Received: 14 June 2026, Revised: 13 July 2026, Accepted: 01 August 2026, Online: 25 August 2026

DOI: https://dx.doi.org/10.55708/js0508002

Identifying and Addressing Supply Chain Data Gaps: Impacts on Predictive Quality and CTQ Parameter Management in EV Battery Production

Sundararaman Ganapathiraman[1], **Sumedha Vijayaram Kumar**[1], **Akshaya Bharadhwaj**[2], **Suresh N**[1], **Ramitha Sundar**[3], **Phani Kumar Pullela**[4]

[1]School of Computer Science And Engineering, R V University, Bangalore, 560059, India

[2]Mukesh Patel School of Technology Management and Engineering, NMIMS, Mumbai, 400056, India

[3]Independent Researcher, Fremont, CA, 94536, USA

[4]Alumni Relations, School of Computer Science and Engineering, R V University, Bangalore, 560059, India

Email(s): vijusundar@gmail.com (S. Ganapathiraman), sumedhavijay04@gmail.com (S. V. Kumar), Akshaya.bharadhwaj86@nmins.in (A. Bharadhwaj), ramitha.sundar@gmail.com (R. Sundar), phanikumarpp@rvu.edu.in (P. K. Pullela)

Corresponding author: Suresh N, RV University, Bengaluru, India, suresh@rvu.edu.in

ABSTRACT: The supply chains for electric vehicles (EVs) have data gaps that hinder traceability, predictive quality control, and management of Critical-to-Quality (CTQ) parameters such as energy capacity, electrode uniformity, thermal stability, state of charge/health, and recyclability. This systematic literature review collates research on raw-material sourcing, manufacturing, in-use monitoring, second-life applications, and recycling. Following a documented PRISMA-style protocol, the review maps data gaps, compares enabling technologies, and proposes an integrated framework linking the Internet of Things, blockchain, digital twins, AI, and battery/digital product passports. The results describe barriers to implementation and offer a roadmap toward reliable, transparent, and sustainable EV battery quality management.

KEYWORDS: Supply Chain Management; Predictive Quality; Critical-to-Quality Parameters; EV Battery Production; Battery Passport; Digital Twin; Blockchain; Explainable AI; Data Integration.

1. Introduction

With electric vehicle (EV) deployment, capacity, internal resistance, electrode coating uniformity, thermal stability, state of charge, state of health, and recyclability are among the many Critical-to-Quality (CTQ) parameters that affect lithium-ion battery performance. Battery value chains extend from mining and refining through electrode and cell production, pack integration, vehicle operation and second use, to end-of-life recovery. Quality decisions are made at each stage based on information created by different actors, in different formats, using different instruments and governance rules. Previous reviews have noted sustainability issues and raw-material risks in EV battery value chains [1, 2] , but quality-oriented supply-chain data integration remains less consolidated.

Recent regulatory and industrial developments increase the urgency of this problem. The European battery regulation and battery passport agenda place stronger emphasis on lifecycle data, traceability, material composition, state-of-health information, and end-of-life instructions [3]. Stakeholder studies on digital product passports for EV batteries show that sustainability and circularity information is important but often not consistently available or accessible across beginning-of-life, second-use, and recycling actors [4]. These requirements move traceability from a compliance activity toward a quality-management capability.

Battery manufacturing also generates large volumes of process, inspection, and performance data. Big-data and artificial intelligence studies emphasize that electrode manufacturing, cell assembly, and cell finishing all generate information that can support performance prediction, process optimization, and defect detection [5]. Recent work on digitalization and AI-driven frameworks argues that digital models, digital shadows, and digital twins can connect manufacturing knowledge with predictive maintenance, quality control, and process optimization[6]. Explainable neural networks have further shown how process variables in mixing and coating can be interpreted for early electrode-quality prediction [7]. These advances are promising, but their usefulness is constrained when upstream provenance data, inline manufacturing data, logistics history, field data, and end-of-life data are fragmented. Figure 1 illustrates the product and data context considered in this review, linking battery cells, modules, and pack-level systems with material identification, process CTQs, performance CTQs, and lifecycle data required for effective quality management.

This review therefore has three novelties. First, it analyzes the information gap at each stage of the supply chain and explicitly connects it to CTQ parameter management. Second, it builds an integrated quality-management framework that combines the literature on predictive quality, traceability, digital product passports, blockchain, IoT, AI, explainable AI, and digital twins. Third, it highlights implementation issues, geographic variability, sustainability concerns, and a practical roadmap for industry adoption. This review differs from reviews that focus mainly on the circular economy, battery materials, or a single digital technology, because it centers on how missing or incomplete data feed into quality problems and weak predictive control.

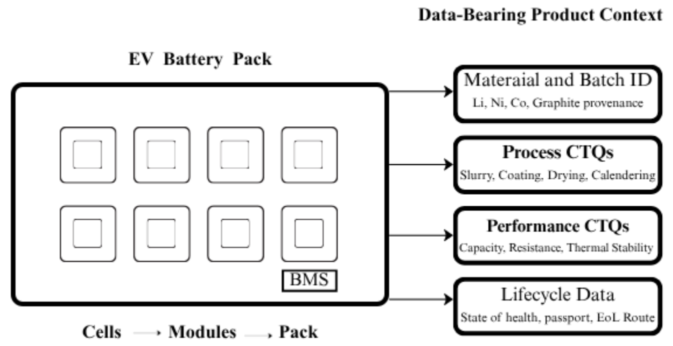

Figure 1: EV battery product context and data-bearing quality attributes considered in this review. The schematic emphasizes how battery cells, modules, pack-level electronics, and lifecycle data records must be connected to support CTQ management.

The study addresses the following research questions:

1. What are the critical data gaps in the EV battery supply chain, and how do they manifest at different lifecycle stages?

2. How does supply-chain data integration influence CTQ parameter management in EV battery production?

3. What challenges limit predictive quality-control frameworks in battery manufacturing?

4. Which advanced technologies can reduce data gaps and improve traceability and quality control?

5. How do supply-chain disruptions and geographic differences influence quality failures and CTQ management?

The rest of this paper is organized as follows. Section 2 describes the systematic review protocol. Section 3 synthesizes the literature by supply-chain stage, CTQ implication, and technology. Section 4 presents the integrated framework and technology comparison. Section 5 discusses industrial, managerial, theoretical, sustainability, and regional implications. Section 6 concludes with limitations and a future research roadmap.

2. Materials and Methods

2.1. Review design and search protocol

A systematic narrative review was carried out using a PRISMA-style workflow [8] as shown in figure 2. The review is not a meta-analysis, since the literature includes conceptual frameworks, review articles, manufacturing studies, regulatory analyses, and technology demonstrations rather than a uniform set of experimental effect sizes. In response to reviewer comments, the protocol was revised to improve transparency and reproducibility.

Searches were conducted from January 2018 to June 2026 and limited to peer-reviewed English-language articles, review papers, and high-relevance technical guidance directly related to battery passports or data-standardization discussion. Backward and forward snowballing was carried out across Scopus, Web of Science, ScienceDirect, IEEE Xplore, SpringerLink, MDPI, Wiley Online Library, and Google Scholar. Search terms combined battery, supply-chain, quality, CTQ, and digital-technology keywords. Examples included: "EV battery" AND "supply chain" AND "data gap"; "lithium-ion battery manufacturing" AND "predictive quality"; "battery passport" OR "digital product passport" AND "electric vehicle battery"; "blockchain" AND "battery supply chain"; "digital twin" AND "battery manufacturing"; and "explainable AI" AND "battery production". The complete review protocol, including the search scope, eligibility criteria, and software used for screening and analysis, is summarized in Table 1.

Table 1: Revised review protocol, search scope, eligibility criteria, and software support.

Element	Specification used in the revised review
Databases and sources	Scopus; Web of Science; ScienceDirect; IEEE Xplore; SpringerLink; MDPI; Wiley; Google Scholar for snowballing.
Publication years	January 2018–June 2026, with older seminal works retained only when still foundational to battery prognostics or remanufacturing.
Core search concepts	EV battery supply chain, data gaps, traceability, predictive quality, CTQ parameters, quality gates, IoT, blockchain, digital twins, battery passport, digital product passport, explainable AI.
Inclusion criteria	Studies addressing data integration, traceability, predictive quality, CTQ-relevant process or lifecycle parameters, digital technologies, or circular supply-chain management for EV/lithium-ion batteries.
Exclusion criteria	Non-English publications; unrelated energy-storage topics; papers with no link to supply-chain data, battery manufacturing quality, or lifecycle traceability; inaccessible full text; duplicate or low-rigor sources.
Screening and software	Zotero was used for reference management and duplicate removal. VOSviewer 1.6.20 was used to support keyword co-occurrence checks and identification of clusters around traceability, predictive quality, and digitalization.

2.2. Screening, extraction, and synthesis

The updated search identified 297 records. After 78 duplicates were removed, 219 unique titles and abstracts were screened. One hundred sixty-four records were excluded as outside the EV battery scope, unrelated to data or quality issues, or not relevant to supply-chain traceability.

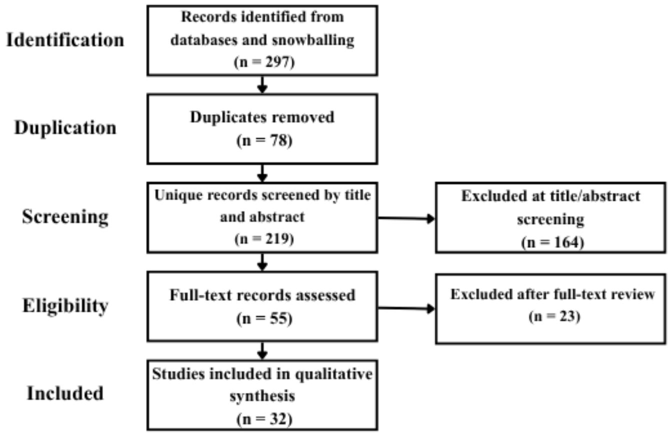

Figure 2: PRISMA-style review procedure. The revised screening workflow reports the number of records identified, duplicates removed, records screened, full-text records assessed, and studies retained for qualitative synthesis.

Fifty-five full-text records were assessed, and twenty-three were excluded after full-text review for insufficient CTQ, predictive-quality, data-integration, or lifecycle relevance. Thirty-two records were retained for qualitative synthesis, while regulatory material was used only for contextual discussion of battery passport requirements.

The data were collected in a matrix that included the following fields: the stage in the supply-chain; the type of data-gap; the CTQ parameter impacted; the technology/method employed; the type of evidence collected; the strengths; the limitations; and the practical implication. The synthesis examined the areas of commonality and differences of the studies, and structured results under five themes: data gaps and CTQ control, predictive quality and quality gates, traceability and data-sharing technologies, lifecycle and circularity and implementation challenges.

3. Literature Review and Synthesis

3.1. Critical data gaps across the EV battery supply chain

Data gaps occur when relevant data are unavailable, delayed, inconsistent, inaccessible, or not interoperable across actors. In raw-material sourcing, gaps include mine/refinery provenance, critical mineral quality, recycled-content claims, and environmental, social, and governance documentation. Geopolitical risk, changing regulations, commodity-price volatility, and uneven availability of lithium, nickel, cobalt, and graphite data intensify these gaps [1, 2, 9].

In manufacturing, gaps arise when process parameters are not connected to intermediate and final quality outcomes. Electrode slurry viscosity, coating thickness, drying temperature, calendering pressure, porosity, mass loading, electrolyte filling, formation history, and aging data are often recorded in equipment-specific systems. When these records are not linked to batch identifiers and downstream performance results, manufacturers cannot reliably determine which upstream deviations caused capacity loss, resistance growth, thermal non-uniformity, scrap, or field reliability problems [5, 7, 10, 11].

In logistics and field operation, missing temperature, humidity, vibration, state-of-charge, and charging-history information limits the ability to distinguish manufacturing-origin defects from use-phase degradation. In second-life and recycling stages, missing state-of-health, chemistry, composition, repair history, and disassembly data reduce the value of remanufacturing and make closed-loop supply chains less predictable [3, 4, 14, 32]. Figure 3 summarizes how these stage-specific gaps propagate into CTQ uncertainty. A cross-study synthesis of these themes, including the main areas of agreement and the remaining limitations identified in the reviewed literature, is presented in Table 2.

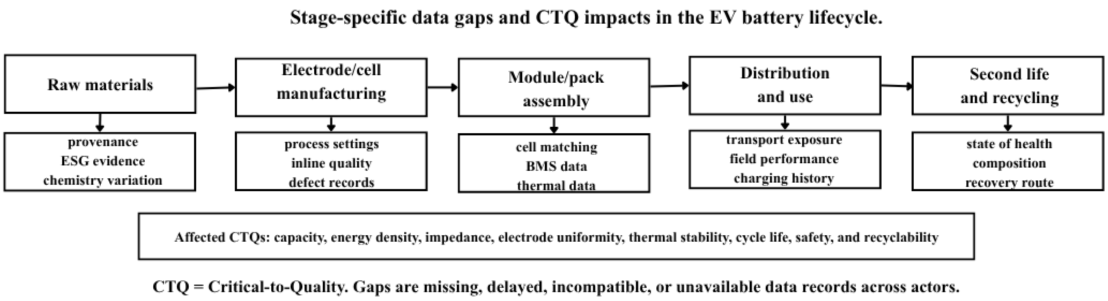

Figure 3: Stage-specific supply-chain data gaps and their CTQ implications. Missing provenance, process, logistics, field, and end-of-life data weaken CTQ monitoring and make predictive quality less reliable.

Table 2: Synthesis matrix comparing the reviewed literature by theme, agreement, and limitations.

Theme	Representative studies	Main agreement	Remaining disagreement or limitation
Raw-material and circularity risk	[1, 2, 9, 12, 13]	Critical-mineral exposure, regulation, and recycling capacity are major sources of uncertainty.	Studies differ in the level of geographic detail and often treat quality effects indirectly.
Data sharing and blockchain	[14, 15]	Secure data sharing can improve transparency and stakeholder trust.	Blockchain alone does not solve data-quality, governance, or interoperability problems.
Traceability in production	[16, 17, 18]	Batch-level tracking and data linkage support root-cause analysis and defect reduction.	Practical deployment depends on automated capture and standardized identifiers.
Predictive quality and quality gates	[10, 11, 19]	Inline data and quality gates can detect deviations before downstream value is added.	Prediction accuracy decreases when intermediate-stage data are sparse or noisy.
Nondestructive evaluation	[20]	NDE improves inline CTQ verification for porosity, thickness, and defects.	High-resolution NDE can be costly and difficult to scale across all process steps.
Battery passport and DPP	[3, 4, 21, 22, 23]	Lifecycle information is becoming central to compliance, circularity, and accountability.	Data ownership, access rights, standards, and regional adoption remain unresolved.
AI, XAI, and manufacturing analytics	[5, 6, 7, 19, 24, 25, 26, 27]	AI can predict performance, safety, health, and production-property relationships.	Models need explainability, robust data pipelines, and monitoring for drift.
Digital twins and digitalization	[6, 28, 29]	Digital twins connect models, sensors, simulation, and feedback control.	Many implementations remain digital models or shadows rather than fully bidirectional twins.
Regional and implementation factors	[16, 17, 18, 30, 12, 31]	Regulation, industrial maturity, and resource geography shape feasible solutions.	Findings from one region may not transfer directly to another without adaptation.

3.2. Data integration and CTQ parameter management

Data integration links process inputs, intermediate measurements, final battery performance, and field behavior, which supports CTQ management. Slurry mixing, coating and drying, calendering, electrode cutting, stacking/winding, electrolyte filling, formation, aging, grading, module assembly, and pack integration are the most quality-sensitive manufacturing stages. CTQ parameters vary by stage: slurry homogeneity and viscosity affect coating uniformity; coating and drying affect electrode thickness, porosity, and adhesion; calendering affects density and impedance; formation and aging affect capacity, self-discharge, and safety; and pack assembly affects cell balancing, thermal behavior, and state-estimation accuracy.

Intermediate product data can be used to predict final product quality and to stop defective parts from moving further up the production line in quality gates and cyber-physical systems [10, 11]. The effectiveness of their use, however, is reliant on continuous data capture and interoperability of manufacturing execution systems, sensor networks, laboratory inspection systems and enterprise/supplier systems. Nondestructive evaluation is also a complementary approach as it can confirm the internal or hidden product properties without destroying cells[20].

The literature reviewed comes together to one single point: CTQ management needs to be predictive if there is a link between the results of the process, material properties, the results of the inspection and the outcome of the lifecycle. If this linkage is not in place, then failures can be blamed on the manufacturer once they happen, but the changes in the supply chain or process that prevent failures cannot be reliably predicted.

3.3. Predictive quality control, AI, and explainability

Predictive quality-control approaches try to forecast future quality outcomes from current and historical data. In battery production, this includes predicting electrode properties, cell capacity, resistance, defect probability, thermal risk, and degradation behavior. Big-data reviews show that the manufacturing chain produces rich data across electrode manufacturing, cell assembly, and finishing, but this data is often underused or disconnected[5]. Machine learning can support performance prediction, process optimization, and defect detection, while battery safety prognostics use learning-based models to estimate faults, aging, and thermal-runaway risks [25].

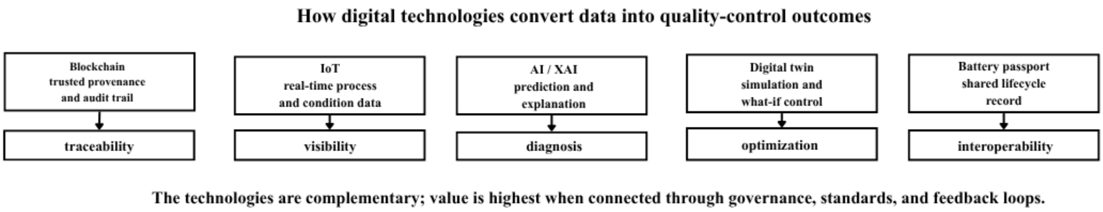

Figure 4: Digital technologies and their complementary roles in converting fragmented supply-chain data into traceability, visibility, diagnosis, optimization, and interoperability outcomes.

Explainability is especially relevant due to the presence of strongly coupled process variables in the production of batteries. The use of interpretable models can aid engineers in understanding how mixing time, solid content, coating speed, and drying conditions affect mass loading or porosity of the electrodes [7]. Explainable AI is also beneficial for management acceptance as it translates the output of the models into actionable root cause and sensitivity analysis information instead of an opaque alarm. The biggest challenge is not lack of algorithms, but lack of reliable labelled stage linked data throughout the lifecycle.

3.4. *Digital technologies for data-gap closure*

The reviewed technologies address different aspects of the data-gap problem. IoT systems capture process, logistics, equipment, and environmental data in real time, improving visibility. Blockchain can strengthen data integrity and auditability when multiple firms share provenance or recycling information [14]. Digital twins and digital shadows connect physical production processes to simulation and predictive analytics [6, 28, 29]. Battery passports and digital product passports provide structured lifecycle records for compliance, circularity, and end-of-life decisions [3, 4, 21, 22, 23]. The complementary roles of these technologies in closing supply-chain data gaps and supporting traceability, visibility, diagnosis, optimization, and interoperability are summarized in Figure 4.

Such technologies should not be considered replacements. Without governance, there is too much data and no trust; without sensor validation, it's possible that the data recorded in a blockchain is inaccurate; without explainability, operator confidence can be reduced; and without standardized identifiers, digital twins won't be connected across supply-chain actors. The best way to achieve this is to have a multi-layered architecture that includes data governance, automated capture, trusted sharing, predictive analytics, and feedback to engineering decisions. Table 3 compares the primary contributions, CTQ and predictive-quality advantages, and implementation limitations of the digital and quality technologies considered in this review.

4. Proposed Integrated Framework

The proposed integrated framework in Figure 5 links the various stages of the supply chain with CTQ parameters, predictive quality, and digital technologies. The framework starts with a data-governance layer which establishes data quality rules, identifiers, ownership, access rights and CTQ variables. The data from the supplier systems, manufacturing equipment, the inspection systems, logistics providers, BMS/field systems, and the recycling actors are then transferred to the stage level. Real-time measurements are possible with the help of IoT sensors and inline inspection, auditability is ensured through the use of blockchain or distributed ledger technologies, AI and explainable AI enable predictions and root cause signals to be derived from the data, process and lifecycle effects are simulated with digital twins, and battery passports or DPPs offer a structured record to provide for compliance and circularity.

The framework produces four operational outputs: predictive quality and quality gates, CTQ control and alerts, compliance and battery-passport documentation, and circularity/field-reliability feedback. In practical terms, the framework lets a battery manufacturer trace a specific field failure back to material batches, manufacturing conditions, cell assembly parameters, or logistics exposures, and lets upstream process control be adjusted before poor-quality cells are assembled into packs.

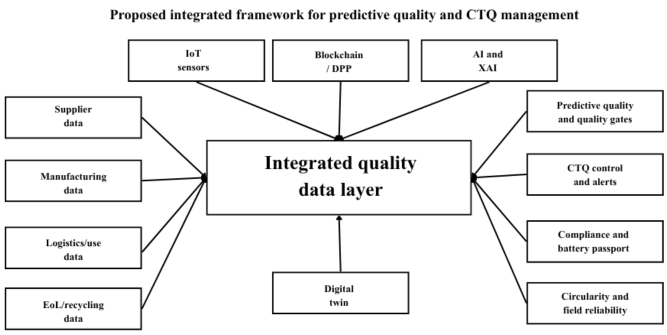

Figure 5: Integrated framework linking lifecycle data, digital technologies, and CTQ-focused predictive quality outputs.

5. Discussion: Implications, Challenges, and Limitations

5.1. *Cross-study interpretation*

There is a consensus in the literature on the need for traceability, data integration, and digitalization to support EV battery quality management. Research on supply-chain sustainability and circularity focuses on provenance, responsible sourcing, and end-of-life recovery [1, 2, 9, 13]. Process-parameter data, inline inspection, and quality gates are studied as significant aspects of manufacturing analytics [5, 10, 11, 19]. Digitalization studies highlight the importance of linking sensors, models, digital twins, and stakeholder responsibilities [6, 28, 29]. The debate is not

Table 3: Comparison of digital and quality technologies for EV battery data-gap closure.

Technology	Primary contribution	Advantages for CTQ and predictive quality	Limitations and implementation needs
IoT and inline sensing	Automated capture of process, logistics, and condition data.	Improves real-time CTQ monitoring and enables dynamic feedback loops.	Requires calibration, cybersecurity, data pipelines, and integration with existing equipment.
Blockchain / distributed ledger	Tamper-resistant provenance and audit trail across firms.	Strengthens trust in material origin, chain-of-custody, recycling claims, and compliance data.	Does not guarantee data accuracy at source; requires governance, standards, and privacy design.
Artificial intelligence and XAI	Prediction, anomaly detection, root-cause analysis, and sensitivity explanation.	Enables early warning, yield improvement, defect reduction, and interpretable process control.	Needs high-quality labelled data, domain expertise, model validation, and drift monitoring.
Digital twin / digital shadow	Virtual representation of production or lifecycle behavior.	Supports what-if simulation, predictive maintenance, process optimization, and quality-gate design.	Full bidirectional twins are complex; benefits depend on model fidelity and data latency.
Battery passport / DPP	Structured lifecycle record linked to a physical battery.	Connects product identity, chemistry, performance, sustainability, and end-of-life data.	Implementation depends on access rights, interoperability, regional regulation, and supplier readiness.
NDE and quality gates	Inline or near-line verification of hidden product features and decision checkpoints.	Reduces downstream defect propagation and supports CTQ verification without destructive testing.	Scaling requires cost-benefit evaluation, throughput compatibility, and data linkage.

about whether data matter, but about how quickly integrated systems can be deployed, who should govern shared data, and how much data must be shared to support quality without exposing commercially sensitive information.

5.2. Industrial, managerial, theoretical, and sustainability implications

Industrial benefits are: increased yield, reduced scrap, quicker root cause determination, better supplier qualification, and more reliable pack assembly. Managers should view CTQ data, not as records solely kept at the plant level, but as an asset to be used along the supply chain. This will need supplier information sharing agreements, investments in automated data capture capabilities, cybersecurity measures and training employees in quality analytics. Theoretical implications are a call to take quality theory for supply chains further than the mere ability to trace back and forth transactions and forward it to predictive rather than reactive quality governance, based on a lifecycle approach. Sustainability implications are related to responsible sourcing, material recovery, remanufacture, second life assessment and regulatory compliance, with better data to help with all of these areas.

5.3. Geographic and regulatory variation

Battery supply chains vary considerably by region. Mining and refining risks are concentrated in resource-rich areas, while cell manufacturing, pack assembly, vehicle integration, and recycling are distributed unevenly across global markets. European policy places strong emphasis on battery passports and lifecycle documentation[3, 23], while other regions may prioritize manufacturing scale, domestic supply security, or different data-sharing rules. As a result, findings from one region may not be generalizable to others. Data models and CTQ frameworks should be adaptable to regional regulations, supplier maturity, infrastructure, and cybersecurity expectations.

5.4. Implementation challenges

Implementation challenges include interoperability with legacy systems, lack of common identifiers, high costs of inline sensors and NDE equipment, data-ownership concerns, cybersecurity risk, insufficient data-science and quality-engineering skills, model drift, and weak incentives for upstream/downstream data sharing. A phased approach is recommended: define CTQ data governance; build traceability and IoT backbones; develop predictive quality models with explainability; connect digital twins and battery passports; and feed field and end-of-life learning back into design and process control. This phased implementation pathway and the associated risk controls are summarized in Figure 6.

5.5. Review limitations and research gaps

Because of the diversity of the literature and the lack of comparable industrial datasets, this review has limitations. Many studies discuss digital technologies conceptually, while relatively few report full-scale industrial validation of end-to-end supply-chain data integration. Some older studies were retained because they remain foundational to remanufacturing or battery health prognostics, and the review was updated with recent 2024-2026 literature on battery passports, digital product passports, AI, explainable AI, and manufacturing analytics. Future research should develop shared benchmark datasets, quantify cost-benefit tradeoffs, test interoperable battery-passport data models, assess cybersecurity risks, and validate predictive quality frameworks across multiple geographic regions and production chemistries.

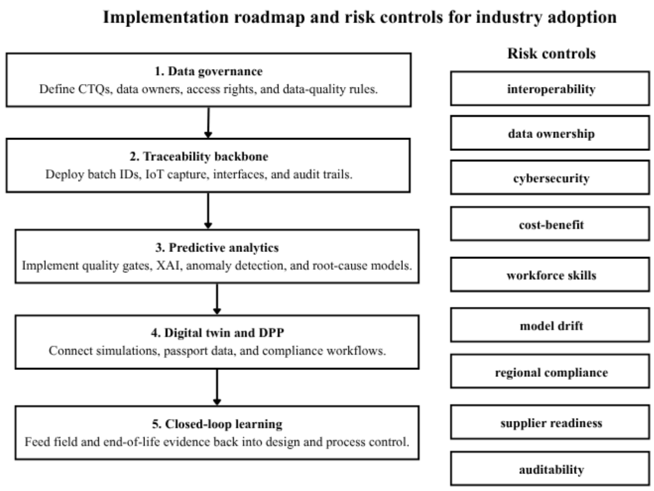

Figure 6: Implementation roadmap for moving from data governance to closed-loop learning, with major risk controls that must be managed during industrial adoption.

6. Conclusion and Future Research Roadmap

This review shows that data gaps across raw-material sourcing, manufacturing, logistics, field operation, second-life applications, and recycling limit the effectiveness of EV battery quality management. These gaps weaken CTQ parameter management, reduce the reliability of predictive quality models, and hinder circularity and compliance. The key contribution of the review is an integrated framework connecting supply-chain stages, CTQ parameters, IoT, blockchain, AI/explainable AI, digital twins, and battery/digital product passports. The findings highlight the need for data governance, interoperability standards, managerial commitment, cybersecurity, and regional adaptation for technology adoption.

There are five future directions that should be considered: (1) industrial validation of CTQ models linked to stages; (2) explainable predictive quality models that identify which process aspects should be acted upon; (3) interoperable battery-passport architectures that link manufacturing, field and recycling data; (4) cost benefit and scalability studies for SME and giga-scale plant; and (5) comparative regional studies to assess how regulation, supplier readiness and infrastructure influence implementation. These areas will be key in transforming existing, disjointed data into robust, transparent and sustainable EV battery quality systems.

Funding: This research received no external funding.

Data Availability Statement: No new empirical datasets were generated. The review is based on published literature and publicly available regulatory or technical guidance.

Conflicts of Interest: The authors declare no conflicts of interest.

AI Use Statement: During the preparation of this manuscript, the authors used ChatGPT (OpenAI) to assist with drafting and revising sections of the text, restructuring the literature synthesis, and formatting the review protocol and technology-comparison tables in response to reviewer feedback. The authors reviewed and verified all AI-assisted content, including checking cited sources against their original publications, and take full responsibility for the accuracy and integrity of the content of this publication.

References

[1] A. J. Niri, G. A. Poelzer, S. E. Zhang, J. Rosenkranz, M. Pettersson, Y. Ghorbani, "Sustainability challenges throughout the electric vehicle battery value chain", *Renewable and Sustainable Energy Reviews*, vol. 191, p. 114176, 2023, doi:10.1016/j.rser.2023.114176.

[2] P. Barman, L. Dutta, B. Azzopardi, "Electric Vehicle Battery Supply Chain and Critical Materials: A Brief survey of state of the art", *Energies*, vol. 16, no. 8, p. 3369, 2023, doi:10.3390/en16083369.

[3] F. Soavi, A. Gregucci, A. Liverani, S. Mojtahedi, E. Petri, F. Mascetti, F. Capodarca, E. B. H. Jrad, "The European Battery Regulation and Digital Battery Passport: Prospects and Challenges", *Batteries*, vol. 12, no. 3, p. 97, 2026, doi:10.3390/batteries12030097.

[4] A. Pohlmann, M. Popowicz, J.-P. Schöggl, R. J. Baumgartner, "Digital product passports for electric vehicle batteries: Stakeholder requirements for sustainability and circularity", *Cleaner Production Letters*, vol. 7, p. 100090, 2024, doi:10.1016/j.clpl.2024.100090.

[5] T. Chen, X. Lai, F. Chen, Y. Wang, X. Han, Y. Zheng, "Empowering lithium-ion battery manufacturing with big data: Current status, challenges, and future", *Journal of Power Sources*, vol. 623, p. 235400, 2024, doi:10.1016/j.jpowsour.2024.235400.

[6] A. Manoharan, *et al.*, "Optimizing lithium-ion battery manufacturing with digitalization and AI-driven frameworks", *The International Journal of Advanced Manufacturing Technology*, vol. 142, pp. 1–37, 2026, doi:10.1007/s00170-025-17129-8.

[7] K. Liu, Q. Peng, Y. Liu, N. Cui, C. Zhang, "Explainable neural network for sensitivity analysis of lithium-ion battery smart production", *IEEE/CAA Journal of Automatica Sinica*, vol. 11, no. 9, pp. 1944–1953, 2024, doi:10.1109/JAS.2024.124539.

[8] M. J. Page, *et al.*, "The PRISMA 2020 statement: an updated guideline for reporting systematic reviews", *BMJ*, vol. 372, p. n71, 2021, doi:10.1136/bmj.n71.

[9] J. T. Marcos, C. Scheller, R. Godina, T. S. Spengler, H. Carvalho, "Sources of uncertainty in the closed-loop supply chain of lithium-ion batteries for electric vehicles", *Cleaner Logistics and Supply Chain*, vol. 1, p. 100006, 2021, doi:10.1016/j.clscn.2021.100006.

[10] A. Kampker, H. Heimes, P. Lingohr, J. Schmied, H. Clever, B. Dorn, "Developing a concept for the implementation of predictive quality in battery production", *Procedia CIRP*, vol. 126, pp. 823–828, 2024, doi:10.1016/j.procir.2024.08.265.

[11] A. Turetskyy, J. Wessel, C. Herrmann, S. Thiede, "Data-driven cyber-physical system for quality gates in lithium-ion battery cell manufacturing", *Procedia CIRP*, vol. 93, pp. 168–173, 2020, doi:10.1016/j.procir.2020.03.077.

[12] M. A. Rajaeifar, P. Ghadimi, M. Raugei, Y. Wu, O. Heidrich, "Challenges and recent developments in supply and value chains of electric vehicle batteries: A sustainability perspective", *Resources, Conservation and Recycling*, vol. 180, p. 106144, 2022, doi:10.1016/j.resconrec.2021.106144.

[13] B. M. Sopha, D. M. Purnamasari, S. Ma'mun, "Barriers and Enablers of Circular Economy Implementation for Electric-Vehicle Batteries: From Systematic Literature Review to Conceptual Framework", *Sustainability*, vol. 14, no. 10, p. 6359, 2022, doi:10.3390/su14106359.

[14] E. R. Da Silva, J. Lohmer, M. Rohla, J. Angelis, "Unleashing the circular economy in the electric vehicle battery supply chain: A case study on data sharing and blockchain potential", *Resources, Conservation and Recycling*, vol. 193, p. 106969, 2023, doi:10.1016/j.resconrec.2023.106969.

[15] C. Udokwu, P. Brandtner, F. Darbanian, T. Falatouri, "Proposals for addressing research gaps at the intersection of data analytics and supply chain management", *Journal of Advances in Information Technology*, vol. 13, no. 4, pp. 338–346, 2022, doi:10.12720/jait.13.4.338-346.

[16] J. Wessel, A. Turetskyy, O. Wojahn, C. Herrmann, S. Thiede, "Tracking and tracing for data mining application in the lithium-ion battery production", *Procedia CIRP*, vol. 93, pp. 162–167, 2020, doi:10.1016/j.procir.2020.03.071.

[17] G. Riexinger, *et al.*, "Integration of traceability systems in battery production", *Procedia CIRP*, vol. 93, pp. 125–130, 2020, doi:10.1016/j.procir.2020.04.002.

[18] R. Silbernagel, C. Wagner, A. Albers, T.-U. Trapp, G. Lanza, "Data-Based supply chain Collaboration - Improving product quality in global production networks by sharing information", *Procedia CIRP*, vol. 104, pp. 470–475, 2021, doi:10.1016/j.procir.2021.11.079.

[19] M. F. Niri, *et al.*, "Quantifying key factors for optimised manufacturing of Li-ion battery anode and cathode via artificial intelligence", *Energy and AI*, vol. 7, p. 100129, 2021, doi:10.1016/j.egyai.2021.100129.

[20] M. E. McGovern, *et al.*, "A review of research needs in nondestructive evaluation for quality verification in electric vehicle lithium-ion battery cell manufacturing", *Journal of Power Sources*, vol. 561, p. 232742, 2023, doi:10.1016/j.jpowsour.2023.232742.

[21] K. Berger, R. J. Baumgartner, M. Weinzerl, J. Bachler, K. Preston, J.-P. Schöggl, "Data requirements and availabilities for a digital battery passport - A value chain actor perspective", *Cleaner Production Letters*, vol. 4, p. 100032, 2023, doi:10.1016/j.clpl.2023.100032.

[22] The Battery Pass Consortium, "Battery Passport Technical Guidance", 2024, version 1.0, March 2024.

[23] European Parliament and Council, "Regulation (EU) 2023/1542 concerning batteries and waste batteries", 2023, official Journal of the European Union.

[24] V. T. D. Sang, Q. H. Duong, L. Zhou, C. F. A. Arranz, "Electric Vehicle Battery Technologies and Capacity Prediction: A Comprehensive literature review of trends and influencing factors", *Batteries*, vol. 10, no. 12, p. 451, 2024, doi:10.3390/batteries10120451.

[25] J. Zhao, *et al.*, "Battery safety: Machine learning-based prognostics", *Progress in Energy and Combustion Science*, vol. 102, p. 101142, 2024, doi:10.1016/j.pecs.2023.101142.

[26] C. Lv, *et al.*, "Machine Learning: An Advanced Platform for Materials Development and State Prediction in Lithium-Ion Batteries", *Advanced Materials*, p. 2101474, 2021, doi:10.1002/adma.202101474.

[27] H. Lipu, *et al.*, "Intelligent algorithms and control strategies for battery management system in electric vehicles: Progress, challenges and future outlook", *Journal of Cleaner Production*, vol. 292, p. 126044, 2021, doi:10.1016/j.jclepro.2021.126044.

[28] F. Naseri, *et al.*, "Digital twin of electric vehicle battery systems: Comprehensive review of the use cases, requirements, and platforms", *Renewable and Sustainable Energy Reviews*, vol. 179, p. 113280, 2023, doi:10.1016/j.rser.2023.113280.

[29] E. Ayerbe, M. Berecibar, S. Clark, A. A. Franco, J. Ruhland, "Digitalization of battery manufacturing: Current status, challenges, and opportunities", *Advanced Energy Materials*, vol. 12, no. 17, p. 2102696, 2022, doi:10.1002/aenm.202102696.

[30] P. Kumar, R. K. Singh, J. Paul, O. Sinha, "Analyzing challenges for sustainable supply chain of electric vehicle batteries using a hybrid approach of Delphi and Best-Worst Method", *Resources, Conservation and Recycling*, vol. 175, p. 105879, 2021, doi:10.1016/j.resconrec.2021.105879.

[31] L. O. Soares, A. Da Cunha Reis, P. S. Vieira, L. Hernández-Callejo, R. A. M. Boloy, "Electric Vehicle Supply Chain Management: A Bibliometric and Systematic Review", *Energies*, vol. 16, no. 4, p. 1563, 2023, doi:10.3390/en16041563.

[32] L. Li, F. Dababneh, J. Zhao, "Cost-effective supply chain for electric vehicle battery remanufacturing", *Applied Energy*, vol. 226, pp. 277–286, 2018, doi:10.1016/j.apenergy.2018.05.115.