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CSH-Informed AI Digital Twin for Battery Management Systems and Fast Charging Control: Boundary Critique and Design Requirements

Mohammad Reza Fathi[1], Mohammad Mostafa Dadras[2], Samaneh Raeesi Nafchi[3*]

[1] *Associate Professor, College of Farabi, University of Tehran, Iran*
[2] *M.Sc. Student in Information Technology Engineering, Noor Tuba Electronic Institute of Higher Education, Tehran, Iran*
[3] *Assistant Professor of Industrial Management, Shiraz University of Technology-Lamerd Higher Education Center, Fars, Iran*
* *Corresponding Author: raeesi@sutech.ac.ir*

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Abstract

The deployment of AI-enabled battery digital twins for battery management systems (BMS) and DC fast-charging control is often approached as a purely technical task focused on improving prediction accuracy and charging speed. This study argues that such deployments are inherently socio-technical, shaped by boundary judgments about system purpose, beneficiaries, measures of success, decision authority, resources, expertise, and legitimacy. Using Critical Systems Heuristics (CSH), we conducted semi-structured interviews with 22 experts and stakeholders spanning BMS/battery engineering, fast-charging operations, system integration, and safety/regulatory perspectives. Interview transcripts were analyzed using template analysis aligned with the four CSH dimensions (motivation, control, expertise, and legitimacy) to contrast "what is" versus "what ought to be" boundary judgments. Results show that current practice is predominantly throughput-driven, with battery longevity, thermal safety, and grid impacts treated as secondary constraints; decision authority is fragmented across vendors, OEM-side BMS logic, operators, and utilities; and resource allocation underinvests in calibration, data governance, cybersecurity, and continuous validation. The boundary critique was translated into a structured set of CSH-informed design requirements, emphasizing health-aware charging control, explicit safety envelopes and fail-safe modes, calibrated sensing and data-quality gates, drift detection and continuous validation, auditable decision logging, and multi-stakeholder governance and representation mechanisms. The study contributes a boundary-aware pathway for designing and governing trustworthy digital-twin-enabled fast charging beyond algorithmic performance.

Keywords: Critical Systems Heuristics; Battery Digital Twin; Battery Management System (BMS); DC Fast Charging; Health-Aware Charging Control.

1. Introduction

The rapid growth of electric vehicles (EVs) and stationary battery energy storage systems has positioned electrochemical batteries as a critical infrastructure for both transportation decarbonization and power system flexibility [10,14]. As EV penetration increases, users' expectations converge toward refuelling-like convenience, making DC fast charging with targets of 10–15 min to 80% state of charge a cornerstone for overcoming range anxiety and enabling widespread adoption [2,12,19,20,22]. However, fast charging imposes severe stresses on lithium-ion batteries, accelerating degradation, exacerbating thermal runaway risks, and creating complex tradeoffs between charging speed, safety, lifetime, and grid impact [2,7,16-19]. Beyond cell-level impacts, these trade-offs also affect charging station operators and power system operators through peak demand surges, voltage deviations, and the need for costly grid reinforcements or local buffering solutions, meaning that "fast charging performance" cannot be reduced to a single technical metric. In practice, the same charging policy that satisfies a user's time preference may impose hidden costs in accelerated battery replacement, elevated operational risk, or adverse impacts on distribution networks especially under uncertain ambient conditions, heterogeneous battery chemistries, and varying battery ages.

These challenges have driven a shift from conventional, embedded battery management systems (BMS) toward AI enabled digital twins, in which a high fidelity virtual battery, continuously updated by real time data, estimates state of charge (SOC) and state of health (SOH), predicts aging, and supports health aware fast charging control in the cloud [9-11,13]. In principle, digital twins can enable individualized charging decisions that adapt to the battery's current condition, thermal state, usage history, and expected duty cycle, rather than relying on conservative one-size-fits-all strategies. They also promise continuous learning from fleet-level operational data, allowing better prediction of degradation pathways, earlier detection of anomalies, and proactive mitigation of safety hazards. Despite these advantages, the deployment of AI-driven digital twins creates new layers of dependency on data pipelines, sensor reliability, connectivity, cybersecurity, and vendor ecosystems. This raises practical questions about robustness: how a fast-charging control strategy should behave under data gaps, sensor drift, domain shift, or communication failures, and which fail-safe mechanisms should take precedence when performance and safety goals conflict. Yet, such cyber–physical architectures are not neutral: choices about which stakeholders, risks, data, and values are represented (or excluded) in the model and its control logic have practical, political, and ethical consequences for safety, equity, and system resilience. For example, prioritizing user charging speed may externalize degradation costs onto consumers through earlier battery replacement; prioritizing asset protection may lead to systematically slower charging for certain battery conditions, potentially disadvantaging users with older vehicles or lower purchasing power. Similarly, decisions about what data are collected and who controls them influence privacy, accountability, and the feasibility of regulatory auditing. Even the definition of "acceptable risk" in thermal safety or the handling of rare but catastrophic events involves value-laden judgments that extend beyond purely technical optimization. As a result, the central problem is not only how to improve prediction accuracy or control performance, but also how to define, justify, and govern the boundaries within which an AI-enabled battery digital twin is designed, validated, and operated.

Critical Systems Heuristics (CSH) directly addresses this problem of boundary setting by providing a structured framework of "is/ought" boundary questions that make explicit who is served, who bears the risks, and which assumptions guide design and evaluation [6,8]. Applying CSH to an AI driven battery digital twin for fast charging is therefore essential to critique and re design its boundaries linking electrochemical, thermal, and grid constraints with societal concerns such as affordability, regulatory oversight, and environmental justice, which are particularly salient in emerging EV markets like Iran, where grid constraints, investment limitations, and air pollution pressures heighten the stakes of fast charging infrastructure decisions. In this context, boundary critique can reveal mismatches between current practice ("is") such as fragmented responsibilities across charger operators, vehicle OEMs, and grid utilities, limited access to high-quality operational data, and unclear liability for safety incidents and the desirable future ("ought") in which transparent governance, auditable models, and equitable service provision are embedded in the charging ecosystem. By making these mismatches explicit, CSH enables the translation of stakeholder concerns into actionable design and governance requirements for digital-twin-enabled fast charging, including requirements for data stewardship, interpretability and auditability, fail-safe control logic, and the alignment of operational incentives with long-term battery health and grid reliability. Accordingly, this study is guided by the following research questions:

RQ1. How are the current boundary judgments surrounding AI-enabled battery digital twins for BMS and DC fast-charging control defined in practice across the CSH dimensions of motivation, control, expertise, and legitimacy?

RQ2. What gaps emerge between current ("is") and desirable ("ought") boundary judgments regarding system purpose, beneficiaries, success criteria, decision authority, resources, expertise, accountability, and stakeholder representation?

RQ3. How can these boundary gaps be translated into actionable design and governance requirements for trustworthy AI-enabled battery digital twins in fast-charging systems?

Accordingly, the necessity and importance of this study stem from a dual gap: first, the technical literature on battery digital twins and AI-based fast charging largely emphasizes model fidelity and algorithmic performance, while offering limited guidance on how to structure boundary judgments that determine real-world safety, accountability, and fairness; second, policy and infrastructure discussions often focus on deployment targets and investment needs without a systematic method to connect societal priorities to the design choices embedded in AI control systems. Addressing these gaps is crucial for avoiding unintended consequences and for ensuring that fast-charging innovation supports sustainable energy transitions rather than creating new inequities or systemic vulnerabilities. By integrating CSH with the design and evaluation of AI-enabled battery digital twins, this article provides a rigorous socio-technical basis for trustworthy fast-charging control one that is responsive to the constraints and priorities of contexts like Iran while remaining generalizable to other emerging EV markets facing similar infrastructural and governance challenges.

Importantly, this study addresses a policy and governance dimension of AI-enabled digital twins for battery management and fast charging that, to our knowledge, has not previously been examined from this perspective. By applying Critical Systems Heuristics, we provide a structured approach to link technical performance with stakeholder priorities, accountability, and socio-technical considerations, highlighting both the novelty and practical relevance of our work. Accordingly, the necessity

2. Literature Review

Saravanakumar et al. [15] presented a comprehensive state-of-the-art review of electric vehicles, focusing on key powertrain components including battery management systems (BMS), power electronics converters, and traction motors. The paper discusses the EV energy conversion chain from the battery through the DC–DC link and inverter to the traction motor, and summarizes commonly used technologies such as Li-ion batteries, boost and full-bridge converters, and PMSM/induction motors. It also reviews renewable-energy-based charging stations and fast-charging specifications for EV applications. Shanmuganathan et al. [16] provided a mini-review on recent advances in EV battery technologies and smart charging, highlighting fast charging as a key enabler for practicality but a major driver of accelerated aging and degradation. The study surveys predictive algorithms and adaptive control strategies often supported by machine learning, real-time monitoring, thermal management, and simulation tools (e.g., Simulink) to improve charging efficiency while preserving battery longevity. It also reviews progress in DC fast-charging infrastructure (e.g., Tesla Superchargers and AVL solutions) and discusses SOC/SOH monitoring approaches to reduce losses and enhance battery management, emphasizing the need to balance charging speed with long-term battery health. Aksoz et al. [1] reviewed recent progress in EV fast-charging technologies and examined battery-assisted DC fast-charging stations as a solution to limitations of conventional grid-dependent chargers. The paper discusses integrating on-site battery storage to charge during off-peak periods and discharge during peak demand, reducing grid reliance and improving grid stability. It also highlights a transformer-less, modular station design for improved scalability and lower installation costs, and explores smart energy management using AI/ML to dynamically adjust charging rates for higher efficiency and cost-effectiveness. Zentani et al. [21] reviewed EV fast-charging technologies, comparing major approaches such as DC fast charging, ultra-fast charging, inductive charging, Tesla Superchargers, bidirectional charging, and battery swapping. The paper also summarizes charging infrastructure (standards, connectors, communication protocols, power levels), charger and DC–DC converter classifications, and control strategies, and outlines key challenges and future trends including interoperability, smart-grid integration, and energy optimization. Karamany et al. [9] examined the evolution of EV charging from Level 1/Level 2 AC to high-power DC fast charging and discussed how improvements in charging speed, connector standardization, battery integration, and infrastructure reduce key adoption barriers such as range anxiety and long charging times. The paper also highlights fast charging’s impacts on battery health and user experience, emphasizing engineering trade-offs and system-level scalability challenges. Tai et al. [17] reviewed advanced battery thermal management systems (BTMS) for Li-ion EV batteries under fast-charging conditions, emphasizing that heat generation can drive temperature rise, safety risks (including thermal runaway), and accelerated aging. The paper surveys state-of-the-art thermal management strategies particularly advanced cooling approaches such as indirect liquid cooling, immersion cooling, and hybrid cooling based on recent studies from 2019–2024, and outlines key findings and future directions for next-generation BTMS to support safe and efficient fast charging. Geng et al. [7] discussed key challenges and recent advances in fast-charging lithium-ion batteries, highlighting how safety concerns and charging-time expectations hinder EV adoption. The paper analyzes limiting factors across multiple levels from materials and cell design to packs, systems, charging stations, and safety (including thermal-runaway implications) and reviews multiscale optimization strategies. It emphasizes high-voltage charging and advanced thermal management as central to future fast-charging solutions, and calls for improved on-board detection of resistance/temperature rise combined with intelligent charging algorithms. Kumar et al. [10] reviewed advances in EV batteries and battery management, covering battery modeling (electrical, thermal, and electro-thermal), SOC/SOH estimation, charging methods, and optimization approaches. The paper summarizes core BMS functions monitoring, protection, balancing, thermal and data management along with balancing circuit types and practical issues such as stressors, reliability, losses, and efficiency. It also identifies key research gaps in battery management systems. Njoku et al. [13] reviewed digital twin (DT) applications for battery management systems, arguing that data-intensive, AI-heavy BMS frameworks often face data limitations that reduce state-estimation accuracy and can compromise performance and safety. The paper summarizes DT concepts and architectures for battery management, surveys research and industry case studies to identify enabling tools and technologies, and proposes an integration framework aimed at scalable, cost-effective, and practical deployment. It also outlines open research challenges and future opportunities for DT-enabled BMS evolution. Recent studies have demonstrated the value of Critical Systems Heuristics (CSH) in analyzing complex socio-technical systems. Etemadi et al. [4] applied a systems thinking approach combining TSI, CSH, and DEMATEL-ANP within a Society 5.0 framework to energy sector stakeholder engagement, emphasizing participatory governance and long-term sustainability. Ebrahimi et al. [3] used CSH to evaluate Iran's Water-Energy-Food nexus, revealing fragmented decision-making, short-term planning, and insufficient interdisciplinary collaboration as key barriers to sustainability. Similarly, Fathi et al. [5] examined stakeholder boundary judgments in Iran’s gas company, identifying gaps between current and ideal practices and highlighting the need for clean energy, modern technologies, and multidisciplinary expertise. Together, these studies illustrate the applicability of CSH for identifying systemic discrepancies and informing governance and design in complex socio-technical systems, supporting its use in AI-enabled battery digital twins for fast-charging applications. The literature synthesis in Table 1 highlights a gap in boundary-aware, governance-oriented design of AI-enabled battery digital twins for fast charging.

3. Research Methodology

This study adopts an applied qualitative design within a soft-OR / socio-technical perspective and is explicitly grounded in two methodological pillars. First, empirical data are collected through semi-structured interviews with experts and key stakeholders involved in DC fast charging and battery management systems. Second, the study conducts a boundary critique using Critical Systems Heuristics by applying the twelve “is/ought” boundary questions to make explicit the underlying boundary judgments and assumptions shaping the design and deployment of AI-enabled battery digital twins for fast charging. In the first step, interviews are used to elicit stakeholders’ experiences, perceptions, concerns, and preferences regarding fast-charging decision-making, data and sensing requirements, thermal management, grid-related constraints, and issues of safety, accountability, and liability. In the second step, the resulting statements and themes are systematically organized and interpreted through the CSH lens, enabling the identification of implicit boundary judgments, the mapping of “what is” versus “what ought to be,” and the extraction of design and governance requirements for implementing an AI-driven battery digital twin in BMS and fast-charging control.

Accordingly, the main analytical outputs include “What is/What ought to be” tables for each CSH dimension (motivation, control, knowledge, and legitimacy), a consolidated set of key boundary gaps, and actionable requirement bundles (e.g., data quality and ownership, auditability and interpretability, fail-safe control logic, and mechanisms for accountability and cross-stakeholder coordination).

Table 1. Summary of prior studies on EV fast charging, battery management, and digital-twin/AI approaches.

Reference	Study type / Scope	Main focus & key insights	Link to the present research (AI–Digital Twin–Fast Charging–CSH)
[15]	Comprehensive review (EV powertrain)	Reviews EV powertrain components (BMS, power electronics converters, traction motors) and the energy conversion chain (battery → DC–DC link → inverter → motor). Summarizes common technologies (Li-ion batteries, boost/full-bridge converters, PMSM/IM) and discusses renewable-based charging stations and fast-charging specs.	Provides broad technical background on EV subsystems and charging context; supports positioning fast charging and BMS as core enabling technologies.
[16]	Mini-review (smart charging & battery aging)	Highlights fast charging as essential for practicality but a driver of accelerated aging. Surveys predictive/adaptive control, often using ML, real-time monitoring, thermal management, and simulation tools (e.g., Simulink). Reviews DC fast-charging infrastructure and SOC/SOH monitoring to reduce losses and improve longevity.	Motivates the need for health-aware fast charging and AI-enabled strategies; connects directly to DT/AI control objectives and degradation mitigation.
[1]	Review & concept exploration (battery-assisted DCFC stations)	Reviews fast-charging advances and explores battery-assisted DC fast-charging stations. Discusses on-site storage for off-peak charging and peak-time discharge to reduce grid dependence and improve stability. Highlights transformer-less modular design (scalable, lower cost) and AI/ML-based energy management to adjust charging rates.	Links fast charging to grid constraints and station-level energy management; supports system-level framing where DT/AI decisions affect both battery health and grid impacts.
[21]	Comprehensive review (EV fast charging ecosystem)	Compares fast-charging approaches (DCFC, ultra-fast, inductive, Tesla Superchargers, bidirectional charging, battery swapping). Summarizes infrastructure (standards, connectors, protocols, power levels), charger/DC–DC converter classifications, and control strategies; outlines challenges and trends (interoperability, smart-grid integration, optimization).	Establishes the breadth of fast-charging technologies and control considerations; helps justify focusing on control/decision support and deployment challenges.
[9]	Review (evolution of charging & adoption)	Traces EV charging evolution (Level 1/2 AC → high-power DCFC). Discusses how speed, connector standardization, battery integration, and infrastructure reduce adoption barriers (range anxiety, long charging times). Highlights impact on battery health and user experience, emphasizing trade-offs and scalability challenges.	Supports adoption-driven motivation for fast charging and highlights system trade-offs that require robust control and governance (a bridge to CSH).
[17]	Review (battery thermal management for fast charging)	Reviews advanced BTMS for Li-ion batteries under fast charging, emphasizing heat generation, temperature rise, safety risks (thermal runaway), and accelerated aging. Surveys cooling strategies (indirect liquid, immersion, hybrid) based on 2019–2024 studies; proposes future directions for next-gen BTMS.	Reinforces thermal safety as a key constraint for DT/AI control; supports inclusion of thermal boundaries and fail-safe requirements in DT-enabled fast charging.

Reference	Study type / Scope	Main focus & key insights	Link to the present research (AI–Digital Twin–Fast Charging–CSH)
[7]	Perspective (fast-charging batteries: limits & opportunities)	Discusses limiting factors from materials/electrolytes/electrodes to cells, packs, systems, stations, and safety (including thermal-runaway impacts). Reviews multiscale optimization strategies; emphasizes high-voltage charging and advanced thermal management; calls for on-board detection of resistance/temperature rise plus intelligent algorithms.	Strengthens the multi-level nature of the problem and the need for intelligent, onboard/operational sensing and control inputs that a DT/AI architecture must integrate.
[10]	Review (batteries, modeling, BMS, SOC/SOH, charging)	Reviews battery modeling (electrical, thermal, electro-thermal), SOC/SOH estimation, charging approaches, and optimization. Summarizes BMS tasks (monitoring, protection, balancing, thermal/data management) and discusses balancing circuits, stressors, reliability, losses, and efficiency; identifies research gaps.	Provides foundational BMS and modeling context for DT development; highlights gaps that motivate improved estimation/control and structured design requirements.
[13]	Review + case-study synthesis (digital twins for BMS)	Argues AI-heavy BMS faces data limitations that reduce estimation accuracy and can impact performance/safety. Reviews DT concepts/architectures; synthesizes research and industry case studies; proposes a scalable, cost-effective DT–BMS integration framework; discusses open challenges and opportunities.	Most directly aligned: supports DT–BMS integration framing and practical deployment concerns; motivates boundary critique (who/what data, risks, responsibilities) that CSH can structure.

The study population consists of experts and stakeholders who play a direct role in the design, development, evaluation, or operation of BMS, DC fast charging, and related infrastructure, or who are directly affected by their safety and performance consequences. This population includes battery and BMS technical experts (battery modeling, SOC/SOH estimation, charging control, thermal management, and safety), fast-charging station operators and O&M managers as well as personnel involved in station-level energy management and power control, industry representatives and system integrators (hardware/software developers, charging-system and telematics integrators, and where feasible, OEM or battery-supplier representatives), and finally experts from standardization, safety, and policy/regulatory domains as well as key affected user representatives to ensure that legitimacy and equity considerations are reflected in the boundary analysis. Sampling is purposive and is complemented by snowball sampling to complete stakeholder groups and capture diverse perspectives; inclusion criteria require relevant professional experience, a decision-making or decision-influencing role, and practical familiarity with fast-charging operations, safety, data issues, and battery performance.

The study includes a fixed sample of 22 experts to ensure adequate stakeholder coverage and conceptual saturation while remaining consistent with the practice of CSH-based qualitative inquiry and the structure of the author’s prior work. Specifically, the sample comprises 8 battery/BMS specialists (SOC/SOH, charging algorithms, thermal management/safety), 6 fast-charging station operators and O&M/energy-management experts, 5 industry and system-integration experts related to charging systems, data, and control, and 3 participants from standardization/safety/policy domains or affected-user representatives to strengthen the legitimacy dimension. Interviews are conducted in a semi-structured and in-depth format using an interview guide aligned with the twelve CSH questions so that, for each question, both the “current practice” narrative (is) and the “desired future” narrative (ought) can be captured. All interviews are recorded (with consent), transcribed, and analyzed using a template analysis approach structured around the four CSH dimensions, with findings reported as boundary judgments, boundary gaps, and the resulting design and governance requirements.

4. Analysis

This section reports the findings derived from the semi-structured interviews with the 22 Iranian experts and stakeholders and presents them through the analytical lens of Critical Systems Heuristics. After transcription, the data were organized using a template analysis aligned with the four CSH dimensions motivation, control, expertise, and legitimacy so that implicit boundary judgments, stakeholder assumptions, and value-laden design choices could be made explicit. Consistent with the CSH approach, the results are not presented as purely technical performance claims; rather, they articulate how design and operational decisions embed boundary choices about who is served, who bears risks, which knowledge is treated as valid, and how accountability is assigned in practice. Across interviews, participants repeatedly emphasized that fast-charging digital-twin architectures are shaped by fragmented responsibilities among charger vendors, EV/OEM-side BMS logic, station operators, and grid utilities, and that this fragmentation often translates into unclear liability, uneven service outcomes, and limited learning from incidents or near-misses. Moreover, experts highlighted that constraints particularly salient in Iran such as local distribution network limitations, investment constraints, and high environmental and public-health stakes make boundary setting especially consequential for safety and long-term system resilience. Table 2 then provides the core CSH output by contrasting “what is” versus “what ought to be” boundary judgments and offering a critical reflection on the main gaps that emerged from the interviews.

Table 2. CSH Boundary Judgments for AI-Enabled Battery Digital Twin (DT) Deployment in DC Fast Charging.

CSH Dimension	Boundary Focus	“What Is” (Current Practice)	“What Ought to Be” (Normative Expectation)	Critical Reflection (Is vs. Ought)
Motivation	System purpose	Fast charging is primarily framed as reducing charging time and increasing station throughput; battery health is often treated as a secondary constraint handled by conservative limits.	A balanced purpose that explicitly optimizes time–safety–battery longevity–grid impact, with safety and long-term sustainability treated as first-class objectives.	The current purpose is throughput-driven; long-term battery and system sustainability remain under-specified, leading to hidden costs and risk transfer.
	Beneficiaries	Main beneficiaries are perceived as charging-station operators (revenue/throughput) and EV users (shorter wait time); OEM interests dominate in vehicle-side decisions.	Beneficiaries should include users, operators, OEMs, grid utilities, regulators, and the public (safety/environment), with explicit protection for vulnerable user groups.	A narrow beneficiary definition marginalizes grid/station externalities and equity (e.g., older batteries/users receiving systematically worse service).
	Measures of success	Success is measured by charging time, availability, number of sessions/day, and basic safety compliance; battery degradation is rarely tracked end-to-end across actors.	Success should include proactive indicators: degradation rate, thermal risk margin, near-miss reporting, model drift alerts, grid-stress KPIs, and learning capacity.	Reactive metrics dominate; without degradation and near-miss indicators, DT/AI performance may look “good” while long-term harm accumulates.
Control	Decision-makers	Decisions are fragmented: charger OEM/software vendor sets station logic, vehicle OEM/BMS controls current limits, operator focuses on uptime; regulators intervene mostly after incidents.	Shared governance with clearly defined roles among station operators, vehicle/OEM representatives, grid utility, safety/regulatory bodies, plus an escalation path for incidents.	Fragmented control mismatches shared risk: when something fails, accountability becomes disputed and corrective learning is slow.

CSH Dimension	Boundary Focus	"What Is" (Current Practice)	"What Ought to Be" (Normative Expectation)	Critical Reflection (Is vs. Ought)
	Resources	Budget prioritizes expansion and uptime; limited investment in calibrated sensors, data quality, cybersecurity, and continuous model validation.	Dedicated resources for sensor calibration, data infrastructure, cybersecurity, validation/verification, and fail-safe testing, plus lifecycle budgeting.	Short-term CAPEX/OPEX pressures crowd out "invisible" reliability investments that are essential for trustworthy DT/AI control.
	Environmental constraints	Grid constraints (voltage drops, peak limits), heat, and supply variability are treated as external "operational headaches," managed ad hoc (load shedding, throttling).	Constraints should be explicitly modeled and managed via adaptive policies: peak-aware scheduling, battery-assisted buffering, dynamic limits, and coordinated utility interfaces.	Treating constraints as external shifts risk downstream (users/batteries) and increases instability; DT value is reduced if the environment is not integrated.
Expertise	Relevant knowledge	Expertise is siloed: battery experts focus on cells/BMS, operators on station uptime, utilities on power quality; field experience is rarely formalized.	Integrated knowledge combining electrochemical, thermal, power-electronic, grid, operational, and human-factor perspectives, with systematic capture of field lessons.	Over-siloing leads to blind spots (e.g., thermal reality vs. model assumptions); tacit operational knowledge is undervalued in DT design.
	Experts	"Experts" are often defined as OEM engineers and vendor data scientists; operators and safety specialists have limited influence on model boundaries.	Cross-functional expert teams including operators, safety analysts, utility engineers, BMS specialists, data scientists, and independent auditors where feasible.	A technocratic expert definition can produce high-performing models that are not operationally usable, auditable, or trusted by safety stakeholders.
	Guarantees of competence	Competence is assumed via certification, vendor claims, and limited pilot testing; continuous monitoring for drift and rare-event behavior is weak.	Competence should be ensured by continuous validation, stress testing, scenario-based training, drift detection, and independent audit trails for decisions.	Formal compliance is not equivalent to real-world competence; without drift monitoring and scenario tests, DT control may degrade silently over time.
Legitimacy	Affected stakeholders	Affected stakeholders (users with older batteries, nearby communities, emergency services, insurers) are rarely included in design/operational policy discussions.	Inclusion of affected groups via structured feedback, incident reporting channels, and engagement with emergency authorities and public safety actors.	Lack of voice undermines legitimacy and can slow adoption after incidents; "silent stakeholders" bear risk without representation.
	Representation	Representation is largely reduced to regulatory compliance and contractual relationships (operator–vendor–OEM); transparency to users is minimal.	Transparent communication: explainable charging decisions, user-facing safety/health messaging, stakeholder engagement, and accountability mechanisms.	Legitimacy cannot rely only on formal approvals; without transparency, trust erodes and disputes increase when charging performance varies by condition.
	Worldview	The system is viewed as a technical charging service (power delivery); AI is seen as an optimization add-on.	The system should be treated as a socio-technical ecosystem where AI/DT decisions embed values about safety, equity, privacy, and responsibility.	A narrow technical worldview hides value-laden boundary choices (who benefits, who pays, who is protected) and limits durable acceptance.

4-1. Responses to Boundary Questions

Boundary Question 1: Purpose of the system (What is / What ought to be / Critical reflection). In current practice, the purpose of an AI-enabled battery digital twin for DC fast charging is mainly defined as increasing charging speed and station throughput, with battery health and wider system impacts handled as secondary constraints. Normatively, it ought to be defined as a safety-first, sustainability-oriented purpose that jointly optimizes charging convenience, thermal/electrochemical safety margins, battery longevity, and grid impacts, while supporting resilience and continuous learning. The key gap is that a throughput-driven purpose tends to externalize long-term costs and risks (e.g., faster degradation and higher operational/grid stress), whereas an explicit multi-objective purpose makes trade-offs transparent and manageable.

Boundary Question 2: Beneficiaries of the system (What is / What ought to be / Critical reflection). In current practice, the main beneficiaries are typically seen as EV users (shorter charging time) and charging-station operators (higher throughput and revenue), with vehicle-side priorities largely shaped by OEM interests. Normatively, beneficiaries ought to be defined more broadly to include users, operators, OEMs, grid utilities, regulators, and the wider public affected by safety and environmental outcomes, with explicit attention to vulnerable user groups (e.g., older batteries) to avoid systematic disadvantage. The key gap is that a narrow beneficiary definition can hide externalized impacts and equity issues shifting costs to battery owners, stressing local grids, and producing uneven service whereas a broadened beneficiary set makes responsibilities and protections more balanced and defensible.

Boundary Question 3: Measures of success (What is / What ought to be / Critical reflection).
In current practice, success is mainly measured by charging time, station availability, utilization/throughput, and basic compliance, while battery degradation and risk signals are rarely tracked end-to-end across actors. Normatively, success ought to include proactive indicators such as degradation rates, thermal risk margins, near-miss reporting, model-drift alerts, and grid-stress metrics alongside user service levels. The key gap is that reactive, throughput-focused metrics can make performance look acceptable while long-term harm accumulates, whereas proactive and lifecycle-based measures enable prevention, learning, and accountable optimization.

Boundary Question 4: Resources controlled by decision-makers (What is / What ought to be / Critical reflection).
In current practice, decision-makers mainly control operational budgets and priorities aimed at expansion and uptime, while investment in calibrated sensing, data quality, cybersecurity, and continuous model validation is limited or treated as optional. Normatively, they ought to control and commit dedicated resources for the full reliability stack sensor calibration and maintenance, secure data infrastructure, verification/validation, fail-safe testing, and lifecycle monitoring so that safety and long-term performance are funded, not assumed. The key gap is that short-term cost and availability pressures often crowd out “invisible” reliability investments, which increases hidden risk and undermines trustworthiness when DT/AI control is deployed at scale.

Boundary Question 5: Decision-makers (What is / What ought to be / Critical reflection).
In current practice, decision-making is fragmented across charger vendors and their control software, EV/OEM-side BMS logic, station operators focused on uptime, and grid utilities managing power-quality constraints, with regulators typically involved indirectly or after incidents. Normatively, decision-making ought to be organized as shared governance with clearly defined roles and escalation paths among operators, OEM/BMS stakeholders, grid utilities, and safety/regulatory authorities, so that responsibility for safety, performance, and incident response is explicit. The key gap is that fragmented decision authority does not match shared and distributed risk, leading to unclear accountability, inconsistent service outcomes, and slower learning when failures or near-misses occur.

Boundary Question 6: External conditions and constraints (What is / What ought to be / Critical reflection).
In current practice, key constraints such as local grid limits (voltage drops and peak caps), high ambient temperatures, supply variability, and site-level operational disruptions are treated as external and handled ad hoc through throttling, manual interventions, or service curtailment. Normatively, these conditions ought to be explicitly represented and managed through adaptive mechanisms peak-aware scheduling, coordinated interfaces with

utilities, battery-assisted buffering where feasible, dynamic operating limits, and robust fail-safe modes that prioritize safety under uncertainty. The key gap is that treating constraints as "outside the system" shifts risk downstream to users and batteries and can increase instability, whereas integrating them into the DT/AI design makes trade-offs visible and enables resilient, context-aware control.

Boundary Question 7: Relevant expertise (What is / What ought to be / Critical reflection).
In current practice, relevant expertise is treated as largely technical and siloed battery and BMS specialists focus on electrochemistry and estimation, station teams focus on uptime and power delivery, and utilities focus on grid constraints while operational and experiential knowledge is rarely formalized in model design. Normatively, relevant expertise ought to be integrated across electrochemical, thermal, power-electronic, grid, operational, and human-factor perspectives, with structured capture of field lessons and incident/near-miss knowledge to inform DT assumptions and control rules. The key gap is that narrow or siloed expertise creates blind spots between model assumptions and real operating conditions, whereas integrated expertise improves robustness, safety margins, and real-world usability of DT-enabled fast charging.

Boundary Question 8: Experts (What is / What ought to be / Critical reflection).
In current practice, "experts" are most often defined as OEM engineers, charger vendors, and data scientists who build models and control logic, while operators, safety specialists, and grid engineers have limited influence on how boundaries and assumptions are set. Normatively, expertise ought to be recognized as cross-functional, involving operators and O&M staff, safety analysts, utility engineers, BMS and thermal specialists, data/AI engineers, and where feasible independent auditors who can challenge assumptions and validate claims. The key gap is that a technocratic definition of expertise can produce high-performing models that are not operationally trusted or auditable, whereas broader expert inclusion improves accountability, practicality, and legitimacy of DT-enabled fast-charging decisions.

Boundary Question 9: Guarantees of competence and success (What is / What ought to be / Critical reflection).
In current practice, competence is largely assumed through certification, vendor claims, and limited pilot testing, with weak ongoing monitoring for model drift, rare-event behavior, or degradation of sensing and data quality over time. Normatively, competence ought to be guaranteed through continuous validation and verification, stress and scenario testing (including extreme heat and grid disturbances), drift detection, robust logging and audit trails for key charging decisions, and regular training and incident-learning routines. The key gap is that formal compliance does not ensure real-world competence in a changing environment, whereas continuous monitoring and auditable learning processes provide the operational confidence needed for safe, scalable DT/AI fast charging.

Boundary Question 10: Challenging the system by affected stakeholders (What is / What ought to be / Critical reflection).
In current practice, affected stakeholders such as users with older batteries, nearby communities, emergency services, and insurers have limited practical channels to question charging policies or contest outcomes, and feedback is typically informal or occurs only after incidents. Normatively, they ought to have structured ways to challenge decisions and surface concerns, including accessible complaint and appeal mechanisms, transparent incident and near-miss reporting, user-facing explanations for throttling or safety limits, and formal engagement with emergency and public-safety actors. The key gap is that weak challenge mechanisms reduce accountability and slow learning, whereas empowering affected stakeholders to question and influence boundaries strengthens legitimacy, trust, and safety-driven improvement.

Boundary Question 11: Representation of marginalized stakeholders (What is / What ought to be / Critical reflection).
In current practice, representation is mostly channeled through regulatory compliance and private contracts among operators, vendors, and OEMs, while marginalized or "silent" groups such as users with degraded batteries, those with lower purchasing power, and parties exposed to safety externalities are rarely represented in boundary setting. Normatively, their interests ought to be represented through transparent stakeholder engagement, user advocacy or consumer-protection mechanisms, safety and public-interest bodies, and clear participation routes for emergency authorities and community actors in defining acceptable risk and service standards. The key gap is that treating representation as mere formal approval can institutionalize inequities and

externalize harms, whereas genuine representation embeds equity and public safety into how DT/AI charging policies are designed and governed.

Boundary Question 12: Worldview (What is / What ought to be / Critical reflection).

In current practice, the system is mainly viewed as a technical charging service focused on delivering power quickly, with AI and the digital twin treated as optimization tools layered onto existing operations. Normatively, the system ought to be defined by a socio-technical worldview in which DT/AI decisions embed and must be accountable for values such as safety, equity, privacy, responsibility, and long-term resilience across the charging ecosystem. The key gap is that a narrow technical worldview obscures value-laden boundary choices and weakens durable trust, whereas a socio-technical worldview makes those choices explicit and governable, supporting safer and more widely accepted fast-charging deployment.

4-2. Synthesis of Boundary Gaps

The boundary critique reveals a consistent set of “is–ought” gaps that shape the feasibility, safety, and legitimacy of deploying AI-enabled battery digital twins for DC fast charging in Iran. First, the prevailing system purpose is largely throughput-driven prioritizing shorter charging times and higher station utilization while battery longevity, thermal safety margins, and grid impacts remain secondary constraints rather than explicit objectives, creating hidden risk and cost transfer over the lifecycle. Second, beneficiaries are commonly framed narrowly around users and station operators, whereas broader beneficiaries (grid utilities, regulators, public safety actors, nearby communities, and future users) are weakly represented in design priorities and performance metrics. Third, decision authority is fragmented across charger vendors, OEM-side BMS logic, station operators, and grid utilities; this fragmented control structure produces unclear liability, uneven service outcomes, and limited learning from incidents or near-misses. Fourth, resource allocation tends to favor expansion and uptime over reliability investments such as calibrated sensing, data governance, cybersecurity, continuous validation, and drift monitoring, weakening robustness under real-world uncertainty. Finally, expertise and legitimacy are often treated technocratically, leaving operational knowledge and affected stakeholders under-represented in boundary setting, which reduces transparency and long-term trust. Collectively, these gaps indicate that improving algorithmic accuracy alone is insufficient; boundary-aware design requirements are needed to make trade-offs explicit, auditable, and defensible in practice.

4-3. CSH-Informed Design Requirements for DT-Enabled Fast Charging

Building directly on the above boundary gaps, the interview findings were translated into a structured set of design and governance requirements for AI-enabled battery digital twins supporting BMS functions and DC fast-charging control. These requirements specify the minimum conditions under which DT-enabled charging can remain safe, robust, and legitimate under heterogeneous battery conditions, variable environments, and constrained infrastructure. They are organized into five clusters DT/AI control and BMS integration, data/sensing/monitoring, safety assurance and fail-safe robustness, auditability and accountability, and governance and legitimacy and are summarized in Table 3.

Taken together, the requirements in Table 3 clarify that trustworthy DT-enabled fast charging depends on more than model accuracy: it requires robust sensing and data stewardship, explicit safety envelopes and fail-safe behavior, continuous validation under real operating conditions, and governance mechanisms that assign accountability and enable affected stakeholders to challenge decisions. In the Iranian context where local distribution constraints, investment limitations, and high public-health and environmental stakes amplify the consequences of fast-charging deployment these requirements provide a practical roadmap for reducing risk transfer, improving resilience, and strengthening legitimacy as the ecosystem scales.

5. Discussion and Conclusion

The findings of this study indicate that deploying an AI-enabled battery digital twin for battery management systems and fast-charging control is not merely a technical matter of improving model accuracy or increasing charging power. Rather, it is a socio-technical challenge whose quality and consequences depend on boundary judgments regarding the system’s purpose, beneficiaries, measures of success, decision structures, resource allocation, what knowledge is treated as valid, and how legitimacy and accountability are established in practice.

Table 3. CSH-Informed Design Requirements for an AI-Enabled Battery Digital Twin in BMS and DC Fast Charging Control.

ID	Requirement cluster	Design requirement	Rationale
R1	DT/AI control & BMS integration	The DT shall implement health-aware charging by coupling SOC/SOH estimation with thermal-state estimation and uncertainty bounds.	Shift's purpose from throughput-only to balanced safety–longevity–performance.
R2		The controller shall enforce explicit safety envelopes (current/voltage/temperature) with conservative margins under uncertainty.	Prevents hidden risk transfer and unsafe optimization.
R3		The DT shall include battery-age and condition stratification so charging policies adapt across new vs. degraded packs.	Reduces inequitable outcomes and systematic disadvantage.
R4		The architecture shall specify edge vs. cloud responsibilities and maximum allowable latency for safety-critical control.	Maintains safety under intermittent connectivity and latency.
R5		Interfaces among charger controller–station EMS–vehicle BMS shall include precedence/negotiation rules to avoid conflicting actions.	Mitigates fragmented decision-making and inconsistent operating policies.
R6		The DT shall support grid-aware charging by incorporating local constraints (e.g., voltage limits, peak caps) where available.	Integrates environmental constraints instead of ad hoc throttling.
R7	Data/sensing/monitoring	Deployment shall include sensor calibration and maintenance protocols for critical measurements (temperature, current, voltage).	Addresses underinvestment in "invisible" reliability fundamentals.
R8		The system shall implement data quality gates (missingness, outliers, sensor drift) that trigger safe fallback behavior.	Prevents control decisions based on degraded or biased data.
R9		Telemetry shall include provenance and traceability (timestamps, device IDs, firmware/model versions).	Enables auditability and root-cause analysis across actors.
R10		Monitoring dashboards shall track battery-health proxies and thermal risk margins alongside throughput KPIs.	Rebalances measures of success toward proactive risk and longevity.
R11		The DT shall include near-miss capture (e.g., repeated throttling, thermal excursions) as a learning signal.	Strengthens prevention and organizational learning capacity.
R12	Safety assurance & fail-safe robustness	The control logic shall include graded fail-safe modes for sensor faults, communication loss, and high-uncertainty estimates.	Ensures safe operation under common field failures.
R13		The deployment shall require continuous validation and drift detection with thresholds for model re-calibration or rollback.	Addresses silent performance degradation over time.
R14		The system shall undergo scenario-based stress testing (high ambient temperature, grid disturbance, peak demand) prior to scaling.	Improves robustness under Iran-relevant operating conditions.
R15		The DT shall support version control and rollback to known-safe configurations after abnormal behavior.	Limits the impact of faulty updates and reduces recovery time.
R16	Auditability & accountability	The system shall maintain decision logs capturing inputs, constraints, actions, and model versions for each charging session.	Enables post-incident reconstruction and regulatory review.
R17		Roles and escalation paths for incidents shall be defined across vendor–operator–OEM–utility interfaces.	Reduces liability ambiguity created by fragmented decision authority.
R18		Users shall receive transparent explanations for throttling and condition-dependent charging outcomes.	Reduces perceived unfairness and improves trust and compliance.

ID	Requirement cluster	Design requirement	Rationale
R19	Governance & legitimacy	A cross-stakeholder governance mechanism shall periodically review boundary judgments and performance indicators.	Keeps boundaries aligned as adoption and constraints evolve.
R20		The deployment shall include channels for challenge and representation (complaints/appeals, stakeholder engagement, safety reporting).	Improves legitimacy and ensures affected stakeholders can influence boundaries.

The results show that current practice is largely oriented toward maximizing charging speed and station service throughput; within this framing, battery lifetime, thermal safety margins, and grid impacts are typically managed as secondary and reactive constraints. In contrast, the normative expectation articulated by experts is a multi-dimensional, safety-first purpose that treats charging time, battery health and lifetime, thermal/electrochemical risk, and grid stress as primary and measurable objectives. From a stakeholder perspective, the findings also show that beneficiaries are often implicitly limited to users and station operators, whereas a more appropriate framing should recognize broader beneficiaries such as grid utilities, safety and regulatory bodies, local communities around charging sites, and future users affected by safety and environmental outcomes. A narrow beneficiary definition can externalize risk and cost to battery owners, intensify inequities in service quality for older or degraded batteries, and increase stress on the grid. At the level of control and governance, the results highlight that fragmented decision authority distributed across charger vendors and their control software, OEM-side BMS logic, station operators, and grid utilities create unclear liability, inconsistent operating policies, and limited learning from incidents or near-misses. Accordingly, a central implication of this study is the need to move toward shared governance and to define clear roles and escalation pathways across key actors so that safety responsibility and grid-constraint management become explicit and coordinated, enabling timely corrective action. In addition, experts consistently emphasized that financial and managerial resources are typically prioritized toward expansion and uptime, while investments in sensor calibration, data governance and quality assurance, cybersecurity, continuous validation, and model-drift monitoring remain weak. Yet, these "invisible" reliability foundations are prerequisites for trustworthy digital-twin deployment and therefore require explicit budgeting and maintenance planning.

Regarding expertise, the findings suggest that "valid expertise" is frequently defined in a technocratic manner and limited to OEM engineering teams, charger vendors, or data specialists, while the operational knowledge of station staff, maintenance experience, and safety- and grid-oriented perspectives have less influence on how model boundaries and control logic are set. This study therefore recommends forming interdisciplinary deployment teams in which, alongside battery, control, and data experts, safety specialists, grid engineers, and station operators actively participate in defining test scenarios, safety envelopes, and decision rules. From the legitimacy perspective, the results show that affected stakeholders such as users with more degraded batteries, emergency and public-safety actors, and other parties outside private contractual arrangements often lack effective formal channels to challenge policies, understand the rationale for throttling, or contribute to defining service standards. Consequently, transparent mechanisms for communication, near-miss recording, feedback collection, complaint handling, and safety reporting at the ecosystem level are recommended to strengthen public trust and organizational learning. Overall, by applying CSH, this study demonstrates that moving from "purely technical optimization" to "defensible and trustworthy deployment" requires translating boundary gaps into concrete design and governance requirements. Based on the results, key recommendations include adopting lifecycle-oriented success metrics (e.g., battery health indicators, thermal risk margins, and grid-stress metrics alongside charging time), implementing fail-safe control logic with fallback modes under sensor faults or connectivity loss, establishing drift monitoring and safe rollback to validated versions, enabling decision logging and auditability for accountability and oversight, and instituting multi-stakeholder governance to periodically review boundary judgments and prevent inequitable risk transfer. Given distribution-network constraints, investment limitations, and the heightened environmental and public-health stakes common in many emerging markets, implementing these recommendations can reduce safety risks, improve grid resilience, and strengthen the social acceptance of fast charging, thereby supporting the responsible and sustainable scaling of charging infrastructure.

Despite providing actionable design requirements for AI-enabled digital twins in battery management and fast-charging control, this study has several important limitations. First, the data were collected from 22 expert interviews conducted in Iran. While sufficient for CSH-based qualitative analysis, the findings may not fully reflect perspectives in other regions with different grid infrastructures, regulatory frameworks, or levels of EV adoption. Second, certain boundary judgments particularly regarding grid constraints, investment limitations, and local environmental conditions are context-specific and may require adaptation for other emerging markets. Third, the study relies on expert perceptions and judgments, without quantitative validation of the proposed digital twin control strategies; thus, empirical testing is needed to confirm their practical effectiveness. Fourth, the research assumes general digital twin architectures and AI integration approaches, whereas real-world implementation may involve specific hardware, software, latency, or proprietary system constraints that were not directly tested. Finally, purposive and snowball sampling may introduce selection bias, as participants with strong opinions or particular experiences could be overrepresented, although efforts were made to capture diverse perspectives.

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Biography

Mohammad Reza Fathi is an Associate Professor, College of Farabi at University of Tehran, Iran. He received his PhD in Industrial Management from University of Tehran. His research interests include Supply Chain Management, Future Study and DEA. He has written several papers about Advanced Supply Chain Management, Multiple Criteria Decision Making and Mathematical Modelling.

Mohammad Mostafa Dadras is MSc Candidate in Information Technology Engineering, Noor Tuba Electronic Institute of Higher Education, Tehran, Iran. His research interests include E-commerce, marketing, SPSS and factor Analysis.

Samaneh Raeesi Nafchi is an Assistant Professor of Industrial Management at Shiraz University of Technology–Lamerd Higher Education Center, Fars, Iran. She received her PhD in Business Management with a specialization in Marketing from the University of Tehran. Her research interests include Marketing, Organizational Studies, Business Process Reengineering, and Multiple Criteria Decision Making. She has published research on organizational readiness, employee turnover intention, and management decision-making methods.