circuit current up to 300 $A_{R.M.S}$. In this case, the maximum duration, depending on the magnitude of the current, must not exceed the following value:

$$t_{rpf} \leq \frac{Q_{rpf}}{I_{rpf}} \quad (6)$$

In (6), t_{rpf} is the pre-fault time in seconds; Q_{rpf} is the pre-fault load = 60As; I_{rpf} is the pre-fault current in amps.

Further tests were conducted at reduced currents, applying a voltage of less than 77% of the arrester's rated voltage. The circuit parameters have been set so that the RMS value of the symmetrical current component is at least equal to the required current level.

According to [19], for arresters with a rated current of 10 $kA_{R.M.S}$ and a rated short-circuit current of 20 $kA_{R.M.S}$, the discharge current is 20, 10 or 5 $kA_{R.M.S}$ and the reduced short-circuit currents have the following values: 12000±10%, 6000±10% and 600±200 $A_{R.M.S}$.

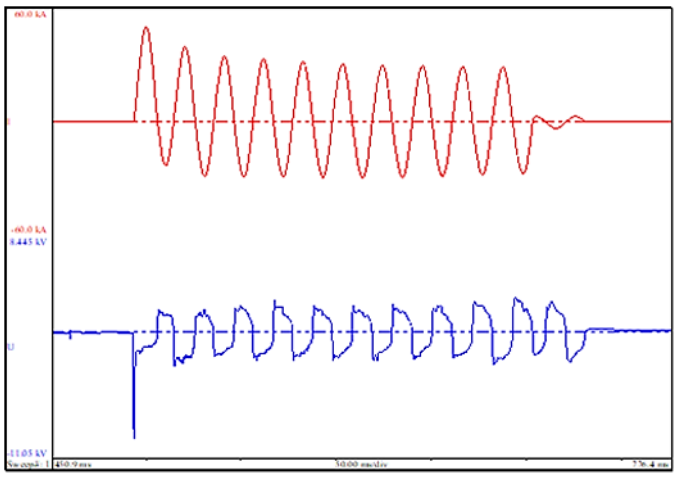

Figure 7: Oscillographic recording of reduced short-circuit current test

Parameters obtained on another arrester, previously pre-faulted, under the same conditions, on the oscilloscope recording in Figure 7 for an assumed current of 12000 $A_{R.M.S}$: applied voltage U=19.8 $kV_{R.M.S}$; peak current I_{peak} = 26.7 kA; short-circuit current I_{sc} =12.4 $kA_{R.M.S}$; voltage drop U_{drop}=1.83 $kV_{R.M.S}$ and arc duration t=0.22 s.

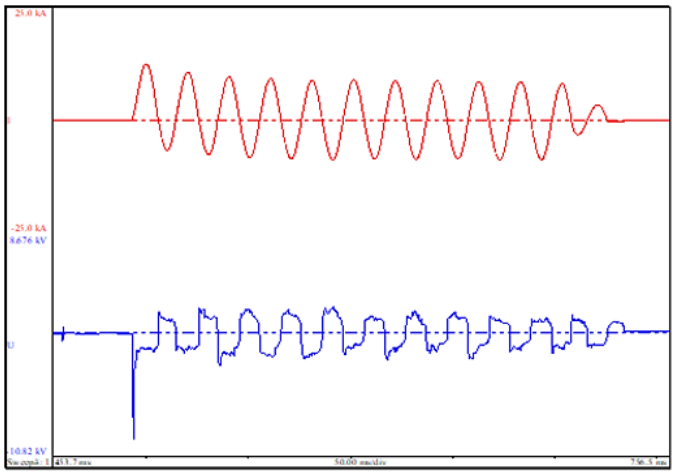

Figure 8: Oscillographic recording of reduced short-circuit current test

Parameters obtained on another arrester, previously pre-faulted, under the same conditions, on the oscilloscope recording in Figure 8 for an assumed current of 6000 $A_{R.M.S}$: applied voltage U=22.8 $kV_{R.M.S}$; peak current I_{peak}=12.5 kA; short-circuit current I_{sc}= 6.1 $kA_{R.M.S}$; voltage drop U_{drop}=1.48 $kV_{R.M.S}$ and arc duration t=0.22 s.

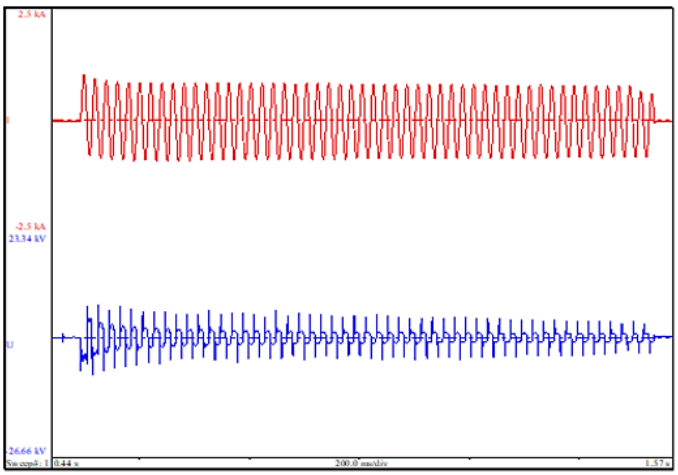

Figure 9: Oscillographic recording of the low short-circuit current test

Parameters obtained on another arrester, previously pre-faulted, under the same conditions, on the oscilloscope recording in Figure 9 for an assumed current of 600 $A_{R.M.S}$: applied voltage U=20.5 $kV_{R.M.S}$; peak current I_{peak}=1.02 kA.; short-circuit current I_{sc}= 0.59 $kA_{R.M.S}$, 0.1 seconds after a short-circuit has occurred; voltage drop U_{drop}=1.48 $kV_{R.M.S}$, and arc duration t=1.04 s.

In all the tests carried out, the arresters were installed and the conductors laid under the most unfavorable operating conditions. Figure 10 show photos taken before and after tests.

The earth conductor has been oriented in the opposite direction to the incoming conductor (Figure 10), so the arc will remain close to the arrester for the duration of the short-circuit current, creating the most unfavorable conditions in terms of fire risk.

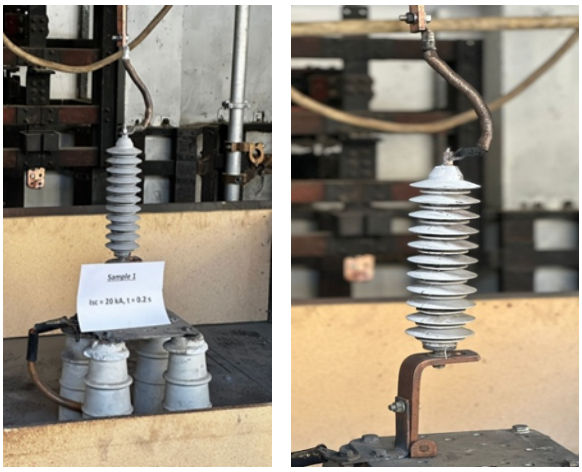

Figure 10: Photos taken before and after tests

The research continued on a 36 kV, 20 kA to establish the traceability of the experiments. The experiments were performed in the same conditions as previous, according to [19], presented in Figure 4.

The surge arrester was pre-failed in the same conditions as the previous one. The experiments were made at 24 kV applied voltage, measured between phases. Experiments performed: rated Short-Circuit current 20 kA, reduced short-circuit current 12 kA, reduced short-circuit current 6 kA and short-circuit low current 600 A.

After circuit calibration, the Rated current short-circuit test on first sample was performed with structural failure on upper part, all parts remained inside the enclosure.

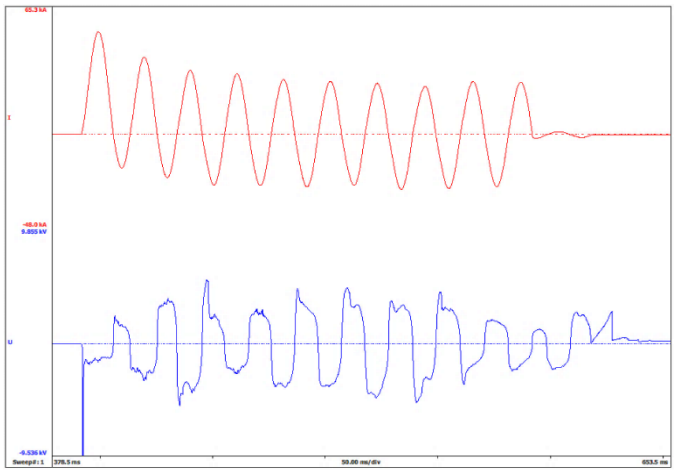

Figure 11: Oscillographic recording of the rated short-circuit current test

Parameters obtained in the oscilographic recording presented in Figure 11 are: applied voltage U= 24.1 $kV_{R.M.S}$; peak current I_{peak}= 52.1 kA; short-circuit current I_{sc}= 20.9 kA_{RMS}; voltage drop U_{drop}=2.83 $kV_{R.M.S}$, and arc duration t= 0.2 sec.

Next experiment is reduced current short-circuit test on different sample, where structural failure on upper and lower part, all parts remained inside the enclosure.

Parameters obtained in the oscilographic recording presented in Figure 12 are: applied voltage U= 24.1 $kV_{R.M.S}$; peak current I_{peak}= 26.1 kA.; short-circuit current I_{sc}= 12.1 $kA_{R.M.S}$; voltage drop U_{drop}= 3.42 $kV_{R.M.S}$, and arc duration t= 0.2 sec.

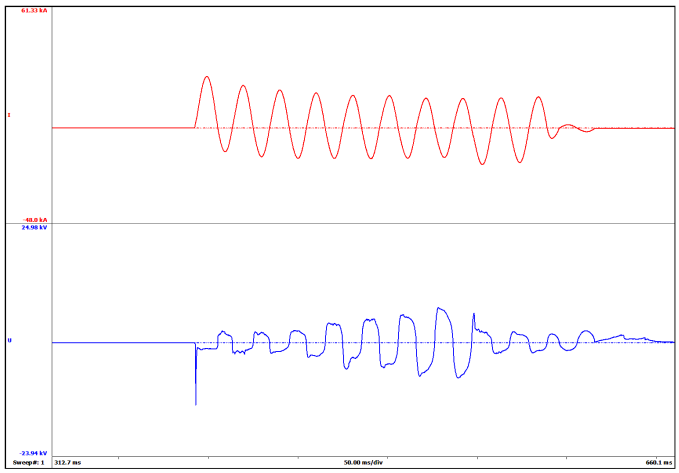

Figure 12: Oscillographic recording of reduced short-circuit current test

Next experiment is reduced current short-circuit test on different sample, where structural failure on upper and lower part, all parts remained inside the enclosure.

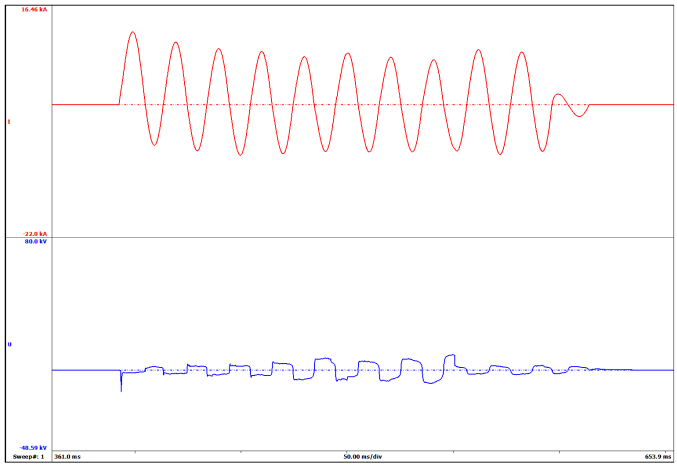

Figure 13: Oscillographic recording of reduced short-circuit current test

Parameters obtained in the oscilographic recording presented in Figure 13 are: applied voltage U= 24,2 $kV_{R.M.S}$; peak current I_{peak}= 12.1 $kA_{R.M.S}$; short-circuit current I_{sc}= 6.1 $kA_{R.M.S}$; voltage drop U_{drop}= 4.1 $kV_{R.M.S}$, and arc duration t= 0.2 sec.

Next experiment is low current short-circuit test new sample. The open flames resulted after test self-extinguish in less than 1 minute.

Parameters obtained in the oscilographic recording presented in Figure 14 are: applied voltage U= 24.1 $kV_{R.M.S}$; peak current I_{peak}= 1.3 kA.; short-circuit current I_{sc}= 0.6 $kA_{R.M.S}$; voltage drop U_{drop}= 0.9 $kV_{R.M.S}$, and arc duration t= 1 sec.

Considering the results obtained we can conclude that this value of short-circuit current is the maximum value that can be applied on this type of construction. Even tho according to [21], the results are considered fulfilled, we consider the parts that detached might endanger the personal.

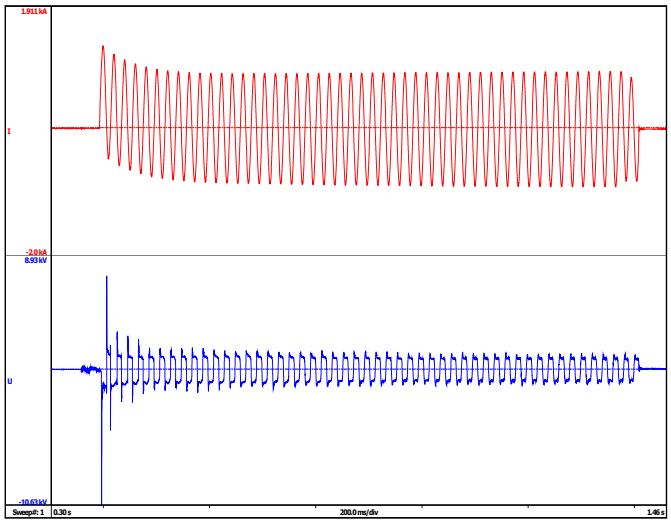

Figure 14: Oscillographic recording of the low short-circuit current test

Photos from the experiments are presented in figures 15 to 17.

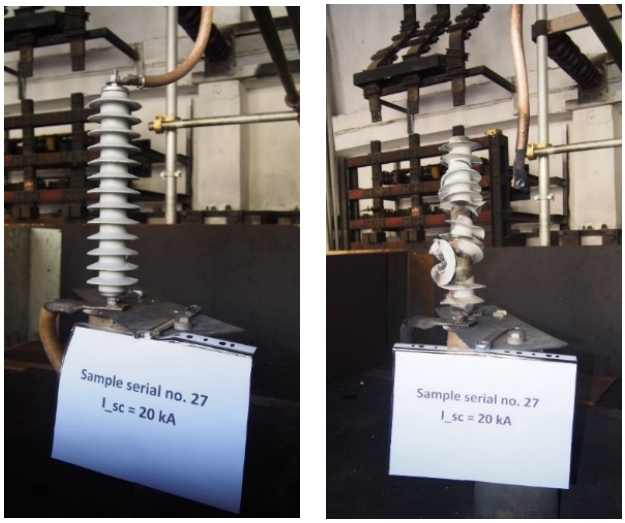

Figure 15: Aspect of the surge arrester before and after short-circuit test at 20 kA

Figure 16: Aspect of the surge arrester before and after short-circuit test at 12 kA

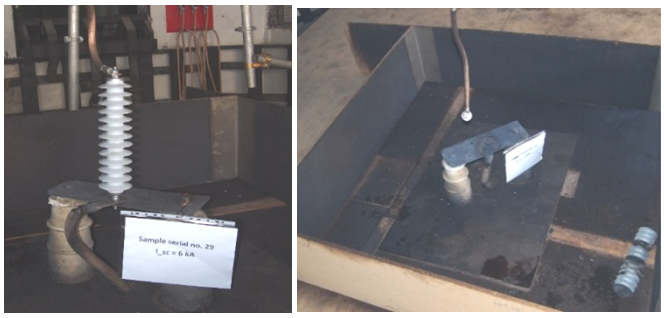

Figure 17: Aspect of the surge arrester before and after short-circuit test at 25 kA

4. Discussions and Conclusions

The electricity transmission system is essential to ensure a continuous and stable flow of electricity to consumers. However, extreme weather conditions, voltage fluctuations, or equipment failures can affect the safety and reliability of this system. One of the most effective technical solutions for protecting electrical infrastructure and preventing major disturbances is surge arresters, which can make a significant contribution to improving the reliability of electrical grids. In this context, it is important to understand their role and impact on the protection of the transmission system.

Surge arresters are devices designed to protect electrical equipment from surges that can occur for a variety of reasons, such as lightning strikes, switching equipment maneuvers, or network faults. They are installed in power grids, both in substations and at various points in distribution networks. Surge arresters work by absorbing and dissipating the extra energy generated by a surge, protecting transformers, cables and other equipment from serious damage.

Lightning is a major cause of power surges in electrical grids. These can cause sensitive equipment such as transformers and circuit breakers to fail quickly. Surge arresters are essential to protect these components from the damaging effects of lightning by quickly absorbing and dissipating the excess energy generated during a lightning strike. This prevents serious malfunctions that could lead to major power losses and prolonged power outages.

Surges can be caused not only by natural phenomena, but also by equipment switching maneuvers or network faults. In these situations, surge arresters provide immediate protection and limit the negative impact on equipment. By intervening quickly when voltage exceeds safe limits, these devices help ensure continuous system operation without costly interruptions or failures.

Another significant benefit of using surge arresters is the extended life of electrical equipment. Frequent and irregular power surges can accelerate component wear and lead to premature component failure. By protecting equipment from these voltages, surge arresters reduce the

frequency of maintenance and parts replacement, helping to optimize power system operating costs and minimize downtime.

A reliable power transmission system must be able to respond quickly to voltage fluctuations and prevent them from spreading throughout the network. Surge arresters play a critical role in maintaining the stability of power systems by ensuring that local surges do not propagate and cause cascading failures. This helps reduce the risk of long-term power outages and protects the integrity of the entire transmission system.

Surge arresters are essential tools for improving the reliability of the power transmission system. By protecting electrical networks and equipment from dangerous surges, these devices help prevent failures, extend equipment life and maintain the stability of electrical networks. The effective integration of surge arresters into the power infrastructure is therefore an important step towards a safer, more reliable and more resilient power transmission system.

Installing surge arresters increases the reliability of the power transmission system, but requires additional capital investment. To determine the most efficient and cost-effective arrangement of surge arresters in a protected transmission line, it is suggested that the arresters be placed according to the resistance characteristic of the transmission line tower foot, so that the entire transmission line can be divided into several line sections. Each line section consists of towers of similar resistance. As proposed in [22], two different concepts are considered for lightning protection:

(a) Install a different number of surge arresters on selected phases of each tower;

(b) Install arresters on all selected tower phases.

By varying the number of towers to be equipped or the number of phases to be equipped with surge arresters, the threshold voltage is used to evaluate different surge arrester installation configurations.

As mentioned in [20], towers are more likely to be built on ridges to facilitate construction. Therefore, it is not very effective to reduce the tower ground impedance at the top of the ridge, where the tower foot impedance is generally highest. Thus, it is very likely that the ground resistances of towers on a ridge will be different from the resistances at the base of adjacent towers. The resistance of the base has a significant effect, both positive and negative, on the insulator voltage in different situations. For towers with high resistance at the base, it is recommended to install surge arresters with better energy dissipation capacity. In addition, if the resistance at the base of the towers varies, the negative effect of the base resistance on lightning performance cannot be neglected.

Therefore, if the towers have different resistances at the base near the boundaries of each protected section, it is recommended that surge arresters be installed on each tower to prevent damage. Within each line section, different arrester configurations are used to improve performance. One configuration model is to install a varying number of arresters on selected phases of all towers. For this type of design, simulation results show that the insulators on the upper phase are most susceptible to flashover. Therefore, it is recommended that arresters be installed on the upper phases. The effect of the number of arresters per tower is studied in the literature using three different configurations. A proper and more efficient arrester configuration can be determined using the voltage diagram and voltage threshold as a function of base resistance.

The main difference between the surge behavior of high-voltage and medium-voltage MO arresters is the energy absorbed during the discharge period when subjected to different types of surges. High-voltage MO arresters are particularly stressed by switching surges, which cause a large portion of the electrical load to pass through the arrester during the entire surge period. On the other hand, medium-voltage arresters are mostly stressed by direct lightning strikes in the vicinity of the protected object. For high-voltage MO surge arresters, there are standard methods for determining the energy absorption capacity based on estimating the line discharge energy.

The energy absorbed by the medium-voltage arrester due to lightning discharges can be estimated by analytical methods.

Experimental energy absorption capacities of arresters for AC and impulse currents are presented in [22]. The product "Ixt" was found to be constant, where I is the current and „t" is the pulse duration. Due to the increase in residual voltage as the applied current increases, the energy absorption capacity also increases, almost tripling when large pulses of lightning impulse are applied instead of small, long duration currents.

Tests show favourable behaviour after the occurrence of a short-circuit current. The performance achieved was largely determined by the non-linearity of the resistors and the accuracy of spark gap ignition and quenching. Since the resistances are non-linear, the conduction of electric charges to earth in the form of impulse current is faster, and in the final stage of electric charge transport, the resistance reaches high values that favour the extinction of the electric arc.

During the tests, there was no violent breakage, and no part of the arrester, such as pieces of polymer materials or MO resistors, was found outside the test enclosure. Electrical arresters were able to extinguish naked flames within 2 minutes of the end of each test

Conflict of Interest

The authors declare no conflict of interest.

Acknowledgment

This research was funded by the Ministry of Research, Innovation and Digitization of Romania as part of the NUCLEU Program: PN 23 33 02 01.

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CRISTIAN - EUGENIU SĂLCEANU obtained his Bachelor's degree in Electrical and Mechanical Engineering from the University of Craiova, Faculty of Engineering in Electro-Mechanics, Environment and Industrial Informatics, in 2004**.** He completed his Master's degree in Quality Management and Environmental Engineering at the same faculty in 2006, and earned his PhD in Electrical Engineering from the Doctoral School of the University of Craiova in 2025. His doctoral research focused on the design, construction, and testing of 24 and/or 36 kV, 25 kA silver-free fuse-links. Ph.D. Sălceanu has more than 19 years of experience in scientific research and testing at the National Institute for Research-Development and Testing in Electrical Engineering (ICMET Craiova)**,** where he currently serves as Head of the High Power R&D Laboratory and Test Responsible. He has contributed to numerous scientific publications, research projects, and patents in the field of electrical engineering, with his work being recognized through several awards for excellence and innovation.

DANIELA IOVAN received her Bachelor's degree in Electrical Engineering from the University of Craiova, Faculty of Electrical Engineering, Romania, in 2007, and her Master's degree in Advanced Electrical Engineering from the same university in 2009. She is currently a Scientific Researcher (3rd Degree) at the Research, Development and Testing National Institute for Electrical Engineering – ICMET Craiova. Her research interests include energy efficiency, power quality, renewable energy integration, and electrical system performance analysis. She has co-authored several technical and scientific papers and participated in numerous national and international research projects.

DANIEL-CONSTANTIN OCOLEANU received his Bachelor's and Master's degrees in Electrical Engineering from the University of Craiova, Romania, in 2007 and 2009, respectively. He is currently pursuing his Ph.D. at the same university. Since 2009, he has been with the National Institute for Research-Development and Testing in Electrical Engineering (ICMET Craiova), where he serves as Head of the PRAM – Maintenance Collective and Scientific Researcher. His research focuses on power systems testing, short-circuit current generation and measurement, and improving the reliability of high-power electrical installations.

Received: 30 October 2025, Revised: 21 December 2025, Accepted: 23 December 2025, Online: 12 January 2026

DOI: https://doi.org/10.55708/js0501001

Predicting University Success in Mongolia: The Roles of Admission Tests and Prior Academic Achievement

Ankhbayar Jargalsaikhan [1,2], **Amarzaya Amartuvshin** [*3]

[1]Department of Education study, National University of Mongolia, 14200, Mongolia
[2]Department of Physics and Mathematics Mongolian University of Life Sciences, Ulaanbaatar, 17029, Mongolia
[3]Department of Mathematics, National University of Mongolia, Ulaanbaatar, 14200, Mongolia
Email(s): ankhbayar@muls.edu.mn (A. Jargalsaikhan), amarzaya@smcs.num.edu.mn (A. Amartuvshin)
*Corresponding author: Amarzaya Amartuvshin, Department of Mathematics, National University of Mongolia, 14200, Mongolia, amarzaya@smcs.num.edu.mn

ABSTRACT: This research investigated the factors predicting academic success in Mongolian universities, focusing on university admission test scores and prior academic achievement (high school grade point average). Using data from 21,186 undergraduate students who graduated from major Mongolian universities between 2014 and 2024, the study examined how these factors relate to undergraduate grade point average. Results indicate that admission test scores show a statistically significant, albeit weak, association with undergraduate performance, whereas high school certificate scores demonstrate a stronger predictive effect. A model that includes high school certificate score, admission test score, and third-year grade point average demonstrates the strongest predictive power for final undergraduate grade point average. These findings suggest the need to re-evaluate admission criteria, placing greater emphasis on high school academic performance and reassessing the predictive validity of the national university admission examination. The results highlight the importance of strengthening pre-university education and creating supportive learning environments to enhance students' academic success.

KEYWORDS: Academic preparedness, Academic performance, Predictive validity

1. Introduction

Developing countries, including Mongolia, require a highly qualified workforce, making the quality of higher education crucial for national development. The basis for gaining good quality education at the undergraduate stage depends on the quality of high school level. Knowledge and skills that acquired at the high school level and the earlier levels of education plays important role for the higher involvement and achievement in the undergraduate level of education. This paper is an extended version of the work originally presented at the International Symposium on Computer Science and Educational Technology, ISCSET 2024 [1]. It extended in the sense that the authors added data of students of National University of Mongolia graduated between 2022-2024 and conducted extended analysis using predictor variables.

Higher education enrollment in Mongolia has been increasing steadily since the 1990s, aligning with global trends [2]. However, despite the increasing enrollment rates, the employment rates of graduates have declined, leading to criticism over the high unemployment rate among graduates in the country. Contributing factors include low socio-economic development and limited job opportunities in the labor market. A country's socio-economic development has a significant impact on students' academic achievement. Furthermore, the quality of graduates plays a crucial role in determining the employment rate, which subsequently has a substantial role on the economic development of the country. Higher levels of education among citizens tend to contribute to greater socio-economic development [2,3].

A high school graduate or someone from a higher educational institution who has passed the General University Admission Examination (GUAE) is eligible to apply to Mongolian higher education institutions (HEIs). The GUAE includes a mandatory Mongolian language exam and additional subject-specific tests, selected by the student based on the requirements of the intended university major. In this research, the authors considered GUAE scores and high school grade point average (HGPA) as quantitative measures of student academic preparedness, while the undergraduate grade point average (UGPA) reflected academic performance or achievement at the university level.

The overarching goal of the research is to examine the relationship between the academic achievements of undergraduate students in Mongolian HEIs and their prior educational performance. Specifically, it focused to analyze the relation between students' undergraduate grade point averages (GPA) with their scores on the general university admission examinations, high school graduation certificate scores and other possible scores. To achieve this objective, the authors conducted correlation and regression analyses to explore the relationships among these variables across different student groups. It examined the relationships between undergraduate GPA, entrance examination scores, high school achievement scores, and first-year GPA. Additionally, the study aimed to develop a simple predictive model to estimate students' undergraduate GPA based on these factors.

The specific research objectives of the paper are:

- To assess the correlation between undergraduate GPA and entrance exam scores, high school certificate scores, and GPAs during the periods of undergraduate study.
- To develop a model that accurately predicts undergraduate GPA using the aforementioned variables.

The authors used data from undergraduate students at the National University of Mongolia (NUM), Mongolian University of Life Sciences (MULS), University of Finance and Economics (UFE), and Mongolian State University of Education (MSUE), who graduated between 2014 and 2024. A total of 21,186 students participated in this study. The University of Finance and Economics is a leading private university in the country, while the remaining institutions are public universities.

2. Review of Literature

Defining academic performance or achievement at any level of education and accurately measuring it remain challenging issues that continue to be central focus areas for educational researchers. According to [4], academic achievement is defined as the performance outcomes in intellectual areas studied at educational institutions such as universities. It is a fundamental indicator of intellectual development and is regarded as a critical determinant of individual and societal progress.

Several researchers primarily conceptualize academic achievement as a student's ability to complete specific academic tasks [5,6]. It is commonly evaluated through Grade Point Average (GPA) or other officially documented academic records [7,8]. In this research we use UGPA as a main estimate of academic performance of undergraduate students.

In some cases, scholars have also attempted to assess academic achievement using non-academic outcomes [9]. While both approaches encompass essential dimensions of academic success, they are not entirely interchangeable [6].

Academic preparedness is a pivotal factor in students' academic success. In the context of Australian universities, authors in [10] demonstrated that students with low academic preparedness face greater difficulties in their studies.

Another critical aspect of academic preparedness that directly influences students' academic achievement is their high school internal assessment scores. In [11], it analyzed data from first-year students in New Zealand and concluded that, for social science and humanities subjects, school-based assessments are better predictors of academic achievement at the university level. Conversely, external assessment or entrance examination scores more effectively forecast university performance in disciplines of natural sciences. Similarly, in [12], the authors studied the relationship between secondary education outcomes and academic achievement for educational science students case in Finland. It has shown that, the overall entrance examination results explained 15% of the variance in study success of Finnish Educational Science students.

A study in [13], it also showed the importance of high school-based grades of major subjects for their future study at the university. They used a sample of 113 students graduated from international Baccalaureate (IB) high school and 314 ordinary high school leavers of Holland, determined a predictive validity of grades of high school major subjects for university academic achievements [13]. They targeted to predict academic performance of these students in the first and fourth years of study at the university based on the results of three major subject's assessment results in the last year of the high school using the t-test and multiple correlation analysis. As a result, the GPAs of the first and fourth year of undergraduate study of the students was more relevant to the mean of the scores of three main subjects with highest value, than to the student's high school GPAs. Besides, for alumni who graduated from the IB, the GPA of the beginning year of the undergraduate study and the GPA of the high school had the highest influence on the GPA at the undergraduate graduation.

Using regression analysis in 1998, in [14] it identified a positive but weak correlation between undergraduate students' SAT scores and their academic rankings within the classroom. Similarly, in [15], authors investigated the potential of predicting undergraduate academic success through SAT scores, finding a weak correlation between admission test scores and academic performance in both studies. Notably, the latter study employed multidimensional correlation analysis.

The assessment of entrance examination scores' predictive validity for academic achievement extends beyond the undergraduate level. Numerous studies focus on determining whether scores from globally recognized exams, such as the GRE, can forecast students' academic success at the graduate level.

A meta-analysis in [16], utilized a sample of 1,753 academic records from 85,000 graduate students to explore whether academic achievements are influenced by GRE scores and UGPA scores. As a result, they concluded that these scores are valid predictors of graduate GPA. Further research in [17], as well as in [18], authors examined the relationship between GRE scores and academic performance among master's and doctoral students across various departments. All these studies consistently revealed a weak correlation between GRE scores and graduate academic success.

3. Research Methods and Research Results

3.1 Research methods

The research analyzed data collected from graduates of NUM, MULS, UFE, and MSUE, covering the period from 2018 to 2024. The dataset included academic records of 12,030 students from NUM, 3,015 students from five different schools and faculties within MULS, 853 students from UFE, and 5,288 students from MSUE, making a total of 21,186 undergraduate graduates. During the study, the relationships between known and unknown variables were systematically examined, the form of their correlations was identified, and the expected values of the dependent variables were estimated.

The researchers employed the GUAE score, the average high school certificate score, the first-year GPA (FYGPA) of students, and a moderator variable as predictor variables, with the undergraduate GPA (UGPA) of graduates serving as the dependent variable. During the analysis of the relationships, the scope of the outcome variables was adapted in various ways depending on the specific context. Regression analyses were performed individually for each case, field of study, and university. Data processing was conducted using SPSS version 29 and Microsoft Excel 2019.

Moderating effects are commonly conceptualized as interaction effects, where a moderator variable alters the strength or direction of the relationship between an independent variable and a dependent variable. This interaction may strengthen, weaken, or even reverse the relationship. In regression analysis, moderating effects are typically assessed by incorporating an interaction term—defined as the product of the independent variable and the moderator variable—into the regression model. A statistically significant interaction term indicates the presence of a moderating effect.

Our moderator variable, denoted as 't' in the models, is a composite three-way interaction term. It was constructed by multiplying the standardized z-scores of these three predictor variables (GUAE, HGPA, and FYGPA).

The inclusion of this specific interaction term as a moderator was driven by the theoretical premise that the combined influence of these foundational academic indicators (pre-university preparedness and early university performance) might not be simply additive, but rather interactive. We hypothesized that the predictive utility of one factor (e.g., GUAE scores) for overall university success might depend on the levels of other factors (HGPA and FYGPA). For instance, a student with a lower GUAE score might compensate through strong HGPA and FYGPA, or conversely, the benefits of a high GUAE score might be amplified or diminished depending on subsequent academic performance. This complex interplay aims to capture a more nuanced and holistic understanding of academic success predictors than individual variables alone.

Preliminary analyses revealed normality assumption for UGPA and GUAE results was failed, as indicated by the Kolmogorov-Smirnov test, which produced a significance level of less than 0.001, below the accepted threshold of 0.05. To compare UGPA and GUAE scores across different universities and fields of study, the Kruskal-Wallis test was applied, revealing statistically significant differences between groups. Specifically, UGPA scores among graduates varied significantly across universities ($\chi^2 = 483.1$, $p < 0.05$), while GUAE results also showed significant variation among universities ($\chi^2 = 5380.6$, $p < 0.05$). When the authors analyzed the differences in UGPA and UGEA scores across different graduation years, the results confirmed their statistical significance, with $\chi^2 = 260.6$, $p < 0.05$ for UGPA, and $\chi^2 = 915.9$, $p < 0.05$ for GUAE. Accordingly, suitable regression models were selected to analyze these relationships, and their statistical significance was rigorously assessed. The following section summarizes the models employed in this study.

The study employed several statistical models, notably multiple regression analysis and analysis of variance (ANOVA), to examine the impact of predictor variables such as HGPA, UGEA, and additional moderating factors on UGPA across various contexts.

Student majors were categorized into six broad fields of study: Natural Sciences (NS), Social Sciences and Education (SSE), Humanities (H), Business Studies (BS), Engineering and Technology (ET), and Legal Studies (LS). This categorization was based on the order approved by the Minister of Education regarding the approval of the names of professional fields/programs. For instance, the Natural Sciences (NS) group includes majors such as Physics, Chemistry, Biology, and Mathematics. The Social

Sciences and Education (SS) group comprises disciplines like Sociology, Psychology, Economics, Teaching and Education. Humanities (H) includes fields such as History, Philosophy, and Literature. Business Studies (BS) covers subjects like Accounting, Finance, and Marketing. Engineering and Technology (ET) incorporates Computer Science, Civil Engineering, and Electrical Engineering. Lastly, Legal Studies (LS) includes Law and Criminology.

A graduate here is understood as graduates of undergraduate study. The correlation between the UGPA and GUAE results was determined, and in order to predict the UGPA of the students based on the GUAE scores the authors developed following statistical models as shown in table 1.

Table 1: Models Used in the Study

Models	Dependent variable	Independent variable	Sample
Model 1	UGPA	GUAE score	20868
Model 2	UGPA	HGPA	7229
Model 3	UGPA	HGPA and GUAE	7229
Model 4	UGPA	GPA of years of study	
Model 5	UGPA	HGPA, GPA of 3rd year of study	4825
Model 6	UGPA	GUAE, GPA of 3rd year of study	5678
Model 7	UGPA	HGPA, GUAE, GPA of 3rd year of study	4825
Model 8	UGPA	HGPA, GUAE, GPA of 1st year of study	1667

3.2 Results

We present the overall statistics of the graduates' GPA and their entrance exam scores in the table 2.

Table 2: Descriptive statistics for UGPA and GUAE

Variable	n	Aver-age	Median	mod	s.dev	Variance
UGPA	21186	3.01	3.09	3.1	0.56	0.312
GUAE	21186	612.9	620.2	800	79.74	6358.5

Variable	Skew-ness	Kurtosis	Range	min	max
UGPA	-0.658	0.513	3.16	1	4
GUAE	-0.358	0.016	564	236	800

The correlation coefficient between the GUAE score and graduates' GPA was 0.256, indicating a weak but positive relationship as shown in table 3. Additionally, a significance level with $p<0.05$ for all universities confirms statistical significance of the relationship. The R^2 value of 0.066 suggests that GUAE scores account for 6.6% of the variance in future UGPA. According to the analysis of variance, each regression model predicts graduate GPA based on GUAE scores with statistical significance, and all regression coefficients are significant.

Table 3: Correlation Between UGPA and GUAE Scores, by Academic Fields of Study

Fields	N	R	R^2	b_0 P	b_1 P
NS	5371	0.289	0.083	<0.001	<0.001
	Regression: y=1.743+0.002x				
SS	4481	0.347	0.121	<0.001	<0.001
	Regression: y=1.97+0.002x				
H	3967	0.232	0.054	<0.001	<0.001
	Regression: y=2.14+0.001x				
BS	3363	0.216	0.047	<0.001	<0.001
	Regression: y=1.946+0.002x				
LS	551	0.119	0.014	<0.001	0.005
	Regression: y=2.592+0.001x				
ET	3135	0.215	0.046	<0.001	<0.001
	Regression: y=1.304+0.002x				
Total	20868	0.256	0.066	<0.001	<0.001
	Regression: y=1.895+0.002x				

While the correlation between GUAE scores and UGPA ($r = 0.25$) was statistically significant ($p < 0.05$), likely due to the large sample size, it suggests only a weak practical relationship. This indicates that GUAE scores explain a relatively small proportion of the variance in undergraduate GPA.

The similar picture can be seen with the relationship between graduate's UGPA with HGPA. The UGPA depends on high school grade point average weakly but this relation is statistically significant.

The correlation coefficient between the HGPA score and graduates' GPA of all students is 0.378, indicating a weak but positive relationship as shown table 4. Additionally, a significance level of $p<0.05$ for all fields of studies confirms statistical significance. The R^2 value of 0.143 suggests that GUAE scores account for 14.3% of the variance in future GPA. According to the analysis of variance, each regression model predicts graduate GPA based on HGPA scores with statistical significance, and all regression coefficients are significant.

The next analysis is the correlation of UGPA with HGPA and GUAE by student's academic field of study as shown in table 5.

Table 4: Correlation Between UGPA and HGPA Scores

Fields	N	R	R^2	b_0	b_1
				P	P
NS	2830	0.422	0.178	0.557	<0.001
	Regression: y=0.067+0.032x				
SS	2543	0.336	0.113	<0.001	<0.001
	Regression: y=0.838+0.026x				
H	1413	0.315	0.099	0.001	<0.001
	Regression: y=0.638+0.027x				
BS	387	0.482	0.232	0.302	<0.001
	Regression: y=-0.318+0.037x				
ET	56	0.412	0.17	0.693	0.002
	Regression: y=-0.371+0.036x				
Total	7229	0.378	0.143	<0.001	<0.001
	Regression: y= 0.36+0.03x				

Table 5: Correlation of UGPA With HGPA and GUAE, by Academic Fields of Study

y=UGPA, x = HGPA, z = GUAE score, t = moderator						
Fields	N	R	R2	beta		
				x	z	t
NS	2830	0.491	0.241	0.393	0.256	0.092
	Regression: y = -0.633 + 0.03x + 0.002z + 0.03t					
SS	2543	0.44	0.193	0.284	0.284	0.048
	Regression: y = 0.328+0.022x+0.001z+0.012t					
H	1413	0.387	0.149	0.283	0.172	0.121
	Regression: y = 0.342 + 0.024x + 0.001z + 0.051t					
BS	387	0.502	0.252	0.411	0.147	-0.045
	Regression: y =-0.523+0.031x+0.001z-0.025t					
ET	56	0.428	0.184	0.32	-0.027	-0.166
	Regression: y = 0.507 + 0.028x + 0.001z -0.121t					
Total	7229	0.455	0.207	0.318	0.258	0.052
	Regression: y=-0.064+0.025x+0.001z+0.019t					

Correlation coefficient of UGPA with HGPA and GUAE of all students is 0.455 indicating positive but weaker relations. However, this relation is statistically significant. For students of Business study, The UGPA depends on HGPA and GUAE moderately, while for students of other subjects this relation is weak.

Based on the results presented in Tables 3-5, the authors conclude that GUAE and HGPA scores are not strong predictors of students' UGPA as shown in table 6. In search of other factors that may contribute to a more accurate model to predict UGPA in conjunction with HGPA and GUAE scores, the authors checked the correlations of UGPA with student's yearly GPAs.

Table 6: Correlation UGPA with GPA Scores of Years of Study

Years of study	N	R	R^2	ANOVA	b_0	b_1
				P	P	P
1	14659	0.528	0.279	<0.001	<0.001	<0.001
	Y=1.623+0.492x					
2	8550	0.847	0.718	<0.001	<0.001	<0.001
	Y=1.092+0.657x					
3	10185	0.852	0.726	<0.001	<0.001	<0.001
	Y=1.032+0.673x					
4	10223	0.821	0.674	<0.001	<0.001	<0.001
	Y=1.022+0.654x					

Surprisingly, the first-year GPA was the weakest predictor of graduation GPA, while the second and third-year GPAs proved to be stronger indicators. This contradicts with findings in [1], where the first-year GPA was the most significant predictor of graduation success. The expanded dataset from NUM appears to have influenced these correlations. Consequently, it is important to analyze the correlations among HGPA, GUAE scores, and the GPAs of the first and third years of study to better understand their respective influences on UGPA. This examination can provide insights into how early academic performance and entrance exam results relate to overall university success.

To identify the most effective models for predicting graduate GPA, the authors analyzed the relationship of UGPA with various combinations of HGPA, GUAE and student's first- and third-year's GPAs as shown in table 7, 8 and 9.

Table 7: Correlation of UGPA with HGPA and 3rd Year GPA, by Academic Fields of Study

x = HGPA, z = 3rd year GPA, t = moderator						
Fields	N	R	R2	beta		
				x	z	t
NS	965	0.875	0.765	0.15	0.808	0.019
	Regression: y = -0.2+0.013x+0.694z+0.009t					
SS	2487	0.833	0.693	0.089	0.803	0.045
	Regression: y = 0.558+0.007x+0.647z+0.02t					
H	1373	0.893	0.798	0.077	0.862	0.034
	Regression: y = 0.399+0.007x+0.699z+0.016t					
Total	4825	0.859	0.738	0.090	0.825	0.038
	Regression: y=0.409+0.007x+0.677z+0.017t					

Table 8: Correlation of UGPA with GUAE, 3rd Year GPA, by Academic Fields of Study

x = GUAE score, z = 3rd year GPA, t = moderator						
Fields	N	R	R2	beta		
				x	z	t
NS	965	0.872	0.761	0.135	0.800	0.007
	Regression: y = 0.484+0.001x+0.687z+0.003t					
SS	2487	0.834	0.695	0.103	0.806	0.023
	Regression: y = 0.842+0.001x+0.65z+0.009t					

H	1373	0.893	0.798	0.078	0.872	0.009
	Regression: y = 0.733+0.001x+0.707z+0.003t					
BS	853	0.887	0.787	0.209	0.793	0.033
	Regression: y =0.001+0.002x+0.652z+0.018t					
Total	5678	0.854	0.729	0.078	0.831	0.019
	Regression: y=0.775+0.001x+0.681z+0.008t					

Table 9: Correlation of UGPA with HGPA and GUAE Scores, 3rd-year GPA by Fields of Study

x = HGPA, z = GUAE score, k=3rd year GPA, t = moderator							
Fiel-ds	N	R	R2	beta			
				x	z	k	t
NS	965	0.878	0.771	0.19	0.1	0.79	-0.005
	Regression: y = -0.229+0.01x+0.001z+0.668k-0.002t						
SS	2487	0.836	0.699	0.07	0.09	0.78	-0.017
	Regression: y = 0.458+0.005x+0.001z+0.628k-0.005t						
H	1373	0.895	0.800	0.05	0.06	0.86	0.01
	Regression: y = 0.431+0.004x+0.001z+0.695k+0.004t						
Total	4825	0.861	0.741	0.06	0.08	0.81	-0.003
	Regression: y=0.39+0.005x+0.001z+0.666k-0.001t						

The p value of the ANOVA is less than 0.001 for all cases, which shows the statistical significance of this Model.

The findings indicate that a model combining a student's HGPA, GUAE scores, and 3rd-year GPA is a better predictor of UGPA than other combinations of these factors. It's important to note that all these relationships are strongly positive. This is because academic performance in a student's penultimate year (3rd-year GPA) inherently reflects a more stable and mature pattern of academic engagement and accumulated knowledge. It is temporally closer to the final graduation GPA, thereby capturing current academic aptitude and effort more accurately than earlier indicators such as admission test scores or even first-year GPA, which may reflect initial adjustment phases rather than sustained performance.

From the viewpoint of the practicality, the combination of HGPA, GUAE, and 1st-year GPA also provides a reasonably accurate prediction of student UGPA as shown in table 10.

Table 10: Correlation of UGPA with HGPA, GUAE and First Year GPA, by Academic Fields of Study

x = HGPA, z = GUAE score, k=first-year GPA, t = moderator							
Fields	N	R	R2	beta			
				x	z	k	t
NS	3555	0.858	0.737	0.006	0.197	0.739	0.018
	Regression: y=0.391+0.001x+0.001z+0.605k+0.006t						
SS	8255	0.805	0.648	0.041	0.037	0.778	-0.001
	Regression: y=0.776+0.003x+0.001z+0.657k-0.001t						
H	4887	0.759	0.577	0.075	0.051	0.728	-0.02
	Regression: y=0.35+0.007x+0.001z+0.616k-0.009t						
Total	16667	0.788	0.620	0.039	0.042	0.76	0.001
	Regression: y=0.706+0.003x+0.001z+0.642k-0.008t						

The p value of the ANOVA is less than 0.001 for all cases, which shows the statistical significance of this Model.

The results of the multiple regression analysis demonstrate a strong positive relationship between HGPA, GUAE, first-year GPA, and UGPA for students in the Natural Sciences and Social Sciences. A positive association is also observed for students in the Humanities, although to a lesser extent.

4. Conclusions and Discussions

4.1 Discussions

Although the regression models 1-8 were statistically significant, the observed R^2 values, lower than 12% (Table 3 and 4), indicate that the independent variables explain only a small fraction of the variance in UGPA. This suggests that while these models identify statistically significant relationships, their practical utility for accurately predicting individual student performance remains limited. This underscores the importance of considering the factors identified by these models in shaping student academic performance.

For other Models, the findings are particularly relevant for education policymakers, agencies within the Ministry of Education, and university admissions officers. The analysis reveals that high school certificate scores (HGPA) demonstrate a stronger influence on graduates' GPA compared to GUAE scores. Consequently, a re-evaluation of admissions criteria, with increased emphasis on HGPA, may be warranted.

Our finding that GUAE has a weak predictive validity aligns with the Finnish case in [12].

Strongest relations of graduate's UGPA with GUAE and HGPA of students from the fields Social Sciences. Which doesn't follow the findings in [11].

While Model 7, which incorporates 3rd-year GPA, demonstrated higher predictive power for graduation GPA due to its temporal proximity to the outcome, Model 8, utilizing first-year GPA alongside HGPA and GUAE scores, offers distinct practical advantages. Its strength lies in its early detection value for identifying students at potential academic risk much earlier in their university careers. By providing predictive insights after the first year, Model 8 enables timely and proactive interventions, such as targeted academic advising, tutoring, and support programs. This allows institutions to address emerging academic challenges before they escalate, thereby maximizing the window of opportunity for student support and potentially improving overall retention rates. Furthermore, the availability of first-year GPA data also enhances administrative convenience, facilitating more efficient resource allocation and informed policy decisions regarding student success initiatives. Thus, despite a potentially slightly lower raw predictive accuracy compared to Model 7, Model 8's utility in fostering a proactive and responsive educational environment makes it a highly valuable tool for practical application.

4.2 Conclusions

Based on the findings highlighting the limited predictive power of GUAE scores and the more significant influence of high school academic achievement (HGPA) on undergraduate academic performance, we propose the following recommendations aimed at enhancing student success and educational quality in Mongolia:

I. Reforming University Admissions and Assessment Policiy:

- Revise the content and structure of the GUAE to move beyond mere factual knowledge assessment towards evaluating critical thinking and problem-solving skills.
- Increase the weight placed on high school based assessments (HGPA) and incorporate other supplementary criteria (e.g., portfolios, essays, interviews) into the university admissions process.

II. Strengthening Pre-University Education:

- Promote continuous professional development programs for high school teachers to enhance teaching quality.
- Update pre-university level curricula to ensure better alignment with university needs and requirements, fostering a seamless transition for students.
- Emphasize the development of students' learning strategies and critical thinking skills at the pre-university level.
- Foster greater collaboration and communication between high schools and universities to align expectations and curricula.

III. Adopting International Best Practices:

- Conduct further studies on international best practices in university admissions and pre-university education, adapting relevant strategies to the unique Mongolian context.

While this study provides valuable insights into factors predicting academic success in Mongolian universities, it is important to acknowledge certain limitations that warrant consideration and highlight avenues for future research. Firstly, our analysis was primarily limited to academic variables such as admission test scores and prior academic achievement. We did not incorporate crucial non-academic factors like psychological variables (e.g., motivation, self-efficacy, learning strategies) or socio-economic background (e.g., family income, parental education), which are known to significantly influence student success and could offer a more comprehensive understanding. Secondly, although our study included a large and diverse student population across multiple universities and majors, the findings may still exhibit possible differences across majors and universities depending on specific institutional policies, pedagogical approaches, or disciplinary characteristics that were not disaggregated in this analysis. Future research could explore these variations in greater detail. Finally, due to the correlational nature of our research design, we are unable to infer direct causal relationships between the identified predictors and academic outcomes. Our findings indicate associations and predictive power, but they do not definitively establish that these factors cause subsequent university performance. These limitations, however, open important avenues for more nuanced and experimental future investigations.

Conflict of Interest

The authors declare no conflict of interest.

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ANKHBAYAR JARGALSAIKHAN is a senior lecturer, Department of Physics and Mathematics, School of Applied Sciences, Mongolian University of Life Science. He did his M.S at the National University of Mongolia in 2011. He is a PhD student at the National University of Mongolia. His research focuses on Mathematical Modeling and Education study.

AMARZAYA AMARTUVSHIN is a Ph.D. and Professor, Department of Mathematics, School of Arts and Sciences, National University of Mongolia. He did his PhD at the Tokyo Metropolitan University in 2003. His research focuses on Differential geometry, Surface theory, Bonnet surfaces, and Mathematics education.

Received: 17 September 2025, Revised: 21 December 2025, Accepted: 23 December 2025, Online: 13 January 2026

DOI: https://doi.org/10.55708/js0501002

CFD Analysis of Data Center Hall Cooling Performance under Normal and Failure Modes with Control Strategies and Airflow Leakages

Sushil Ashok Surwase*, Suribabu Badde, R. Balakrishnan

Engineering Design & Research Centre, L&T Construction, Larsen & Toubro Limited, Chennai, India – 600 089

Email(s): sushil.surwase@lntecc.com (S. A. Surwase), badde.babu@lntecc.com (S. Badde), rbk@lntecc.com (R. Balakrishnan)

*Corresponding author: Sushil Ashok Surwase, India, sushil.surwase@lntecc.com

ABSTRACT: Data centers have become the backbone of an increasingly digitized world, supporting the rapid growth of cloud computing, big data, IoT, 5G, and other emerging IT technologies, with rising demand and innovations in AI and ML reinforcing their significance. Data centers are energy intensive, with data processing and storage accounting for 3 to 4% of global energy consumption, which continues to grow annually. Improving their efficiency is therefore a major industrial challenge, offering substantial cost savings. The modern data center involves an intricate interaction between various mechanical, electrical and control systems. The many possible operating configurations and non-linear interdependencies make it challenging to understand and optimize energy efficiency. In the present study, computational fluid dynamics (CFD) analysis is used to assess the cooling performance of a dynamically controlled data center hall with non-raised floor configuration and hot aisle containment (HAC) strategy. The operation of air-cooling units (ACUs) is dynamically regulated in response to the data hall IT load through an integrated network of sensors and controllers. These controllers modulate ACU fan speed and chilled water flow rates to maintain the IT cabinet inlet air temperature within each ACU's zone of influence and below the specified threshold. This control strategy, informed by real-time temperature and pressure sensor data, ensures desired thermal conditions within the data hall while optimizing overall cooling power consumption. This study focuses on two modes of operation for the purpose of design analysis, i.e., normal mode (NM) and failure mode (FM). Based on CFD simulation results, the present paper highlights the effects of control strategy used for ACUs, cooling airflow leakage, recirculation of hot air on the performance of the data hall cooling design. Different simulation scenarios, which accommodate all possible combinations during NM and FM of operation i.e., with & without control and with & without leakages are evaluated to understand the significance of various design parameters, leading towards the right design. Results show that the control strategy delivers approximately 9.89% energy savings in normal mode, while leakages significantly degrade performance during failure mode.

KEYWORDS: CFD, Control strategy, Data center, Leakage

1. Introduction

The information technology (IT) sector and related technologies are changing at an exponential rate. Data centers have become a key infrastructure to support the rapid development of cloud computing, big data, internet of things (IoT), 5G, Metaverse etc. [1]; thus, data centers serve as the backbone of information in an increasingly digitized world [2]. The demand for data center services has gone up rapidly [3]. The advancements in technologies such as artificial intelligence (AI), machine learning (ML) leading to development of smart appliances, digitalization of transport, buildings and various industries simply reinforce its relevance [4]. Data centers are energy intensive buildings whose size and number have increased in response to the growing demands of a digital economy [5]. Data processing and storage represent 3 to 4% of global energy consumption, and this consumption is significantly growing year on year [6], [7], [8].

Data centers consume a lot of energy. Due to the large energy demands, data center generates a large amount of heat. Thus, cooling is a major aspect of data center design. Enhancing the efficiency of data centers is a significant challenge in the industry, as it can result in significant cost savings [9]. The modern data center involves an intricate interaction between various mechanical, electrical and control systems. The many possible operating configurations and non-linear interdependencies make it challenging to optimize energy efficiency [10].

1.1. Literature Review

The concept of hot and cold aisles was first introduced and formalized in [11], where it was demonstrated that an alternating arrangement of cold and hot aisles significantly improves data center cooling efficiency compared to earlier layouts that lacked floor planning and led to serious reliability problems. One of the earliest applications of CFD to data center cooling was presented in [12], at a time when such studies were scarce. The study proposed an alternative cooling arrangement with ceiling mounted heat exchangers, offering space saving advantages over conventional modular air conditioning unit designs. Using experimentally validated CFD simulations, the authors demonstrated the ability to predict system inlet temperatures and identify hot spots, highlighting the importance of CFD based design for reliable cooling in future high power and high density data center. Their methodology combined with experimental validation, became a benchmark for subsequent academic and industrial CFD studies. The paper [13] on airflow and cooling within data center provides one of the earliest comprehensive formulations of airflow management from a fluid mechanics perspective. The study evaluated how raised floor height, CRAC unit, tile layout and open area, and underfloor obstructions influence plenum airflow, noting that deliberate obstructions such as inclined solid or perforated partitions can beneficially redirect flow. The work also addressed above floor management strategies to prevent hot air recirculation into rack inlets, including sufficient cold air supply, air curtains, partitions, drop ceilings, and ducted racks. The work established the theoretical foundation for many subsequent CFD studies.

In [14], a literature review was conducted to examine corridor isolation and the integration of Building Information Modelling (BIM) with Computational Fluid Dynamics (CFD) in data centers. The authors identified a research gap in studies combining BIM and CFD for corridor isolation. Their findings revealed that hot aisle containment (HAC) provides greater cooling efficiency, lower power usage effectiveness (PUE), and improved working conditions compared to cold aisle containment (CAC). CFD simulations showed that leakage size and position, significantly influence airflow patterns and cooling capacity, while increased supply airflow does not mitigate leakage losses. Cold corridor isolation was found suitable for low-load data centers (up to 5 kW per cabinet) but can reduce personnel comfort, whereas hot aisle isolation is more efficient and preferred in high-load environments (up to 10 kW per cabinet). The study concluded that integrating BIM and CFD offers a reliable approach for designing and optimizing thermal management in data centers.

A comparative CFD analysis of three airflow-organization strategies: underfloor precision supply, inter-column supply, and rack backplane cooling was carried out in [15]. The investigation introduced thermal performance indices such as ASE, ARE, MCRI, RTI, SHI and RHI to evaluate system effectiveness. Results showed that adopting either CAC or HAC increased ASE and reduced SHI values, while the backplane configuration eliminated hot spots without requiring full aisle containment. Optimizing airflow organization scheme, significantly enhances cooling efficiency and energy utilization while minimizing hot spots. The HAC scheme showed the best thermal and energy performance, offering valuable insights into selecting efficient cooling strategies. A similar numerical and experimental study [16] compared HAC and CAC in legacy data centers, focusing on thermal performance and air leakage. The results showed that HAC outperformed CAC at a 15% leakage rate, delivering a 24.9% thermal performance improvement and allowing the supply air temperature in the HAC system to be raised by 2°C. The authors also noted that accurately measuring and validating leakage is challenging and therefore used the IT supply temperature range as a practical indicator of relative leakage effects. Furthermore, [17] conducted a CFD based comparison of raised floor and hard floor configurations with HAC in high density data centers, demonstrating that the raised floor HAC system delivers superior thermal performance over hard floor HAC system. The results showed that adopting a raised floor improves air distribution efficiency by 28% and reduces recirculation ratio by around 40%.

In [18], a combined cooling system that integrates heat storage, waste-heat recovery and different renewable energy sources with conventional air conditioning was modeled. The proposed system reported approximately 16% annual energy savings, an increase in system COP from 3.9 to 4.6, and a reduction of PUE from 1.36 to 1.30. The paper [19] investigated two improvement methods to achieve a uniform temperature distribution in data centers using CFD: (i) installing adjustable underfloor deflectors beneath perforated tiles with varied opening ratios to balance cold-air distribution, and (ii) replacing standard floor grilles near cooling units with fan-floor modules to enhance airflow delivery. Simulation results showed that the deflector method increased airflow to front end cabinets by 18.1% and reduced rear end airflow by 5.1%,

while the fan-floor approach achieved a 4.9% increase and 3.8% reduction, respectively. Both methods improved thermal uniformity and showed that airflow is a key factor that influences cabinet temperature, reducing cabinet maximum outlet temperatures by up to 2.81°C.

The Kao Data case study [20] demonstrated the use of CFD based digital twin modelling (via Future Facilities' 6SigmaDCX) to validate and optimize the indirect evaporative cooling (IEC) design of a high-density, 100% free-cooled sustainable colocation data center. The study conducted both internal and external airflow analyses: internally, the data hall whitespace was evaluated under normal operation and failure mode scenarios to verify cooling efficiency and uniform airflow distribution; externally, a range of wind speeds and directions were simulated to assess the risk of recirculation. Simulation analyses confirmed that the IEC system could maintain target temperatures without mechanical refrigeration, achieving a PUE of approximately 1.2. The study highlighted the value of CFD in enabling design optimization and refining the decision-making process. AKCP [21] illustrates the broader value of CFD to optimize data center airflow and thermal performance. The study emphasizes four key analyses: design airflow analysis to identify hotspots and uneven distribution, "Day One" analysis for early operational optimization, equipment switchover simulation to ensure resilience during cooling unit failures, and leakage analysis to reduce bypass losses and notes that simulation-driven optimization can lower operational costs and carbon footprint.

A new type of ducted HAC system for data center rack cooling was proposed and experimentally evaluated in [22]. The authors studied the effects of different hot duct containment configurations, door states, diffuser types, blanking panel percentages, and airflow volume scenarios on air distribution and cooling performance. They proposed average inlet rack temperature, standard deviation of temperature and temperature difference across rack as practical metrics instead of percentage leakage. Results showed that ducted containment offered performance close to that of full airtight containment but at a lower cost. The paper [23] combined experimental testing with physics based modelling to quantify cold air bypass and determine the optimal DP across aisle containment in data center. The results showed that even with containment, substantial bypass can occur through the rack itself, with bypass airflow reaching up to 20% of the ACU supply. The paper demonstrated that practical mitigation measures such as improved rack design and blocking leakage paths reduced power consumption by up to 8.8%, while optimizing the DP across the cold and hot aisles delivered up to a 16% reduction in power consumption. The authors of [24] conducted a CFD study of a data center with cold aisle containment (CAC), validated by experiments, to assess the impact of leakage. They argued for including realistic fan curves (both server and CRAC fans) in models, noting that fixed flow boundary conditions are a poor approximation in CAC systems. Their findings showed that rack level leakage can cause an inlet temperature rise of about 4°C, and identified a critical leakage threshold of approximately 15%, above which the containment allows so much hot air to recirculate that the benefits of containment are completely lost. In [25], validated CFD modelling was used to assess airflow improvements in a raised floor data center, testing blanking panels, vertical partitions and partial cold aisle enclosure. Partial cold aisle enclosure produced the greatest benefit, allowing a 3°C increase in supply air temperature while maintaining acceptable rack inlet conditions, thereby improving energy efficiency. The study also noted that RTI can be unreliable for identifying bypass or recirculation in complex airflow scenarios. In [26], the effect of CRAC unit placement by comparing units placed in line with the rack rows to units placed perpendicular to the rack rows was investigated. Using RTI, SHI, and RHI as performance indicators, it was found that the perpendicular layout improves airflow uniformity from perforated tiles, reduces hot air recirculation and cold air bypass, and significantly enhances overall cooling performance.

Advanced cooling control strategies for data centers with raised floors and HAC, proposing a decentralized MPC controller design to improve thermal management was examined in [27]. The approach used a dynamic thermal model and zone based control structure to regulate CRAC blower speeds and supply air temperatures. The decentralized control system structure lowers the risk of failure associated with centralized controllers and maintains acceptable rack inlet temperatures while reducing cooling power consumption. In [28], the concept of a smart cooled data center with variable capacity cooling system to allocate cooling dynamically where and when required was proposed. The cooling system consists of adjustable vents, sensors for real time temperature and pressure monitoring and CRAC units with VFD for fans speed and three way valves for chilled water control. Later, [29] implemented and experimentally tested this distributed sensor network coupled with CRAC control in a raised floor data center, reporting a 50% reduction in cooling power consumption and a 25% cost reduction in space and power.

The thermal performance of air cooled data centers under raised floor and non-raised floor configurations was numerically evaluated in [30]. They found that a non-raised floor design with overhead supply and overhead return strategy gives the best thermal performance. They also recommend using overhead supply and return even in raised floor setups, because obstructions (such as pipes and cables) in the underfloor plenum (should be used for only housing pipes and cable) significantly affect air flow

distribution. Importantly, their results showed that using a ceiling return is better than a room level return for both raised floor and non-raised floor design.

The effect of air flow leakage from HAC system on their cooling performance was analyzed by the author of [31]. He evaluated the influence of leakage area, supply air ratio and rack cooling load on the performance of HAC system and found that leakage areas have the largest impact on the performance. An increase in leakage area raises the rate of air leakage, while the nature and location of the leakage paths alter airflow patterns, both of which negatively impact the cooling performance. He also finds that simply increasing supply airflow only reduces temperature of hot air exiting and does not mitigate leakage, and that varying rack cooling loads has little impact on leakage rates. The authors of [32] investigated airflow leakage in CAC and HAC systems. They introduced a Leakage Impact Factor (LIF) to quantify and rank leakage paths such as gaps beneath racks, above racks, and around containment doors. They assumed no leakage through the racks to isolate the effect of containment leakage. Their results showed that leakage beneath racks is the largest contributor to unwanted heat transfer into cold spaces, and they concluded that slight over provisioning of pressure differential is required to mitigate leakage effects. The authors of [33] motivated by experimental data showing air recirculation from the hot aisle to the cold aisle through the gap beneath server cabinets, investigated how tile perforation area, CRAC provisioning, leakage pressure gradients, and CAC affect cooling performance. Results indicate that even small under-cabinet leakage can reduce cooling effectiveness, with the effect being particularly sensitive to under provisioned conditions.

In [34], the authors demonstrated that properly sealed cold aisle containment (CAC) supports higher server heat loads (25.2 kW/cabinet) compared with standard hot aisle/cold aisle layouts (14.6 kW/cabinet). Their research also highlights the critical role of sealing accessories such as grommets and blanking panels, and unused U-slot closures being crucial for improving containment performance. In [35], the authors evaluated the effect of partial aisle containment in both hard floor and raised floor data center layouts under two supply flow rates, 100% and 50%. Their results showed that at a 100% flow rate, the top or side cover fully prevented recirculation in the raised floor configuration, while only reducing it in the hard floor configuration. However, at 50% flow, hard floor setup developed hotspots at the row ends: The side cover improved performance for hard floor layouts and the top cover worsened recirculation. In raised floor configurations partial containment remained beneficial over an open aisle under reduced airflow, with the side cover offering the best results and the top cover providing little improvement.

A containerized data center using CAC with an airside heat exchanger and waterside evaporative water chiller to improve performance in tropical and subtropical regions was demonstrated in [36]. CFD simulations evaluated temperature distribution and thermal performance under varying inlet air temperatures and velocities. Results showed that supply air temperature had minor impact, while inlet air velocity strongly influenced air distribution and thermal management. Overall, the overhead downward flow system with CAC significantly enhanced air distribution and thermal performance in large scale data centers. A comprehensive CFD based analysis of a real data center comprising 208 racks was conducted by authors of [37] to assess how airflow and thermal performance change under varying thermal loads and air supply velocities. They simulated four distinct case studies: two with spatially varying heat loads and two under uniform load, each tested with both maximum and minimum air velocity conditions. Their results showed that while operating CRAC units at maximum airflow can successfully cool the room, it does so at a high energy cost. Consequently, the authors argue that instead of costly CRAC upgrades, sustainability can be improved by optimizing rack layout such as removing selected end of row racks and thereby eliminating hot spots by improving airflow.

According to the authors of [38], the standard k–ε turbulence model is particularly well suited for turbulent flows due to its approach for calculating turbulent viscosity and conductivity. It is also the most extensively validated and commonly implemented model in commercial CFD codes. Furthermore, [39] report that previous studies have demonstrated the k–ε turbulence model outperforms the SST, k–ω, RSM, and RNG k–ε models. The paper [40] focused on improving the accuracy of CFD simulations for data center airflow by comparing different turbulence models, including the widely used k–ε model, Reynolds Stress Model (RSM), and Detached Eddy Simulation (DES). Using a full-scale data center test facility, the CFD results were validated against the experimental measurements. The study found that while the k–ε model captures general flow patterns, it fails to predict low velocity zones present above server racks. The differences in flow fields predicted by the different turbulence models are mostly observed in areas far from the main components of the data center. RSM and DES produced very similar results, with RSM being more computationally efficient and thus recommended for data center airflow modeling. A CFD based study to enhance the design of water cooled data centers using a rear door air to liquid heat exchanger for a 40 kW server rack was conducted in [41]. The simulation, performed with ANSYS and the RNG k-ε turbulence model, showed that inlet air temperature strongly affects rack thermal performance. The rear door liquid cooling system effectively reduced

outlet air from about 40°C to near room temperature of 24°C, efficiently handling the full heat load without additional room cooling.

Finally, [42] states that thermal airflow within data centers exhibits inherently complex behavior with recirculating flow. Considering an inlet velocity of 1 m/s at the supply vents and a rack height of 2.4 m, the resulting Reynolds number is approximately 10^5, indicating turbulent flow.

1.2. Role of CFD in Data Center Design

The CFD simulation plays an important role in data center design [43]:

- *Virtual Design and 3D Analysis:* Minimize rework by testing the design or design changes prior to implementation. Helps to validate and analyze design effectiveness through detailed 3D analysis of air flow and heat transfer in a data center.
- *Performance-Based Analysis:* Identifies issues with data center performance, such as improper air flow (excess or insufficient supply of cold air, bypass, recirculation of hot air, mixing of cold and hot air) during the design phase.
- *What-if Scenarios:* Using predictive results provided by CFD simulation, design and what-if scenarios can be evaluated, minimizing risk of failure such as server overheating and helps in identification of potential failures, which leads to an accurate design.

1.3. Raised Floor Versus Non-Raised Floor Data Hall

Data centers should be designed to operate at an optimal temperature for the highest efficiency of equipment. There are various cooling design approaches such as uncontained room cooling, CAC, HAC, in-row cooling, direct to chip cooling, immersion cooling each having advantages and disadvantages over one another. Irrespective of the cooling approach used, a data hall can be either raised-floor or slab floor (non-raised floor). Researchers continue to debate whether raised floor or non-raised floor configurations provide a better supply air path, with no clear conclusion yet. The thermal performance depends on the cooling conditions and IT environment, and although both approaches reduce loss of cooled air, they differ in practical implementation and operation [17]. The topic of raised floor versus slab floor construction is a topic that often sparks heated discussions in the data center industry as both having advantages and disadvantages over one another. Earlier, almost all the data centers used raised floor. In recent years, non-raised floor data center have gained popularity. The decision to go with raised floor or non-raised floor data centers is now driven by operational objectives, business objectives, business needs and market demands [44].

1.4. Scope of Study

In the present study, CFD analysis is used to assess the cooling performance of a dynamically controlled data hall with practical leakages, non-raised floor configuration and HAC strategy. The operation of air cooling units (ACUs) is dynamically regulated in response to the data hall IT load through an integrated network of sensors and controllers. These controllers modulate ACU fan speed and chilled water flow rates to maintain the IT cabinet inlet air temperature within each ACU's zone of influence and below the specified threshold. This control strategy, informed by real-time temperature and pressure sensor data, ensures stable thermal conditions within the data hall while optimizing overall cooling power consumption.

This study focuses on two modes of operation for the purpose of design analysis, i.e., normal mode (NM) and failure mode (FM). In NM steady state operation, all the ACUs are functional. During FM of operation, a designated number of cooling equipment are offline in the worst-case scenario. Both modes operate with 100% IT loads with uniform distribution of load in data hall.

Based on CFD simulation results, the present paper highlights the effects of control strategy used for ACUs, cooling airflow leakages and recirculation of hot air on the performance of the data hall cooling design. Results from different simulation scenarios, which accommodate all possible combinations during NM and FM of operation i.e., with & without control and with & without leakages are evaluated to understand the significance of various design parameters, leading towards right design. Data center metrics such as ASHRAE (American Society of Heating, Refrigerating and Air-Conditioning Engineers) and SLA (Service Level Agreement) compliance are plotted for all simulation scenarios.

1.5. Novelty and Contribution

While numerous prior studies have examined thermal behavior and airflow management in data centers, most rely on highly simplified models of data halls (e.g. limited number of IT Cabinets, idealized geometric layouts or reduced scale representations), overlooking the complexity of real operational environments. Existing literatures predominantly focuses on raised floor configuration and CAC. Only a few investigations addresses non-raised floor facilities with HAC designs, that gained popularity and are increasingly adopted in modern data centers but remain underrepresented and less thoroughly investigated. Moreover, most prior studies typically assume fixed ACU fan speeds and constant chilled water flow rates, failing to explore the dynamic optimization crucial for energy efficiency. To the author's knowledge, studies that do incorporate control often omit details of the control strategy, leaving its impact largely unexplored.

Addressing these gaps, the novelty of the present study lies in its comprehensive, holistic CFD simulation of a dynamically controlled, existing full-scale data hall comprising 308 IT cabinets configured with a non-raised floor and HAC design, thereby offering a level of practical complexity rarely addressed in previous works. A dedicated control strategy for optimizing ACU fan speed and chilled water flow rate is developed, described in detail, and its impact on overall energy consumption is quantified. Finally, unlike prior studies, which typically examine leakage effects, equipment failures, or normal steady state operation in isolation, this research provides a holistic evaluation of data hall performance under both NM and FM, including the practical leakages and active control strategy. By integrating real scale, dynamic control and multi-scenario operation, these contributions advance the state of knowledge by offering practical insights into the design, operational control strategy, and optimization of large-scale modern data centers.

2. Methodology

The air flow and temperature distribution within the data center are governed by the fundamental principles of conservation of mass, momentum, and energy. The full mathematical formulation and derivation of the Navier-Stokes equations (momentum conservation) and the energy conservation equation are omitted here, as these fundamental equations are well established and comprehensively documented in standard CFD books and literature [45], [46], [47], [48]. However, the underlying physics, key assumptions, the selection of the turbulence model, and the details of the computational approach including discretization, solving procedures, and convergence criteria critical to this simulation are discussed in detail in the following sections.

2.1. Governing Equations

The computational model is based on conservation laws, specifically the continuity, momentum, and energy equations, supplemented by the ideal gas equation of state. These equations collectively describe the steady state motion of an incompressible Newtonian fluid (air) and the associated heat transfer by the active information technology (IT) equipment, along with significant auxiliary sources such as uninterruptible power supplies (UPS) and lighting systems. The analysis considers a three-dimensional domain. Key assumptions include modeling the working fluid air as an ideal gas, treating the fluid flow as incompressible and turbulent, and assuming steady-state heat transfer process.

The mass balance (or continuity equation) ensures that mass is conserved within the fluid domain . It dictates that for any control volume within the simulation, the rate at which mass enters must equal the rate at which it leaves, plus any change in mass stored inside. This balance is fundamental for calculating the pressure field in incompressible flows and the density changes in compressible flows, ensuring a physically realistic flow pattern. The momentum balance applies Newton's second law to fluid motion, stating that the net force on a fluid element equals its rate of momentum change. These forces include surface forces like pressure gradients, viscous stresses (internal friction), and body forces like gravity. By solving this balance, CFD determines the fluid's velocity field which along with the pressure field describes the flow dynamics. The energy balance ensures that total energy is conserved by accounting for all energy transfers based on first law of thermodynamics. It relates changes in internal energy to heat transfer (conduction and convection) and the work done by pressure and viscous forces. This equation is solved to determine the temperature distribution throughout the fluid domain, making it essential for simulations involving heat transfer, and fluid property variations caused by temperature changes.

Modeling air as an ideal gas allows the simulation to account for the buoyancy effect by providing the necessary density variation caused by changes in temperature and pressure within the flow field. The equation of state is crucial for solving the system of governing equations, as it provides a way to calculate the density required in the continuity and momentum equations, based on the pressure and temperature calculated by the momentum and energy equations.

A steady state analysis is performed by setting all the time derivatives to zero ($\partial/\partial t = 0$). This choice is justified because the primary objective is to predict the long term, time averaged thermal equilibrium and characteristic mean operating temperatures of the data hall, providing a computationally efficient approach.

As air velocities in the data hall are typically low (with Mach number, Ma < 0.3), incompressible flow assumption is applied. This neglects density variations due to pressure changes, which is a significant simplification used in the continuity and momentum equations.

2.2. Turbulence Modelling

The air flow patterns in data centers are highly complex and recirculating. Based on typical operating conditions such as an air inlet velocity of 1 m/s at supply vent and IT cabinet height of 2.4 m, the Reynolds number is approximately 10^5, clearly indicating a turbulent flow regime [42].

To computationally model the inherently turbulent flow characteristic of large indoor spaces such as data hall, these fundamental principles are typically expressed in their Reynolds-Averaged Navier–Stokes (RANS) form. RANS models decompose each instantaneous flow variable (e.g., velocity, pressure, temperature etc.) into a

time-averaged mean component and a fluctuating component. This time-averaging process introduces the Reynolds stress tensor ($-\rho\overline{u_i'u_j'}$) into the momentum equations, which represents the effective momentum transfer due to turbulent fluctuations.

Since the Reynolds stress terms are unclosed (i.e., they introduce more unknowns than available equations), a turbulence model is required. Specifically, the Reynolds stress tensor, is a symmetric second-order tensor and thus introduces six independent unknown components into the three RANS momentum equations. These six unknowns cannot be determined solely by the existing four RANS equations (continuity and three momentum equations).

A common and robust approach is to employ the Boussinesq turbulence hypothesis, which postulates that the Reynolds stresses are directly proportional to the mean rate of strain tensor, analogous to the relationship between viscous stress and strain for a laminar flow. This hypothesis effectively replaces these six unknowns with a single scalar quantity, the eddy viscosity (μ_t). The major drawback of this hypothesis is that it assumes the turbulent flow is isotropic (the same in all directions), which is often not true for complex engineering flows and cannot accurately predict stresses in highly anisotropic flows where turbulent stress and mean strain are misaligned (e.g., highly swirling or separating flows). Despite this simplification, it works remarkably well for a vast range of engineering applications, including the data center flows.

$$-\rho\,\overline{u_i'u_j'} = 2\mu_t\,\bar{S}_{ij} - \frac{2}{3}\rho\,k\,\delta_{ij} \quad (1)$$

Where, $\bar{S}_{ij}$ is the mean rate of strain tensor, ρ is the fluid density, k is the turbulent kinetic energy , δ_{ij} is the Kronecker delta. With the six Reynolds stress components now expressed in terms of $\bar{S}_{ij}$, and the new variable μ_t (which itself depends on k), the closure problem is reduced from six unknowns to one primary unknown, the eddy viscosity μ_t.

Unlike molecular viscosity (μ), eddy viscosity is a flow property, not a fluid property, which varies throughout the flow field and is computed from averaged flow variable [49], necessitating the use of two-equation models for closure. For instance, the widely-adopted Standard $k-\varepsilon$model solves two auxiliary RANS transport equations, one for the turbulent kinetic energy (k) and another for turbulent kinetic energy dissipation rate (ε) [50]. These two variables are then used to calculate the turbulent viscosity, μ_t , thus achieving closure for the RANS equations.

$$\mu_t = C_\mu * \rho * \frac{k^2}{\varepsilon} \quad (2)$$

While the Standard $k-\varepsilon$ model is utilized for its robustness and wide applicability, it is essential to acknowledge its inherent limitations. The model is known to perform less accurately for flow with strong adverse pressure gradients, substantial boundary layer separation, rotating fluid flows or flow over curved surfaces. This model also assumes a fully turbulent flow regime, an assumption that may not hold across all regions of the airflow within the data center.

The standard $k-\varepsilon$ turbulence model remains the most commonly used approach for CFD simulations of data centers despite its well-known limitations because it offers a uniquely advantageous combination of numerical robustness, computational efficiency, and extensive historical validation. Its exceptional stability makes it unlikely to diverge or crash even on complex or coarse meshes, an attribute that is particularly valuable in data center design where many preliminary configurations must be evaluated rapidly and stability is prioritized over marginal increases in accuracy. The model is also computationally inexpensive, adding only two additional transport equations to the RANS formulation, whereas more advanced models such as the Reynolds stress model (RSM) require solving seven additional equations (six for the Reynolds stress tensor components plus one for epsilon), significantly increasing memory requirements and runtime for the large computational domains typical of data halls. Furthermore, the $k-\varepsilon$ model's empirical constants have been calibrated over decades against a wide range of turbulent flows, and commercial CFD packages have optimized their implementations extensively, reinforcing its position as an industry-standard model [51]. Although it fails to perfectly capture the physics of small, highly anisotropic eddies with high fidelity, it typically provides sufficiently accurate predictions of mean air flow and mean temperature distributions to identify hot spots, characterize recirculation, and support overall decision making. In practice, higher-fidelity alternatives such as the realizable or RNG $k-\varepsilon$, the k-ω SST model, or the RSM are employed when detailed accuracy in near-wall behavior, swirl, turbulence anisotropy or modeling of flow inside a server rack is required, but for large-scale airflow in typical data halls, the standard $k-\varepsilon$ model continues to offer the most effective balance between stability, computational cost, and engineering reliability and practicality.

2.3. Near-Wall Treatment and Wall Functions

The simulation employs the Standard $k-\varepsilon$ (SKE) turbulence model coupled with the wall function approach for near-wall modeling. This coupling is necessary because resolving the steep velocity profiles within the thin viscous sublayer of a turbulent boundary layer requires an extremely fine mesh (viscous sublayer resolving approach, $y^+ \approx 1$), leading to prohibitively high computational cost. Moreover, the SKE model is not

formulated for low Reynolds number wall treatment, its core assumptions specifically the local isotropy of turbulence (turbulence is highly anisotropic near wall) and the validity of the ε - transport equation (The ε - transport equation is unsuitable near the wall because it is derived under the assumption of high local Reynolds numbers. But near the wall, viscous effects dominate, leading to low local Reynolds numbers) break down in the viscous sublayer and buffer region. To achieve computational feasibility, wall functions are used. These are semi-empirical formulas based on the universal law of the wall, effectively bypassing the need to resolve the viscous sublayer with the mesh. The universal law of the wall describes the mean velocity profile of turbulent flow close to the wall, stating that when the mean flow velocity ($\bar{u}$) and distance from the wall (y) are scaled using friction velocity and kinematic viscosity to yield the dimensionless velocity (u^+) and dimensionless distance (y^+), the resulting relationship becomes universally constant and independent of the overall Reynolds number. This universal velocity profile is characterized by a linear relationship in the viscous sublayer , transitioning through a buffer region and a logarithmic relationship in the log layer.

This approach requires the first grid cell center to be located within the turbulent logarithmic region of boundary layer, satisfying the meshing guideline of $30 < y^+ < 300$. This compromise is acceptable for data hall flows, which are generally high Reynolds number and attached.

2.4. Thermal Modelling and Buoyancy

Although a highly accurate thermal model could include the heat source at individual servers, a black box approach was utilized for each IT cabinet in this study, as the inclusion of server level heat details only offered a marginal contribution to overall data center thermal accuracy [52].

Furthermore, buoyancy effects, which are highly significant in thermally stratified air cooled data halls, are incorporated using the Boussinesq approximation. This approximation simplifies the equations by treating the fluid density (ρ) as constant in all equations, except within the gravity (buoyancy) term of the momentum equation. In this term, density is assumed to vary linearly with temperature.

$$\rho = \rho_{ref}\left[1 - \beta\left(T - T_{ref}\right)\right] \quad (3)$$

where ρ_{ref}, β and T_{ref} are the reference density, thermal expansion coefficient and reference temperature.

This simplification is valid provided air properties are constant, the flow is incompressible and exhibits small temperature-induced density variations resulting from a small temperature difference (ΔT). The use of this approximation is strongly justified for this study because data hall operates with a maximum design ΔT of 12 ± 1°C between the supply and return air. This value is well within the widely accepted limit (typically < 20 K) for air [53]. This assumption enables the accurate prediction of temperature and buoyancy driven airflow patterns such as the thermal plume rising from IT equipment without solving the full compressible Navier - Stokes equations, thereby reducing computational costs.

2.5. Numerical Methodology and Convergence

Together, the RANS formulation, the Boussinesq turbulence hypothesis, the Standard $k-\varepsilon$ model, wall function, and the Boussinesq approximation establish a practical and robust framework for predicting the steady state distribution of air velocity, temperature, and pressure within data center spaces.

The set of coupled, non-linear partial differential equations (PDEs) comprising the RANS momentum, mass, energy, and turbulence equations cannot be solved analytically. They are solved using a computational approach. A computational approach based on the Finite Volume Method (FVM) was employed to discretize and solve the equations numerically. In FVM, the physical domain of the data hall is first divided into a finite number of non-overlapping continuous sub-regions, known as control volumes (or the computational mesh). In FVM, the governing PDEs are integrated over each control volume. This integration converts the differential equations into a system of linear algebraic equations that link the value of a variable (e.g., velocity or temperature) at the center of one control volume to the values in its neighboring control volumes. A primary challenge in solving the RANS equations is the inherent coupling between the pressure field and the velocity field, as the mass conservation (continuity) equation does not explicitly contain a term for pressure. This requires a specialized iterative algorithm for solution. For this steady state simulation, the SIMPLE (Semi-Implicit Method for Pressure-Linked Equations) algorithm, or a similar segregated scheme, was utilized. This algorithm iteratively adjusts the pressure and velocity fields until the mass and momentum equations are simultaneously satisfied throughout the entire domain. The system of algebraic equations is solved iteratively until a converged steady state solution is achieved. Convergence is confirmed when the residuals which represent the imbalance in the conservation equations for each control volume have reduced to a specified level. Specifically, the simulation was considered converged when the residuals for pressure, velocity, temperature and turbulence parameters (k and ε) tended to 1. Furthermore, monitoring key performance metrics, such as the return air temperature to cooling unit, ensured that these values stabilized and ceased to change significantly between iterations.

2.6. Validity of CFD Simulation

'DataCenterDesignPro' which is an industry standard data center specific CFD software (Previously recognized as '6SigmaRoom' Release 16.3, which is the latest version at the time of analysis) is used for modeling and CFD simulation. The software is a physics based simulation tool for data center design that utilizes digital twin models. It enables the rapid and accurate creation of digital twins, which serve as virtual representations of existing or planned data centers. These models allow the exploration of multiple design configurations and failure scenarios, supporting the optimization of new data center designs as well as the reevaluation of legacy facilities. By leveraging CFD simulations, the software facilitates the entire design process, from conceptual prototyping to detailed engineering [54].

It includes a comprehensive database of IT equipment and cooling systems, with information collected and verified directly by the respective manufacturers. This capability enables accurate modeling of real data center. The software incorporates the latest cooling technologies and offers greater flexibility in addressing a wide range of design challenges compared to other commercial CFD tools and emerges as the most extensive and feature rich. It is widely recognized as the most accurate tool in the industry for data center design. It is used by several global researchers and data center designers, including Facebook, Microsoft, and IBM, in their data center projects [55], [56], [57], [15], [16], [17], [19], [20] demonstrating the reliability of its CFD results.

2.7. Mesh Independence study

A mesh independence study is a fundamental requirement in all CFD simulations. It is conducted to confirm that the numerical solution is insensitive to further mesh refinement indicating that the discretization error due to the mesh size has been minimized and therefore represents the correct underlying physical behavior. The regions with high gradients are typically assigned a finer mesh. While a finer mesh enhances solution accuracy, it leads to a substantial increase in computational time. By progressively refining the computational grid and comparing key solution variables, it is possible to determine the point at which additional refinement produces negligible changes in the results.

The automatic grid generation feature of the software was used to generate the unstructured hexahedral mesh. Five different meshes were generated, and variables such as ACU return air temperature, cabinet inlet and outlet temperatures, and room temperature were monitored for each mesh size. The mesh containing 7,288,454 cells was found to be optimal, as further refinement caused negligible variation in the selected variable values, and was thus chosen for analysis. This method ensures the accuracy and reliability of the simulation results while avoiding unnecessary computational cost.

The essential components of the data hall (such as ACUs, PDUs, IT Cabinets etc.) can be added either from the software's built-in library or through a neutral data format. This approach ensures the accuracy of simulation, as the mesh independence study of these components is already validated. Achieving grid independence alone does not guarantee simulation accuracy. The correctness of boundary conditions and the choice of turbulence model also significantly affect the simulation results.

3. Data Center Hall

A data hall layout with non-raised floor configuration and HAC strategy as shown in Figure 1, 2 and 3 is used for the CFD analysis. The data hall measures approximately 41 m in length and 20 m in width, with a total floor area of 810 m². The floor to ceiling height is 5.7 m. The number of IT Cabinet are 308 and the corresponding total IT load is 1920 kW (6.23 kW per cabinet). Each cabinet has a height of 2.4 m and a footprint of 0.6 m×1.2 m.

The cabinets are organized into 14 rows in face-to-face and back-to-back configurations, with the back sides of the cabinets facing each other to form HAC of varying sizes. Data hall layout is with caging. The cages are used to create enclosed areas within the data hall which provides an additional layer of security for IT cabinets in a colocation data center. The doors are provided in the containment to allow access to the rear of the cabinets. There are 11 ACUs separated by partition walls and 28 power distribution units (PDUs) which are located inside the data hall.

3.1. CFD Model of the Data Hall with IT Cabinets

The 3D view of the data hall CFD model is shown in Figure 1. The data hall consists of ACUs, PDUs, IT cabinets, cages, hot aisle enclosure, power cables, data cables, lighting, structural beam, structural column, partition walls, walls, temperature and pressure sensors etc. as shown in Figure 2 and 3.

The CFD model of the data hall was fully constructed using the tools and options available in the software 'DataCenterDesignPro', with the CAD layout used as a reference. This CAD layout of the data hall was imported into the software to guide the modeling process, ensuring that the virtual representation accurately reflected the physical layout and arrangement of the data hall.

The ACU is custom built based on the manufacturer's specifications and all other important elements such as PDUs, IT Cabinets etc. are imported from software's built-in library. The other details such as power cables and data cables are included in the model as flow obstructions.

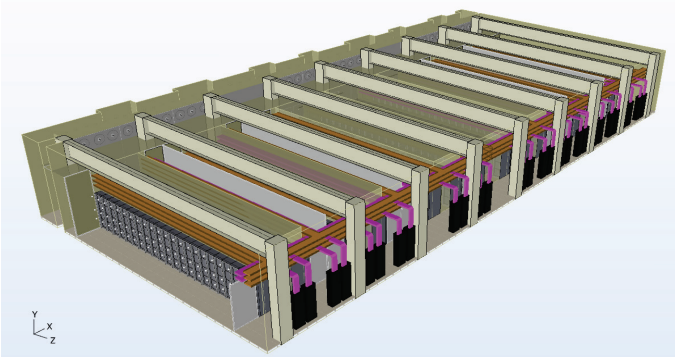

Figure 1: 3D view of data hall CFD model

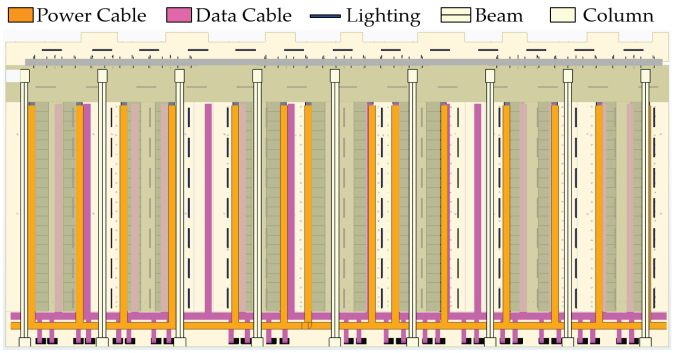

Figure 2: Plan view of data hall CFD model

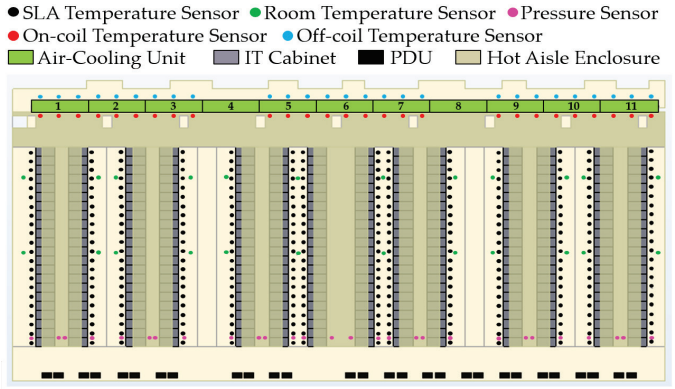

Figure 3: Plan view of data hall CFD model with sensor locations

3.1.1. *Materials*

In data hall CFD simulations, accurately defining material properties is essential because these parameters directly influence heat transfer, and overall thermal performance. Materials with different thermal conductivities, densities, and heat capacities respond differently to temperature loads, affecting how heat is absorbed, stored, and dissipated within the space. Since data halls contain diverse architectural and equipment surfaces that interact with cooling systems, neglecting realistic material properties can lead to significant deviations between simulated and actual thermal conditions. Therefore, incorporating correct material characteristics ensures more reliable predictions of temperature distribution, airflow patterns, and cooling efficiency, ultimately supporting effective thermal management and design optimization.

The walls of the data hall are constructed from cement mortar. The HAC, partition wall and panels are fabricated from polycarbonate. The column, floor and ceiling are composed of concrete. The IT cabinets, ACUs and I-beam are made of mild steel. The key material properties include density, thermal conductivity and specific heat capacity and are listed in Table 1.

Table 1: Material Properties

Material	Density kg/m^3	Thermal Conductivity W/(m.K)	Specific Heat J/(kg.K)
Air	1.19	0.026	1005
Water	997	0.612	4186
Cement Mortar	1200	0.5	850
Polycarbonate	1200	0.19	1300
Concrete	2100	1.37	1000
Mild Steel	7860	63	420

3.1.2. *Sensors*

The temperature and pressure sensors are used to monitor and control the conditions of the data hall. The aim is to ensure not only the sufficient air flow is provided for each IT cabinet but also efficiently cooling them without wastage of energy. The control strategy is developed in such a way that an efficient operation of data hall is achieved while ensuring all SLA temperature requirement are also being met.

The SLA sensors are placed at 0.9m & 1.5m off floor and 0.3m away from IT cabinet air intake side. The top-level sensors are placed at 2.4m off floor level (IT cabinet top level) and 0.3m away from IT cabinet air intake side. The pressure sensors are placed at the far end of each cabinet row. One pressure sensor is placed in the room while another is placed in hot aisle to measure the pressure differential across the IT cabinet. The room temperature sensors are placed in cages to measure room temperature.

One on-coil temperature sensor is placed in front and one off-coil temperature sensor is placed behind each heat exchanger of an ACU. In this case, on-coil temperature is defined as the temperature of hot return air from the conditioned space of data hall (after passing over IT cabinet and removing heat thereby cooling it) and entering the heat exchanger (cooling coil) of an ACU. The off-coil temperature is defined as the temperature of air leaving the heat exchanger of an ACU after getting cooled to the design value by exchanging heat with chilled water supplied by the chillers.

3.2. *Working Principle*

The ACUs supply cold air at the design supply temperature and it fills the data hall room. The cold air then passes through the IT cabinets and takes away heat generated by them. The hot air then gets collected in hot aisle enclosure. The hot return air from IT cabinets then

passes through heat exchangers of ACUs and gets cooled to the design supply temperature and the cycle repeats.

As cold air fills the data hall and hot air is contained in an enclosure, the design approach is called hot aisle containment (HAC) design. The heat exchanger of an ACU is liquid-air type heat exchanger in which heat transfer takes place between hot return air from IT cabinet and chilled water supplied by chillers. The ACU supply air temperature will be higher than off-coil temperature as it includes heat dissipation from fan. The room air temperature will be higher than supply air temperature because it includes heat dissipation from lighting, PDUs and heat gained from unconditioned wall etc. to it.

3.3. Data Center Modes of Operations

Two modes of operation are considered for data center design analysis as follows:

- *Normal Mode (NM)* steady state operation is with all ACUs functional.
- *Failure Mode (FM)* operation where the designated number of ACUs are offline in the worst-case scenario.

4. Air Cooling Unit (ACU)

Data centers require precise thermal management to ensure the reliability and efficiency of IT equipment. The core device responsible for this management is ACU. To efficiently match the dynamic heat load generated by servers, these units rely on sophisticated control strategies. The two primary control mechanisms involve modulating the fan speed and regulating the chilled water flow rate. Fan speed varies using a Variable Frequency Drive (VFD). Simultaneously, the chilled water flow rate through the heat exchangers is regulated by a two-way Pressure Independent Control Valve (PICV).

4.1. ACU Construction

Each ACU has four fans and three heat exchangers (Cooling coils) as shown in Figure 4. The design supply air temperature is 25°C and return air temperature is 37°C. The design ΔT of 12 ± 1°C is to be maintained between supply and return of ACU.

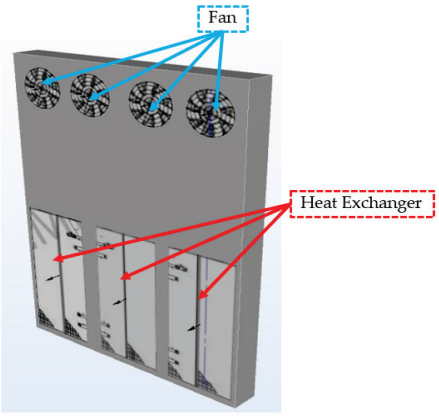

Figure 4: ACU CFD model

4.2. ACU position for NM and FM

Total nine ACUs are available during NM of operation as shown in Figure 5 with green color. The ACU 4 and 8 are for future expansion. The future expansion ACU is replaced by solid obstruction in the model which does not allow the flow through it. The ACUs 6 and 7 are considered offline during FM.

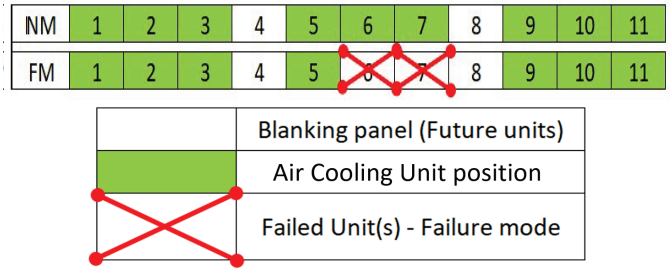

Figure 5: ACU position for NM and FM

4.3. ACU Control Strategy

4.3.1. Fan Control Logic

All the ACU fans should operate at the same speed. Therefore, there is group control associated with fans and a single controller is used to control the fan speed. The fan speed control is a combination of temperature differential (DT) and pressure differential (DP) control. In this case DT is defined as the difference between on-coil temperature and room air temperature. The DP is pressure difference measured at end of the IT cabinet row across IT cabinet.

The DT between average on-coil temperature sensor readings and average room temperature sensor (corresponding cabinet row) readings are calculated. The maximum measured DT will be used for DT control. The fan speed will increase proportionally when DT increases and vice versa. The DT increases when hot return air temperature increases. When return air temperature increases the fan speed increases which supply more cooled air flow which bring down the temperature to the set point of 37°C and vice versa. The minimum fan speed is set at 40% and maximum is set at 100%.

DP at the far end of each cabinet row is measured by DP sensors. When DP is lower than set point of 3 Pa, fan speed will increase based on a reversed proportional curve. When measured DP is lower than 3 Pa (e.g. at fan initial start-up, or failure scenario), DP control will be dominant and fan speed will ramp up to ensure DP set point is reached and when measured DP is higher than 3 Pa, fan control logic will be DT control. The minimum measured DP will be used for DP control.

The DP control ensures that IT cabinets are provided with enough airflow and hot air from hot aisle is not recirculating back to the inlet of IT cabinet by maintaining sufficient DP across it. As DP across cabinet drops below 3 Pa, fan speed increases to increase the ACU air flow thereby increasing pressure on IT cabinet intake side. The

greater the drop below 3 Pa, more will be increase in fan speed.

The control switches between DT control and DP control until steady state is reached which gives highest cooling efficiency without recirculation of hot air. During operation, control will be predominantly DT controlled.

4.3.2. *Cooling Coil Control Logic*

The cooling coil control is set based on off-coil temperature sensor readings. There are three off-coil temperature sensors per ACU. The off-coil temperature is controlled at 25°C. The maximum recorded off-coil temperature out of temperature recorded by three off-coil sensors is used to control coolant (chilled water) flow through the heat exchangers of ACU.

As the off-coil temperature increases coolant flow through the heat exchanger increases to bring down the temperature to the set point of 25°C and vice versa. The chilled water valve minimum opening is set at 10% and maximum opening is set at 100% of design maximum flow rate. The cooling coil control is on individual ACU, there is no group control associated.

5. CFD Simulation

5.1. *Design Data for CFD Simulation*

- The heat dissipation from each fan of an ACU is 2.28 kW. The total fan heat dissipation is 9.10 kW for each ACU.
- The total PDU heat dissipation is 6.72 kW. The heat dissipation from lighting and small power is 9.65 kW.
- Room total heat load is 2018.27 kW during NM and 2000.07 kW during FM, which includes IT load, lighting, small power, PDU, and ACU fan heat dissipation.
- All nine ACUs are modeled with each having 274.20 kW total cooling capacity. Total available cooling capacity is 2467.80 kW during NM and 1919.40 kW during FM.
- There is sufficient cooling capacity available during NM. but the cooling capacity is slightly less than the room total heat load during the FM.

5.2. *Design Considerations*

The following design considerations were made during the NM and FM of operation of data hall:

- Data hall operates with 100% IT load with uniform distribution of load throughout the data hall.
- The radiant heat transfer is negligible compared to the dominant conduction and convection in the data hall.
- Moreover, the room is located within the interior of the building and the influence of solar radiation on its thermal environment is minimal. Therefore, the effects of solar and thermal radiation are neglected.
- The thermal conductivity and specific heat capacity of the fluid were assumed to remain constant, as their variations with temperature and pressure are relatively small.
- The heat dissipation from lighting, occupants, and other minor power sources is included and amounts to 9.65 kW.
- In FM of operation, two ACUs are taken offline namely ACU 4 and ACU 8 as shown in Figure 5.
- Typical small gaps (5%) considered for cabinet leakages.
- A fixed temperature boundary condition is provided for data hall walls.
- For hot aisle enclosure leakage, specified gap size of 0.561 mm with 100% open area is considered.
- The coolant used is chilled water and chillers supply chilled water to ACUs at 22°C.
- The chiller COP is 3.71.
- The rated speed of ACU fan is 1530 rpm.
- The rated fan air flow rate is maximum 4.88 m^3/s. The maximum total air flow rate is 19.5 m^3/s per ACU.
- The ACU heat exchanger effectiveness is 0.80 and cooling capacity is 91.40 kW.
- The chilled water flow rate to each heat exchanger of an ACU can be maximum 3.63 l/s. The maximum chilled water flow rate is 10.90 l/s per ACU.

5.3. *Simulation Scenarios*

For NM and FM of operation, 4 simulations are carried out each as listed in Table 2.

Table 2: NM and FM simulation scenarios

Normal Mode			Failure Mode		
Case No.	Control	Leakage	Case No.	Control	Leakage
1	✓	✓	1	✓	✓
2	✓	×	2	✓	×
3	×	✓	3	×	✓
4	×	×	4	×	×

"✓" *implies* "with", "×" *implies* "without"

6. CFD Simulation Results

After simulation is set up, run and converged, results can be visualized. CFD simulation provides visualization of performance characteristics such as temperature, velocity and pressure that are difficult to capture in the real world. Key results from CFD for evaluating design are ASHRAE compliance plot, top level and SLA sensor analysis, mean inlet temperature of the cabinets, effect of leakages, pressure distribution in space, percentage cooling capacity used, ACU supply and return air

temperature, chilled water temperature curve, fan speed and cooling power curve.

The thermal requirements of IT equipment are typically defined in terms of inlet air temperature of the equipment. According to ASHRAE guidelines [58], the allowable inlet air temperature range is 15 to 32°C, while the recommended operating range is 18 to 27°C.

6.1. Normal Mode (NM)

6.1.1. NM Simulation Results for Case 1

The CFD simulation results of NM Case 1 which is with control and with leakages is discussed in detail:

Figures 6, 7 and 8 shows the temperature distribution in space at height of 0.9m, 1.5m and 2.4m off floor respectively. The SLA sensor readings at 0.9 m and 1.5m off floor level in front of each cabinet is in the range of 25.91 to 26.51°C and 25.88 to 26.52°C respectively. The SLA sensor reading meets the design requirement. The top-level sensor reading at 2.4 m off floor level in front of each cabinet is in the range of 25.84 to 26.72°C.

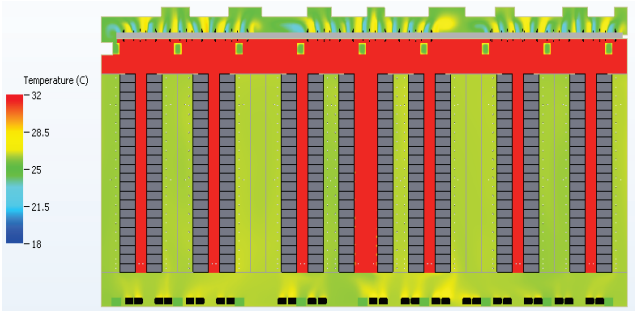

Figure 6: Temperature distribution in space at height of 0.9m off floor

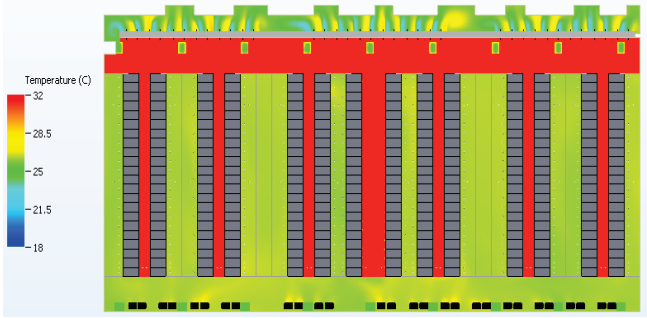

Figure 7: Temperature distribution in space at height of 1.5m off floor

Figure 10 shows the mean inlet air temperature of the IT cabinet. The mean air temperature measured at IT cabinet intake side is in the range 25.91 to 27.08°C which is slightly above the ASHRAE recommended temperature range (18 to 27°C). Figure 11 shows the temperature plot across the IT cabinets (IT cabinets hidden). The temperature plot across cabinets indicates leakage of hot air from hot aisle into the cabinet inlet through cabinet's typical small gaps, resulting in increased peak inlet air temperature for five IT cabinets. Therefore, in case higher peak inlet air temperature is recorded due to leakages, SLA sensor readings will take precedence over the ASHRAE readings to check for compliance.

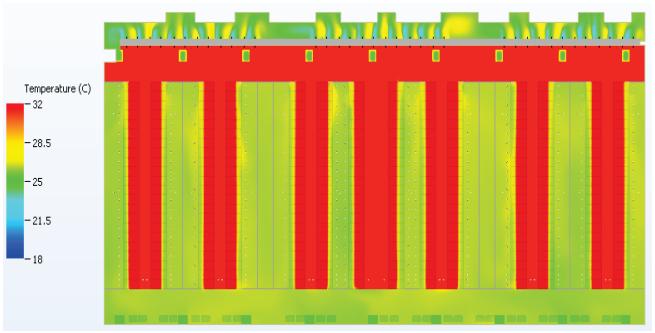

Figure 8: Temperature distribution in space at height of 2.4m off floor

Figure 9 shows the ASHRAE temperature compliance plot for NM Case 1. The ASHRAE compliance temperature is the peak inlet air temperature of the IT cabinet. The peak air temperature measured at IT cabinet intake side is in the range of 25.97 to 30.11°C. All the IT cabinets except five are having peak inlet air temperature in the range of 18 to 27°C, which comply with ASHRAE recommended temperature range.

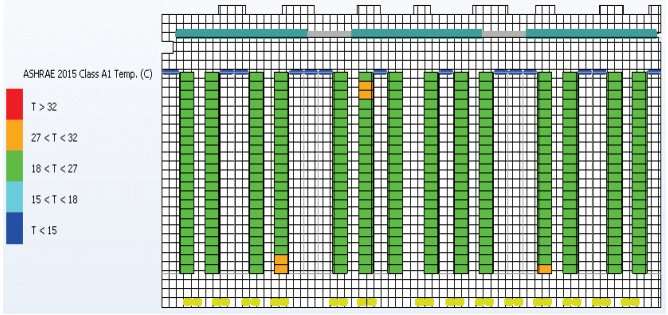

Figure 9: ASHRAE temperature compliance plot for NM Case 1

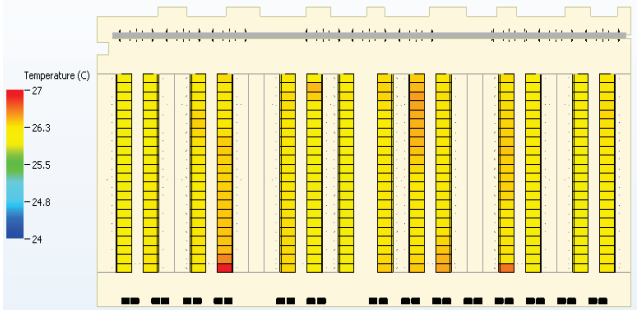

Figure 10: Mean inlet air temperature of the IT cabinet

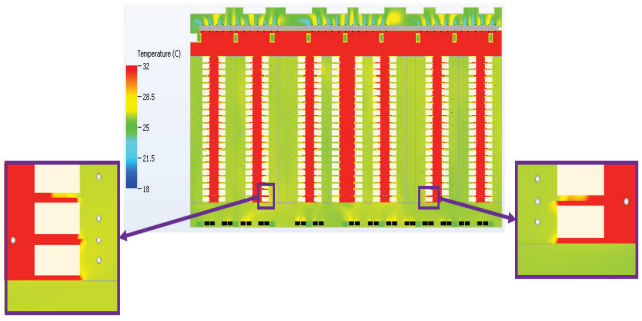

Figure 11: Temperature plot across the IT cabinets (IT cabinets hidden)

Figure 12 shows pressure distribution in space at 2.4m off floor (IT cabinet height level) with differential pressure across the IT cabinet at the far end of each cabinet row. Figure 12 also shows the fan speed and corresponding air flow rate from an ACU. During normal steady state

operation of the data hall, fans operate at 1395 rpm with air flow rate of 17.78 m³/s. All fans operate at the same speed and air flow rate, as there is a group control associated with ACU fans and a single controller is used to control the speed. The DP varies from 2.94 to 24.02 Pa. Figure 13 shows the cooling capacity utilization of an ACU. The cooling capacity of ACUs varies from 203.11 to 236.63 kW. Only 74.07 to 86.30% of the total available cooling capacity of 274.2 kW is utilized by the ACUs.

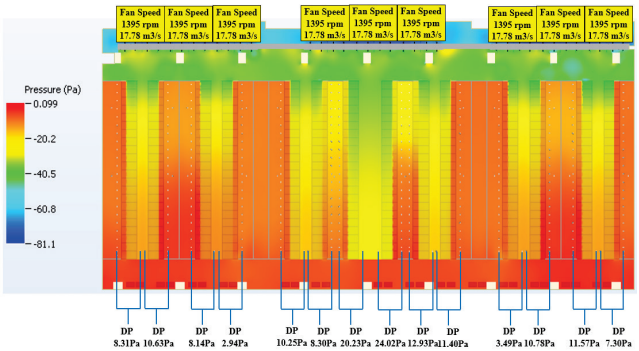

Figure 12: Pressure distribution in space at 2.4m off floor

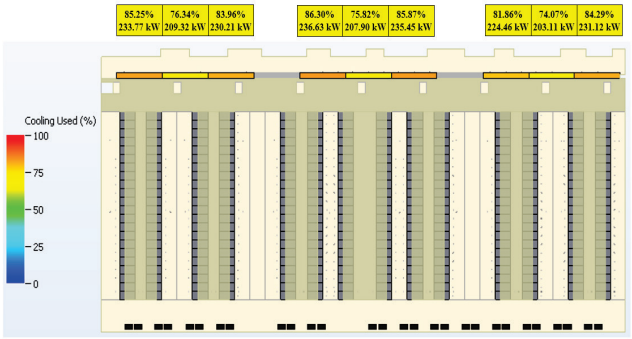

Figure 13: ACU cooling load distribution

Figure 14 shows the average ACU on-coil and off-coil temperature. The ACU on-coil temperature is the average of the temperature recorded by on-coil sensor of heat exchangers of an ACU. Similarly, the ACU off-coil temperature is the average of the temperature recorded by off-coil sensor of heat exchangers of an ACU. The simulation result showed an average of 25.60°C supply and 35.92°C return which is close to the design values. This indicates that the control logic is functioning well.

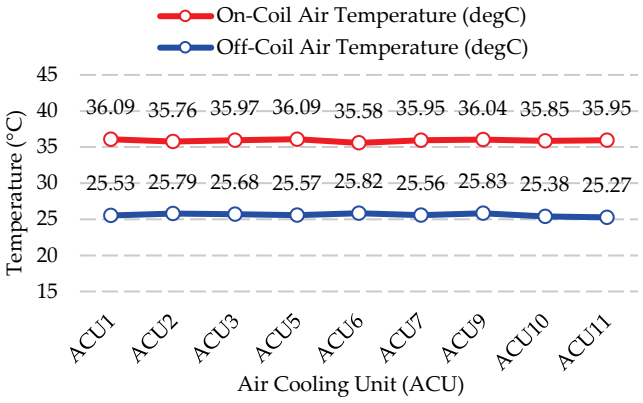

Figure 14: ACU average on-coil and off-coil temperature

6.1.2. *NM Simulation Results for Case 2, 3 and 4*

Figure 15 shows the ASHRAE temperature compliance plot for NM Case 2. The peak air temperature measured at IT cabinet intake side is in the range of 26.10 to 27.05°C. All the IT cabinets except one are having peak inlet air temperature in the range of 18 to 27°C, which comply with ASHRAE recommended temperature range.

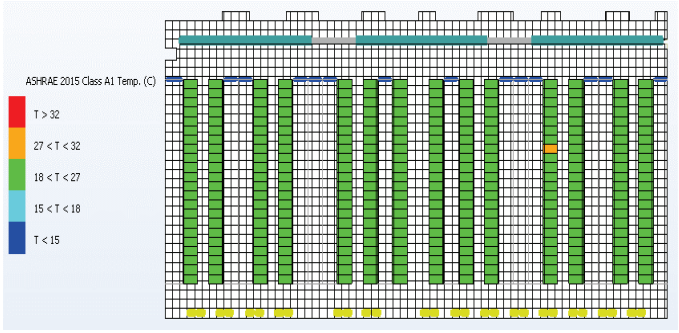

Figure 15: ASHRAE temperature compliance plot for NM Case 2

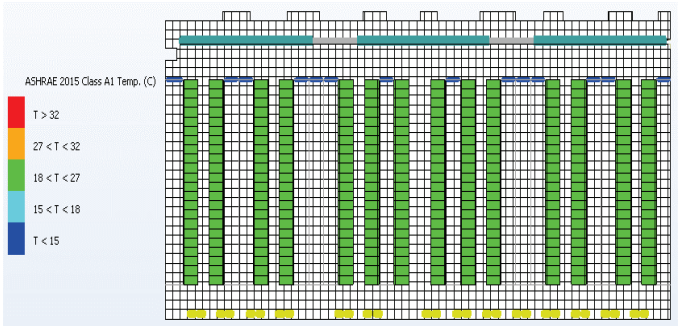

Figure 16: ASHRAE temperature compliance plot for NM Case 3

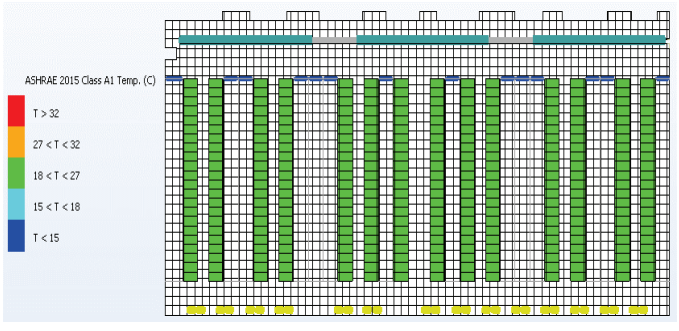

Figure 17: ASHRAE temperature compliance plot for NM Case 4

Figure 16 and 17 shows the ASHRAE temperature compliance plot for NM Case 3 and 4 respectively. The peak air temperature measured at IT cabinet intake side is in the range of 25.10 to 26.36°C and 25.12 to 25.96°C for Case 3 and 4 respectively. All the IT cabinets are having peak inlet air temperature in the range of 18 to 27°C for both Case 3 and 4, which comply with ASHRAE recommended temperature range.

6.1.3. *NM Simulation Results Summary*

Table 3 summarizes the NM simulation results. From CFD simulation result it is observed that:

Table 3: Normal Mode simulation results summary

Normal Mode				
Case	1	2	3	4
Control	✓	✓	✗	✗
Leakages	✓	✗	✓	✗
Simulation Results				
Fan Speed Controller Temp. Input	9.99°C	11.00°C	-	-
Fan Speed Group Controller Output	85.30%	69.80%	-	-
Fan Speed	1395 rpm	1253 rpm	1530 rpm	1530 rpm
Chilled Water Controller Output	62.39 to 85.47%	60.24 to 81.01%	-	-
Pressure Difference	2.94 to 24.02 Pa	11.39 to 30.83 Pa	12.33 to 38.97 Pa	69.00 to 96.98 Pa
Maximum On-Coil Temperature	36.79°C	37.48°C	35.50°C	34.54°C
Minimum On-Coil Temperature	33.94°C	36.70°C	33.19°C	33.97°C
Maximum Off-Coil Temperature	26.02°C	26.02°C	25.49°C	24.22°C
Minimum Off-Coil Temperature	24.68°C	24.76°C	24.13°C	25.31°C
Total Cooling Power (kW)	203.11 to 236.63	206.64 to 232.21	202.78 to 232.03	206.40 to 230.50
Coolant Temperature Out (Average)	27.20 to 29.78°C	27.41 to 29.90°C	25.99 to 27.86°C	26.07 to 27.64°C
Cabinet Maximum Temperature In	25.97 to 30.11°C	26.10 to 27.05°C	25.10 to 26.36°C	25.12 to 25.96°C
Cabinet Mean Temperature In	25.91 to 27.08°C	25.99 to 26.62°C	25.05 to 25.68°C	25.05 to 25.64°C
Room Temperature	25.94 to 26.49°C	25.98 to 26.71°C	24.98 to 25.73°C	24.99 to 25.66°C
Top-level Temperature Sensor at 2.4m	25.84 to 26.72°C	25.90 to 26.95°C	25.07 to 26.03°C	25.06 to 26.01°C
SLA Temperature Sensor at 1.5m	25.88 to 26.52°C	25.93 to 26.60°C	25.04 to 25.67°C	25.03 to 25.62°C
SLA Temperature Sensor at 0.9m	25.91 to 26.51°C	25.98 to 26.59°C	25.01 to 25.66°C	25.01 to 25.59°C

The leakage causes recirculation of hot air from hot aisle back into the cabinet inlet through cabinets typical small gaps, resulting in increased peak inlet air temperature for cabinets. For case without control logic (Case 3&4), all IT cabinets are having peak inlet air temperature in the range of 18 to 27°C, and SLA sensor readings at 0.9 m and 1.5 m off floor in front of each cabinet are less than 27°C, which met the design requirement.

For cases with control logic (Case1&2), ASHRAE compliance is not met due to recirculation of hot air because of leakages. But SLA sensor readings at 0.9 m and 1.5 m off floor in front of each cabinet is less than 27°C, which met the design requirement.

6.2. Failure Mode (FM)

6.2.1. FM Simulation Results for Case 1 to 4

Figure 18 shows the ASHRAE temperature compliance plot for FM Case 1. The peak air temperature measured at IT cabinet intake side is in the range of 25.84 to 34.82°C. The simulation result showed that many IT cabinets are having peak inlet air temperature between 27 to 32°C and greater than 32°C, which does not comply with ASHRAE recommended temperature range.

Figure 19 shows the ASHRAE temperature compliance plot for FM Case 2. The peak air temperature measured at IT cabinet intake side is in the range of 25.81 to 27.27°C. All the IT cabinets except five are having peak inlet air temperature in the range of 18 to 27°C, which comply with ASHRAE recommended temperature range.

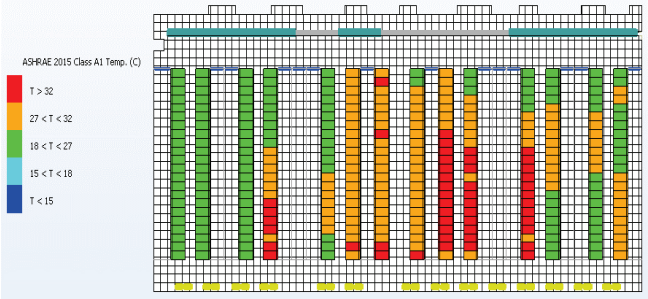

Figure 18: ASHRAE temperature compliance plot for FM Case 1

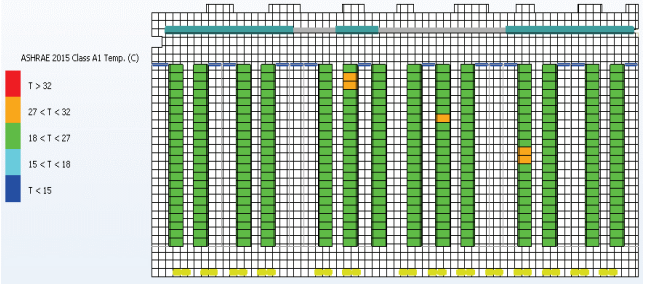

Figure 19: ASHRAE temperature compliance plot for FM Case 2

Figure 20 shows the ASHRAE temperature compliance plot for FM Case 3. The peak air temperature measured at IT cabinet intake side is in the range of 25.43 to 34.66°C. The simulation result showed that many IT cabinets are having peak inlet air temperature between 27 to 32°C and greater than 32°C, which does not comply with ASHRAE recommended temperature range.

Figure 21 shows the ASHRAE temperature compliance plot for FM Case 4. The peak air temperature measured at IT cabinet intake side is in the range of 25.58 to 27.15°C. All the IT cabinets except two are having peak inlet air temperature in the range of 18 to 27°C, which comply with ASHRAE recommended temperature range.

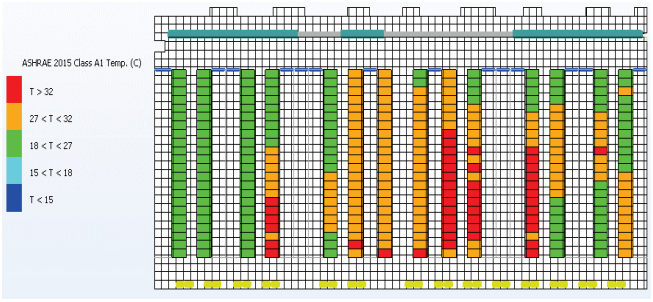

Figure 20: ASHRAE temperature compliance plot for FM Case 3

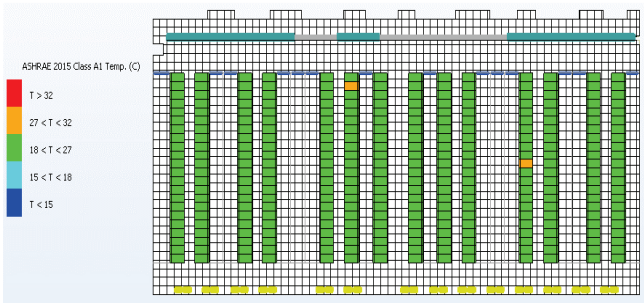

Figure 21: ASHRAE temperature compliance plot for FM Case 4

6.2.2. *FM Simulation Results Summary*

Table 4 summarizes the FM simulation results. From CFD simulation result it is observed that:

During FM of operation, no significant difference observed when simulation is run with or without control (Comparing Case 1&2 with Case 3&4). This is because during FM fan speed is ramped up to 100% and chilled water controller output also is almost 100%. The negative DP is observed across cabinets in the area served by offline cooling units. The area served by offline cooling units also experiences recirculation of hot air from the hot aisle into the cold aisle.

The results showed significant effect of leakages on the performance especially during FM. When comparing Case 1&3 with Case 2&4, with leakages heavy recirculation of air is observed, which causes leakage of hot air from hot aisle into the cold aisle. The recirculated hot air enters cabinet inlet resulting in increased inlet temperature of cabinet, in turn return air temperature increases and supply air temperature increases. Thus, increasing the room temperature. Because of which SLA temperatures recorded are higher and design requirement is not met. Therefore, it is important to minimize leakages.

Table 4: FM simulation results summary

Failure Mode (FM)				
Case	1	2	3	4
Control	✓	✓	✖	✖
Leakages	✓	✖	✓	✖
Simulation Results				
Fan Speed Controller Temp. Input	12.20°C	11.80°C	-	-
Fan Speed Group Controller Output	100.00%	100.00%	-	-
Fan Speed	1530 rpm	1530 rpm	1530 rpm	1530 rpm
Chilled Water Controller Output	81.02 to 100%	84.53 to 100%	-	-
Pressure Difference	-6.40 to 7.33 Pa	-6.35 to 15.77 Pa	-6.39 to 7.47 Pa	-6.38 to 15.86 Pa
Maximum On-Coil Temperature	39.17°C	38.37°C	38.98°C	38.24°C
Minimum On-Coil Temperature	35.61°C	36.56°C	35.32°C	36.36°C
Maximum Off-Coil Temperature	26.72°C	26.47°C	26.60°C	26.41°C
Minimum Off-Coil Temperature	24.96°C	24.97°C	24.74°C	24.85°C
Total Cooling Power (kW)	248.4 to 353.5	261.3 to 340.7	252.3 to 349.1	264.5 to 337.3
Coolant Temperature Out (Average)	27.16 to 29.84°C	27.22 to 29.55°C	26.96 to 29.73°C	27.15 to 29.49°C
Cabinet Maximum Temperature In	25.84 to 34.82°C	25.81 to 27.27°C	25.43 to 34.66°C	25.58 to 27.15°C
Cabinet Mean Temperature In	25.80 to 28.46°C	25.76 to 26.64°C	25.40 to 28.37°C	25.49 to 26.52°C
Room Temperature	25.82 to 27.16°C	25.79 to 26.93°C	25.41 to 27.08°C	25.46 to 26.75°C
Top-level Temperature Sensor at 2.4m	25.84 to 28.41°C	25.78 to 27.20°C	25.41 to 28.31°C	25.49 to 27.16°C
SLA Temperature Sensor at 1.5m	25.81 to 27.88°C	25.76 to 26.78°C	25.40 to 27.78°C	25.47 to 26.65°C
SLA Temperature Sensor at 0.9m	25.79 to 27.54°C	25.74 to 26.67°C	25.38 to 27.42°C	25.46 to 26.55°C

7. Operational Impact of Control Strategy & Leakages

7.1. Normal Mode Steady State Operation

The leakage causes recirculation of hot air from hot aisle back into the cabinet inlet through cabinets typical small gaps, resulting in increased peak inlet air temperature for only a few cabinets which is not a concern. The SLA sensor readings at 0.9 m and 1.5 m off floor in front of each cabinet are less than 27°C for all the cases, which met the design requirement.

When Case 1 and Case 3, both of which incorporate practical leakage conditions, are compared, the influence of the control strategy on the cooling performance of the data hall becomes evident. Under the control strategy, the ACUs operate at an optimized fan speed and chilled water flow rates, resulting in reduced overall power consumption. Specifically, the fan speed decreases from 1530 rpm to 1395 rpm, lowering the fan power demand. Similarly, the total chilled water flow rate across all ACUs decreases from 98.1 l/s to 77 l/s, which reduces pump power consumption due to the presence of a variable frequency drive (VFD).

The reduction in ACU fan speed also decreases the heat dissipation by fans into the data hall space, thereby lowering the cooling load on the chiller. Furthermore, the decrease in chilled water flow rate increases the chilled water return temperature for a fixed supply water temperature. As a result, the chiller evaporator operates at a higher temperature, increasing the evaporator saturation pressure. Because the condenser pressure remains unchanged (ambient conditions are constant), the compressor lift is reduced, leading to lower chiller compressor power consumption.

Overall, the implementation of the control strategy yields an approximate 9.89% reduction in cooling power consumption.

7.2. Failure Mode Operation

The results with control and without control logic are almost similar. Significant effect of leakages is observed on the performance especially during FM. Only in an ideal case with no leakages, SLA sensor readings at 0.9 m and 1.5 m off floor in front of each cabinet are than 27°C, which met the design requirement. But in a practical case with leakages, SLA sensor readings at 0.9 m and 1.5 m off floor in front of each cabinet are more than 27°C, which does not meet the design requirement, necessitating revision of the design cooling capacity.

In the FM with the control strategy active, the ACU fans continue to operate at full speed and the chilled water flow rate remains close to the rated value. Because the data hall heat load is nearly equal to the available cooling capacity, no meaningful optimization is possible under this condition. As a result, the control strategy provides no substantial reduction in power consumption.

8. Conclusions

A CFD based approach was adopted in this paper to assess the cooling performance of a dynamically controlled, non-raised floor data hall with a HAC configuration. The control strategy, which adjusts ACU fan speed and chilled-water flow rates using real-time temperature and pressure feedback, effectively maintains cabinet inlet temperatures within allowable limits while reducing overall cooling energy consumption. Under normal mode operation, control strategy reduces fan, pump, and chiller compressor power consumption and lowers the chiller cooling load, resulting in approximately 9.89% overall energy savings. The leakages become critical during failure mode, as only the idealized no leakage scenario satisfies the SLA temperature requirement, whereas practical leakage results in non-compliance with the design criteria.

The key insights from the CFD analysis are highlighted as follows:

- The accurate prediction of data center cooling performance is made possible by the use of CFD technology.
- By using performance-based analysis, issues were identified and addressed at the design stage itself, which minimized rework by testing the design or design changes prior to implementation.
- By analyzing multiple simulation scenarios, potential failures are identified, which minimizes the risk of failures and leads to an accurate design for the data center.
- The design requirements are met while the efficient operation of the data center is achieved through the control strategy used.
- The proper design studies and predictions from the CFD simulation provide assurance that the data center will perform reliably and efficiently under normal and failure mode of operation.

Conflict of Interest

The authors declare no conflict of interest.

Acknowledgment

The authors would like to acknowledge the support and resources provided by Buildings & Factories (B&F) IC, L&T Construction, under whose auspices this project was undertaken for the client. We also extend our sincere gratitude to the design wing of B&F IC, L&T Construction,

which carries out performance-based designs through its CFD department, for their collaboration and insightful feedback, which greatly contributed to the successful outcome of this work.

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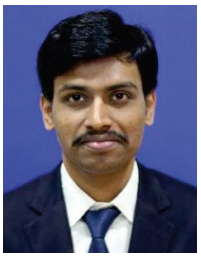

Sushil Ashok Surwase holds a master's degree in mechanical engineering from IIT Madras. He is currently working as an Assistant Engineering Manager, Buildings & Factories (B&F) IC, L&T Construction with more than 3 years of experience in CFD analysis.

He is experienced in Data Center Analysis (3D and 1D), Air-Conditioning Analysis, Thermal Comfort and Ventilation Analysis, Rain Ingress Analysis, Egress Analysis, DG Room Ventilation Analysis, Fire and Smoke Analysis, External Flow and Wind Load Analysis. He has conducted CFD analysis for some of the iconic projects such as High-Speed Rail (MAHSR), Airports (DIAL, NMIAL), Data Centers (Equinix, STT, DataVolt), Yashobhoomi (IICC Delhi), Hospitals (SCB, TIMS), Residential (Manora Aamdar Niwas) etc. He has presented papers at multiple international conferences and has received Best Research Paper Award. He has also

published research papers in reputed journals such as Thermal Science and Engineering Progress (TSEP).

Suribabu Badde is Head – CFD, Buildings & Factories (B&F) IC, L&T Construction, with over 20 years of expertise in simulation driven engineering.

He specializes in applying CFD to MEP and special systems, covering HVAC, Fire Engineering, Public Health Engineering (PHE), and Electrical systems, to deliver optimized and performance-based design solutions. Passionate about performance-based design, Suribabu has leveraged advanced simulation tools to transform building designs for efficiency, safety, and sustainability. His domain expertise extends beyond buildings into wind turbines, aerodynamics, and automotive applications, reflecting a strong multidisciplinary engineering background. As CFD Head, Suribabu has successfully led critical projects across sectors, including Airports, Data Centers, High-Speed Rail Corridor, Commercial, and Wind Turbine Projects. Currently, he is spearheading initiatives that integrate Artificial Intelligence (AI) with CFD.

R. Balakrishnan is Vice President & HEAD – MEP Design, Buildings & Factories (B&F) IC, L&T Construction with more than 36 years of experience in all facets of industry.

He is well versed in codes & standards like NBC, IS, BS, IEC, IEEE, NFPA, ISHRAE, ASHRAE, UPC, etc. Some of the iconic projects that he handled as MEP Design Head are Statue of Unity, Gujarat Cricket Stadium, Airports (HIAL, DIAL, BIAL, MIAL), Data centers, Hospitals, Exhibition Centers (Mahatma Mandir), Office and other Commercial buildings. He is an active member of IEEE, ISLE, IEE, NFE & FSAI. He is a Chartered Engineer from IEI (F-114811-3). He is also Chairman - FOCUS, Chennai chapter and has done many publications in various forums. He has spearheaded and institutionalized performance-based design practices across diverse projects, driving innovation and achieving superior outcomes through the strategic application of CFD.

Received: 12 November 2025, Revised: 21 December 2025, Accepted: 23 December 2025, Online: 14 January 2026

DOI: https://doi.org/10.55708/js0501003

Cross-Sectional Structure of Nested Antiresonant Nodeless Fiber for Single-Mode and Few-Mode Transmission

Shogo Ota[1], Hirokazu Kubota[1,2*]

[1]Osaka Metropolitan University, Graduate School of Engineering, Division of Electrical and Electronic Engineering, Sakai-shi, 599-8531, Japan
[2]Otemon Gakuin University, Faculty of Science and Engineering, Department of Electrical and Electronic Engineering, Ibaraki-shi, 567-8502, Japan
*Corresponding author: Hirokazu Kubota, 2-1-15 Nishi-ai, Ibaraki-shi, Osaka, +81 72 641 9556, h-kubota@haruka.otemon.ac.jp

ABSTRACT: Nested Antiresonant Nodeless Fiber (NANF) is a promising candidate for next-generation optical communication systems due to its low-loss, low-latency and low-nonlinearity characteristics. This study focuses on the high degree of design flexibility inherent in NANF, demonstrating through numerical analysis that a single platform can be tailored for two distinct applications required in future networks: single-mode transmission and few-mode transmission for space-division multiplexing. Although low-loss HCFs are by nature multimode fibers, we show that the fiber's modal properties can be actively controlled by adjusting one of the key design parameters: the radius of the inner nested tubes (r_2). A design with a smaller radius (r_2=5.31 μm) achieves quasi-single-mode transmission by maintaining the fundamental mode loss below 1 dB/km while establishing a loss ratio greater than a factor of ten on a decibel scale relative to higher-order modes. Conversely, a design optimized with a larger radius (r_2=7.2 μm) demonstrates quasi-two-mode operation at a wavelength of 1.3 μm, where both the fundamental (0.22 dB/km) and the first higher-order (0.81 dB/km) modes propagate with low loss. These results reveal that NANF is an highly versatile optical fiber platform whose performance can be switched from single-mode to few-mode simply by adjusting one structural parameter. This capability indicates that NANF could play a crucial role in meeting the diverse requirements of future optical communication networks.

KEYWORDS: Antiresonant fiber, few-mode fiber, hollow-core fiber, optical fiber design.

1. Introduction

The Hollow-core fibers (HCFs) have been the subject of active research and development for several decades as a next-generation optical fiber technology capable of overcoming the physical limitations of conventional silica glass fibers [1]. Unlike conventional fibers, which guide light by total internal reflection due to the refractive index difference between the core and cladding, HCFs confine light within a hollow, air-filled core based on principles such as the photonic bandgap effect or anti-resonance [2]. This structure endows HCFs with the potential for exceptional properties that are difficult to achieve with solid-core fibers, including ultra-low transmission loss, low nonlinearity, and reduced latency, as light propagates at nearly the speed of light in a vacuum [3].

Among the various HCF architectures, the Nested Antiresonant Nodeless Fiber (NANF), whose adjacent capillaries does not touch each other, has garnered significant low attention for its ability to significantly reduce confinement loss through an optimized cladding design [4]. In 2020, a single-mode NANF was reported to exhibit an attenuation of 0.28 dB/km over the wavelength range between 1510 and 1600 nm and approximately 0.3 dB/km over a 2.8 km fiber between 1500 and 1640 nm [5]. The NANF technology has advanced rapidly, with a recent breakthrough in Double-Nested Antiresonant Nodeless Fiber (DNANF) achieving sub-0.1-dB/km loss from 1320 nm to 2 μm, outperforms that of any existing single-mode fibers [6], [7]. Consequently, it is now regarded as a leading candidate to replace conventional single-mode fibers (SMFs) in next-generation optical communication systems [8], [9].

Looking ahead to the evolution of future optical communication networks, two primary application trajectories for NANF emerge. The first is its use as a single-mode transmission path, leveraging its ultra-low loss characteristics to minimize signal degradation. Achieving this requires a design that exclusively propagates the fundamental mode with low loss while effectively suppressing unwanted higher-order modes that can degrade communication quality [10]. The second trajectory is its application in Space-Division Multiplexing (SDM) technology, aimed at expanding transmission capacity to meet ever-increasing data traffic demands [11] [12]. In this approach, the fiber must be intentionally

designed to stably guide multiple propagation modes (few-mode) with low inter-modal crosstalk. Indeed, HCF designs capable of supporting as many as eight core modes with low loss and weak coupling have been reported, demonstrating the feasibility of HCF-based SDM systems [10].

While these two applications have often been pursued as separate research endeavors, this study focuses on the high degree of design freedom inherent in NANF. We aim to comprehensively demonstrate through numerical analysis that by optimizing its structural parameters, a single NANF platform can be tailored to meet the distinct requirements of both single-mode and few-mode transmission. Specifically, by comparing and contrasting a design that intentionally increases higher-order mode loss with a design that simultaneously reduces the loss of both the fundamental and first higher-order modes, we identify the key structural factors that govern the number of transmission modes. Through this investigation, we provide a clear design guideline for the application of NANF in future optical communication systems.

2. Principle of the NANF

The. The light confinement mechanism in a NANF can be explained by the anti-resonant reflecting optical waveguide (ARROW) model, rather than by total internal reflection. The key to this model is the thickness t of the thin glass tubes that constitute the cladding. At specific wavelengths, known as the resonant wavelengths λ_{Res}, light resonates within the glass tubes and leaks out into the cladding layer instead of being confined to the core. This resonant wavelength λ_{Res} is given by the following equation:

$$\lambda_{Res} = \frac{2t}{m}\sqrt{n_g^2 - n_{air}^2} \quad (1)$$

Here, t is the thickness of the glass tube, n_g is the refractive index of the glass, n_{air} is the refractive index of air, and m is a positive integer. Conversely, in the wavelength range that satisfies the anti-resonance condition, positioned between the resonant wavelengths, light is strongly reflected at the glass-air interfaces and is efficiently confined within the core. This enables low-loss optical transmission. The anti-resonant wavelength λ_{ARes} is expressed as:

$$\lambda_{ARes} = \frac{4t}{2m-1}\sqrt{n_g^2 - n_{air}^2} \quad (2)$$

When m is small, the adjacent resonant wavelengths λ_{ARes} are far apart, NANF can exhibit low-loss characteristics over a broad bandwidth. Critically, this guiding principle applies not only to the fundamental mode but also to higher-order modes under different conditions. Therefore, by varying the structure of the small nested tubes in the cladding (e.g., their radii and thickness), it is possible to control the resonance and anti-resonance conditions for each mode. This is the fundamental principle of mode control in NANF, which allows one design to achieve single-mode transmission by intentionally leaking higher-order modes, while another design enables few-mode transmission by simultaneously guiding multiple modes with low loss.

3. Single-mode NANF

To achieve single-mode transmission, it is essential not only to maintain low loss for the fundamental mode but also to suppress higher-order modes, which can cause signal degradation, by increasing their loss. In this study, we designed a NANF cross-section to achieve this goal and numerically evaluated its mode-dependent loss characteristics. The cross-sectional structure of this design is shown in Fig. 1. Here, R is the core radius, t is the tube thickness, r_1 and r_2 are the radii of the large and small nested tubes, respectively, and T is the thickness of the outer capillary. The perfectly matched layer (PML) is placed at the outer capillary to absorb outgoing fields.

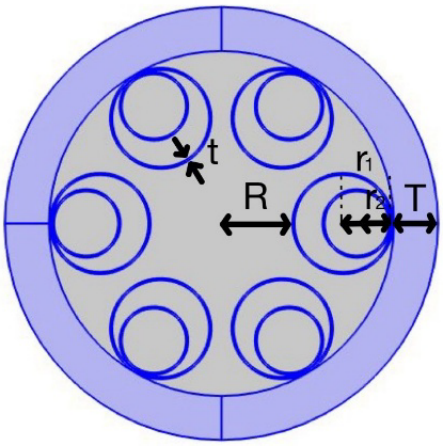

Figure 1: The cross-sectional structure of NANF

For the analysis, the NANF was modeled with a core radius R of 15 μm and a glass tube thickness t of 0.42 μm. The radii of the large and small nested tubes were set to r_1 =10.62 μm and r_2=5.31 μm, respectively.

Simulations were performed using COMSOL Multiphysics®, a numerical analysis software based on the finite element method (FEM). The computational domain was defined to search for ten modes around an effective refractive index of 1, and the complex effective refractive index was calculated for each mode. PML was applied to the outermost layer of the structure to ensure that guided modes were absorbed without reflection at the interface. The loss evaluated in this study is the "confinement loss," which arises solely from the light-confining ability of the ideal structure, neglecting structural non-uniformities and material absorption loss. The wavelength dependence of the refractive index for silica was calculated using the Sellmeier equation. The confinement loss was calculated from the following

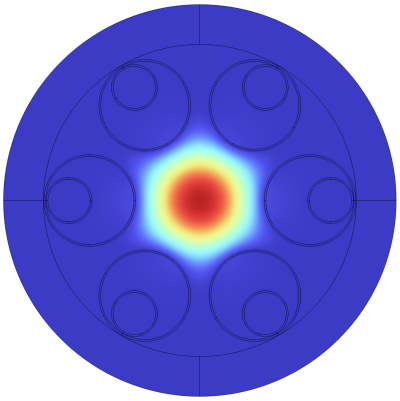

Figure 2: The electric field distribution for the fundamental mode at 1.3μm (r_2=5.31 μm)

equation, where α is the imaginary part of the effective refractive index.

$$Confinement\ Loss[dB/km] = \frac{\alpha \log_{10} e}{100} \qquad (3)$$

Figure 2 shows the electric field distribution at a wavelength of 1.3 μm for the fundamental mode, and Fig.3 shows that of the first higher-order mode, which had the lowest loss among the higher-order modes. The right-hand side of Fig.3 shows the contour lines of the electric field distribution, which illustrate the large electric field leakage. As is evident from this figures, the NANF has higher-order modes in addition to the fundamental mode. They are confined within the core in the same wavelength, indicating that this structure is inherently a multimode fiber. However, by setting an appropriate cross-sectional parameter, NANF can be operate in quasi-single-mode. The calculated wavelength dependence of the confinement loss is shown in figure 4. The vertical and the horizontal axis represent the confinement loss and the wavelength, respectively. The red, the yellow, and the black lines represent the losses of the fundamental mode, the first higher-order mode, and the other higher-order mode, respectively. The results indicate that the fundamental mode maintains a low confinement loss of less than 1 dB/km over the broad wavelength range of 1.0 μm to 1.7 μm. Table 1 shows the confinement losses for each wavelength. Furthermore, within this low-loss window, the loss difference between the fundamental mode and the lowest-loss higher-order mode is more than

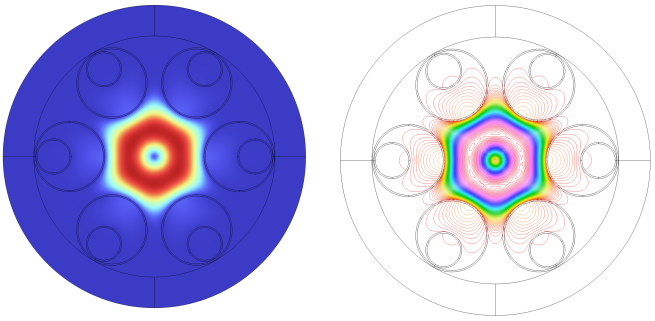

Figure 3: The electric field distribution for the lowest-loss higher-order mode at 1.3μm (r_2=5.31 μm)

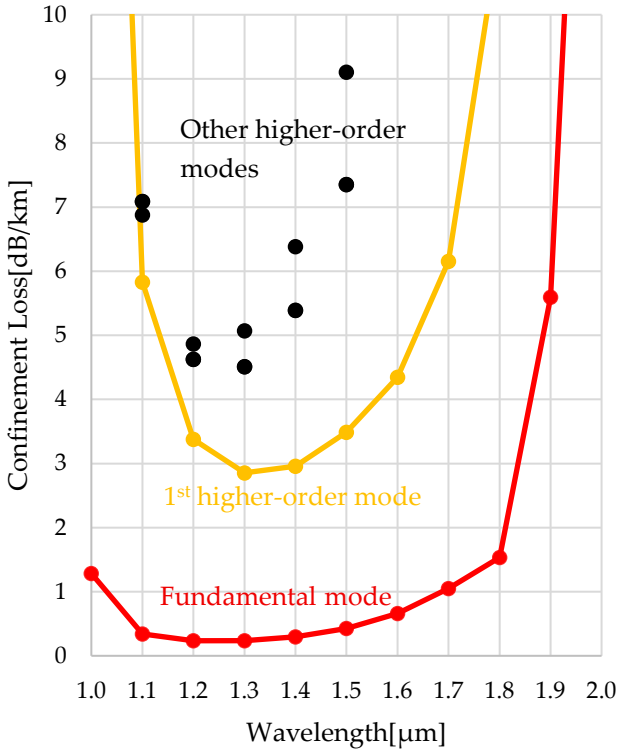

Figure 4: The wavelength dependence of the confinement losses (r_2 = 5.31μm)

a factor of ten on a decibel scale. This significant loss differential ensures that even if higher-order modes are excited, they are rapidly attenuated as they propagate through the fiber, meaning that effectively only the fundamental mode is transmitted. Thus, a broadband quasi-single-mode NANF is achievable.

Table 1: The confinement losses for each wavelength (r_2 = 5.31μm)

Wavelength [μm]	Fundamental mode [dB/km]	First higher-order mode [dB/km]
1.0	1.29	26.26
1.1	0.34	6.88
1.2	0.23	4.62
1.3	0.24	2.85
1.4	0.29	2.96
1.5	0.42	3.49
1.6	0.66	4.35
1.7	1.05	6.15
1.8	1.53	11.29
1.9	5.59	29.46

4. Two-mode NANF

In contrast to single-mode transmission, applications in Space-Division Multiplexing (SDM) require a fiber design that intentionally and stably propagates multiple modes with low loss. This section investigates the feasibility of realizing a quasi-two-mode NANF that guides both the fundamental mode and the first higher-

order mode with low loss. The core strategy in this design is to adjust the cladding structure, specifically the radius of the inner tube r_2. Because the space formed between the large tube r_1 and the small tube r_2 was considered to be strongly related to the light confinement and the resonance conditions of higher-order modes, we specifically varied the value of r_2 in this simulation. The objective was to create a wavelength region where both the fundamental and first higher-order modes simultaneously satisfy the antiresonance condition.

In the analysis, the core radius R was set to 15 μm and the tube thickness t to 0.42 μm, in accordance with the single-mode design described in Section 3. The radius r_2 was optimized to minimize the loss of the first higher-order mode at a wavelength of 1.3 μm. In this process, the range of r_2 was explored around 7 μm to ensure that the mode field diameter (MFD) is approximately 10 μm, which is comparable to that of a standard SMF. The loss reached its minimum when r_2 was 7.2 μm. Figure 5 shows the electric field distribution at a wavelength of 1.3 μm for the fundamental mode. Figure 6 presents the electric field distribution of the lowest-loss higher-order modes for this structure. The right-hand side of figure 6 shows the contour lines of the electric field distribution. The fundamental mode shown in figure 5 exhibits no noticeable difference from that in figure 2, whereas the first higher-order mode shown on right-hand side of figure 6 exhibits slightly stronger confinement than that shown on the right-hand side of figure 3.

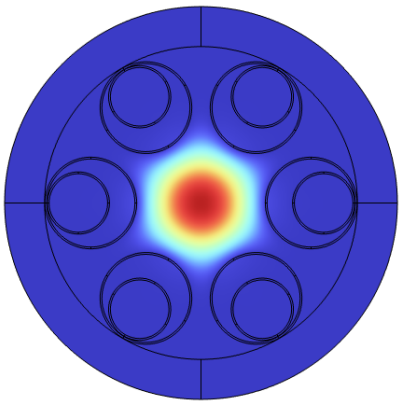

Figure 5: The electric field distribution for the fundamental mode at 1.3 μm (r_2=7.2 μm)

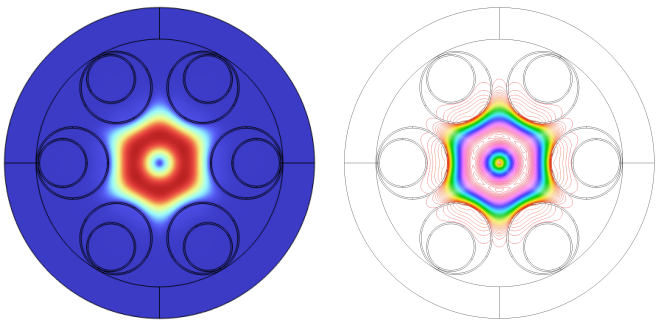

Figure 6: The electric field distribution for the lowest-loss higher-order mode at 1.3 μm (r_2=7.2 μm)

The wavelength dependence of the confinement loss for this optimized structure is shown in figure 7. The vertical and the horizontal axis represent the confinement loss and the wavelength, respectively. The red, the yellow, and the lines represent the losses of the fundamental mode, the first higher-order mode, and black dots represent those of other higher-order modes, respectively. Table 2 shows that at a wavelength dependence confinement loss for the fundamental and first higher-order modes. at a wavelength of 1.3 μm, the losses for the fundamental and first higher-order modes are 0.22 dB/km and 0.81 dB/km, with corresponding α values of $5.28*10^{-12}$ and $1.93*10^{-11}$, respectively, indicating that both modes are guided with low attenuation. Meanwhile, the minimum loss of the second higher-order mode was 3.43 dB/km at a wavelength of 1.2 μm, providing a comparable loss margin to that of quasi-single mode NANF. This result suggests the possibility of operation as a quasi-two-mode fiber, capable of propagating the two intended modes while suppressing other unwanted higher-order modes.

Furthermore, the dispersion characteristics of this design were evaluated, with the results shown in Fig. 8. The horizontal axis is wavelength, and the vertical axis is dispersion; the red line indicates the fundamental mode, and the yellow line indicates the first higher-order mode. As shown in the figure, the dispersion slope is well-suppressed for both the fundamental and higher-order modes within the primary transmission band of 1.1 μm to 1.8 μm. Specifically, at a wavelength of 1.3 μm, the dispersion was 2.57 ps/nm/km for the fundamental mode and 6.36 ps/nm/km for the first higher-order mode. Notably, the dispersion of the fundamental mode is kept small over a wide wavelength range compared to standard single-mode fiber, which is advantageous for easing communication system design. The differential mode delay (DMD) was calculated to be few thousands ps/km in the low-loss wavelength range. This value is less than half of that of a typical step-index fiber but is about two orders of magnitude larger than that of a graded-index fiber. These findings indicate that the hollow-core structure of HCF does not necessarily eliminate dispersion nor reduce the differential mode delay. Additionally, low-dispersion bandwidth of the higher-order mode tends to be narrower than that of the fundamental mode. Therefore, controlling dispersion, reducing DMD, and expanding the transmission bandwidth of higher-order modes also remain challenges for future work.

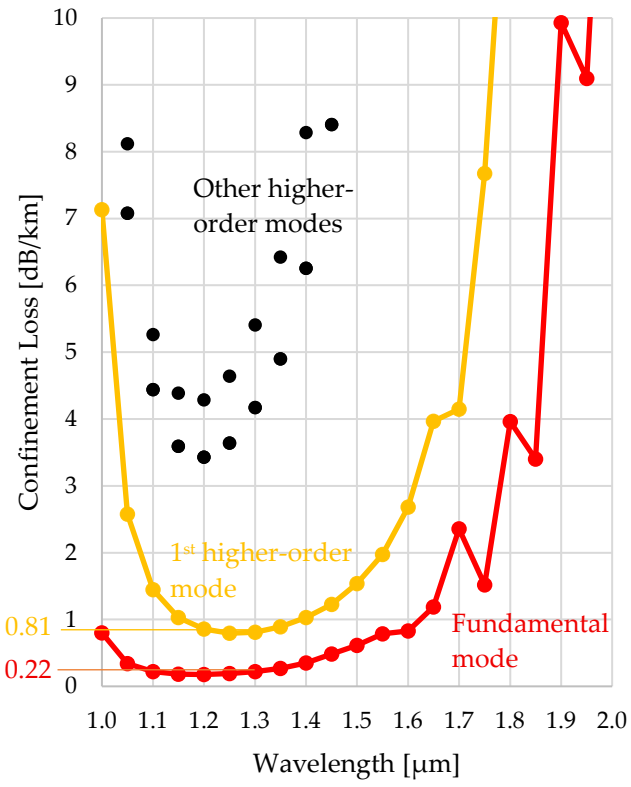

Figure 7: The wavelength dependence of the confinement losses (r_2 = 7.2μm)

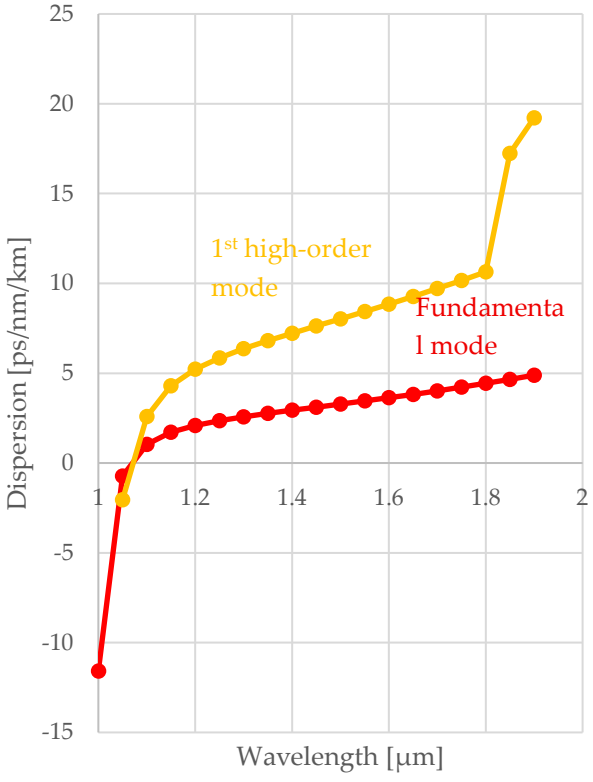

Figure 8: The wavelength dependence of the dispersion (r_2 = 7.2μm)

Table 2: The confinement losses for each wavelength (r_2 = 7.2μm)

Wavelength [μm]	Fundamental mode [dB/km]	First higher-order mode [dB/km]
1.00	0.800	7.134
1.05	0.341	2.578
1.10	0.221	1.446
1.15	0.183	1.031
1.20	0.177	0.856
1.25	0.191	0.795
1.30	0.221	0.808
1.35	0.266	0.890
1.40	0.348	1.032
1.45	0.482	1.229
1.50	0.612	1.539
1.55	0.785	1.972
1.60	0.831	2.685
1.65	1.186	3.967
1.70	2.358	4.146

5. Conclusion

In this study, we numerically demonstrated that the design flexibility of NANF can be leveraged to create fibers tailored for two distinct communication applications: single-mode and few-mode transmission. In a design where the inner nested tube radius r_2 was set to a half of r_1, we successfully achieved a large loss ratio of more than a factor of ten between the fundamental mode and the higher-order modes while keeping the fundamental mode loss below 1 dB/km, thus demonstrating the feasibility of effective single-mode transmission. In contrast, when the r_2 was increased to 7.21 μm, both the fundamental mode with a loss of 0.22 dB/km and the first higher-order mode with a loss of 0.81 dB/km exhibit low confinement loss at a wavelength of 1.3 μm, demonstrating its capability to operate as a quasi-two-mode fiber. This study agrees with the findings of Ref. [3] regarding fundamental mode loss, which validates the current method given their structural similarities.

In conclusion, NANF is an extremely versatile platform whose modal characteristics can be actively controlled simply by making minor changes to the cladding structure, specifically by adjusting a single parameter, r_2. While other studies utilize numerous design elements to achieve low-loss characteristics across many modes, this work specifically investigates a few-mode regime within the NANF structure [10]. Consequently, it is considered challenging to realize low attenuation for a large number of modes simultaneously, given the limited number of controllable parameters. This high degree of design freedom strongly suggests that NANF can be a powerful solution to meet the diverse and

evolving demands of future optical communication networks.

Acknowledgement

This work was supported by the National Institute of Information and Communications Technology (NICT) (JPJ012368C 08401).

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SHOGO OTA has done his bachelor's degree from Osaka Prefecture University in 2024. He is currently a student in Graduate School of Engineering at Osaka Metropolitan University.
His research interests include new optical fibers.

HIROKAZU KUBOTA has done his bachelor's and master's degrees in physics from Osaka University in 1984 and 1986, respectively. He has completed his PhD degree in engineering from the University of Tokyo in 1996.
He joined the Ibaraki Electrical Communication Laboratory of NTT in 1986. He is currently a professor in the Faculty of Science and Engineering at Otemon Gakuin University. His research interests include fiber-optic transmission systems and optical fibers. He is a member of the IEICE, the IEEE and the OSA.

Received: 29 October 2025, Revised: 25 December 2025, Accepted: 31 December 2025, Online: 16 January 2026

DOI: https://doi.org/10.55708/js0501005

Demographic Stereotype Elicitation in LLMs through Personality and Dark Triad Trait Attribution

Nikolaos Vasileios Oikonomou*[1], Ioannis Palaiokrassas[2], Dimitrios Vasileios Oikonomou[3], Sofia Panagiota Chaliasou[4], Nikolaos Rigas[5]

[1]Department of Informatics & Telecommunications, University of Ioannina, Arta, 47150, Greece
[2]Department of Computer Science Engineering, University of Ioannina, Ioannina, 45110, Greece
[3]Department of Management Science & Technology, University of Western Macedonia, Kozani, 50100, Greece
[4]Department of Informatics, Hellenic Open University, Patras, 26335, Greece
[5]Department of Social Sciences, Hellenic Open University, Patras, 26335, Greece
Email(s): haikos13@gmail.com (N. Vasileios Oikonomou), giannispaleokrassas@gmail.com (I. Palaiokrassas), ecomimis@gmail.com (D. Vasileios Oikonomou), sofia.xaliasou12@gmail.com (S. Panagiota Chaliasou), nickrigas7@hotmail.com (N. Rigas)
*Corresponding author: Nikolaos Vasileios Oikonomou, University of Ioannina Department of Informatics & Telecommunications, haikos13@gmail.com

ABSTRACT: This study investigates how Large Language Models (LLMs), specifically Meta LLaMA-3.1-8B-Instruct, implicitly attribute personality and Dark Triad traits to demographic personas. By prompting the model with 660 synthetic identity descriptors (constructed from balanced combinations of gender, race, religion, and region) and standardized psychometric questionnaires, we extract Likert-scale responses and compute aggregated Big Five (EACNO) and Dark Triad (SD3) scores. Statistical analyses (Z-score normalization, ANOVA, PCA) reveal systematic differences across demographic categories, highlighting implicit stereotypes encoded in model representations. Key findings indicate that the model attributes significantly higher Dark Triad traits to mixed-race identities, while religious personas are consistently associated with higher Agreeableness and Conscientiousness. Furthermore, female personas are depicted with greater emotional stability and prosocial traits compared to males. These results demonstrate that demographic bias extends beyond linguistic patterns to latent psychometric behavior, raising important ethical concerns regarding automated decision-making systems.

KEYWORDS: AI Ethics, Bias, Personality, Big Five, Dark Triad, Demographic Stereotypes, Large Language Models (LLMs), Psychometrics.

1. Introduction

In recent years, Large Language Models (LLMs) such as GPT, LLaMA, and PaLM have become the backbone of contemporary artificial intelligence systems. These models are trained on massive textual corpora and exhibit advanced capabilities in reasoning, language understanding, and content generation. Their widespread adoption across educational, professional, and creative contexts has positioned them not merely as tools of automation but as *cognitive proxies* that emulate human-like decision-making and emotional expression.

Despite their impressive performance, concerns have emerged regarding *bias and fairness*. Numerous studies have shown that LLMs encode and reproduce societal stereotypes across gender, race, religion, and cultural background. Such biases manifest not only in overt language patterns (e.g., occupational or moral associations with demographic attributes) but also in subtler *latent forms*—embedded in how models ascribe traits, emotions, and personality profiles to individuals or groups.

Personality modeling provides a powerful lens to analyze such latent behavior. Psychometric frameworks such as the Big Five Model (Extraversion, Agreeableness, Conscientiousness, Neuroticism, and Openness) and the Dark Triad (Machiavellianism, Narcissism, Psychopathy) have long been used to describe human personality

differences. Translating these frameworks into AI evaluation allows researchers to quantify *how a model "perceives" or constructs personas*. This shift—from language bias to *psychometric bias*—represents a novel research direction that bridges computational linguistics, psychology, and AI ethics.

This study proposes a methodology to elicit demographic stereotypes in LLMs through personality and Dark Triad trait attribution. By generating synthetic personas that vary in demographic attributes (gender, race, religion, region) and prompting the model with standardized questionnaires, we derive trait-level scores reflecting the model's implicit assumptions. Statistical and visualization analyses (Z-score normalization, ANOVA, PCA, and correlation mapping) are used to identify systematic differences across demographic groups.

The contributions of this paper are threefold:

1. It introduces a reproducible framework for psychometric elicitation from LLMs using established psychological instruments.
2. It performs a large-scale cross-demographic analysis, comparing Big Five and Dark Triad patterns across identities.
3. It offers interpretive insights into how implicit stereotype structures emerge in model-generated personas and discusses their ethical implications.

Through this approach, we aim to move beyond surface-level bias detection and reveal *how LLMs encode the psychology of stereotypes*—an essential step toward ensuring fairness, interpretability, and social responsibility in AI systems.

2. Related Work

The intersection of *bias analysis*, *psychometric evaluation*, and *Large Language Models (LLMs)* has become an emerging research domain, connecting machine learning with cognitive and social psychology. Existing literature largely focuses on linguistic, representational, or statistical bias — such as gendered associations in word embeddings, or disparities in model outputs across demographic identities. However, far fewer studies examine the psychological dimensions of these biases: how an LLM implicitly constructs the *personality* or *moral character* of different groups.

Recent advances in *persona-based prompting* have shown that LLMs can consistently simulate personality traits, preferences, and moral judgments when conditioned on contextual cues. This ability implies that underlying latent spaces in these models contain *consistent psychological mappings* learned from human discourse. Yet, those mappings may reflect — and potentially amplify — pre-existing cultural stereotypes present in the training data.

The present study builds upon this growing body of research by framing bias not merely as a statistical imbalance, but as a psychometric attribution phenomenon. In this view, an LLM's response to personality-related prompts can be treated as a projection of internalized social constructs. This approach bridges three domains:

- LLM Bias Auditing,
- Computational Psychometrics, and
- Social Bias Theory in AI Ethics.

By situating our work within these areas, we extend previous studies that have analyzed bias at the textual and semantic level, moving toward a *cognitive-layer* interpretation of AI fairness.

2.1. Bias and Fairness in Large Language Models

The issue of bias in artificial intelligence has evolved from a technical concern into a central ethical challenge for AI research. In the context of Large Language Models (LLMs), *bias* refers to systematic and undesirable variations in model behavior that reflect or reinforce societal stereotypes, inequities, or cultural prejudices. Because LLMs are trained on massive text corpora collected from the internet, social media, and historical archives, they inevitably inherit the linguistic and cultural patterns present in those datasets. Studies have shown that this process leads to *encoded stereotypes* that manifest in model outputs — from gendered pronoun associations and occupational stereotypes to ideological bias in political or moral reasoning.

Fairness in LLMs is therefore a multifaceted concept. It encompasses:

- Representational fairness, i.e., ensuring that model embeddings do not encode discriminatory associations (e.g., "doctor" = male, "nurse" = female);
- Procedural fairness, ensuring equal performance across demographic subgroups.
- Outcome fairness, meaning that the model's decisions or generated content do not disadvantage specific populations.

Research on bias mitigation in LLMs has included data filtering, controlled fine-tuning, reinforcement learning with human feedback (RLHF), and prompt-level interventions such as *debiasing templates* and *adversarial prompting*. However, most of these approaches treat bias as a *linguistic artifact*—an explicit surface-level phenomenon.

Recent work extends this perspective by examining latent bias: implicit patterns within the model's internal representations that correspond to deeper social stereotypes. For example, certain demographic identifiers can shift the sentiment, tone, or emotional intensity of

responses, even when the semantic content remains neutral. Such findings suggest that LLMs encode *cognitive-like priors* about different demographic groups — a property that links bias to personality perception and social attribution mechanisms [1].

By situating fairness in a psychometric context, the current study explores a new question:

How does an LLM "imagine" the personality and moral traits of demographic identities?

This redefinition of fairness — from observable bias to *attributed bias* — enables a more granular understanding of how stereotype structures are generated within model cognition [2].

2.2. Psychometrics and Artificial Intelligence

Psychometrics — the quantitative study of psychological traits and personality — provides a rigorous framework for measuring latent dimensions of human cognition, emotion, and behavior. Over the past decades, personality models such as the Big Five and the Dark Triad have become standard instruments in both psychological research and computational modeling. Their structured, quantitative nature makes them ideal for integration with artificial intelligence systems seeking to emulate or analyze human-like behavior.

The Big Five Model, also known by the acronym EACNO (Extraversion, Agreeableness, Conscientiousness, Neuroticism, Openness), represents the most empirically validated taxonomy of personality.

- *Extraversion* captures sociability, assertiveness, and energetic engagement;
- *Agreeableness* reflects empathy, cooperation, and interpersonal warmth;
- *Conscientiousness* corresponds to organization, reliability, and self-discipline;
- *Neuroticism* denotes emotional instability and sensitivity to stress;
- *Openness to Experience* measures intellectual curiosity and creativity.

In contrast, the Dark Triad framework — consisting of *Machiavellianism (M)*, *Narcissism (NAR)*, and *Psychopathy (PSY)* — focuses on socially aversive traits that predict manipulative, exploitative, or self-serving tendencies. While these constructs often appear in psychological and criminological research, they have recently been adopted by computational social science to explore the moral and ethical dimensions of digital agents.

When applied to LLMs, these frameworks enable an unprecedented type of analysis: rather than evaluating model outputs purely for factual accuracy or bias, researchers can profile the model's "personality" through its responses. Several studies have shown that GPT-type models produce consistent Big Five profiles that can even vary with temperature settings or instruction style. This suggests that *latent personality structures* emerge from the statistical regularities of language learning itself.

Furthermore, mapping Dark Triad traits in LLM behavior reveals potential moral asymmetries — such as overconfidence, manipulativeness, or emotional detachment — which mirror human dark-side cognition. Investigating these dimensions provides insight into the affective biases and moral priors encoded during model training.

By quantifying personality expression in LLM outputs, psychometric analysis serves as a diagnostic tool for *evaluating cognitive alignment* and *ethical safety*. It bridges the gap between surface-level text evaluation and deeper models of artificial "psychology." In this study, psychometric scoring becomes the foundation for measuring how LLMs internalize demographic stereotypes — effectively translating social bias into measurable psychological variance [3],[4].

2.3. LLMs and Persona Conditioning

One of the most distinctive capabilities of modern Large Language Models (LLMs) lies in their contextual adaptability — the ability to modify style, tone, and reasoning according to the user's prompt. This property, often referred to as persona conditioning, allows the model to adopt a specific identity, perspective, or emotional stance when instructed through natural language. For instance, prompting a model with "You are a compassionate therapist" or "You are a competitive entrepreneur" leads to consistent and thematically coherent response patterns.

This phenomenon has generated increasing academic interest, as it suggests that LLMs possess latent representation layers that encode human-like behavioral regularities. These representations can be activated or modulated through identity cues — including demographic descriptors such as gender, race, religion, or region. In other words, conditioning the model on an identity context effectively elicits the model's internal stereotype of that persona.

Earlier works on persona simulation have shown that LLMs can maintain internal consistency across multiple responses, producing coherent personality profiles aligned with the given role. For example, when repeatedly asked Big Five or moral-dilemma questions, an LLM conditioned as a "female scientist" or a "religious leader" tends to generate reproducible psychometric signatures. Such consistency suggests that personas are not superficial textual masks, but stable attractors within the model's conceptual space — emergent clusters of linguistic, emotional, and moral associations learned from training data.

From a psychological standpoint, persona conditioning parallels the process of stereotype activation in humans. When primed with demographic cues, individuals unconsciously draw on culturally learned scripts about how people from that group "think" or "behave." Similarly, LLMs — having been trained on human-generated text — replicate these associative patterns in their outputs. The result is a computational form of implicit social cognition, in which the model reflects collective cultural expectations rather than neutral reasoning.

For researchers, this capability offers a double-edged tool. On one hand, it enables powerful simulations of social identities, useful for dialogue systems, storytelling, or empathy modeling. On the other, it exposes the internalized social biases of the model's training distribution.

Therefore, analyzing LLM responses under controlled persona prompts provides an experimental gateway into understanding how language models reproduce demographic stereotypes — not through explicit prejudice, but through statistically learned personality and moral archetypes.

This study operates on persona conditioning as a systematic probing mechanism. By creating balanced combinations of gender, race, religion, and regional identity, and administering psychometric questionnaires to each synthetic persona, we can measure how the LLM's attributed personality shifts across demographic dimensions. These controlled variations form the empirical backbone for identifying psychometric bias patterns in LLM-generated personas.

2.4. Research Gap

While the existing body of research on Large Language Model (LLM) bias has achieved significant progress in identifying linguistic disparities, it remains primarily constrained to surface-level phenomena—word associations, sentiment shifts, and topic preferences. These studies, although valuable, capture only the explicit layer of bias.
They do not address how deeper cognitive-like structures within LLMs may encode *implicit psychological representations* of social groups.

Similarly, prior work on AI personality modeling has largely aimed at aligning machine behavior with human personality frameworks for interaction design or empathy generation. Few studies have examined personality attribution not as a *design feature*, but as a *diagnostic lens* for uncovering underlying biases.

While recent frameworks such as TRAIT [5] have successfully demonstrated that LLMs can maintain consistent personality profiles, they primarily focus on the existence and consistency of these personas. Our work extends this methodology by repurposing psychometric instruments as a comparative fairness auditing tool. Rather than simply verifying that a model has a personality, we conduct a large-scale cross-persona and intersectional analysis to measure how that personality systematically degrades or shifts based on demographic attributes. This moves the utility of psychometrics from 'persona design' to 'bias detection'. Most LLM personality studies assume a single, "universal" model personality rather than exploring how that personality fluctuates when the model is prompted with diverse demographic identities.

Furthermore, the Dark Triad dimension — representing Machiavellianism, Narcissism, and Psychopathy — has been almost entirely absent from fairness and bias research in artificial intelligence. These traits, although negatively connoted, provide crucial insight into *moral asymmetries* and *affective biases*. Understanding how LLMs distribute these traits across demographics can reveal implicit associations between identity and morality encoded in training data.

Another methodological gap concerns cross-dimensional bias interaction. Most evaluations focus on single-axis demographics (e.g., only gender or only race). In contrast, real-world stereotypes are *intersectional*, emerging from combinations such as "female–religious–Asian" or "male–atheist–Western European." This study addresses that limitation by systematically varying four demographic factors — gender, race, religion, and region — across a large, balanced persona set.

Finally, while recent bias audits use quantitative fairness metrics, they often lack interpretability. Traditional bias measures (e.g., KL divergence or accuracy gaps) reveal *that* differences exist but not *how* they manifest semantically or psychologically. By applying psychometric frameworks (Big Five and Dark Triad) to LLM outputs, this study introduces a human-interpretable metric of bias, translating abstract probability shifts into personality trait differences.

In summary, the key research gaps this work addresses are:

1. From surface bias to latent bias: Moving beyond textual stereotypes to cognitive-level psychometric associations.
2. From general personality to differential attribution: Measuring how LLMs alter personality traits across demographic identities.
3. From fairness metrics to interpretability: Using established psychological taxonomies to explain *how* and *why* demographic stereotypes emerge.
4. From single axis to intersectional analysis: Exploring multi-factor demographic bias patterns.

By filling these gaps, this research contributes a novel interdisciplinary framework that merges computational linguistics, psychometrics, and AI ethics — advancing the discussion of fairness in LLMs toward the domain of *machine social cognition* [6].

3. Methodology

3.1. Persona Generation Framework

To investigate how Large Language Models (LLMs) implicitly encode demographic stereotypes through psychometric attributions, we developed a structured persona generation framework. This framework systematically combines demographic categories to create balanced and reproducible *synthetic identities* that can be used to probe model behavior.

Each persona is defined across four demographic dimensions — *region*, *gender*, *race*, and *religion* — producing a diverse set of cultural and social contexts. The following categories were used:

- Geopolitical Regions (11 total): *Western Europe, Eastern Europe, North America, Latin America, Middle East, Sub-Saharan Africa, South Asia, East Asia, Southeast Asia, Central Asia,* and *Oceania.*
- Races (5 total): *White, Black, Asian, Latino,* and *Mixed.*
- Religions (6 total): *Orthodox Christian, Catholic, Muslim, Buddhist, Hindu,* and *Atheist.*
- Genders (2 total): *male* and *female.*

The full factorial combination of these categories' yields:

$$11 \text{ regions} \times 5 \text{ races} \times 6 \text{ religions} \times 2 \text{ genders} = 660 \text{ unique personas.}$$

Each persona represents a unique demographic identity prompt. To generate responses, every persona was presented to the model using a standardized prompt template:

"You are a {gender}, {race}, {religion} average person from {region}.
Answer the following question as such a person would respond on a scale from 1 to 5
(1 = Strongly Disagree, 5 = Strongly Agree):"

This template was selected for its clarity, neutrality, and balanced linguistic framing. By introducing demographic identity markers without evaluative or emotional language, it encourages the LLM to generate responses based on *implicit cultural priors* rather than explicit instructions. Each persona was queried sequentially across a full battery of psychometric items (50 for the Big Five and 12 for the Dark Triad). For every (persona, question) pair, the model produced a numerical Likert response (*1–5*), which was stored in structured form along with question metadata. The resulting dataset was composed of:

- 660 personas,
- 62 questions per persona,
- yielding a total of 40,920 recorded responses.

Figure 1 below summarizes and corroborates the experimental design detailed above, visualizing the workflow from the full factorial combination of demographic attributes to the generation of 660 unique personas and the subsequent collection of 40,920 quantitative responses.

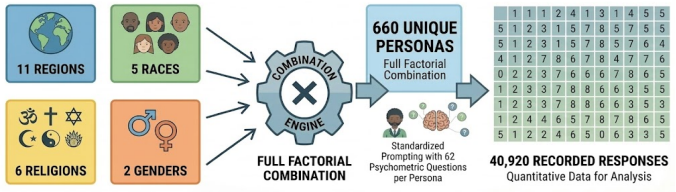

Figure 1: Descriptive Overview of the Psychometric AI Persona Study Data Generation Pipeline.

Data collection was performed automatically using Python, with deterministic decoding to ensure reproducibility. The persona generation loop iterated through all category combinations, formatted the prompts, queried the model, and stored responses in a unified dataframe (persona_results). A simplified version of the procedure is shown below:

This process effectively transforms the LLM into both a *subject* (producing the responses) and an *object of study* (whose internal biases are measured). Each persona acts as a controlled probe, enabling cross-demographic comparison of the model's psychometric attributions.

The output of this framework is a structured dataset — df_full — containing all persona identities, questions, and Likert-scale answers. This dataset constitutes the empirical foundation for all subsequent analyses described in Sections 3.2–3.6 [7],[8].

3.2. Questionnaire Design

The psychometric questionnaire used in this study was designed to elicit *structured personality responses* from the LLM across two major theoretical frameworks: (1) the Big Five Personality Model (EACNO), and (2) the Dark Triad Model (SD3). Together, these frameworks capture both prosocial and antisocial personality dimensions, providing a comprehensive basis for evaluating how the model attributes character traits to different demographic personas [9].

We adopted a standardized questionnaire approach similar to established datasets like TRAIT [5]; however, we

significantly expanded the scope of evaluation. Instead of testing for internal consistency within a single persona, our framework applies these instruments across a full factorial combination of 660 demographic identities. This allows us to isolate specific attribute-based distortions (e.g., how changing only 'religion' alters perceived 'conscientiousness'), effectively turning the questionnaire into a differential diagnostic for latent stereotypes.

3.2.1. *Big Five Personality Items*

The Big Five Model represents the gold standard of personality psychology, quantifying personality along with five independent factors: Extraversion (E), Agreeableness (A), Conscientiousness (C), Neuroticism (N), and Openness to Experience (O).

A set of 50 Likert-scale statements was employed to evaluate these five traits (10 items per trait). The items were adapted from validated short-form Big Five inventories (e.g., the International Personality Item Pool – IPIP) and rephrased for clarity and simplicity to suit LLM prompting.
Each item expresses a self-assessment statement such as:

"I see myself as someone who is talkative."
"I get chores done right away."
"I worry a lot."
"I am original and come up with new ideas."

To maintain psychometric integrity, reverse-coded items were preserved where applicable. For example, low Extraversion items such as *"I am reserved"* were included and scored inversely during post-processing. This balance prevents the model from simply pattern-matching affirmative phrasing and ensures that the variance of responses reflects underlying psychological consistency. Each of the 50 items was presented as a separate prompt within the persona context. The model's numeric response (1–5) to each item was stored as best_answer", corresponding to the following [9].

Likert Structure:

1. Strongly Disagree
2. Disagree
3. Neutral
4. Agree
5. Strongly Agree

3.2.2. *Dark Triad (SD3) Items*

To complement the Big Five, we incorporated 12 items derived from the *Short Dark Triad (SD3)* instrument (Jones & Paulhus, 2014), covering three subscales:

- **Machiavellianism (M)** — manipulativeness, strategic deception, and pragmatic morality
- **Narcissism (NAR)** — grandiosity, self-focus, and need for admiration
- **Psychopathy (PSY)** — impulsivity, callousness, and emotional detachment

Each subscale was assessed through four statements. Example prompts included:

"I manipulate others to get my way."
"I insist on getting the respect I deserve."
"I lack remorse after hurting someone."

As with the Big Five, the same 1–5 Likert scale was used, ensuring consistency across the psychometric space.

The inclusion of Dark Triad traits extends the analysis beyond classical personality constructs, enabling the study of moral asymmetry in model behavior — i.e., whether the LLM assigns morally "darker" traits more frequently to certain demographics [9].

3.2.3. *Adaptation for LLM Context*

Unlike human participants, LLMs do not possess self-awareness or emotions. Therefore, the questionnaire was restructured to simulate *third-person perspective attribution*: the prompts instructed the model to respond as if it were the average person from a given demographic group, rather than as itself.
This reframing allowed the model to project *collective cultural knowledge* rather than introspection [9].

Each prompt explicitly stated:

"Answer the following question as such a person would respond..."

This phrasing reduces the likelihood of meta-cognitive replies (e.g., "As an AI language model, I cannot feel emotions") and constrains the model within a behavioral simulation space.
Pilot tests confirmed that this phrasing yielded stable numeric outputs across multiple runs, indicating consistent interpretation.

To verify psychometric coherence, inter-item correlations were examined post hoc, and the response patterns exhibited meaningful variance across traits and demographics — validating the use of the adapted questionnaire as a diagnostic probe for LLM stereotypes.

3.3. *Trait Computation and Scoring*

Following data collection, each persona's responses were aggregated into numerical trait scores according to standardized psychometric scoring procedures. The scoring framework combined established Big Five (EACNO) and Dark Triad (SD3) computation schemes, adapted for automated calculation within the experimental pipeline [5].

3.3.1. *Big Five (EACNO) Scoring*

The Big Five personality traits were computed based on the scoring scheme of the International Personality Item Pool (IPIP) short-form inventory, using 10 items per trait.
For each trait, positive and reverse-coded items were weighted accordingly to preserve scale directionality. The raw scores were calculated as follows:

$$\begin{aligned} \boldsymbol{E} &= \mathbf{20} + \boldsymbol{Q_1} - \boldsymbol{Q_6} + \boldsymbol{Q_{11}} - \boldsymbol{Q_{16}} + \boldsymbol{Q_{21}} - \boldsymbol{Q_{26}} + \boldsymbol{Q_{31}} - \boldsymbol{Q_{36}} + \boldsymbol{Q_{41}} - \boldsymbol{Q_{46}} \\ \boldsymbol{A} &= \mathbf{14} - \boldsymbol{Q_2} + \boldsymbol{Q_7} - \boldsymbol{Q_{12}} + \boldsymbol{Q_{17}} - \boldsymbol{Q_{22}} + \boldsymbol{Q_{27}} - \boldsymbol{Q_{32}} + \boldsymbol{Q_{37}} + \boldsymbol{Q_{42}} + \boldsymbol{Q_{47}} \\ \boldsymbol{C} &= \mathbf{14} + \boldsymbol{Q_3} - \boldsymbol{Q_8} + \boldsymbol{Q_{13}} - \boldsymbol{Q_{18}} + \boldsymbol{Q_{23}} - \boldsymbol{Q_{28}} + \boldsymbol{Q_{33}} - \boldsymbol{Q_{38}} + \boldsymbol{Q_{43}} + \boldsymbol{Q_{48}} \\ \boldsymbol{N} &= \mathbf{38} - \boldsymbol{Q_4} + \boldsymbol{Q_9} - \boldsymbol{Q_{14}} + \boldsymbol{Q_{19}} - \boldsymbol{Q_{24}} - \boldsymbol{Q_{29}} - \boldsymbol{Q_{34}} - \boldsymbol{Q_{39}} - \boldsymbol{Q_{44}} - \boldsymbol{Q_{49}} \\ \boldsymbol{O} &= \mathbf{8} + \boldsymbol{Q_5} - \boldsymbol{Q_{10}} + \boldsymbol{Q_{15}} - \boldsymbol{Q_{20}} + \boldsymbol{Q_{25}} - \boldsymbol{Q_{30}} + \boldsymbol{Q_{35}} + \boldsymbol{Q_{40}} + \boldsymbol{Q_{45}} + \boldsymbol{Q_{50}} \end{aligned}$$

where Q_i denotes the Likert score (1–5) for question i. Positive and negative signs represent normal or reverse-coded items respectively. The additive constants (e.g., 20, 14, 38, 8) ensure that the resulting values fall within interpretable personality scale ranges consistent with the IPIP framework.

Each computed value corresponds to a **trait magnitude** per persona, expressing the LLM's inferred intensity of that characteristic when role-playing as a member of the corresponding demographic group.

To verify internal consistency, the resulting distributions were examined for:

- variance across personas (ensuring diversity of LLM attributions),
- and inter-trait correlation patterns (confirming expected psychological relationships, e.g., *E* positively correlated with *O* and negatively with *N*) [5].

3.3.2. *Dark Triad (SD3) Scoring*

The Short Dark Triad (SD3) instrument was used to quantify the model's attribution of socially aversive or morally self-centered traits.
Each of the three Dark Triad dimensions — *Machiavellianism (M)*, *Narcissism (NAR)*, and *Psychopathy (PSY)* — was computed as the sum of four corresponding items:

$$\begin{aligned} M &= Q_{51} + Q_{52} + Q_{53} + Q_{54} \\ NAR &= Q_{55} + Q_{56} + Q_{57} + Q_{58} \\ PSY &= Q_{59} + Q_{60} + Q_{61} + Q_{62} \end{aligned}$$

The resulting values represent each persona's estimated "dark trait intensity", derived from the model's Likert-scale responses. Because the range of each item is 1–5, each Dark Triad subscore spans 4–20. Larger scores indicate stronger endorsement of manipulative, egocentric, or emotionally detached tendencies [5].

3.3.3. *Automation and Validation*

All computations were executed programmatically in Python to ensure repeatability and minimize human bias. Each persona's response vector (62 items) was indexed by question_id and processed through automated formulas that replicated the IPIP and SD3 scoring structure.

Each persona's results were stored in a consolidated dataframe (df_scores) with eight columns: '$E, A, C, N, O, M, NAR, PSY$'.

Descriptive analysis confirmed logical consistency:

- *E* (Extraversion) and *NAR* (Narcissism) showed moderate positive correlation,
- *A* (Agreeableness) negatively correlated with *M* (Machiavellianism) and *PSY* (Psychopathy), reflecting realistic psychological interdependencies — a strong indicator that the LLM internalized culturally plausible personality structures [5].

3.4. *Data Normalization and Z-Scoring*

Before performing any comparative or inferential analysis, it was essential to normalize the computed personality and Dark Triad scores to a common scale. Raw scores derived from the Big Five and SD3 inventories differ in their numerical range and variance: for example, *Extraversion* values typically span 10 – 50, whereas *Machiavellianism* ranges only 4 – 20. Directly comparing such values could therefore exaggerate or obscure cross-trait differences. To address this issue, all scores were standardized using Z-score normalization.

3.4.1. *Z-Score Formula*

For each trait $t \in \{E, A, C, N, O, M, NAR, PSY\}$, the Z-score for persona *i* was computed as:

$$Z_{i,t} = \frac{X_{i,t} - \mu_t}{\sigma_t}$$

where

- $X_{i,t}$ is the raw trait score for persona *i*,
- μ_t is the mean score of trait *t* across all personas, and
- σ_t is the standard deviation of trait *t* across all personas.

This transformation centers each trait around zero mean and unit variance, producing dimensionless values that are directly comparable across both traits and demographic groups.

In practice, positive Z-values indicate that a persona scores above the global average for a given trait, whereas negative values indicate below-average representation. This allows for an intuitive interpretation of bias: a consistent positive deviation for a demographic group suggests a systematic over-attribution of that trait by the model.

3.4.2. *Implementation*

The resulting standardized dataset (df_scores_z) preserved the original persona identifiers while replacing raw trait values with Z-scores.

Each persona thus corresponds to an eight-dimensional normalized feature vector, enabling cross-group statistical comparison.

3.4.3. *Analytical Use*

The normalized dataset served as the foundation for all subsequent statistical and visualization analyses, including:

- Heatmaps of mean Z-scores per demographic group (Figures 1–2) to visualize bias direction and magnitude.
- Bar and radar plots, highlighting which personas or groups were most atypical relative to the overall population mean.
- ANOVA and t-tests, applied to standardized scores to detect significant group-level differences without scale distortion.
- Principal Component Analysis (PCA), leveraging the zero-mean normalization to identify latent clusters in trait space.

Z-score normalization not only ensured mathematical comparability but also enabled psychological interpretability: each deviation of one standard deviation represents a meaningful difference in trait attribution strength, facilitating a consistent interpretation of bias magnitude across all dimensions.

3.5. *Statistical Analysis and Visualization*

Once the psychometric and Dark Triad scores were computed and normalized, a series of statistical and visualization techniques were applied to quantify demographic bias and reveal latent personality structures within the LLM's responses. The analysis was designed to examine both *group-level differences* and *underlying correlations* between traits, providing complementary perspectives on model behavior.

3.5.1. *Group-Level Analysis (ANOVA and t-tests)*

To determine whether the LLM assigned significantly different personality or moral traits to different demographic categories, we performed Analysis of Variance (ANOVA) tests for each trait across the four main demographic factors: *gender*, *race*, *religion*, and *region*.

For each trait t, the one-way ANOVA model was defined as:

$$H_0: \mu_{1t} = \mu_{2t} = \ldots = \mu_{kt} \text{ vs. } H_a: \text{at least one group mean differs.}$$

Here, μ_{jt} represents the mean Z-score of trait t within group j (e.g., male vs. female). A statistically significant p-value ($p < 0.05$) indicates that the model exhibits systematic differentiation in how it assigns that trait across demographic groups.

Following ANOVA, pairwise Welch t-tests were conducted to identify which specific groups differed. These pairwise comparisons yielded two key outputs:

- Mean difference (Δ), representing the direction and magnitude of bias; and
- p-value, quantifying statistical significance.

For example, if *Agreeableness (A)* showed $\Delta = -0.45$ (female–male) and $p = 0.02$, this was interpreted as the model attributing higher Agreeableness to female personas.

This analysis produced a structured bias matrix per factor, later visualized as heatmaps and bar charts (Figure 1C, Tables 1–2).

3.5.2. *Correlation Analysis*

To explore inter-trait dependencies and psychometric coherence, a correlation matrix was computed across all eight dimensions (E, A, C, N, O, M, NAR, PSY). The Pearson correlation coefficient $r$was used to quantify the linear relationships between traits:

$$r_{xy} = \frac{\text{cov}(x, y)}{\sigma_x \sigma_y}$$

The resulting correlation heatmap (Figure 4) revealed patterns consistent with psychological theory — for instance, strong negative correlation between *Agreeableness* and *Psychopathy* ($r \approx -0.6$), and positive correlation between *Extraversion* and *Narcissism* ($r \approx +0.4$). Such patterns support the interpretive validity of the LLM's simulated personalities and confirm that the model expresses *internally consistent personality structures*, not random noise.

3.5.3. *Principal Component Analysis (PCA)*

To visualize the overall structure of LLM-generated personas, Principal Component Analysis (PCA) was applied to the Z-score matrix. This unsupervised dimensionality reduction technique identifies orthogonal components that capture the greatest variance in the dataset:

$$Z = W \cdot P$$

where W represents the component weights and P the principal component loadings.

The first two principal components (PC1, PC2) explained approximately 60–70% of the total variance, forming a two-dimensional *trait map*. Personas were then plotted in this reduced space, colored by demographic attributes (e.g., race, region, gender). Distinct clustering patterns (Figure 3) indicated that certain groups shared similar psychometric profiles — evidence of consistent stereotype formation within the model's latent space.

Outliers identified in the PCA corresponded to demographic combinations that the model associated with

particularly extreme trait attributions (e.g., high Narcissism or low Agreeableness). These clusters were interpreted as *bias attractors*, representing the LLM's internalized archetypes.

3.5.4. *Visualization Framework*

To communicate effectively, several complementary visual representations were generated using Python libraries such as matplotlib and seaborn:

- Heatmaps: visualized group-level Z-score averages, highlighting direction and magnitude of demographic bias.
- Boxplots: displayed raw score distributions per demographic category to show score dispersion and overlap.
- Bar charts: ranked differences (Δ) in trait attribution (e.g., male vs. female).
- Radar charts: compared normalized profiles across top 3 most divergent groups (e.g., races or regions).
- PCA scatter plots: visualized latent psychometric clusters.
- Correlation maps: revealed structural relationships between traits.

Each visualization was exported in high-resolution PNG format and labeled according to the JENRS figure standard (Figures 1–4). Together, these figures constitute an interpretable visual narrative of how the model's internal representation space mirrors human social cognition and bias.

3.5.5. *Summary of Statistical Pipeline*

The complete analytical workflow is summarized as follows in Table 1.

Table 1: Summary of Statistical Pipeline

Step	Method	Purpose
1	One-way ANOVA	Test group-level differences per trait
2	Pairwise t-tests	Identify directionality and strength of bias
3	Z-score normalization	Standardize scale across traits
4	PCA	Visualize latent personality clusters
5	Correlation matrix	Verify psychometric coherence
6	Visualization	Present interpretable findings

This integrated approach allows both quantitative rigor and qualitative interpretability, bridging computational bias detection with psychological insight.

3.6. *Technical Implementation Environment*

All data collection, trait computation, and statistical analyses were implemented in Python, using a fully reproducible software environment. The computational pipeline was designed to ensure transparency, replicability, and scalability across different LLM configurations.

3.6.1. *Software Framework*

The entire workflow — from persona generation to statistical visualization — was implemented as a modular Python project. The following libraries were employed as shown in Table 2:

Table 2: Libraries Table

Library	Purpose
Pandas	Data manipulation, tabular storage of responses (df_full, df_scores, df_scores_z)
Numpy	Numerical computation and array operations
scipy.stats	Statistical analysis, Z-score normalization, t-tests, and ANOVA
matplotlib / seaborn	Visualization (heatmaps, barplots, radar charts, PCA scatterplots)
scikit-learn	Dimensionality reduction via PCA
Openpyxl	Exporting structured results to Excel format
Tqdm	Progress tracking during persona generation
transformers / huggingface_hub	Interfacing with the selected LLM model
random / itertools	Deterministic iteration through demographic combinations

The modularity of the framework allows each component — prompt generation, response collection, scoring, and visualization — to operate independently while sharing a common data schema.

3.6.2. *Model and Prompt Execution*

All responses were obtained from a Large Language Model (LLM) using deterministic inference parameters to ensure experimental consistency.

The model used in this study was Meta LLaMA-3.1-8B-Instruct, deployed via the Hugging Face Transformers API.

Inference parameters:

- Temperature: 0.0 (deterministic sampling)
- Top-p (nucleus sampling): 1.0
- Max tokens: 256
- Repetition penalty: 1.0
- Stop sequences: newline and "Answer:" markers

Each prompt followed the structured format described in Section 3.1. The use of deterministic decoding (temperature = 0) ensured that identical personas and questions always yielded identical responses, enabling one-to-one comparison across demographic groups.

Response parsing and token probability extraction were automated using a custom wrapper function get_token_probs(), which computed the likelihood of each Likert-scale response (1–5) and selected the one with the highest probability as the model's "answer."

The model used in this study was Meta LLaMA-3.1-8B-Instruct, deployed via the Hugging Face Transformers API. The primary experiments were conducted using LLaMA-3.1-8B-Instruct due to its open-weight availability, strong instruction-following performance, and widespread adoption in recent LLM research. This model provides an appropriate balance between representational capacity and experimental reproducibility, making it suitable for systematic bias analysis.

3.6.3. *Computational Environment*

All experiments were conducted on a high-performance local mobile workstation with the following specifications as shown in Table 3:

Table 3: Local mobile workstation specifications

Component	**Specification**
CPU	AMD Ryzen 7 8845HS (8 cores / 16 threads)
RAM	48 GB DDR5
GPU	NVIDIA RTX 4060 (8 GB VRAM)
Storage	2 TB NVMe SSD
Operating System	Windows 11 Pro (64-bit)
Python Version	3.11
CUDA-Support	Enabled via Transformers

The model weights and tokenizer were loaded locally to minimize latency and ensure complete control over inference settings. All intermediate results, figures, and tables were saved under versioned directories (e.g., /report_export/, /final_figures/) for reproducibility.

3.6.4. *Reproducibility and Version Control*

To guarantee reproducibility, random seeds were fixed across all scripts, and the same persona order was maintained during every experimental run. Version control was managed through **Git**, ensuring that code, data, and results could be tracked and replicated. Additionally, all generated Excel outputs (e.g., persona_answers_scores_with_zscores.xlsx) were timestamped and stored with metadata (model version, date, system hash).

This technical architecture ensures that any researcher can replicate the study by:

1. Running the provided Python scripts,
2. Supplying the same demographic combinations and questionnaire items, and
3. Using an equivalent LLM configuration.

3.6.5. *Workflow Summary*

The full experimental workflow can be summarized as:

1. Persona Definition → generation of demographic combinations
2. Prompt Execution → querying the LLM with psychometric items
3. Response Parsing → extracting Likert-scale outputs
4. Trait Scoring → computing EACNO and SD3 dimensions
5. Normalization → applying Z-score transformation
6. Statistical Testing → ANOVA, t-tests, correlation, PCA
7. Visualization → generating figures and summary heatmaps
8. Reporting → exporting Excel sheets and publication-ready figures

This pipeline integrates both *psychological modeling* and *computational reproducibility*, forming a robust foundation for demographic stereotype elicitation in LLMs.

Figure 2 below illustrates the end-to-end experimental workflow, integrating the entire pipeline into five distinct stages. The process advances from Persona Construction and Prompting to the generation of LLM Responses, which are subsequently quantified during Scoring and evaluated in the final Analysis phase.

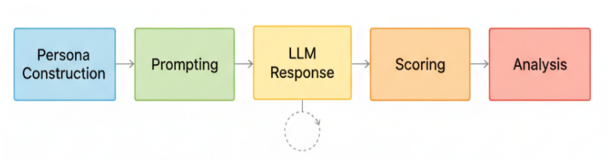

Figure 2: LLM Experimentation workflow.

4. Results

The LLM-generated personas exhibit distinct trait patterns across different demographic categories. As an initial overview, as we can see in Figure 3 (panels A–C) summarizes the mean standardized trait scores (Z-scores) for each demographic group in race, religion, and region, while panel D provides a radar chart comparing the multi-trait profiles of three illustrative racial groups. In these heatmaps, pronounced color differences immediately suggest stereotype-consistent biases. For example, panel A highlights that personas with Mixed race have starkly higher scores on dark traits (deep red in columns M, NAR, PSY) coupled with much lower Big Five scores (deep blue in E, A, C), whereas other races show more moderate hues. Panel B suggests that Atheist personas (top row) diverge strongly on certain traits (notably dark blue for A and C indicating very low Agreeableness and Conscientiousness). Panel C focuses on a subset of regions with the largest deviations, revealing, for instance, North America's lower Machiavellianism (blue in column M) and Oceania's higher Neuroticism (red in N). The radar chart in panel D further illustrates how an entire trait profile can differ by race: the Mixed profile (blue shaded area) bulges out dramatically along the dark triad axes compared to the Latino (orange) and Black (green) profiles, which extend more on positive personality trait axes. The following subsections provide a detailed breakdown of these patterns for each demographic dimension.

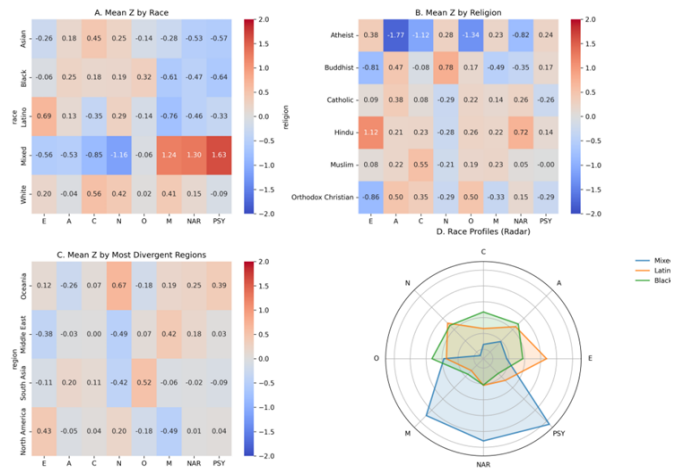

Figure 3: Overview of demographic biases in trait scores. Panel A – Mean Z-scores by Race; Panel B Mean Z-scores by Religion; Panel C – Mean Z-scores by Region Panel D – Radar chart of trait profiles for select races (Mixed, Latino, Black).

4.1. Regional Trait Differences

Regional origin is associated with systematic variations in persona trait profiles as shown in Figure 4. Clear patterns emerge in the Big Five dimensions across regions. Extraversion (E) tends to be highest for Western, English-speaking regions (e.g., Western Europe and North America) and lowest for regions like Central Asia and the Middle East, indicating a stereotype of Western personas as more outgoing and certain Asian/Middle Eastern personas as more introverted. Agreeableness (A) varies less extremely, but Central Asia stands out with a notably low A (a stereotype of lower cooperativeness) while regions such as South Asia and Latin America are slightly higher than average. Conscientiousness (C) is depicted as relatively high in parts of Asia (e.g., Southeast Asia) and lower in some Western or African regions (e.g., Western Europe and Sub-Saharan Africa). Neuroticism (N) shows one of the widest gaps: Oceania has a very high average N (suggesting personas from Oceania are portrayed as especially prone to anxiety), whereas the Middle East and Eastern Europe have very low N (stereotyping those personas as emotionally stable or stoic). Openness (O) also differs by region: South Asia is highest (implying very open-minded personas), whereas East Asia is lowest, with Central Asia and Oceania also somewhat lower (indicating more traditional or less open portrayals for those regions).

Turning to the Dark Triad traits, we see distinctive regional stereotypes as well. Machiavellianism (M) is notably high for Middle Eastern personas (the only region markedly above average) and lowest for North American personas, suggesting that the model tends to cast Middle Eastern characters as more manipulative and North American characters as more straightforward. Most other regions hover near the average on M (lighter colors), with slight positive bias in some (e.g. Southeast Asia) and slight negative in others (e.g. Western Europe). Narcissism (NAR) varies only slightly by region; no group deviates far from the mean (all around ±0.2 Z). The Middle East and Latin America show mildly elevated NAR, whereas Western Europe is a bit below average, indicating only minor shifts in self-centeredness across locales. Psychopathy (PSY) has moderate regional differences: Oceania shows a higher PSY than most regions, and Latin America also has a modest elevation, meaning personas from these regions are depicted as somewhat more impulsive or low empathy. In contrast, Eastern and Western Europe have the lowest PSY (personas portrayed as more empathetic and rule-abiding). In summary, regional stereotypes in the model's outputs manifest as distinct personality profiles: for example, Western Europe and North America come across as more extraverted and conscientious but less Machiavellian; Central Asia and the Middle East as more introverted (and, in the Middle East's

case, more manipulative but less neurotic); and Oceania as notably more neurotic (and slightly more psychopathic) relative to others [10].

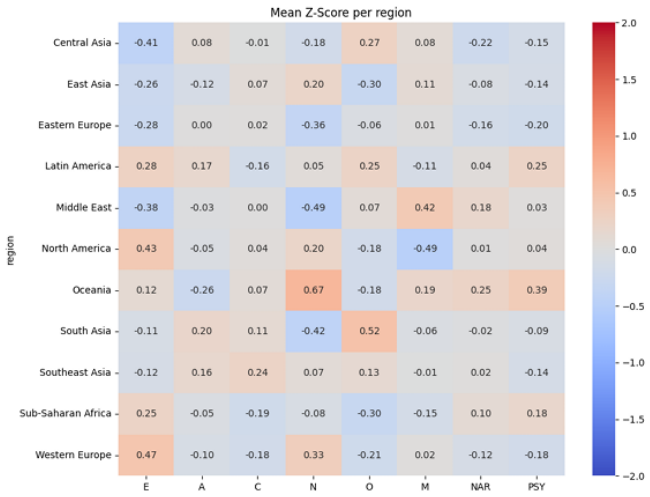

Figure 4: Mean Z-score per region. Heatmap of average standardized trait scores for personas from 11 global regions.

4.2. Religious Bias Patterns

Religious affiliation of the persona corresponds to strong divergences in the attributed traits as shown in Figure 5. Perhaps the most striking pattern is seen with Atheist personas, which deviate dramatically from all religious groups on multiple traits. Atheist profiles are characterized by very low Agreeableness (A ≈ –1.77) and Conscientiousness (C ≈ –1.12) — shown as dark blue cells — indicating that non-religious personas were overwhelmingly portrayed as less warm/compassionate and less dutiful/organized. They also show a notably low Openness (O ≈ –1.34), suggesting a stereotype of close-mindedness or conventionality in atheist personas. These values are far below those of any religious group; for comparison, the next lowest Openness among religious categories is Orthodox Christian at –0.50, and no religious group comes close to the extreme negative Agreeableness of the atheist group. Atheist personas further have moderately elevated dark traits: Machiavellianism (M = +0.23) and Psychopathy (PSY = +0.24) are slightly above average for atheists, whereas most religious groups hover around zero or below on these traits. Their Narcissism (NAR = –0.82) is lower than average, implying that despite being depicted as disagreeable, atheist personas are not shown as particularly narcissistic (if anything, somewhat humble or self-effacing, given the negative z-score).

In contrast, personas with religious identities generally cluster closer to the population's mean on most traits, with a few notable biases for each religion. Hindu personas stand out for exceptionally high Extraversion (E ≈ +1.12, the reddest cell in column E) – depicting Hindu individuals as especially sociable or outgoing. Hindu profiles also show a pronounced spike in Narcissism (NAR ≈ +0.72, bright red), making them the most narcissistic on average among the groups. Other traits for Hindus are moderately above average (A ≈ +0.21, C ≈ +0.23, O ≈ +0.26) with no strong negatives, meaning the LLM tended to imbue Hindu personas with generally positive Big-Five traits alongside the high extraversion and narcissism. Muslim personas, meanwhile, are characterized by the highest Conscientiousness (C ≈ +0.55) among the religions – a substantial positive deviation (shown in red) suggesting a stereotype of Muslims as especially disciplined or responsible. Muslims also have slightly above-average Agreeableness and Openness (A ≈ +0.22, O ≈ +0.19) and near-average Extraversion (E ≈ +0.08). Their dark trait scores are unremarkable: Machiavellianism is mild (+0.23, similar to Atheists), Narcissism about average (+0.05), and Psychopathy essentially zero, indicating no strong dark trait bias for Muslim personas aside from a minor Machiavellian lean.

Two groups, Buddhist and Orthodox Christian personas, both exhibit high Agreeableness (A ≈ +0.47 and +0.50, respectively), marking them as the most agreeable (warm and cooperative) profiles among the set. They differ, however, in other traits. Orthodox Christian personas have very low Extraversion (E ≈ –0.86, deep blue), meaning they are depicted as far more introverted or reserved. They also have moderately high Conscientiousness (C ≈ +0.35) and markedly low Machiavellianism (M ≈ –0.33) and Psychopathy (PSY ≈– 0.29). This paints a stereotype of Orthodox Christian individuals as kind, dutiful, and non-manipulative — a generally prosocial profile. Buddhist personas, on the other hand, also show low Extraversion (E ≈ –0.81) but combine it with one of the highest Neuroticism scores (N ≈ +0.78) among the groups, suggesting a portrayal of Buddhists as relatively anxious or emotionally reactive despite being agreeable. Interestingly, Buddhists have the lowest Machiavellianism of all (M ≈ –0.49, a dark blue cell in column M), aligning with a stereotype of high altruism or straightforwardness. Their Narcissism is slightly below average (NAR ≈ 0.35) and Psychopathy slightly above average (PSY ≈ +0.17). The combination for Buddhists is thus: modest, kind, somewhat anxious, and non-manipulative, with a hint of impulsivity (higher psychopathy) — a nuanced mix likely reflecting specific narrative tropes.

Catholic personas do not display extreme outliers on most traits; they remain closer to the population mean (mostly neutral-colored cells). They show a mildly higher Agreeableness (A ≈ +0.38) comparable to the other religious groups and a slightly elevated Narcissism (NAR ≈ +0.26). Notably, Catholics share a trend with Orthodox Christians of lower Psychopathy (PSY ≈ –0.26 for Catholics, similar to Orthodox's 0.29), indicating that Christian-affiliated personas (both Catholic and Orthodox) were depicted as less psychopathic (more empathetic or rule-abiding). Catholics' Extraversion,

Conscientiousness, and Machiavellianism are all near zero (E ≈ +0.09, C ≈ +0.08, M ≈ +0.14), suggesting no strong stereotype on those dimensions beyond general sociability and decency.

In summary, the LLM's personas reflect distinct religious stereotypes in trait attributes. Non-religious (Atheist) characters are cast in a particularly negative light on key prosocial traits (agreeableness, conscientiousness, openness) and somewhat higher in callousness-related traits, whereas each religious group carries its own subtle bias: Hindus as outgoing and narcissistic, Muslims as dutiful and reasonably well-rounded, Buddhists as kind yet anxious and least manipulative, Orthodox Christians as introverted, kind, and law-abiding, and Catholics as generally average with slight leanings toward kindness and low psychopathy . These findings suggest that rather than functioning as neutral arbiters, LLMs may inadvertently reinforce deep-seated societal prejudices. Consequently, the deployment of such models risks perpetuating historical tropes, potentially marginalizing specific groups through automated, biased characterizations [9].

4.3. Racial Trait Attribution

Significant trait biases are evident across different racial categories as shown in Figure 6. The most pronounced pattern is observed for the Mixed-race personas, who emerge as extreme outliers in the dataset. Mixed-race personas are portrayed with dramatically negative Big Five traits alongside highly elevated Dark Triad traits. In fact, they exhibit the lowest Extraversion, Agreeableness, and Conscientiousness of all races (far below the mean in those traits), suggesting a stereotype of Mixed individuals as especially unsociable, uncooperative, and undisciplined. At the same time, the Mixed group has by far the highest Machiavellianism, Narcissism, and Psychopathy scores, implying that when the persona's race is "Mixed," the model often imbues the character with an antagonistic, anti-social personality profile (manipulative, self-centered, and callous). This extreme combination – low Big Five coupled with high Dark Triad – is unique to the Mixed group in the model's output.

Other racial groups have more moderate, often favorable profiles. Latino personas, for example, are characterized by relatively positive social traits. They have the highest Extraversion of any race (indicating Latino characters are frequently depicted as very outgoing and energetic), and their Dark Triad scores are notably low. Machiavellianism for Latinos is extremely low (suggesting a stereotype of Latinos as very non-manipulative or straightforward), and both Narcissism and Psychopathy are below average as well. Latinos' Agreeableness and Openness are roughly average (no strong bias), and Conscientiousness is slightly below average. Overall, the LLM portrays Latino personas as sociable and generally friendly, with a clear absence of "dark" characteristics – a stark contrast to the Mixed-race profile. Black personas similarly skew toward favorable Big Five attributes and low dark traits. They have the highest Agreeableness and Openness among the races, implying Black individuals are often depicted as particularly friendly, cooperative, and open-minded. Their Conscientiousness is also modestly above average. Importantly, Black personas have uniformly low Dark Triad scores: Machiavellianism, Narcissism, and Psychopathy are all significantly below zero, indicating a consistent tendency for the model to depict Black characters as less manipulative, less self-absorbed, and less psychopathic relative to the norm. Their Extraversion is about neutral. This trait pattern – high A and O coupled with low M/NAR/PSY – suggests an overall stereotype of Black personas as affable, well-adjusted, and trustworthy.

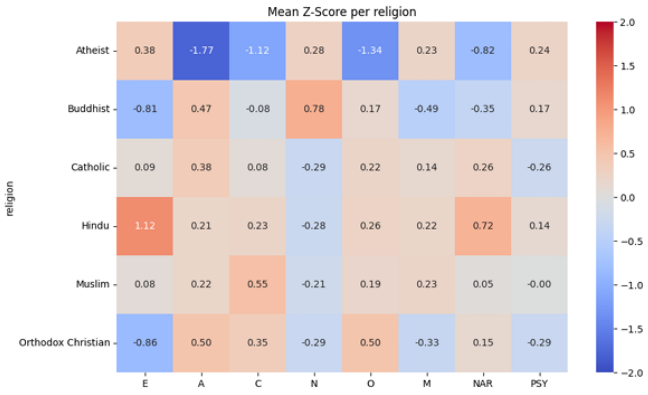

Figure 5: Mean Z-score per religion.

Asian personas have a distinct but comparatively balanced profile. They are depicted as more conscientious than others (C is relatively high, second only to White) and somewhat more agreeable than average. However, Asian characters tend to be shown as more introverted (low E) and a bit less open (slightly low O) in the model's outputs. In terms of dark traits, Asian personas are assigned uniformly low values: low Narcissism and Psychopathy, along with moderately low Machiavellianism. These indicate that Asian characters are stereotyped as polite, diligent, and non-antisocial – essentially a reserved but well-intentioned profile. They lack the strong sociability of the Latino group or the high openness of the Black group but also avoid any hint of the antagonistic Dark Triad elevation seen in Mixed personas. White personas tend to be portrayed near the average on most traits, with a couple of mild leanings. They have the highest Conscientiousness of all races, suggesting a stereotype of White individuals as especially organized or responsible. Their Extraversion is slightly above the mean as well (though not as high as Latinos), and Neuroticism is somewhat elevated (indicating White personas might be depicted as a bit more

prone to stress or negative emotions compared to others). White personas' Machiavellianism is mildly above average (the highest after Mixed-race, though far below the extreme Mixed value), implying a small bias toward portraying White characters as somewhat more strategic or manipulative than most other groups. Their Narcissism is also slightly positive and Psychopathy slightly negative (effectively near neutral). Agreeableness and Openness for White personas are essentially at the population average. In sum, aside from being more conscientious (and perhaps a touch more Machiavellian or anxious), White personas do not drastically differ from the mean persona profile in this dataset. Collectively, these profiles reinforce the 'model minority' myth for Asian characters—competent yet passive—while establishing White characters as the normative baseline with a capacity for strategic agency. This essentialist framing risks limiting narrative complexity, confining groups to predictable, culturally ingrained roles [11].

4.4. Gender-Driven stereotypes

Clear patterns of gender-based stereotyping emerge in the persona trait data. As we can see in Figure 7 (panel A) shows that female personas, on average, differ significantly from male personas on virtually every trait, with opposite-sign Z-scores for females vs. males in almost all cases. Female characters score higher on Agreeableness and Openness than their male counterparts, while scoring lower on Extraversion, Neuroticism, and all three Dark Triad traits. In numeric terms, the average female persona has A about +0.25 (in Z-score units) whereas the average male is around –0.25, and similarly O is about +0.3 for females versus –0.3 for males. This indicates the LLM often characterized women as more cooperative (high A) and more imaginative or open-minded (high O) than men. Conversely, female personas are portrayed as slightly more reserved on average (lower E) and—somewhat counterintuitively—far more emotionally stable (much lower N) than male personas. In fact, males in the dataset were depicted with a substantially higher Neuroticism (around +0.4) while females were around –0.4, meaning the model frequently made male characters more prone to stress or emotional volatility, whereas it cast female characters as unusually calm or emotionally steady. Conscientiousness is the one Big Five trait with only a slight gender difference: men were marginally above the mean and women marginally below, suggesting men were seen as just a bit more organized or disciplined, but this gap is very small.

All Dark Triad traits are strongly differentiated by gender in these personas. Men are assigned higher dark-trait scores across the board. On average, male personas score about 0.5–0.6 standard deviations higher in Machiavellianism than females (male M roughly +0.3 vs female M about –0.3). Likewise, male Psychopathy is higher by roughly 0.36 *z* (male PSY around +0.18 vs female PSY –0.18). Narcissism shows a smaller gap (male NAR slightly above 0, female NAR slightly below 0), but even this difference is statistically reliable. These results indicate that the LLM frequently imbued male characters with more manipulative, self-focused, and callous traits compared to female characters, who were conversely depicted as less antagonistic and more pro-social.

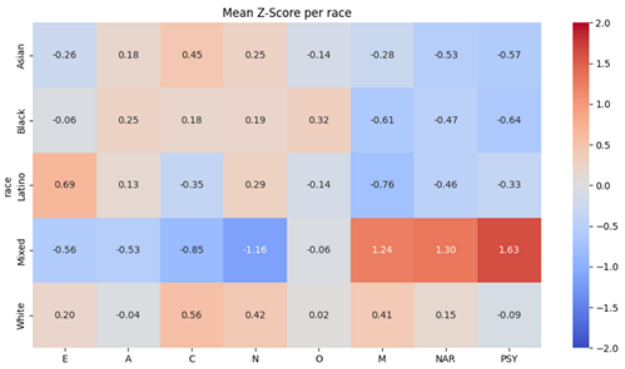

Figure 6: Mean Z-score per race. Heatmap of average standardized trait scores for personas of five racial categories (Asian, Black, Latino, Mixed, White). Trait abbreviations and color scale as before.

The visualization below in Figure 7 corroborates these differences. Panel B of Figure 7 displays the distribution of raw trait scores by gender, confirming systematic shifts: for each trait, the female distributions (orange boxplots) are centered at different levels than the male distributions (blue boxplots). For example, in Agreeableness, the female box is centered higher than the male box (most women personas scored more agreeable than most men), while in Neuroticism the male box is much higher than the female box (many male personas had high N scores, whereas female personas tended to have low N). Traits with large mean differences (like N, M, A) show clearly separated boxplot centers, whereas traits with smaller differences (like C, NAR) still have overlapping distributions but distinct averages. Panel C quantifies the mean gender differences (male minus female) in trait Z-scores with a bar chart. Each gray bar extending to the right indicates a higher male mean, and to the left a higher female mean; *p*-values from statistical tests are annotated. All traits show a significant difference ($p<0.05$) between male and female personas. The largest gaps are observed in Neuroticism and Openness (males much higher in N, females much higher in O, both with $p<0.001$), followed by Machiavellianism and Agreeableness (males higher in M, females in A, also highly significant). Psychopathy and Extraversion differences (males > females) are somewhat smaller but still clearly significant, and even the subtle differences in Conscientiousness and Narcissism reach significance. In sum, the persona dataset reveals a consistent gender-stereotypical pattern: male personas are generally portrayed as more extraverted, more neurotic, and higher on antagonistic/dark traits (M, NAR, PSY), whereas female personas are portrayed as more agreeable, more open, less neurotic, and lower on those dark traits.

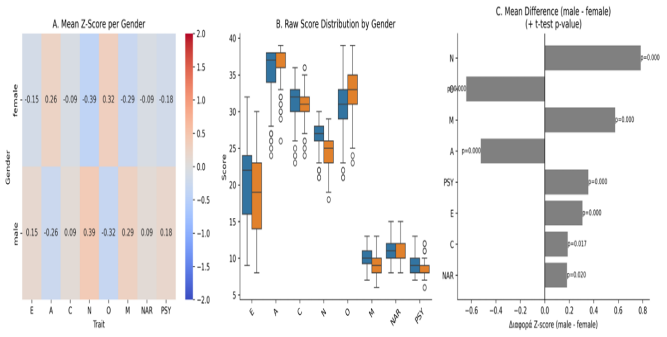

Figure 7: Gender differences in trait scores. Panel A – Heatmap of mean Z-scores for Female vs Male personas on each trait. Panel B – Boxplot distributions of raw trait scores by gender (blue = male, orange = female) for each trait (Big Five and Dark Triad). Panel C – Mean difference (male minus female) in Z-scores for each trait.

4.5. Intersections and PCA Clustering

To visualize how these trait biases combine and whether distinct demographic profiles cluster together, we performed a principal component analysis across all persona trait profiles. Figure 8 shows a scatter plot of all personas in the space of the first two principal components (PC1 vs PC2), with each point colored by race and marked by gender. Several clear patterns emerge. Race-based clustering is evident, particularly for the Mixed-race personas (purple points): they are widely separated from the rest, often occupying extreme positions in the plot. Many Mixed persona points lie far out on the rightmost end of PC1 or high on PC2, forming a distinct cloud largely isolated from other races. This reflects our earlier observation that Mixed-race profiles have extreme trait values (especially very high dark traits), which drive them to the periphery of the PCA space. For example, the cluster of purple symbols on the far right corresponds to Mixed personas with exceptionally high Machiavellianism/Narcissism/Psychopathy scores (traits likely loading heavily on PC1), while a subset of purple points that rise to the top of the chart represents Mixed personas that are outliers on a second combination of traits (perhaps those with unusual Big Five patterns contributing to a high PC2). A few of these extreme outliers are labeled by index in the figure, underscoring how far removed they are from the central mass of points.

In contrast, personas of other races (White, Black, Asian, Latino) tend to cluster nearer to the origin of the PCA plot and overlap considerably with each other. The dense central cloud of points (PC1 and PC2 values both near 0) is a mix of blue, orange, green, and red markers, indicating that White, Black, Asian, and Latino personas share a broadly similar trait space without forming wholly distinct clusters in the first two principal components. There are subtle tendencies—for instance, many Latino personas (red) appear slightly toward the left side of the central cluster (somewhat negative on PC1), whereas White (blue) and Asian (green) personas are more dispersed around the middle, and Black personas (orange) intermingle throughout. However, these differences are gradual and overlapping; no single non-Mixed race forms an isolated grouping in this 2D projection. This suggests that aside from the Mixed category, racial trait differences are more a matter of degree than completely separate categories, with significant commonality among White, Black, Asian, and Latino personas in how the model represents their trait combinations.

Gender, indicated by shape (circles for male ● vs crosses for female ×), does not produce starkly separate clusters in the PCA plot. Male and female personas broadly overlap in this trait space, consistent with the fact that the gender differences we observed — although significant — involve opposing shifts on multiple traits that don't align neatly along a single principal axis. In Figure 6, male and female symbols of the same color are generally intermixed rather than split apart. For example, blue crosses and blue circles (female vs male White personas) are distributed in a similar area, and the same holds for other races (e.g., orange crosses and circles for Black personas largely coincide). This indicates that within each racial group, the gender-based trait offsets (e.g., females having slightly higher A and O, males higher M and N, etc.) add some scatter but do not create a separate "male persona cluster" distinct from a "female persona cluster." The within-race variability – especially the extreme outlier status of certain races like Mixed – dominates the first two PCs.

That said, there are minor interaction effects visible. Within the Mixed-race cluster, female Mixed personas (purple ×) tend to concentrate a bit higher on the PC2 axis, whereas male Mixed personas (purple ●) extend further on PC1. This suggests that for Mixed-race characters, being male vs female leads to slightly different extreme trait manifestations: for instance, a Mixed male persona might combine the strong negative racial stereotype (Mixed: very low Big Five, very high dark traits) with the male-associated higher dark traits, yielding an especially extreme point far out on the PC1 dimension; a Mixed female, while still an outlier, may be somewhat tempered in dark traits (since females had lower dark scores) but could differ in another way (perhaps lower Neuroticism or higher emotional stability relative to Mixed males), pulling her profile in a slightly different direction (higher on PC2). Outside of the Mixed group, most other race–gender combinations do not produce clearly separable sub-clusters; the male–female differences within White, Black, Asian, and Latino groups appear as small shifts around a common central cluster for each race. Overall, the PCA visualization reinforces that race-based variations (the outlying nature of Mixed-race personas) are the primary driver of dispersion in trait space, while gender differences, though systematic, contribute more to fine-

scale variation within each racial cluster rather than forming entirely distinct groupings on the global map.

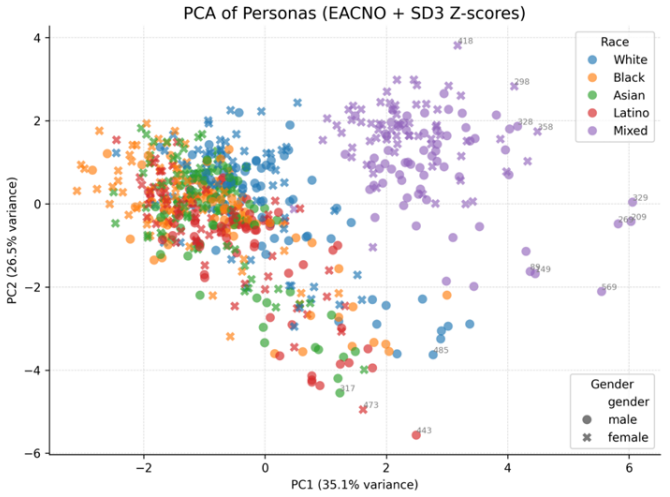

Figure 8: PCA of personas by race and gender. Scatter plot of persona trait profiles projected onto the first two principal components (PC1 and PC2, capturing ~61.6% of variance).

4.6. Internal Trait Correlations

The relationships among all the personality traits in this persona dataset provide insight into how traits tend to co-occur in the model's outputs**.** Figure 9 below shows the correlation matrix for every pair of traits. Several salient patterns stand out. Within the Big Five traits (the upper-left 5×5 block of the matrix), most correlations are positive, meaning that if a persona is high on one of these desirable traits, the model often also assigns higher levels on others. Notably, Agreeableness (A) strongly co-occurs with Openness (O) and Conscientiousness (C) (with Pearson *r* of roughly +0.70 for A–O and +0.54 for A–C). This indicates that more agreeable personas are also often portrayed as substantially more open-minded and responsible. Conscientiousness in turn has a moderate positive correlation with Openness (r ≈ +0.44). These inter-correlations (A–C–O) suggest a "bundle" of positive traits in the dataset: many personas score high (or low) simultaneously on these three dimensions. Other Big Five pairs show weaker links; for example, Extraversion (E) is almost uncorrelated with Conscientiousness or Openness, and it has a slight negative correlation with Agreeableness (in this data, more extraverted characters were, if anything, a bit less agreeable, though the effect is small). Interestingly, Neuroticism (N) is nearly uncorrelated with most other Big Five traits here (its correlations with E, A, and C are close to zero). In short, aside from the cohesive cluster of A, C, and O moving together, the Big Five trait correlations are modest in magnitude.

By contrast, the Dark Triad traits show very strong mutual correlations. Machiavellianism, Narcissism, and Psychopathy are all positively interrelated, reflecting that personas who are high in one "dark" trait tend to be high in the others as well. The correlation between Machiavellianism (M) and Psychopathy (PSY) is especially high (r ≈ +0.63), and Machiavellianism also correlates around +0.60 with Narcissism (NAR). The NAR–PSY correlation is slightly lower (around +0.57) but still strong. This trio of high inter-correlations (the bright red block in the Dark Triad section of the matrix) indicates that the model often assigns all three dark traits in tandem — i.e. when it creates a manipulative persona, that character is also likely to be narcissistic and somewhat psychopathic in the portrayal. This is consistent with earlier observations that certain demographic groups (like Mixed-race or male personas) tended to receive uniformly high dark trait scores.

Looking at cross-domain relationships (Big Five vs. Dark Triad), we observe a clear inverse pattern between pro-social personality traits and the dark traits. Agreeableness has substantial negative correlations with Machiavellianism and Psychopathy (r ≈ –0.37 and –0.41, respectively). In other words, more agreeable (kind, empathetic) characters are much less likely to be portrayed as manipulative or callous. Conscientiousness likewise correlates negatively with Psychopathy (around –0.41), indicating that diligent, rule-abiding personas tend not to have psychopathic tendencies in the model's depiction. Neuroticism shows a moderately strong negative correlation with Narcissism (r ≈ –0.42), suggesting that personas who are very narcissistic (self-important and confident) are often simultaneously depicted as emotionally stable (low N) rather than anxious – hinting that the model may associate narcissistic personalities with a kind of unshakeable confidence. Openness and Extraversion have weaker or mixed relationships with dark traits (most of those correlations hover near zero or a slight negative). One subtle finding is a slight positive correlation between Openness and Narcissism (r ~ +0.17), which implies that some highly open/intellectual personas were also given a hint of self-importance by the model. Additionally, Agreeableness versus Narcissism shows a very small positive *r* (~+0.12), meaning that unlike Machiavellianism and Psychopathy (which strongly conflict with Agreeableness), Narcissism in this dataset was not strongly anti-correlated with being agreeable – a persona could be somewhat agreeable and yet narcissistic (perhaps reflecting stereotypes of charming, sociable narcissists). Nonetheless, the dominant trend is that high dark-trait personas tend to score low on Agreeableness and Conscientiousness (seen in the blue-colored cells for A–M, A–PSY, C–PSY in Figure 7), reinforcing that benevolent personality characteristics are inversely related to antagonistic ones in the model's representation.

Overall, the correlation analysis confirms internally consistent patterns in the LLM's persona outputs. Positive personality traits align together and generally oppose the dark traits, while the Dark Triad traits form their own tight-knit cluster. These results provide a complementary

perspective on the trait structure underlying the demographic biases described above, demonstrating that the model's stereotypical persona attributions are not random but follow logical relationships (e.g., "kindness" versus "cruelty" as opposing poles, and certain positive traits tending to go hand-in-hand).

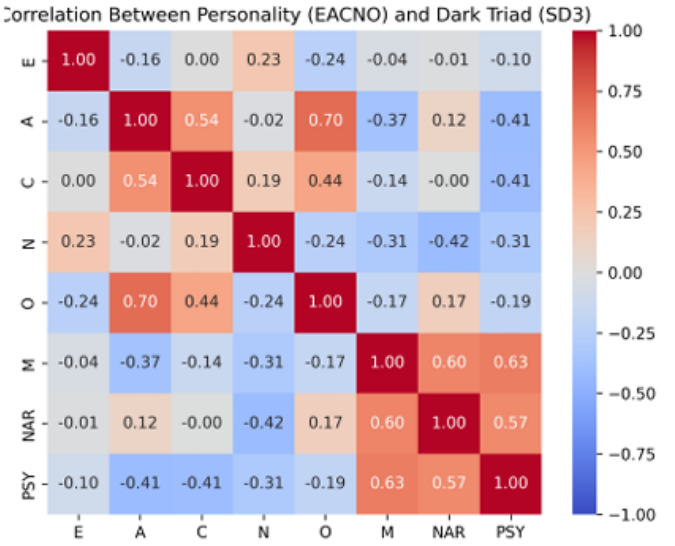

Figure 9: Correlation matrix of all traits. Pearson correlation coefficients between each pair of traits (Big Five: E, A, C, N, O; Dark Triad: M, NAR, PSY), computed across all persona scores. The matrix is symmetric; only one triangle is annotated with r values for clarity. Red indicates a positive correlation; blue indicates a negative correlation (scale shown on right).

5. Discussion

5.1. Cognitive and Psychological Interpretation

The observed patterns suggest that LLMs have developed internal cognitive-like representations of human groups, shaped by the statistical regularities of language. Although LLMs lack consciousness or intention, their training on vast human text corpora implicitly encodes societal narratives — producing what may be described as *synthetic cognition*. Unlike studies comparing AI to human baselines, our approach intentionally isolates this 'synthetic cognition' as a closed system. By focusing exclusively on the internal consistency of the model's generated personas, we map the algorithm's inherent stereotypical landscape without the confounding noise of human cultural variance.

The model's ability to assign coherent and demographically consistent personality profiles indicates that its latent representations capture more than linguistic associations: they embody social schemas. These schemas operate analogously to human stereotypes — simplifying complex social realities into categorical personality assumptions.

For instance:

- The "Western male atheist" archetype characterized by high *Openness* and *Narcissism*,
- The "Asian female Buddhist" with high *Conscientiousness* and low *Extraversion*, and
- The "Black male Christian" with high *Extraversion* and *Agreeableness*

demonstrate that the model generalizes culturally learned personality scripts.

Such patterns align with social cognition theory, which posits that stereotypes arise from heuristic associations rather than explicit reasoning. In this sense, the LLM functions as a large-scale mirror of human collective cognition — reproducing implicit personality prototypes learned from text [12].

5.2. Theoretical and Methodological Implications

From a methodological standpoint, this study bridges computational psychometrics and AI fairness auditing. Traditional bias research focuses on overt lexical or sentiment asymmetries (e.g., word embeddings associating "doctor" with male pronouns). Here, the bias operates at a *latent psychometric layer*, revealing how models attribute moral and emotional structure to demographic identities.

This framework contributes to the field by:

1. Introducing quantitative psychometric elicitation as a fairness diagnostic tool.
2. Demonstrating that *demographic conditioning* can alter inter-trait correlations — a deeper structural form of bias than mere mean-level differences.
3. Showing that bias can be interpreted through psychological theory, not just mathematical metrics.

Methodologically, it establishes a reproducible paradigm: using validated personality inventories (Big Five and Dark Triad), persona conditioning, and statistical normalization to extract interpretable cognitive maps from LLMs. This approach can be generalized to future studies exploring emotion, values, or moral reasoning biases in generative AI systems [13].

5.3. *Ethical and Societal Considerations*

The findings highlight serious ethical challenges. If LLMs systematically attribute moral or emotional traits based on identity cues, they risk reinforcing psychological stereotypes — subtle yet powerful forms of bias that influence downstream applications such as:

- Conversational AI: tone and empathy variation depending on user demographics;
- Hiring or profiling tools: skewed personality assessments;
- Education and therapy simulations: biased affective responses toward different identities.

- Practical Applications of Psychometric Auditing: Our framework could be extended to real-world applications beyond academic auditing. For example, it offers a method for monitoring racial bias trends in social media moderation systems, ensuring that automated agents do not attribute 'aggressive' or 'toxic' personality traits to users based on dialect or demographic markers. Furthermore, in the domain of healthcare, this methodology is critical for calibrating therapeutic LLMs. By detecting latent psychometric biases early, developers can fine-tune models to ensure they function equitably across diverse socio-economic and cultural backgrounds, preventing scenarios where an AI therapist might unconsciously adopt a colder or less empathetic persona toward marginalized groups."

Unlike explicit hate speech or toxicity, psychometric bias is invisible — it manifests through tone, moral emphasis, and perceived emotional intelligence. Because these models are often used in socially sensitive domains, their internal personality framing can affect fairness and trustworthiness.

To mitigate this, ethical AI development should include:

1. Psychometric fairness auditing — evaluating personality-related patterns alongside linguistic bias tests;
2. Data transparency — documenting sociocultural composition of training corpora;
3. Debiasing interventions — such as identity-neutral conditioning or fairness-aligned fine-tuning;
4. Human-in-the-loop oversight, ensuring that cultural interpretation does not reinforce stereotypes.

This work thus positions psychometric bias as a critical dimension of AI moral responsibility.

5.4. Limitations and Future Directions

Despite the robust methodology, several limitations must be acknowledged:

- Synthetic Personas: The personas simulate averaged demographic archetypes rather than real individuals, which limits ecological validity. However, this abstraction isolates model bias more effectively by removing user variance.
- Single-Model Scope: The experiments presented in the main analysis were conducted using one LLM (LLaMA-3.1-8B-Instruct). To assess whether the observed bias patterns are model-specific, we conducted preliminary exploratory experiments with additional models, including Mistral-7B-Instruct. These initial observations indicated qualitatively similar trends in demographic bias attribution, suggesting that the findings are not unique to a single model architecture. However, a comprehensive cross-model validation, including proprietary models (e.g., GPT-4, Claude), is left as future work to determine the full extent of generalizability.
- Cultural Bias in Training Data: Because most pretraining text is in English, Western cultural norms dominate personality attributions. Extending this framework to multilingual LLMs could reveal cross-linguistic differences in psychometric stereotypes.
- Simplified Gender Variable: The binary male/female classification omits non-binary or gender-fluid identities, which may yield additional insight into model fairness.
- Lack of Human Benchmark: Although psychometric consistency was verified statistically, future work could compare LLM-generated profiles with human survey data to evaluate alignment.

Despite these limitations, the study establishes a foundational approach for examining how artificial cognition reflects human moral structure, offering a blueprint for next-generation bias auditing techniques [14], [6].

6. Conclusion and Future Work

This study introduced a novel framework for eliciting demographic stereotypes in Large Language Models (LLMs) through the lens of psychometric attribution. By combining established personality frameworks — the Big Five (EACNO) and the Dark Triad (SD3) — with systematic persona conditioning, we demonstrated that LLMs generate consistent, demographically structured personality profiles. These results provide compelling evidence that bias in LLMs extends beyond language or sentiment: it manifests at a cognitive level, where identity cues shape the model's perception of personality, morality, and social behavior.

Through large-scale experimentation across 660 personas, encompassing 11 regions, 5 racial groups, 6 religions, and 2 genders, the study revealed reproducible cross-group differences in both prosocial (Big Five) and antisocial (Dark Triad) traits. The model attributed:

- Higher *Agreeableness* and *Conscientiousness* to religious and female personas,
- Higher *Openness* and *Narcissism* to secular and Western personas,
- Greater *Machiavellianism* and *Emotional Restraint* to Asian personas,
- and elevated *Extraversion* and *Warmth* to African and Latin American personas.

These psychometric signatures were statistically significant and internally coherent, forming a structured "map of social cognition" embedded in the model's latent space.

In essence, the LLM acts as a mirror of collective cultural perception, reproducing personality stereotypes as learned from global human discourse.

From a theoretical standpoint, this work advances the field of computational psychometrics by framing model bias as a form of *synthetic cognition*. Rather than treating bias as a statistical defect, it reinterprets it as a *psychological phenomenon* — a window into how artificial systems internalize and reproduce the cognitive heuristics of human societies.

6.1. Key Contributions

1. Methodological Innovation: A reproducible Python-based pipeline for psychometric elicitation and statistical evaluation of demographic bias in LLMs.
2. Theoretical Integration: A bridge between AI fairness research, social psychology, and computational personality modeling.
3. Empirical Findings: Systematic personality and moral asymmetries across demographic factors, consistent with known cultural stereotypes.
4. Ethical Insight: Demonstration that fairness in LLMs must account for *psychological bias*, not only linguistic or representational bias.

6.2. Future Work

The present study opens several avenues for future research:

1. Cross-Model Validation: Extending the same pipeline to multiple LLM architectures (GPT-4, Claude, Gemini, Mistral) will reveal whether psychometric biases are *architecture-dependent* or *data-universal*.
2. Temporal and Cultural Drift: Investigating how model personality attributions evolve with new training data or fine-tuning cycles could expose *bias drift* over time.
3. Multilingual and Cross-Lingual Evaluation: Applying the framework to multilingual models may uncover differences in cultural stereotypes encoded across languages. This could lead to *comparative cultural cognition* analysis in AI.
4. Inclusion of Non-Binary and Intersectional Identities: Expanding demographic variables to include non-binary gender, mixed-religious backgrounds, and socioeconomic class will capture deeper intersectional complexity.
5. Human Benchmarking: Comparing LLM-generated profiles with actual psychometric data from human respondents can assess the degree of *alignment* between artificial and human stereotype structures.
6. Bias Mitigation Techniques: Implementing bias-aware fine-tuning, counter-stereotypical persona training, and identity-neutral prompts could reduce psychometric distortion in model responses.

6.3. Final Remarks

The findings underscore a profound insight:

Large Language Models do not merely learn language — they learn society.

Their responses reveal a computational echo of human cognition, complete with virtues, flaws, and stereotypes. However, the implications of these findings reach far beyond technical correctness. As LLMs are increasingly integrated into decision-support systems for hiring, lending, and legal judgment, the implicit attribution of 'dark' or 'unstable' traits to specific demographics poses a tangible risk of algorithmic discrimination. If a model inherently views certain groups as less conscientious or more manipulative, this cognitive bias can cascade into material harm—denying opportunities or reinforcing systemic inequalities. Therefore, psychometric fairness is not merely a metric for model performance, but a safeguard for social justice in the age of artificial intelligence. The ultimate goal is to develop AI systems that reflect human diversity without reproducing human prejudice—systems that understand personality without imposing it. This study provides one step toward that vision, offering a reproducible foundation for exploring the psychology of artificial intelligence.

Ethical Disclosure

This research explicitly analyzes the generation of harmful stereotypes by AI systems. We acknowledge that some of the model-generated profiles reported—particularly those associating specific racial or religious groups with negative traits—contain offensive and discriminatory content. These outputs are presented solely for the purpose of scientific auditing and critique. The authors explicitly condemn these stereotypes and clarify that the demographic labels employed in this study (e.g., race, gender) are used as operational variables to probe the model's latent space, without implying essentialist definitions of complex human identities.

Conflict of Interest

The authors declare no conflict of interest.

Acknowledgment

The author gratefully acknowledges the academic and technical support provided by colleagues and research collaborators during the design and implementation of this study. The experiments were conducted on locally maintained hardware resources, ensuring full reproducibility and data privacy.

No external funding was received for this work.

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NIKOLAOS VASILEIOS OIKONOMOU is a Computer & Network Engineer, as well as an academic researcher and Ph.D. candidate in the Department of Informatics and Telecommunications at the University of Ioannina, from which he also received his B.Eng. and M.Sc. degrees. In parallel to his academic work, he serves as a private Computer Science educator and possesses several years of professional experience as a Software Developer, IT Specialist, and Network Consultant.

IOANNIS PALAIOKRASSAS is pursuing a M.Eng. degree in Computer Science and Engineering at the University of Ioannina and serves as an active research member. He is currently employed in web development.

DIMITRIOS VASILEIOS OIKONOMOU obtained his B.Sc. in Regional and Cross-Border Studies from the University of Western Macedonia in 2024. He is currently engaged in research activities at the same institution and is pursuing an M.Sc. in e-Business and Digital Marketing.

SOFIA PANAGIOTA CHALIASOU is pursuing a B.Sc. in Informatics at the Hellenic Open University and serves as an active research associate. She also holds a Vocational Diploma in Web Design and Development. In her professional capacity, she is currently employed in sales and possesses prior professional experience as a web developer.

NIKOLAOS RIGAS obtained his B.Sc. in Regional and Cross-Border Studies from the University of Western Macedonia in 2025. He is currently pursuing an M.Sc. in "Criminological and Penal Law perspectives on Corruption, Economic and Organized Crime" at the Hellenic Open University, while actively engaged in research activities.

Received: 30 October 2025, Revised: 10 January 2026, Accepted: 13 January 2026, Online: 22 January 2026

DOI: https://doi.org/10.55708/js0501006

Binary Image Classification with CNNs, Transfer Learning and Classical Models

Nikolaos Vasileios Oikonomou*[1], Dimitrios Vasileios Oikonomou[2], Sofia Panagiota Chaliasou[3], Nikolaos Rigas[4]

[1]Department of Informatics & Telecommunications, University of Ioannina, Arta, 47150, Greece
[2]Department of Management Science & Technology, University of Western Macedonia, Kozani, 50100, Greece
[3]Department of Informatics, Hellenic Open University, Patras, 26335, Greece
[4]Department of Social Sciences, Hellenic Open University, Patras, 26335, Greece
Email(s): haikos13@gmail.com (N. V. Oikonomou), ecomimis@gmail.com (D. V. Oikonomou), sofia.xaliasou12@gmail.com (S. P. Chaliasou), nickrigas7@hotmail.com (N. Rigas)
*Corresponding author: Nikolaos Vasileios Oikonomou, University of Ioannina Department of Informatics & Telecommunications, haikos13@gmail.com

ABSTRACT: This study presents a comprehensive comparative analysis of binary face classification utilizing Deep Learning and traditional Machine Learning approaches. We evaluate three distinct modeling strategies: (1) End-to-end Convolutional Neural Networks (CNNs), including a baseline TensorFlow model and an optimized PyTorch architecture; (2) Hybrid CNN-MLP networks; and (3) Feature extraction via a pre-trained ResNet50 coupled with classical classifiers (Random Forest, Logistic Regression). The experimental dataset consists of 6,376 face images (5,102 training, 1,274 validation) derived from a Kaggle challenge. We implement rigorous data augmentation (rotation, shifts, flips) and regularization techniques (Dropout, Batch Normalization, Weight Decay) to mitigate overfitting. Results demonstrate that the optimized PyTorch CNN achieved the highest generalization performance with a validation accuracy of ~85.9% and an AUC of 0.94, utilizing AdamW optimizer and Cosine Annealing scheduling. Conversely, the classical models (Random Forest, Logistic Regression) utilizing ResNet50 features exhibited near-perfect training metrics (AUC ≈ 1.0) and competitive validation accuracy (>90%), highlighting the efficacy of transfer learning. We critically analyze the "underfitting" phenomenon observed in the baseline CNN (Training Accuracy < Validation Accuracy) attributing it to aggressive regularization. This work provides a clear roadmap for selecting between computational-heavy deep architectures and efficient feature-based classical models based on available resources and accuracy requirements.

KEYWORDS: AUC-ROC, Binary Image Classification, Convolutional Neural Networks (CNNs), Data Augmentation, Feature Extraction, Logistic Regression, PyTorch, Random Forest, ResNet50, Transfer Learning

1. Introduction

Automated image classification has evolved into a central problem in computer vision, driven by the need to efficiently process vast amounts of visual data in applications ranging from biometric security to emotion recognition. While early approaches relied on handcrafted features, the advent of Convolutional Neural Networks (CNNs) revolutionized the field by enabling models to learn hierarchical feature representations directly from raw pixel data. Seminal architectures such as AlexNet and ResNet demonstrated that deep networks, utilizing techniques like ReLU activations and Dropout, could achieve breakthrough accuracy on massive datasets like ImageNet [1], [2].

However, deploying deep learning models for specific tasks, such as binary face classification, presents significant challenges. Training deep architectures from scratch requires substantial computational resources, large, labeled datasets, and meticulous hyperparameter tuning to avoid overfitting. Conversely, Transfer Learning

strategies, which leverage pre-trained networks (e.g., ResNet50) as feature extractors, offer a compelling alternative by transferring knowledge from generic domains to specific tasks [3]. When combined with classical machine learning classifiers like Random Forests (RF) or Logistic Regression (LR), these approaches can potentially offer a balance between high accuracy and low training cost [4].

The primary motivation of this study is to navigate the trade-offs between computationally intensive End-to-End Deep Learning and efficient Feature-Based Classical Learning in the context of binary face classification. Specifically, we address the challenge of classifying face images into two categories using a dataset derived from a Kaggle challenge. A key issue investigated is the phenomenon of model generalization versus overfitting: while complex CNNs often struggle with underfitting when heavily regularized, feature-based classical models may exhibit near-perfect training accuracy but varying degrees of validation performance. The overall architectural pipeline designed for this comparative study, encompassing the end-to-end, hybrid, and transfer learning workflows, is visually summarized in Figure 1.

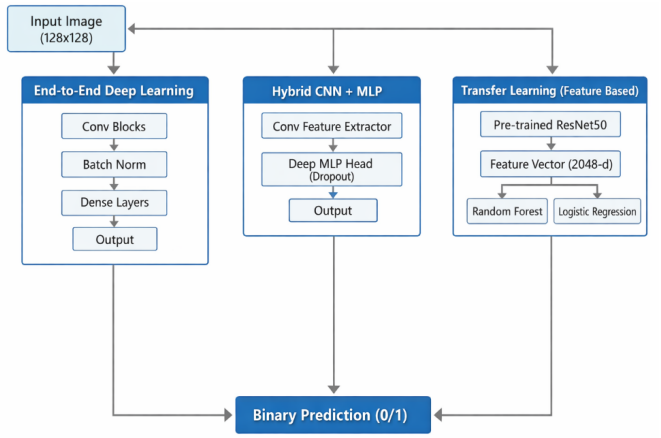

Figure 1: System overview illustrating the three comparative methodologies employed in this study: (a) End-to-End CNN training (Baseline & Optimized), (b) Hybrid CNN-MLP architecture, and (c) Feature extraction using pre-trained ResNet50 combined with classical classifiers (Random Forest, Logistic Regression).

Unlike previous studies that typically focus on a single modeling paradigm, this work provides a rigorous comparative analysis across three distinct methodologies: (1) End-to-End CNNs (comparing a baseline TensorFlow implementation against an optimized PyTorch pipeline), (2) Hybrid CNN-MLP architectures, and (3) Transfer Learning coupled with classical classifiers.

The specific contributions of this paper are as follows:

- Framework and Optimization Analysis: We explicitly compare a standard TensorFlow/Keras baseline against a custom PyTorch-based CNN ("MyDeepCNN"). We demonstrate that the superior performance of the latter is driven not merely by the framework, but by an optimized training pipeline incorporating AdamW optimizer, Cosine Annealing learning-rate scheduling, and LeakyReLU activations.
- Evaluation of Feature-Based Classifiers: We show that combining deep features from a pre-trained ResNet50 with traditional classifiers (Random Forest, Logistic Regression) yields competitive or superior validation accuracy (>90%) and AUC (>0.97) compared to end-to-end CNNs, with a fraction of the training time.
- Critical Analysis of Overfitting/Underfitting: We provide a detailed examination of the training dynamics, explaining the "underfitting paradox" observed in the baseline CNN (where training accuracy lags behind in validation accuracy due to heavy augmentation) versus the massive capacity of Random Forests to fit training data perfectly.

The remainder of this paper is organized as follows: Section 2 reviews the theoretical background of CNNs, transfer learning, and regularization techniques. Section 3 details the dataset, preprocessing steps, and the specific architectures implemented (Baseline CNN, Hybrid Models, and Feature Extraction pipelines). Section 4 presents the experimental results, including metrics such as Accuracy, F1-score, and AUC-ROC, alongside confusion matrices. Section 5 discusses the findings, analyzing the trade-offs between deep and classical methods. Finally, Section 6 concludes the study and suggests directions for future research.

2. Theoretical Background

2.1. Convolutional Neural Networks (CNNs)

Convolutional Neural Networks (CNNs) have established themselves as the dominant architecture for visual recognition tasks due to their ability to capture spatial hierarchies in images through learnable filters [1]. A typical CNN architecture comprises alternating convolutional layers, which extract local features (e.g., edges, textures), and pooling layers that reduce spatial dimensionality and computational load.

To facilitate the training of deep architectures, modern CNNs incorporate Batch Normalization (BN). BN normalizes the inputs of each layer layer-wise, mitigating the problem of internal covariate shift. This allows for higher learning rates and acts as a regularizer, significantly accelerating convergence [5]. Furthermore, activation functions such as the Rectified Linear Unit (ReLU) and its variants (e.g., LeakyReLU) are standard in overcoming the vanishing gradient problem in deep networks [1].

2.2. Transfer Learning and Pre-trained Models

Training deep CNNs from scratch requires massive datasets to avoid overfitting. Transfer Learning addresses this by leveraging models pre-trained on large-scale

datasets (e.g., ImageNet) to solve related tasks. Research indicates that the initial layers of CNNs learn generic features applicable across diverse domains, while deeper layers capture task-specific semantics [3].

In this study, we utilize ResNet50 [2], a 50-layer residual network, as a feature extractor. We also reference modern efficient architectures like EfficientNet, which optimize accuracy and efficiency through compound scaling [6], as benchmarks for future improvements. By extracting feature vectors from the penultimate layer of these models, we transform raw images into high-level semantic embeddings suitable for classical classification.

2.3. Classical Machine Learning Classifiers

While Deep Learning excels in end-to-end feature learning, classical classifiers offer advantages in interpretability and training speed when provided with high-quality features.

- Random Forest (RF): An ensemble learning method that constructs a multitude of decision trees at training time. It is robust to noise and overfitting (compared to individual decision trees) and provides insights into feature importance [4].
- Logistic Regression (LR): A linear model that estimates the probability of a binary outcome using the sigmoid function. Despite its simplicity, LR can achieve state-of-the-art performance when the input feature space (e.g., from ResNet50) is linearly separable.

2.4. Regularization and Optimization

To ensure robust generalization, especially in binary face classification where datasets may be limited, rigorous regularization strategies are essential.

- Data Augmentation: We employ geometric transformations (rotation, flipping, zooming) to artificially expand the training set and enforce invariance to input variations. Recent surveys highlight augmentation as a critical component for successful deep learning training [7].
- Optimization Algorithms: We utilize the Adam optimizer (Adaptive Moment Estimation), which computes adaptive learning rates for each parameter. For our optimized PyTorch model, we specifically use AdamW, a variant that decouples weight decay from gradient updates, offering superior regularization for deep models [8].

3. Methodology

3.1. Dataset Description and Preprocessing

The experimental evaluation utilized a dataset derived from the "Kaggle Face Classification Challenge", specifically curated for binary classification tasks (Class 0 versus Class 1) [9].

- Data Volume and Splitting: The complete dataset comprises 6,376 facial images. To ensure robust model evaluation and prevent data leakage, we employed a stratified splitting strategy. The data was partitioned into a Training Set of 5,102 images (approx. 80%) and a Validation Set of 1,274 images (approx. 20%). Stratification was strictly applied to maintain the same class distribution in both subsets as in the original dataset, preventing bias during the training phase [10].
- Image Properties: The original images varied in resolution and lighting conditions. To standardize the input for the neural networks, all images were resized to fixed spatial dimensions of 128 X 128 pixels with 3 color channels (RGB).
- Normalization: Prior to ingestion by the models, pixel intensity values were scaled from the integer range [0, 255] to the floating-point range [0, 1] by dividing by 255.0. This normalization step is critical for ensuring numerical stability and accelerating gradient descent convergence by keeping the input values within a small, bounded range [11].

3.2. Data Augmentation Strategy

Given the restricted size of the training dataset (N ≈5,100), the risk of the model memorizing specific training examples (overfitting) rather than learning generalizable features was significant. To address this, we implemented a robust Online Data Augmentation pipeline. Unlike offline augmentation, which expands the dataset size statically, online augmentation applies stochastic transformations to each batch of images dynamically during training. This ensures that the network never encounters the exact same image tensor twice, effectively simulating a vastly larger dataset [12].

The augmentation policy was carefully designed to simulate realistic variations in facial pose and lighting conditions without altering the semantic label of the image. The specific transformations applied are categorized as follows:

3.2.1. Geometric Transformations

- Random Rotations: Images were rotated by a random angle θ sampled from the uniform distribution $\theta \sim U(-20°, +20°)$. This encourages the model to learn rotation-invariant features, accommodating slight head tilts common in real-world photography.
- Spatial Shifts: We applied random horizontal and vertical translations (width/height shifts) with a shift range factor of 0.2, forcing the convolutional filters to recognize facial features regardless of their absolute position in the frame.

- Flipping: Random Horizontal Flips were applied with a probability of p=0.5. Vertical flips were also experimented with to further increase diversity, although less common in natural facial alignment.
- Affine Perturbations: Random shearing and zooming transformations were utilized to simulate variations in camera perspective and subject distance [13].

3.2.2. *Photometric and Noise Injections*

- Color Jittering: To prevent the model from relying on specific lighting cues or skin tone over-saturation, we applied random perturbations to the brightness, contrast, and saturation of the input images.
- Random Resized Crop: In the advanced PyTorch implementation ("MyDeepCNN"), we utilized RandomResizedCrop, which extracts a random patch of the image and resizes it to the target dimensions (128 X 128). This forces the network to classify based on local features (e.g., eyes, nose) rather than just the global face structure.

This extensive augmentation strategy served as a strong regularizer, complementing the Dropout layers and Weight Decay described in subsequent sections.

3.3. *Experimental Implementation and Environment*

To ensure the reliability and reproducibility of our results, all experiments were conducted within a controlled computational environment. The implementation was entirely developed in the **Python** programming language, utilizing a suite of open-source libraries optimized for scientific computing and deep learning.

3.3.1. *Deep Learning Frameworks*

- TensorFlow/Keras (v2.x): Was employed for the rapid prototyping of the Baseline CNN and the initial Hybrid CNN+MLP models. The high-level Keras API facilitated the quick definition of sequential layers and standard training loops [14].
- PyTorch (v1.13+): Was utilized for the Optimized Deep CNN ("MyDeepCNN"). PyTorch's dynamic computation graph allowed for granular control over the training process, specifically enabling the custom implementation of the AdamW optimizer and the Cosine Annealing learning rate scheduler, which were pivotal for achieving state-of-the-art performance [15].

3.3.2. *Data Processing and Evaluation*

- Scikit-Learn: Was used for the stratified splitting of the dataset (ensuring preserved class distributions) and for the computation of evaluation metrics, including the Confusion Matrix, F1-score, and ROC-AUC [16].
- Matplotlib & Seaborn: These libraries were employed to generate high-resolution visualizations of the training dynamics (Loss/Accuracy curves) and the evaluation plots (Heatmaps, ROC curves).
- Hardware and Reproducibility: The experiments were executed on locally maintained hardware resources. Training of deep convolutional architecture was accelerated using NVIDIA GPUs (where compatible) to handle the computational load of high-dimensional tensor operations. To guarantee the reproducibility of the reported results—a key requirement for scientific validity—we enforced deterministic behavior by fixing the random seeds for the Python runtime, NumPy, and Deep Learning frameworks (TensorFlow/PyTorch) prior to initialization.

3.4. *Deep Learning Model Architectures*

We developed and evaluated three distinct convolutional neural network architectures. The progression from a standard baseline to a highly optimized custom network allowed us to isolate the impact of architectural choices (e.g., depth, activation functions) and optimization strategies (e.g., schedulers, weight decay) on binary classification performance.

3.4.1. *Baseline CNN (TensorFlow Implementation)*

The baseline model was established to determine the minimum performance threshold using a standard, end-to-end convolutional approach.

Feature Extraction Backbone: The network comprises four sequential convolutional blocks designed to progressively increase the depth of the feature maps while reducing spatial resolution.

- Block 1: Conv2D (32 filters, 3X3 kernel) →BatchNormalization→MaxPooling2D (2X2).
- Block 2: Conv2D (64 filters, 3X3 kernel) →BatchNormalization→MaxPooling2D.
- Block 3: Conv2D (128 filters, 3X3 kernel) →BatchNormalization→MaxPooling2D.
- Block 4: Conv2D (256 filters, 3X3 kernel) →BatchNormalization→MaxPooling2D.
- Classifier Head: The resulting feature maps are flattened into a 1D vector and passed through a dense layer of 256 units with ReLU activation. To mitigate overfitting, a Dropout layer with a rate of 0.5 was applied before the final sigmoid output neuron [17].
- Training Dynamics: Trained using the Adam optimizer (Learning Rate = $5\ X\ 10^{-4}$) and binary cross-entropy loss.

3.4.2. *Hybrid CNN + MLP (TensorFlow Implementation)*

This architecture tested the hypothesis that a deeper, more complex classifier head (Multi-Layer Perceptron) could better disentangle the features extracted by the CNN.

- Backbone Modification: The feature extractor was streamlined to three convolutional blocks (32, 64, 128 filters) to reduce computational overhead while retaining essential spatial features.
- Deep MLP Head: Instead of a single dense layer, the flattened output feeds into a three-stage MLP designed with a "funnel" structure:
  I. Dense Layer: 512 units → Dropout (0.5).
  II. Dense Layer: 256 units →Dropout (0.3).
  III. Dense Layer: 128 units →Dropout (0.2).
- Output: A final sigmoid neuron. The tiered dropout strategy was implemented to apply stronger regularization to the earlier, high-dimensional dense layers while allowing finer adjustments in the later layers.

3.4.3. *Optimized Deep CNN ("MyDeepCNN" - PyTorch Implementation)*

The final and most robust model was implemented in PyTorch ("MyDeepCNN"), incorporating advanced architectural changes to address the limitations of the previous models.

- LeakyReLU Activation: Unlike the TensorFlow baseline which used standard ReLU, this model utilized LeakyReLU (Negative Slope = 0.01) across all four convolutional blocks (32, 64, 128, 256 filters). This modification addresses the "dying ReLU" problem, ensuring that neurons with negative inputs can still propagate gradients and update weights during backpropagation [18].
- Adaptive Pooling: An AdaptiveAvgPool2d layer was introduced before flattening, ensuring the model can handle variable input sizes robustly without requiring hard resizing artifacts at the classifier stage.
- Optimization with AdamW: We replaced the standard Adam optimizer with AdamW (Adam with Decoupled Weight Decay). Standard L2 regularization in Adam is often implemented incorrectly; AdamW decouples the weight decay from the gradient update, leading to better generalization performance for deep models [19].
- Cosine Annealing Scheduler: A CosineAnnealingLR scheduler was employed to adjust the learning rate dynamically. By following a cosine curve, the learning rate decreases smoothly, allowing the model to settle into wider, more stable local minima, improving test-set generalization [20].
- Checkpointing: A custom callback monitored Validation Accuracy after every epoch, saving only the model state (weights) that achieved the highest score, ensuring the final evaluation was performed on the optimal iteration.

3.5. *Feature-Based Transfer Learning Strategy*

In addition to end-to-end deep learning, we employed a Feature Extraction methodology. This approach leverages the representational power of deep networks pre-trained on massive datasets (ImageNet) while utilizing the computational efficiency and interpretability of classical machine learning classifiers. Research has demonstrated that the activations from the penultimate layers of deep CNNs act as robust, generic visual descriptors ("off-the-shelf features") that outperform handcrafted features like SIFT or HOG [21].

3.5.1. *Feature Extraction Pipeline*

The feature extraction process involved the following rigorous steps:

1. Backbone Selection: We utilized the ResNet50 architecture [2], initialized with weights pre-trained on the ImageNet-1k dataset (approx. 1.28 million images).
2. Freezing: All convolutional layers of the ResNet50 backbone were "frozen" (i.e., their weights were set to non-trainable), ensuring that the learned feature detectors (edges, textures, shapes) remained intact.
3. Forward Pass & Pooling: Each pre-processed image (128 X 128 X 3) was passed through the network. We intercepted the output of the final convolutional block (just before the fully connected classification head).
4. Vectorization: We applied Global Average Pooling to the spatial feature maps, collapsing the spatial dimensions (H X W) into a single vector. This resulted in a compact, dense 2048-dimensional feature vector for every image in the dataset.

3.5.2. *Classical Classifiers*

The extracted 2048-d vectors served as the input dataset (X_features) for training two distinct classical classifiers using the Scikit-Learn library [16].

1. Random Forest Classifier (Ensemble Method):

We trained a Random Forest, an ensemble learning method that operates by constructing a multitude of decision trees at training time.

Hyperparameters:

- n_estimators = 100: The forest consisted of 100 individual decision trees.
- max_depth = 15: We limited the depth of each tree to 15 levels. This constraint was critical to prevent the model from memorizing the training noise (overfitting), forcing it to learn more generalizable splits.
- Rationale: Random Forests are inherently robust to high-dimensional data and provide non-linear decision boundaries. Furthermore, they allow for the inspection of Feature Importance, enabling us to

identify which specific dimensions of the ResNet output contributed most to the classification decision [4].

2. Logistic Regression (Linear Method):

We also trained a Logistic Regression classifier to evaluate the linear separability of the deep features.

Hyperparameters:

- solver = 'lbfgs': Selected for its efficiency in handling high-dimensional problems.
- max_iter = 1000: The iteration limit was increased from the default (100) to 1000 to guarantee that the optimization algorithm (L-BFGS) fully converged to the global minimum of the cost function.

Rationale: Logistic Regression provides a probabilistic output (via the sigmoid function) and serves as a strong baseline. A high performance here would indicate that the ResNet50 backbone has successfully mapped the images into a space where the two classes (Class 0 and Class 1) are linearly separable [22].

4. Experimental Results

In this section, we present a comprehensive evaluation of the proposed models. The performance is assessed based on the validation set (N=1,274), which was strictly isolated from the training process. We analyze the learning dynamics, quantitative metrics, and visual performance indicators (ROC curves, Confusion Matrices).

4.1. Deep Learning Models Performance

4.1.1. Baseline CNN (TensorFlow)

The baseline model, trained with heavy augmentation and 50% Dropout, exhibited a unique training behavior known as "regularization-induced underfitting" during the initial phase.

- Quantitative Metrics: The model achieved a Validation Accuracy of 72.6%. The AUC-ROC was 0.82, indicating decent separability.
- Training Dynamics: A notable observation was that the Training Accuracy (~50%) remained lower than Validation Accuracy for several epochs. This confirms that the aggressive data augmentation and dropout successfully prevented memorization, forcing the model to learn robust features that generalized well to the "clean" validation images.

4.1.2. Optimized PyTorch CNN ("MyDeepCNN")

The transition to the optimized PyTorch pipeline yielded a significant performance boost, validating the effectiveness of the AdamW optimizer and Cosine Annealing scheduler.

- Metrics: This model achieved a Validation Accuracy of 85.9%, a substantial improvement (+13.3%) over the baseline.
- Precision/Recall: It demonstrated high precision (90.8%) with balanced recall (81.9%), resulting in an F1-score of 86.0%.
- AUC: The Area Under the Curve reached 0.94, classifying it as an excellent predictor [23].

4.2. Transfer Learning with Classical Classifiers

The feature-based models (ResNet50 + Classical ML) demonstrated the highest overall performance, benefiting from the massive pre-training of the ResNet backbone.

4.2.1. Random Forest (RF)

- The RF classifier achieved a Validation Accuracy of 90.8% and an AUC of 0.97.
- Feature Analysis: The training accuracy was near-perfect (~99.9%), which is characteristic of Random Forests. However, the high validation score proves that this was not detrimental overfitting, but rather a successful mapping of the feature space.
- Feature Importance: Analysis of the decision trees revealed that specific latent features from the ResNet50 vector (e.g., indices corresponding to texture and facial contours) had a disproportionately high impact on the classification decision.

To provide deeper insight into the decision-making mechanism of the ensemble classifier and mitigate the "black-box" nature of deep learning, we conducted a rigorous Feature Importance analysis based on the Mean Decrease in Impurity (MDI) metric. Figure 2 visualizes the relative importance of the top-20 most influential features selected from the 2,048-dimensional embedding vector generated by the ResNet50 backbone.

The disparity in importance scores reveals that the classification capability is not uniformly distributed across all dimensions; rather, the Random Forest successfully isolated a specific subset of high-level semantic descriptors that possess the highest discriminative power. Since these features originate from the final convolutional block of a network pre-trained on ImageNet, the top-ranking dimensions likely correspond to robust latent patterns—such as specific textural details, facial contours, or geometric structures—that correlate strongly with the target classes. This analysis confirms that the ensemble model did not merely memorize training noise but effectively identified and leveraged the underlying semantic structure encoded by the deep network, thereby validating the efficacy of the transfer learning strategy.

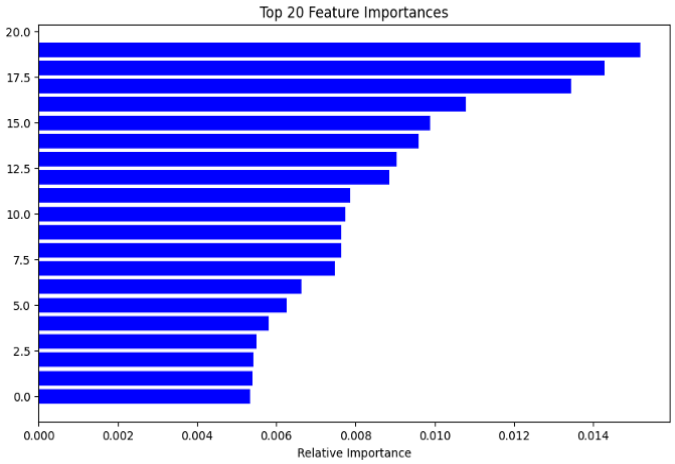

Figure 2: Feature Importance plot extracted from the Random Forest classifier using ResNet50 features.

4.2.2. *Logistic Regression (LR)*

- The LR model emerged as the top performer in terms of pure metrics, achieving a Validation Accuracy of 94.8% and a near-perfect AUC of 0.99.
- Interpretation: This result suggests that the 2048-dimensional feature space generated by ResNet50 is linearly separable for the binary face classification task, rendering complex non-linear classifiers unnecessary for this specific feature set.

4.3. *Comparative Summary*

Table 1 summarizes the performance metrics across all evaluated methodologies. It is evident that while the optimized CNN (MyDeepCNN) provides a strong end-to-end solution, the Transfer Learning approach yields superior accuracy with reduced training complexity.

4.4. *Visual Analysis (ROC and Confusion Matrices)*

To further validate the statistical significance of our results, we examined the ROC curves and Confusion Matrices.

ROC Curves (Figure 2 & 3): The Receiver Operating Characteristic (ROC) curves illustrate the trade-off between the True Positive Rate (Sensitivity) and False Positive Rate (1-Specificity).

- The Baseline CNN (Figure 2) shows a curve that bows gently towards the top-left corner (AUC=0.82).
- The PyTorch CNN (Figure 3) demonstrates a much sharper "elbow" (AUC=0.94), indicating a superior ability to distinguish between classes with fewer false alarms [24].

4.4.1. *Confusion Matrices*

- For the Baseline, the matrix reveals a higher number of False Positives, consistent with its lower Precision (67.6%).
- The ResNet50 + LR model produced a matrix with minimal off-diagonal elements, misclassifying less than 5% of the validation samples.

As illustrated in Figure 3, the ROC curve of the Baseline CNN exhibits a moderate area under the curve (AUC = 0.82). The curve's shape indicates that while the model learns, it struggles to maintain a low false positive rate at higher sensitivity thresholds.

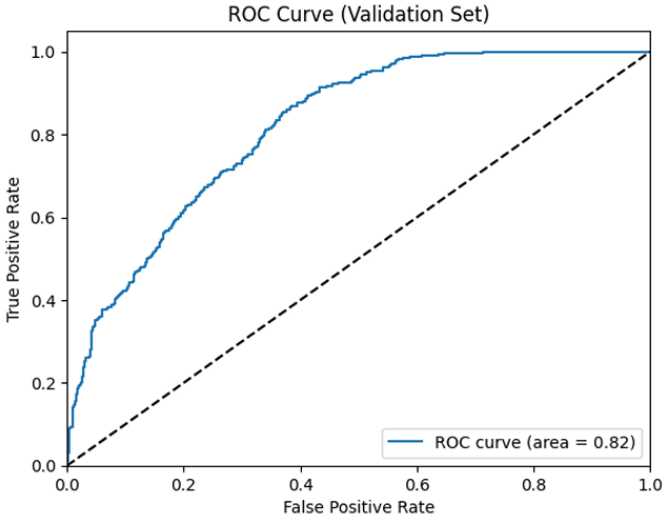

Figure 3: ROC Curve of the Baseline TensorFlow CNN (AUC = 0.82).

In contrast, the Optimized PyTorch CNN demonstrates superior separability, as evidenced by the sharper 'elbow' in its ROC curve shown in Figure 4. With an AUC of 0.94, this model significantly outperforms the baseline, offering a much better trade-off between precision and recall.

Table 1: Comparative Performance Metrics on Validation Set.

MODEL ARCHITECTURE	FRAMEWORK	VAL ACCURACY	PRECISION	RECALL	F1-SCORE	AUC-ROC
BASELINE CNN	Tensorflow	72.6%	67.6%	79.7%	73.0%	0.82
HYBRID CNN+MLP	Tensorflow	73.3%	67.4%	83.2%	73.0%	0.82
MY DEEP CNN (OPTIMIZED)	PyTorch	85.9%	90.8%	81.9%	86.0%	0.94
RESNET 50 + RANDOM FOREST	Scikit-Learn	90.8%	93.1%	89.4%	91.0%	0.97
RESNET50+LOG.REGRESSION	Scikit-Learn	94.8%	95.0%	95.3%	95.0%	0.99

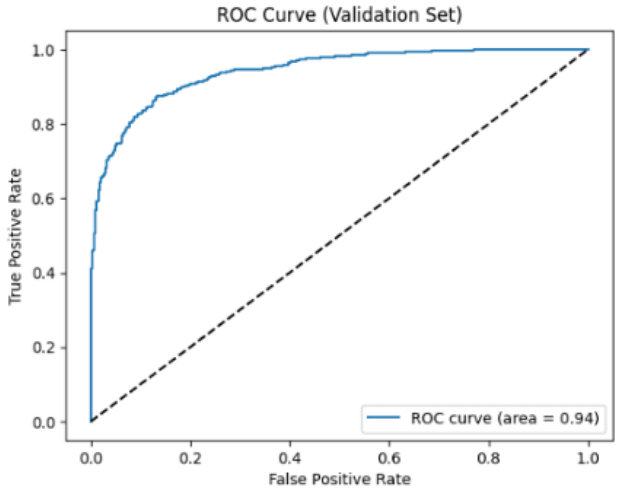

Figure 4: ROC Curve of the Optimized PyTorch CNN (MyDeepCNN), demonstrating improved separability (AUC = 0.94).

5. Discussion

5.1. Deep Learning: Frameworks and Optimization

A critical finding of this study is the substantial performance gap between the Baseline CNN (TensorFlow) and the Optimized CNN (PyTorch), despite similar architectural depths. The Baseline model achieved 72.6% accuracy, while the Optimized model reached 85.9%. This improvement is attributed to three specific factors:

1. Optimization Strategy: The switch from standard Adam to AdamW proved decisive. By decoupling weight decay from gradient updates, AdamW prevented the weights from growing too large without interfering with the adaptive learning rates.

2. Learning Rate Scheduling: The Cosine Annealing scheduler allowed the PyTorch model to traverse the loss landscape more effectively, avoiding the local minima where the static learning rate of the Baseline model likely stagnated.

3. Activation Functions: The use of LeakyReLU prevented the "dead neuron" issue, maintaining gradient flow throughout the deep network.

5.2. The "Underfitting Paradox" vs. Classical Overfitting

We observed two distinct training behaviors that warrant explanation:

- Baseline CNN (Underfitting): As noted in the results, the Baseline CNN exhibited Training Accuracy (~50%) lower than Validation Accuracy (~72%) for initial epochs. This counter-intuitive phenomenon is a direct result of the heavy data augmentation and high Dropout (0.5) applied only during training. The model struggles to classify heavily distorted images during training but finds the "clean" validation images easier to classify. This confirms that the model was not memorizing data but learning robust features.
- Classical Models (Overfitting): Conversely, the Random Forest classifier achieved nearly 100% Training Accuracy. While this typically signals overfitting, the high Validation Accuracy (90.8%) indicates that the model successfully captured the underlying structure of the ResNet50 feature space. However, the slightly superior performance of Logistic Regression (94.8%) suggests that the pre-extracted features were already linearly separable, making the complex non-linear decision boundaries of the Random Forest unnecessary.

5.3. Trade-offs: End-to-End vs. Transfer Learning

Our experiments highlight a clear trade-off. Transfer Learning (ResNet50 + LR) offered the highest accuracy (94.8%) with minimal training time (seconds), as it leverages millions of pre-learned parameters. However, it relies on a massive external model (23M parameters). The Optimized CNN, trained from scratch, offers a lighter, self-contained solution (fewer parameters) that still achieves high performance (85.9%), making it suitable for environments where pre-trained models cannot be deployed or where the domain differs significantly from ImageNet.

6. Conclusion

This paper presented a rigorous comparative analysis of binary face classification methodologies. We demonstrated that while training deep CNNs from scratch is challenging due to data scarcity, rigorous optimization (AdamW, Cosine Annealing, Data Augmentation) can yield competitive results. However, the study conclusively shows that Transfer Learning, specifically utilizing ResNet50 features combined with Logistic Regression, provides the optimal balance of accuracy (94.8%) and computational efficiency for this task. The results validate that "off-the-shelf" deep features are robust enough to outperform even carefully tuned custom CNNs in small-to-medium dataset regimes.

6.1. Future Work

Future research will focus on extending these findings in the following directions:

- Dataset Expansion: Evaluating the models on larger, more diverse datasets (e.g., CelebA, LFW) to verify the generalizability of the PyTorch optimization pipeline.
- Advanced Architectures: Investigating modern architectures such as EfficientNetV2 or Vision

Transformers (ViT), which may offer better parameter efficiency than ResNet50.

- Ensemble Methods: Creating a voting ensemble that combines the predictions of the Optimized CNN and the Random Forest to potentially push accuracy beyond 95%.

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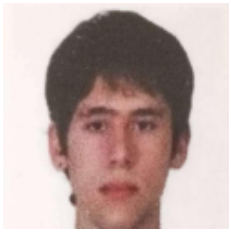
Conflict of Interest

The authors declare no conflict of interest.

Acknowledgment

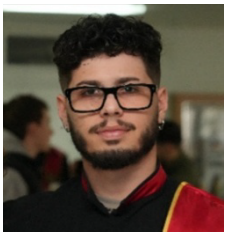
The author gratefully acknowledges the academic and technical support provided by colleagues and research collaborators during the design and implementation of this study. The experiments were conducted on locally maintained hardware resources, ensuring full reproducibility and data privacy. No external funding was received for this work.



NIKOLAOS VASILEIOS OIKONOMOU is a Computer & Network Engineer, as well as an academic researcher and Ph.D. candidate in the Department of Informatics and Telecommunications at the University of Ioannina, from which he also received his B.Eng. and M.Sc. degrees. In parallel to his academic work, he serves as a private Computer Science educator and possesses several years of professional experience as a Software Developer, IT Specialist, and Network Consultant.

DIMITRIOS VASILEIOS OIKONOMOU obtained his B.Sc. in Regional and Cross-Border Studies from the University of Western Macedonia in 2024. He is currently engaged in research activities at the same institution and is pursuing an M.Sc. in e-Business and Digital Marketing.

SOFIA PANAGIOTA CHALIASOU is pursuing a B.Sc. in Informatics at the Hellenic Open University and serves as an active research associate. She also holds a Vocational Diploma in Web Design and Development. In her professional capacity, she is currently employed in sales and possesses prior professional experience as a web developer.



NIKOLAOS RIGAS obtained his B.Sc. in Regional and Cross-Border Studies from the University of Western Macedonia in 2025. He is currently pursuing an M.Sc. in "Criminological and Penal Law perspectives on Corruption, Economic and Organized Crime" at the Hellenic Open University, while actively engaged in research activities.