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Review Paper

A Systematic Literature Review of Risk Assessment Methodologies for Battery Electric Vehicles

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Abstract

This systematic literature review investigates risk assessment methodologies for Battery Electric Vehicles (BEVs), highlighting their diversity and effectiveness in addressing emerging safety challenges. With the rapid global adoption of BEVs, there is an increasing need for robust methodologies to assess risks such as thermal runaway (TR), degradation, and operational failures. This review highlights techniques such as fuzzy failure mode and effect analysis (FMEA), hybrid neural networks, bayesian networks (BN), and entropy weight methods. These tools effectively identify and mitigate risks; however, they face challenges in providing holistic, system-level safety assessments and adapting to long-term, real-world conditions. Unlike previous works, this study integrates interdependent BEV subsystems into unified risk models and examines underexplored areas such as maritime transport safety. The transport of BEVs by vessels presents unique risks, including high humidity and confined cargo spaces, which intensify the battery safety challenges. Tools like FMEA and real-time monitoring systems are critical to mitigate these risks. The findings highlight the growing reliance on real-time diagnostics and advanced algorithms for enhancing BEV safety and reliability. By identifying gaps and proposing recommendations, this review aims to support the development of standardized frameworks to ensure BEV safety across various environments and operational scenarios, contributing to their continued global adoption.

Keywords: Battery electric vehicles; Electric vehicles; Risk assessment; Risk analysis; Safety protocols

1. Introduction

The global transportation sector is undergoing a significant transformation driven by the growing adoption of electric vehicles (EVs), particularly BEVs. This shift is driven by the urgent need to mitigate greenhouse gas emissions, as transportation constitutes a substantial share of global emissions, with passenger vehicles being major contributors. BEVs are a more environmentally sustainable option because they generate no direct emissions, effectively reducing the transportation sector's carbon footprint [1], [2], [3], [4], [5]. These environmental benefits, coupled with advancements in renewable energy integration, position BEVs as a critical component of the energy transition [4], [6], [7], [8], [9].

Despite their environmental benefits, the adoption of BEV introduces new challenges, particularly related to the safety and risk management of battery systems. BEV batteries are prone to TR, chemical instability, and other risks that require robust safety protocols. Despite their significant environmental advantages, the increasing complexity of BEV systems and their widespread adoption underscore the importance of comprehensive risk assessments. Addressing these risks is critical for ensuring the safe integration of BEVs into the transportation ecosystem.

Several reviews have explored topics such as battery performance, charging technologies, Life Cycle Analysis (LCA), market trends, and control algorithms. For instance, studies by Sanguesa et al. and Suganya et al. emphasize battery technologies, highlighting their critical role in EV performance, efficiency, and market dynamics, while future technologies and parameter estimation algorithms are explored [10], [11]. Celadon et al. and Usman et al. emphasize sustainability aspects, including lifecycle management, circular economy models, and resource recycling [12], [13]. Others, like Long et al., Khadake et al., and Roy et al., have focused on technical challenges, such as energy management systems, range anxiety, and advancements in battery technologies [14], [15], [16]. Macharia et al. and Halim et al. provided a broader overview of EV technologies, including battery management systems, architectures, and cybersecurity challenges [17], [18]. Muji et al. presented a bibliometric analysis of EV research trends in Indonesia, Malaysia, and Thailand from 2015 to 2025, revealing an exponential growth in studies, particularly led by Malaysian universities [19], while Kaleg et al. reviewed the advancements in EVs, focusing on battery technology trends, charging methods, and the current market situation [20]. While these studies provide valuable insights into various aspects of EV development, none specifically address risk evaluation methodologies for BEVs. The safety of EVs is a fundamental concern as their adoption increases. Standards, training, and certification play crucial roles in ensuring the safety of EVs, not only in terms of their operation but also in maintaining compatibility between jurisdictions and ensuring environmental sustainability.

This gap is particularly significant given the safety concerns posed by BEV batteries and their operation in diverse environments. This paper addresses this critical gap by systematically reviewing methodologies for assessing BEV-related risks, particularly those associated with their batteries.

The objective of this systematic literature review is to provide a comprehensive overview of the various methods used to assess the safety risks of EVs and to respond to the following questions:

a. Which safety risk assessment methods have been used for BEVs, and what are the strengths and weaknesses of each method?
b. How effective are the existing risk assessment methods in identifying and managing the safety risks related to BEV batteries and their operation in various environments?
c. What are the gaps in current risk assessment methods and what recommendations can be made for developing more effective safety standards for BEVs based on the evaluation of these methods?

The structure of the paper is as follows: Section 1 sets out the general framework for the development of EVs/BEVs and introduces the importance of the risk analysis of BEVs. The relevant studies are presented in Section 2. In Section 3, we discuss the methodology of this study. Section 4 provides a comprehensive state-of-the-art overview of the scientific literature, and Section 5 discusses the risk assessment methodology of BEV. Finally, Section 6 presents the conclusions of this research.

2. Relevant Studies

The growth of electric vehicle adoption is further supported by technological advancements and the commercial viability of renewable energy resources [21]. These advancements, particularly in battery technology, have led to improved performance, increased driving range, and reduced costs, making EVs increasingly attractive to consumers. However, the growing sophistication of battery systems has also introduced a higher complexity of risks, such as TR, operational failures, and safety concerns, necessitating the development of more advanced and integrated risk assessment approaches. Additionally, the increasing availability of public and private charging infrastructure has helped to address the concerns of range anxiety, further driving the adoption of EVs [22].

2.1. Thermal Runaway Risk

One of the most critical safety concerns in EVs is the potential for thermal runaway (TR) in battery systems, which can lead to catastrophic consequences, such as fire hazards [23]. As the global market for electric vehicles continues to grow exponentially, with projections of a 20-fold increase by 2030, the need to address these risks has become increasingly paramount [24]. The design and chemistry of the battery pack and its associated systems play a crucial role in determining the safety, reliability, and life of EVs [25]. Factors such as unexpected temperature rises and internal reactions within the battery system can significantly impact vehicle overall resilience. Effective battery management systems (BMS) are essential to mitigate these risks by monitoring and controlling the performance, charging, and safety of batteries. Wang et al. used a comparative research methodology to examine the TR behavior of lithium-ion batteries (LIBs) using three prevalent cathode materials: nickel cobalt manganese (NCM), lithium iron phosphate (LFP), and lithium cobalt oxide (LCO). An innovative safety evaluation approach grounded in seven critical parameters was introduced for the assessment of TR risks and hazards, thereby offering a thorough analysis of battery safety [26].

The comparison of the findings from multiple studies highlights both consensus and variability in thermal management approaches. For example, Adeniran and Park investigated the thermal implications of various cooling configurations, including ambient and liquid cooling strategies for 65 Ah pouch-type batteries, whereas Cui et al. found that TR can be detected earlier using gas signals rather than traditional indicators like temperature or voltage [27], [28]. Li et al. employed a dynamic Bayesian framework to evaluate transportation-related risks, with a focus on self-heating and handling deficiencies as predominant TR contributors [29]. Zhu et al. reported benefits for predicting development patterns and more significant risks for reducing the impact of TR hazards [30]. The findings demonstrate that the total mass loss (TML) and peak heat release rate (pHRR) exhibit comparable positive correlations, when applied to a power function, in relation to the surface area of the exposed thermal source.

2.2. Battery Design and Safety

The design of lithium-ion batteries is instrumental in addressing safety concerns. Haber et al. conducted a comprehensive analysis of the stress factors that affect EV batteries by gathering and assessing field data from various driving campaigns, totalling 228 million km and 7.8 million trips. The study identified high mid-SOC cycling and idle times as critical for BEVs, whereas high power cycling was crucial for hybrid electric vehicles (HEVs) [31]. Huang et al. presented a novel safety risk assessment method for automotive battery packs, focusing on voltage inconsistency analysis across cell and pack levels. The proposed method effectively captures the impacts of mechanical deformation and provides a framework for real-time safety monitoring [32]. Maddipatla et al. presented an extensive design and process failure mode and effects analysis (DFMEA and PFMEA) with an emphasis on the safety considerations pertinent to cylindrical lithium-ion batteries [33]. The proposed method identifies significant failure modes, causes, and effects related to battery design and manufacturing processes, emphasizing the importance of each element's influence on safety. Omakor et al. explored a comprehensive review of battery reliability assessments for electric transportation modes [34]. The method used first, through the operating principles of Li-ion batteries, patterns, and other models, is briefly discussed using qualitative and quantitative approaches. Fadillah et al. conducted a safety evaluation of Lithium-ion NCA (Nickel-Cobalt-Alumina) batteries under the influence of crash impact loading [35]. Chen et al. studied the safety of lithium-ion battery circularity activities using lithium-ion batteries (LIBs) to support sustainability. This foundational methodology combines risk analysis with multi-criteria decision-making (MCDM) [36].

Fire hazards remain a critical issue. Zhicheng et al. summarized the crash risk characteristics from 2018 to 2021 and proposed a crash risk characteristic matrix to improve BEV safety [37]. Bisschop et al. emphasized the potential risks in lithium-ion battery combustion incidents and proposed preventive strategies, whereas Zhang et al. utilized fault tree analysis (FTA) and BN to assess maritime transportation fire incidents [38], [39]. Findings indicated that the critical contributors to these fire accidents included ineffective firefighting systems for lithium battery fires, elevated humidity levels, and the absence of real-time alarm functionalities in monitoring equipment.

2.3. Charging infrastructure risks

Adequate charging infrastructure is essential for safe and reliable EV operation because it can significantly impact user satisfaction and the efficiency of recharging services [40]. Habib et al. developed a framework for the stochastic estimation of EV charging to provide insights into the operational processes of future networks. This framework uses a realistic and probabilistic model to analyze EV charging patterns effectively [41].

In terms of risk analysis, Zhang et al. analyzed EV sharing is necessary for achieving carbon neutrality [21]. This study proposes a comprehensive framework to manage risks and enhance the efficiency of self-service EV operations. The proposed framework seeks to optimize service performance by addressing key challenges while ensuring safety and reliability in self-service EV systems. Wang et al. established an index system for assessing fire risks in electric bicycle charging facilities within old urban communities, drawing on accident case studies and relevant laws, regulations, and standards [42]. Zhang et al. discovered that the presence of harmonics and voltage variances within a distribution network engenders considerable safety issues in the operational functionality of charging stations [43]. To mitigate this concern, a Norton equivalent circuit for a direct current charger at a charging station was formulated, accompanied by constraints pertinent to station connectivity. Reeh et al. studied the rapid expansion of electrification in the transportation sector, which is a field of integration of plug-in EVs and demands smart charging infrastructure [44]. These systems, which rely on real-time data gathering and decision-making, regulate charging demand to enable the extensive integration of plug-in electric vehicles (PEVs) into power grids. Hwang et al. explained to propose systematic management strategies by analyzing the risks associated with specific components using FMEA [45]. The analysis incorporates the risk priority number (RPN) index based on severity, occurrence, and detection and the severity index (SI), which considers severity, detection, and information score scales. This research focuses on 7-kW EV chargers installed in South Korea as of 2023. Wang et al. analyzed EV charging and route selection and revealed that the initial state of charge and individual attitudes play a significant role in determining the timing of charging decisions [46]. Gao et al. developed an integrated safety assessment method by analyzing the interactions between the truck, pile, and grid [47]. The results demonstrate that the GA_BP network achieved greater accuracy and lower error rates than the standard BP neural network. Zhang et al. explained a novel method based on synthetic weighting to enhance the electrical safety of EV charging [48]. The method quantifies the abstract concept of electrical safety, and its effectiveness is validated through testing on actual charging equipment. Mousavi et al. introduced a sustainable assessment of energy sources for EV charging stations through the use of R-numbers and an integrated compromise solution methodology (R–COCOSO) [49]. Considering that the establishment of EV charging stations requires the incorporation of advanced technologies and frequently presents significant financial, operational, and risk-related challenges, the combinatorial distance-based assessment (CODAS) methodology, augmented by R-numbers, was formulated to proficiently assess project-related risks. The study conducted by Liu et al. systematically examined the safety risks associated with EV charging piles, identifying key risk factors with a particular focus on the impact of EV integration into the power grid [50]. Zhang et al. explained the crosschecking process using entropy weighting (EWM) and the gray relational analysis method (GRA). This study enhances the comprehensiveness of power system assessment by integrating advanced methods and techniques [51].

Several authors have analyzed fire hazards due to TR during charging processes and found that TR and the resulting fires in EV lithium-ion batteries produce distinct contamination [52]. Practical TR experiments were conducted using lithium-ion battery modules from a commercially approved EV to evaluate the potential risks to critical infrastructure and human health. Wang et al. examined smoke movement, temperature variations, visibility, and CO distribution in different fire scenarios [53]. The study also analyzes the spread of fire and associated risks in EV charging and swapping stations (EVCSS), offering crucial technical support for adequate fire prevention and evacuation planning in such facilities. Wang et al. expanded charging services at existing gasoline stations to save land and speed up the construction of charging stations [54]. This paper first compares gasoline and charging stations and then analyzes the risks of combined EV charging and gasoline filling stations, including policy, management, market, and technology risks. Finally, this study explores construction models and offers practical suggestions, providing a reference for implementation.

In terms of policies and strategies, Mastoi et al. conducted a study on the efficient use of EV charging infrastructure in city parking facilities. These strategies improve user experience, optimize energy consumption, and reduce the environmental impact of EV charging [55]. Bogomalova conducted research on stakeholders and developed a framework for strategically positioning EV charging stations (EVCSs) to ensure successful implementation and promote sustained growth in the EV market [56]. This section highlights the risk factors associated with the placement and operation of EVCSs and provides guidance for selecting the most suitable equipment for each location.

To integrate EV charging, which includes power batteries, charging stations, and power distribution grids, data are gathered using data mining technology. These studies highlight the complexity of charging infrastructure safety and the need for integrated risk management strategies.

2.4. Qualitative and Quantitative Risk Assessment

Successful risk management requires a combination of qualitative and quantitative methods and a deep understanding of the specific project context and potential risks [57]. Ashtiani implemented a risk assessment methodology for advancements in battery technology, focusing on hybrid, electric, and plug-in batteries [58]. This study employed hazard modes and risk mitigation analysis (HMRMA). Niu et al. conducted a study on the safety assessment of ground assembly surfaces. Based on heat transfer theory, a thermal analysis was conducted using transient-state FEM simulations [59]. Ye and Li identified the potential risk factors of the EVCS project, including 12 secondary indicators from policy, technical, market, and construction [60]. The empirical analysis demonstrates the proposed model's effectiveness, enhances investors' responsiveness, and improves risk prevention. Liu and Wei studied the development of EV projects, which are a serious concern worldwide [61]. This research explores risk factors based on questionnaire surveys and calculations using the fuzzy order preference with the similarity to ideal solution (Fuzzy TOPSIS) method. Gupta et al. examined and analyzed the risk factors associated with public-private partnership (PPP) projects in the EV sector across India [62]. Risk factors were identified through a comprehensive literature review and industry expert insights. These factors are categorized into four primary groups: financial, market, political/legal, and operational risks. Abdou and Tkiouat presented a failure risk-based ranking framework for EV projects that uses the analytical hierarchy process (AHP) as the ranking methodology [63]. The AHP hierarchy structure includes risk categories, risk factors, and EV project candidates at various decision levels. By defining the failure risk categories and associated risk factors, the framework facilitates the ranking of EV project failure risks and prioritizes EV projects through pairwise comparisons within the AHP model. Hosseini and Sarder found that BN tools are highly effective for managing risk assessment and decision-making in situations of uncertainty [64]. This paper is crucial for introducing a fresh research perspective by integrating uncertainty and qualitative and quantitative factors. Singh and Pahuja presented the types of fault/failure, the effect of failure, and the causes of the use of fuzzy FMEA [65]. The higher value of RPN will be the risk and lower the value of RPN. Jia et al. introduced an empirical methodology that uses real-world operational data to evaluate the safety risks associated with EV battery systems [66]. Five pivotal parameters concerning voltage and temperature were carefully selected from the lifecycle data of both standard and thermally runaway EVs, with features meticulously extracted based on fluctuations in parameter distributions. A dynamic safety risk evaluation model (DSREM) was developed using a triadic procedural framework. Scala et al. examined a prototypical covered parking facility whose dimensions were established by calculating the mean of various conventional parking space sizes [67]. The assessment was performed using the computational fluid dynamics software OZone, which was created through a collaborative effort between the University of Liege and Arcelor Mittal.

These studies underscore the importance of integrating diverse methodologies to address the multifaceted nature of risks in EV systems. The findings emphasize the critical need for robust frameworks to enhance safety and reliability across the EV ecosystem.

3. Method

This study utilized a systematic review design to consolidate the findings of multiple primary studies [68]. The subsequent paragraphs will detail the criteria for selecting studies to be included in the review. This systematic review follows the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines [69]. This section begins with an introduction outlining the study's background and objectives, followed by a detailed method section that describes the comprehensive literature search strategy across multiple databases, including the inclusion and exclusion criteria for selecting relevant studies.

3.1. Search Strategy

For this systematic literature review, we conducted an extensive search of three major electronic databases: Scopus, Web of Science, and PubMed. These platforms were chosen due to their comprehensive interdisciplinary and specialized field coverage. The search was designed using a combination of keywords and Boolean operators to capture all relevant studies. The keywords used were: ((“safety risk assessment*” OR “Safety Assessment*” OR “Risk Assessment*” OR “Risk Analysis” OR “Safety Analysis”) AND (method* OR Methodology)) AND (“battery electric vehicle*” OR “electric vehicle*”). This strategy ensured that the search results included publications that address various methodologies in the safety risk assessment or safety analysis related explicitly to battery electric vehicles and electric vehicles in general. The search was limited to documents published in English, with no time restrictions, to encompass the broadest spectrum of relevant literature.

While Scopus, Web of Science, and PubMed were selected for their interdisciplinary reach and specialization in fields relevant to this study, some databases, such as IEEE Xplore, were not included. IEEE Xplore is a highly respected source in engineering and technology research, particularly relevant to BEV safety and risk assessment. The exclusion criteria were institutional access limitations at the time of this review. Future studies may consider integrating IEEE Xplore to provide a more comprehensive perspective on engineering-focused methodologies for BEV safety.

3.2. Inclusion and Exclusion Criteria

Studies were included if they satisfied the following criteria: published in English, passed through peer-reviewed processes, and published within the last decade. Additionally, future studies should focus specifically on BEVs and evaluate the safety risks associated with these vehicles. This focus ensures the relevance and currency of data and analyses in the rapidly advancing field of battery electric vehicle safety.

Studies were excluded if they addressed aspects beyond the direct safety risks associated with BEV battery systems. This category encompasses papers discussing BEV ecosystems without a specific focus on battery-related issues, such as charging infrastructure or driver safety factors. In addition, studies centered on environmental risk assessments and the life cycle of EVs were excluded because they did not align with the narrow focus on safety risk assessments required for this review. These exclusion criteria helped to refine the selection of studies that are strictly pertinent to the safety evaluation of BEV technologies.

3.3. Data Extraction and Synthesis

The study selection process is then illustrated using a PRISMA flowchart that describes the identification, screening, eligibility, and inclusion of articles. The results section presents the key findings of the selected studies, comparing existing risk assessment methodologies and analyzing their strengths and weaknesses. Additionally, the methodological limitations stemming from database exclusions, such as IEEE Xplore, are acknowledged, emphasizing the importance of broadening database access in future systematic reviews to capture diverse perspectives. This discussion explores the implications of the review's results on the current literature, identifies research gaps, and offers recommendations for future studies. Finally, the conclusions summarize the main contributions of this review by addressing the literature gap related to safety risk assessment in EVs.

4. Results and Discussion

4.1. Results

As shown in **Figure 1**, our search strategy initially identified 275 articles. After removing the duplicates, 251 articles remained. These articles were sourced from three databases: 150 from Scopus, five from PubMed, and 120 from Web of Science.

4.1.1. Identification, Screening, and Eligibility Results

Figure 2 highlights the central focus on EVs (104 mentions), which is underpinned by risk assessment concerns (102 mentions). Prominent technical aspects such as lithium-ion batteries (26 mentions), optimization (26 mentions), and stochastic systems (21 mentions) play a significant role in advancing EV technologies. The key challenges included managing risk perception (19 mentions), ensuring system reliability (18 mentions), and performing risk analysis (17 mentions). Environmental considerations, such as air pollution (14 mentions) and greenhouse gas emissions (13 mentions), are integral to sustainability discussions. In addition, topics like

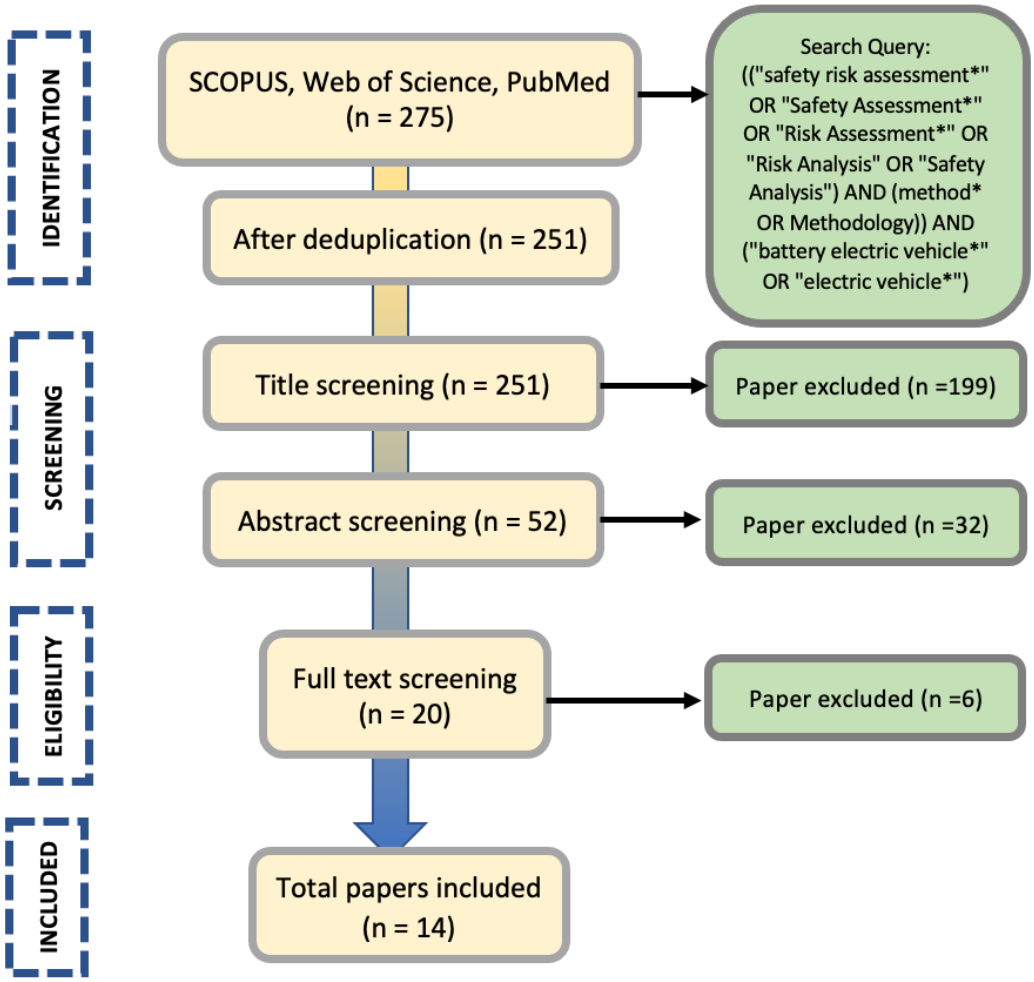

Figure 1. Flowchart depicting the methodology employed in the selection process; PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses)

Figure 2. Treemap of EV risk assessment

energy management, charging systems, and uncertainty analysis (each with 12 mentions) emphasize EV integration's operational and managerial complexities. Issues such as TR, state of charge and safety assessment also demand attention due to their critical implications for health risks (10 mentions) and infrastructure resilience. Finally, incorporating advanced methods like finite element modeling and stochastic models demonstrates the field's commitment to rigorous, data-driven problem-solving in developing safer, more efficient EV systems.

Although these technical aspects dominate the literature, their interconnections and the factors driving this focus require further exploration. For instance, the prominence of lithium-ion batteries and TR reflects ongoing safety concerns, but the specific drivers behind these risks, such as manufacturing trends and material properties, require further contextualization.

Figure 3 indicates that China leads significantly with 116 articles, accounting for 46.2% of the total contributions, followed by Iran (18 articles, 7.2%) and the USA (17 articles, 6.8%). Notably, China has the highest number of single-country publications (SCP), at 98, with a moderate proportion of multi-country publications (MCP), at 15.5%. Iran and the USA similarly exhibit substantial SCP contributions (14 each), but their MCP proportions are slightly higher at 22.2% and 17.6%, respectively. Other notable contributors include India (10 articles, 3.98%) and Spain (8 articles, 3.18%), with varying balances between the SCP and the MCP. Despite contributing only three articles, Portugal has the highest proportion of MCP (66.7%). More minor contributors, such as Bangladesh, the Czech Republic, and Ireland (each with one article), present MCPs exclusively, indicating strong international collaboration. In contrast, countries such as Korea, Poland, and Brazil make contributions exclusively through SCPs, with a focus on domestic research. This distribution highlights dominant contributors and collaborative dynamics in the global research landscape.

The dominance of China in this field is partly attributable to its substantial investments in EV technologies and supportive government policies aimed at fostering innovation. Additionally, China's focus on domestic manufacturing and battery production has positioned it as a leader in EV safety research. This trend reflects a strategic emphasis on addressing safety issues to support the nation's EV market growth.

It is important to note that most authors are based in China, as illustrated in Figure 4. This finding offers valuable insights for researchers seeking to improve their research productivity by fostering collaborations with prominent experts in

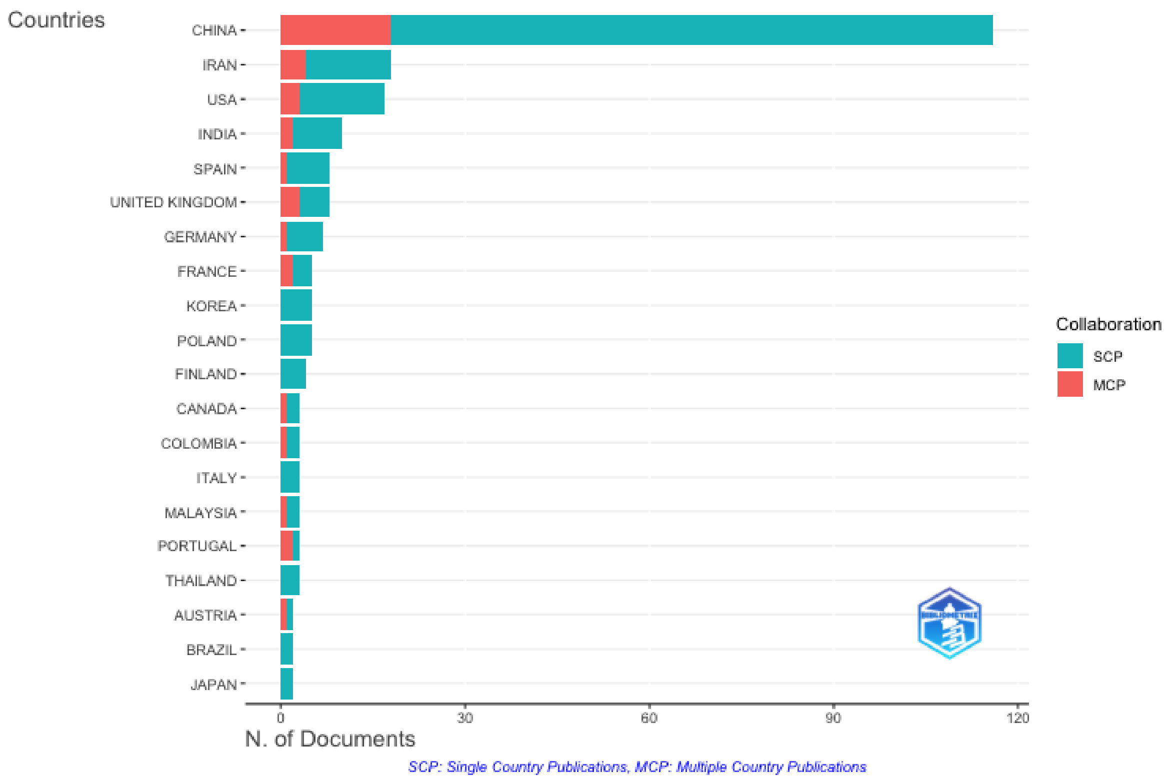

Figure 3. Corresponding author's countries diagram

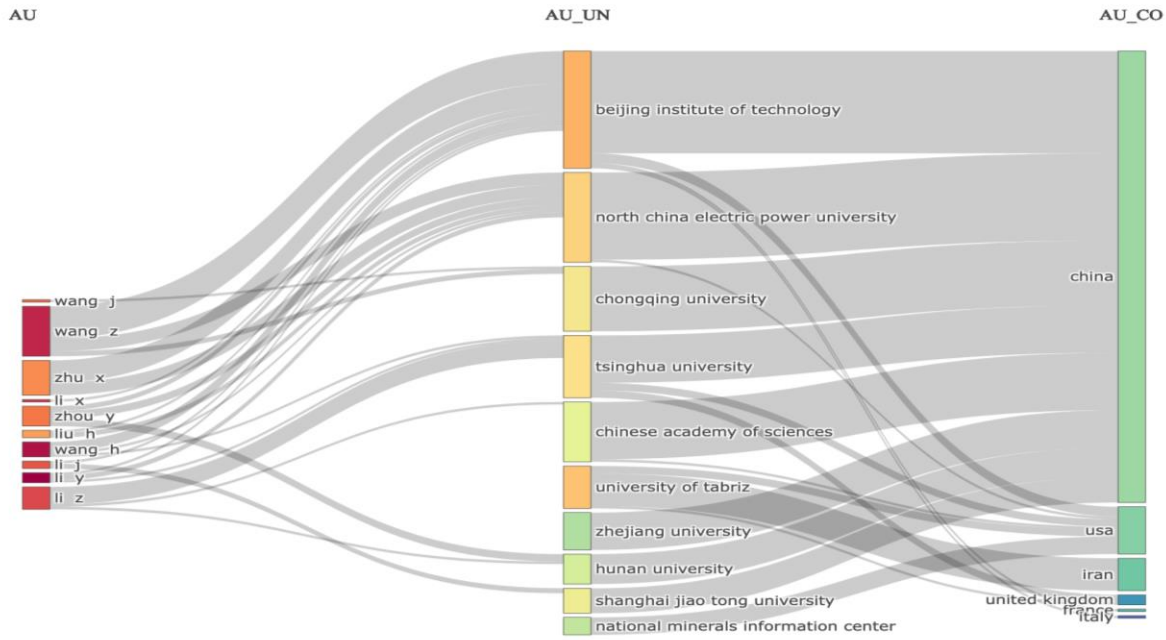

Figure 4. Authors, affiliations, and country network diagrams

the field. Moreover, the high proportion of SCP contributions from China encourages a focus on localized research that can benefit from increased international collaboration to incorporate diverse perspectives and practices.

As shown in Figure 1, 231 articles were excluded after reviewing their titles and abstracts for relevance to the study criteria. Specifically, many studies have focused on infrastructure, microgrids, power converters, policy considerations, battery innovations, and power suppliers. Some studies tested hypotheses using simulation models to assess the capabilities and limitations of BEVs, while others focused on medical science. After reviewing the abstracts, 32 more studies were excluded for the following reasons: 12 studies focused on unrelated algorithms, such as (i) traffic density-based energy consumption models, (ii) queueing theory applications, and (iii) substitution-efficiency-detour route optimization. Eight studies concentrated on business models specific to BEVs, including (i) security governance and (ii) battery ownership or leasing combined with enhanced charging services, and 12 studies were repetitions of data from articles previously published by the same authors.

After reading the complete text, six more studies were excluded because one was limited to specific conditions that are not broadly applicable across different types of lithium-ion cells or EV models; 1 investigation exclusively concentrated on a singular category of vehicle equipped with an identical variant of lithium-ion battery, and the instances of failure were constrained; consequently, the applicability of the methodology has not been comprehensively substantiated; 1 paper only focused on the charging of EV; 2 paper were not explaining the risk analysis of lithium-ion battery in the EV, only the safety of lithium-ion battery in general; and one was not focused on the safety risk assessment for battery EVs but an overview of various costs and vulnerabilities associated with different vehicle types.

These exclusions underscore the importance of focusing on studies that address the core research questions related to safety risk assessments in BEVs while highlighting gaps in other related areas that warrant future investigation.

Table 1 shows that this systematic literature review predominantly originated from China, illustrating a strong regional focus on advancing battery safety technologies for EVs. Eleven of the 14 studies analyzed were conducted in China [26], [32], [50], [70], [71], [72], [73], [74], [75], [76], [77], one in Iran [78], one in Spain [79], and one in Korea [80]. The studies employed various methodologies, with a focus on quantitative descriptive analyses using both experimental and observational data. Several studies have also incorporated qualitative components to deepen the evaluation of risk assessment frameworks.

The reviewed studies were categorized under three primary frameworks: Battery Risk Assessment (ten studies focusing on various battery types and management systems, employing tools like FMEA, neural networks, and safety assessments), BMS with an emphasis on compliance and safety standards (one study), and broader EV safety integrating risk assessments and structural optimizations (four studies focusing on holistic vehicle safety and battery integration). The research approaches varied significantly, from experimental setups testing battery responses under stress conditions (TR, mechanical abuse) to sophisticated data-driven models for predicting battery behavior and lifespan. Notably, Huang et al. and Li et al. employed advanced machine learning algorithms to predict and monitor battery safety, whereas Jeong and Park utilized optimization techniques to enhance the structural integrity of EVs [30], [68], [80].

Each study provided critical insights into the safety mechanisms of batteries in EVs, focusing on specific risks like TR, explosion, and mechanical failure and proposing innovative solutions to mitigate these risks. This concentrated effort reflects the growing importance of safety in the rapidly evolving field of EVs, particularly in the context of increasing global adoption and the technological advancement of battery systems.

In order to answer our research questions, the following paragraph reported: 1) the safety risk assessment methods that have been used for EVs, including the strengths and weaknesses of each method; 2) how effective the existing risk assessment methods are in identifying and managing safety risks related to the battery and operation of EVs in various environments; 3) the gaps in the current risk assessment methods, and recommendations that could be made for developing more effective safety standards for EVs based on the evaluation of these methods.

4.1.2. *Safety Risk Assessment Methodologies*

The rapid rise of EVs has revolutionized the transportation industry by offering cleaner and more sustainable alternatives to traditional gasoline-powered cars. However, this transition also introduces new challenges, particularly in terms of risk assessment and management of EV battery systems. Risk assessment is a critical component of effective project management because it enables decision-makers to identify,

Table 1. Description of the reviewed studies

No	Author; Year; Country	Study Type	RA Framework	Setting Method	Assessment Tools	Outcome and Main Result
1	Huang, P.F., et.al; 2024; China	Quantitative descriptive	Battery pack	Big data, experiments	Deviation and outlier analysis, clustering algorithms, experimental tests, scatter diagrams	This study presents an innovative methodology for assessing the safety risks associated with automotive battery packs, with a particular emphasis on voltage discrepancies at both individual and overall pack levels. This methodology quantifies the variations in voltage and their respective angles throughout various states of charge to determine the associated safety risks. The proposed approach incorporates clustering algorithms to detect anomalies and evaluate safety risks, which was substantiated through cycling experiments conducted on battery modules. The investigation identifies potentially hazardous vehicles and evaluates the possibility of defective cells, as well as providing a systematic grading of battery inconsistencies along with safety alerts. The proposed framework enhances safety surveillance and aspires to facilitate real-time online notifications concerning variations in voltage consistency.
2	Li, D., et al.; 2023; China	Quantitative descriptive	Battery	historical data	hybrid neural network model	Identifies battery safety issues as a significant barrier to the broader application of EVs, particularly TR caused by abnormal internal resistance (IR). A novel approach for estimating IR using sparse electrical data is proposed, which improves the accuracy of practical scenarios. A hybrid neural network architecture was created to forecast typical IRs, resulting in a mean relative error of 1.78. This technique can accurately distinguish between unsafe and normal batteries with a precision of 98.6%, thereby contributing to an effective safety risk assessment in EVs.
3	Xie, Z. R., et al.; 2023; China	Quantitative descriptive	EV	Experiment	binary logistic regression and entropy weighting	Identified key characteristic indexes related to the power loss risk in EVs. The assessed parameters included battery voltage, motor temperature, and various temperature readings, and they were analyzed via binary logistic regression. The entropy weight method was applied to evaluate the EV power loss risk, achieving a detection accuracy of 82% from 1000 alarm data points.
4	Borujerd, S. V. N., et al.; 2023; Iran	Quantitative descriptive	battery pack	Observations and laboratory studies	FMEA	Fuzzy FMEA to assess the risks associated with immersion-cooled battery packs (ICBP) in EVs. This study critical failure modes and their causes, emphasizing the importance of the sealing method, BMS function, and thermal management. This study introduces a control plan table to manage the production and installation of problematic parts, leading to significant improvement in reliability. The results

No	Author; Year; Country	Study Type	RA Framework	Setting Method	Assessment Tools	Outcome and Main Result
						The results highlight the necessity of modular design and effective thermal management to enhance battery performance and safety.
5	Wang, J. F. et al.; 2024; China	Qualitative, Quantitative RCT	Lithium Battery	Experiment	Safety assessment method based on seven experimental characteristics	LFP batteries exhibit the lowest overcharging tolerance but the lowest TR hazard, only releasing smoke without explosion or fire. NCM and LCO batteries present more severe TR hazards, with LCO batteries reaching the highest peak temperature (917.2°C) under high-rate overcharging. A novel safety assessment method was proposed to evaluate TR risks and hazards based on seven key parameters. The results indicate that LFP batteries have the best safety performance. The findings guide battery selection and risk management for EVs, emphasizing the need for enhanced safety monitoring for LFP and improved protective measures for NCM and LCO batteries.
6	Liu, P. J., et al.; 2023; China	Quantitative descriptive	Lithium Battery	Empirical data and experiments	TCNESA 1004 Standard, grading matrix, and safety assessment	We conducted overheating experiments on four large format lithium-ion batteries (LIBs) with different chemistries, revealing that all NCM cells caught fire and underwent TR when heating was stopped at safety venting (SV), whereas LFP cells did not ignite spontaneously and only sprayed electrolyte during TR. The NCM cells' triggering temperatures were similar and close to the SV temperature for LFP cells, ranging from 250.1-260.8°C, whereas LFP cells had a higher triggering temperature of 357.3°C, indicating better safety. A safety assessment method was established to grade the fire hazards. The results indicated that LFP cells have lower TR risks but higher TR hazards compared to NCM cells.
7	Li, D., et al.; 2021; China	Quantitative descriptive	Battery	Real-world operational data	A short-term memory recurrent neural network using the equivalent circuit model, prejudging model, and modified adaptive boosting method	The proposed battery fault diagnosis method effectively combines a long short-term memory recurrent neural network with an equivalent circuit model, leading to improved diagnosis accuracy through a modified adaptive boosting method and a prejudging model that reduces computational time and enhances reliability. The proposed method demonstrates the capability to assess potential failure risks in battery systems, taking into account driver behavior, and can issue early warnings for TR, with verification results indicating accurate fault diagnosis for potential battery cell failures and precise identification of TR cells.

No	Author; Year; Country	Study Type	RA Framework	Setting Method	Assessment Tools	Outcome and Main Result
8	Marcos, D., et al.; 2021; Spain	Quantitative descriptive	BMS	Historical data	Failure Modes, Effects, and Diagnostics Analysis (FMEDA); Advanced estimation algorithms	This study presents a comprehensive design methodology for an enhanced automotive BMS that complies with ISO 26262 functional safety standards, specifically targeting automotive safety integrity level (ASIL) C requirements. A hazard and risk assessment was conducted to identify intrinsic hazards such as fire, electric shock, and vehicle accidents due to loss of functionality. The methodology includes a safety architecture with a three-subsystem configuration comprising sixteen BMS slides, one BMS Master, and a power monitoring and disconnection unit (PMDU). The results indicate that the developed BMS effectively addresses the safety concerns associated with lithium-based batteries in automotive applications.
9	Shan, T.X., et al.; 2022; China	Quantitative non-RCT	Lithium Battery	Experiment	Battery explosion safety assessment	We investigated the explosion behaviors of a 40 Ah Li-ion pouch cell induced by overcharge and identified four distinct stages of the overcharge-to-explosion process based on the voltage and temperature data. It was found that the explosion involved both physical and chemical processes, with the physical explosion being primarily due to pouch rupture and the chemical explosion linked to oxygen consumption. The results highlighted the significant influence of the C-rate on the TR and explosion dynamics, with higher C-rates leading to increased shock wave pressure and explosion parameters. A safety assessment method was proposed to evaluate the explosion risks using sensitivity and severity indicators.
10	Zhu, X. Q., et al.; 2023; China	Quantitative descriptive	Lithium Battery	Experiment; observations	Modified safety assessment; Postmortem; scanning electron microscopy (SEM)	As the state of charge (SoC) of LFP lithium-ion pouch cells increases, their capacity to endure elevated temperatures diminishes, resulting in an augmented mass loss ratio and peak temperature during TR, thereby signifying more pronounced TR reactions and associated hazards. It has been noted that Ni NCM lithium-ion cells present a greater hazard during TR events because they ignite and release smoke and sparks, in contrast to LFP cells, which predominantly emit white smoke. Furthermore, the prismatic lithium-ion cells exhibited a postponed onset of TR due to the efficacy of the pressure relief valve, which markedly mitigated the risk associated with TR.
11	Wen, Z. H., et al.; 2022; China	Quantitative descriptive	Battery	Experiment	Empirical Mode Decompositio n (EMD); Kriging model	The proposed EMD-Kriging model demonstrated superior prediction accuracy for the remaining useful life (RUL) of rolling bearings, achieving a root mean square error (RMSE) of 0.0425, which is significantly lower than the RMSE of 0.1290 obtained using the traditional Kriging model. The average prediction error

No	Author; Year; Country	Study Type	RA Framework	Setting Method	Assessment Tools	Outcome and Main Result
						of the EMD-Kriging model was found to be less than 60, indicating its effectiveness compared to other methods. The health indicator constructed by this method can sensitively perceive bearing degradation, with thresholds established for different degradation stages.
12	Jeong M.H. and Park G.J.; 2023; Korea	Quantitative non-RCT	Battery pack	Historical data; experiment	Nonlinear dynamic structural optimization; equivalent static load method (ESLM); Finite Element Method (FEM)	The optimization process significantly reduced the total mass of the EV's frame from 154.9 kg in the initial design to 125.3 kg after four design cycles. The design constraints related to the pack crush and pole impact tests were satisfied, ensuring the safety of the battery pack during physical shocks. The optimization results demonstrated that the proposed method effectively integrates multiple safety tests into the design process, thereby enhancing the overall crashworthiness of EVs.
13	Chen, J., et al.; 2022; China	Qualitative; quantitative descriptive	EV	Mixed method; expert judgment	WBS-RBS-BN (Work Breakdown Structure-Risk Breakdown Structure-Bayesian Network)	Identified 15 risk factors leading to EV fires, with external collision ignition being the most significant, followed by battery failure, artificial modification, battery-pack flooding, and charging equipment failure. A Work Breakdown Structure (WBS) and Risk Breakdown Structure (RBS) were developed to systematically analyze these risks. The fuzzy BN was used to evaluate the risks, providing a ranked list of risk factors, which serves as a reference for safety measures in EVs. The proposed methodology effectively identified and ranked the risk factors associated with EV fire accidents.
14	Chai, Z., et al.; 2024; China	Quantitative descriptive	Lithium Battery	Research study; experiment	Regression model; GL980 data acquisition instrument (DAQ)	The TR dynamics and safety evaluation of LFP batteries subjected to mechanical stress were examined, elucidating essential insights into internal short circuits (ISC) and TR occurrence. It delineates four distinct phases during mechanical stress: battery deformation, ISC onset, TR, and subsequent battery cooling. This research describes regression models to delineate battery safety thresholds and assess TR risk, effectively quantifying mechanical abuse conditions and their relationship with battery behavior. The results of this study contribute to a deeper understanding of battery safety assessment methods under mechanical abuse scenarios.

analyze, and mitigate potential risks that could impact the success of a project. Over the years, various risk assessment methods have been developed and applied in different contexts, each with strengths and weaknesses. A commonly used approach is scenario-based risk analysis, which involves identifying and assessing potential risk scenarios that could occur during a project. This method allows for a more nuanced understanding of risks by considering multiple possible outcomes; however, it can also be time-consuming and resource-intensive, particularly for complex projects with many potential risk scenarios. Another approach is simulation-based risk assessment, which uses computer models to simulate the behavior of a system or process under different risk conditions. This method can provide a more comprehensive and quantitative risk analysis. However, it requires significant data and computational resources, and the accuracy of the results is heavily dependent on the quality of the input data and the validity of the underlying models. Data-driven risk assessment methods, such as those based on machine learning or statistical analysis, have also gained traction recently. These approaches leverage large datasets to identify patterns and correlations that inform risk assessment and decision-making. While these methods can be highly effective in specific contexts, they are also limited by the availability and quality of the data and are susceptible to biases and other potential sources of error.

The studies employed various assessment tools for evaluating battery safety and risk, each with its own strengths and limitations. Clustering algorithms [32] were used to identify outliers and classify battery modules based on voltage inconsistencies. These algorithms excel at detecting patterns in large datasets; however, they require extensive data preprocessing and may not always provide clear insights into the underlying causes. Hybrid neural network models [70] were used to predict the IR and classify the battery safety. These models are highly effective for capturing complex nonlinear relationships in battery data; however, they can be computationally intensive and require large datasets for accurate training. Fuzzy FMEA was applied to identify and assess failure modes in immersion-cooled battery packs [78]. This method is beneficial for identifying critical failure modes and prioritizing risk mitigation strategies. However, it is subjective and depends heavily on expert judgment, which can introduce bias. Binary logistic regression [72] was used to assess the risk of power loss in EVs. This simple and interpretable method helps identify key risk factors. However, its limitations include assumptions of linearity and reliance on the availability of accurate data. BN [76] was used to analyze and rank risk factors, such as EV fire risks. BNs effectively incorporate uncertainty and expert knowledge, making them useful in risk analysis. However, the quality of the results depends heavily on the accuracy of the expert input and data, and they can be computationally demanding. Postmortem analysis was conducted using SEM to analyze battery failure after TR events. Postmortem analysis provides detailed insights into the causes of failure, whereas SEM provides high-resolution images of the internal structure of the cells [74].

However, both methods are time-consuming and require physical access to the battery samples. The empirical mode decomposition (EMD) was combined with the Kriging model to predict the remaining useful life (RUL) of rolling.

In summary, each assessment tool has distinct advantages based on its research goals. Clustering algorithms and neural networks excel at processing large datasets and identifying hidden patterns, while methods like FMEA, regression models, BN, and WBS-RBS-BN provide more precise insights into risk prioritization and mitigation. Postmortem analysis and SEM provide valuable insights into the mechanisms of battery failure, whereas EMD-Kriging models excel in predictive maintenance. However, the trade-offs include the need for extensive data, high computational costs, potential biases in expert judgment, and the limitations of physical or time-consuming assessments. The selection of an assessment tool depends on the specific risk factors being studied, available data, and the required level of accuracy.

4.1.3. Application Areas

The risk assessment methodologies applied to BEVs vary widely depending on the application area, with a strong focus on battery safety, charging infrastructure, road operations, maritime transport and overall systemic safety.

The most commonly used tools for battery safety and performance risk assessment are clustering algorithms and hybrid neural network models. These tools are particularly effective in detecting deviations in battery performance, such as voltage inconsistency, and predicting battery IR, which can prevent incidents like TR [32], [70]. In addition, fuzzy FMEA systematically prioritizes failure modes in battery packs, particularly those related to thermal management and sealing methods, thereby reducing the probability of critical failures [78]. Postmortem analysis, combined with SEM, allows for a more in-depth investigation into the physical failure mechanisms of batteries, shedding light on the microscopic causes of incidents like TR [74].

BN is particularly useful for managing uncertainty in risk analysis by integrating expert judgment to evaluate interdependent risks, such as battery fires. These networks assist decision-making by providing ranked probabilities for various risk scenarios and identifying the most critical factors [76]. Together, these tools enhance the accuracy and reliability of battery safety assessments and help mitigate the risks associated with EV battery failures. In the context of charging risk assessment, tools like failure modes, effects, and diagnostics analysis (FMEDA) and WBS-RBS-BN are widely used to evaluate risks associated with charging infrastructure and BMS. FMEDA identifies hazards like fire, electric shock, and BMS malfunctions during charging, ensuring compliance with safety standards such as ISO 26262 [79]. Additionally, WBS-RBS-BN incorporates a BN approach to systematically assess risks such as battery failure or equipment malfunction during charging, thereby helping to identify the most critical risk factors and informing the design of safer charging systems [76]. These methodologies improve the understanding of charging safety by focusing on mitigating risks such as fire hazards and system malfunctions during EV charging processes.

Environmental factors such as extreme temperatures, humidity, and poor road conditions also pose significant risks to the safety of BEVs. For example, FMEA and BNs can be used to evaluate the intensities of TR under these conditions or their impact on battery integrity. Advanced clustering algorithms and neural networks can analyze data from real-life operations in diverse environments and identify patterns that indicate increased risks under specific conditions.

By explicitly linking each methodology to specific battery risks, this section underscores the effectiveness of advanced tools like FMEA, BN, and clustering algorithms in addressing critical safety challenges in BEVs. Future research should further refine these methodologies to account for real-world environmental complexities and improve their application to ensure BEV safety under diverse operating conditions.

Risk assessment tools are often employed for road operations to assess BEV performance under real-life driving conditions. Techniques like binary logistic regression are used to analyze operational risks related to power loss in EVs, with key factors such as motor temperature and battery voltage identified as major contributors [70]. Finite Element Method (FEM) and nonlinear dynamic structural optimization are also crucial tools for evaluating the crashworthiness of BEVs, ensuring that the battery pack remains intact during physical impacts or accidents [80]. These tools help optimize vehicle safety by simulating the impact of various road conditions and accidents on an EV's battery and other critical components. In maritime transport, where BEVs are shipped by sea, risk assessment tools such as clustering algorithms and Fuzzy FMEA are employed to monitor the safety of BEVs in transit, particularly concerning battery integrity and the potential for TR or fire [32], [80]. These tools help assess the risks associated with transport by monitoring real-time data from EVs and identifying potential hazards before they escalate. Integrating safety measures during transit is crucial for preventing incidents that could compromise vehicle and ship safety. For broader systemic safety assessments, methodologies like BN and FMEDA assess the interdependent risks across multiple EV components, including the battery, BMS, charging infrastructure, and vehicle operation. WBS-RBS-BN extends this by incorporating a structured approach to analyze complex risk scenarios, such as fires or system failures, by evaluating the likelihood and impact of various risk factors across the BEV ecosystem [76]. These tools are essential for ensuring that safety is maintained throughout the lifecycle of a BEV, from production to operation and eventual decommissioning.

4.1.4. Gaps and Challenges

A significant gap in the existing research on BEVs is the scarcity and variability of high-quality data, which are crucial for training robust predictive models. Many advanced analytical tools, such as neural networks and clustering algorithms, rely on extensive datasets to predict failures and assess risks accurately. However, the lack of comprehensive real-world data, especially for newer battery chemistries and emerging BEV designs, limits the ability of researchers and engineers to develop reliable predictive models [32], [70]. This data deficiency hinders the accuracy and reliability of risk assessments, particularly under diverse and untested operational conditions. Furthermore, the research often isolates specific aspects of battery safety or operational efficiency without considering the holistic interactions between various vehicle systems and external conditions. There is a crucial need for integrated approaches that encompass a broader range of risk factors, including environmental impacts, user behavior, and long-term degradation, to provide a more comprehensive understanding of the risks associated with BEVs and allow for more effective mitigation strategies [72], [78].

The absence of universally accepted standards and protocols for risk assessment across the BEV industry poses significant challenges, leading to inconsistencies in risk management practices and safety evaluations that could potentially compromise the safety and reliability of BEVs across different markets [76], [79]. Additionally, the limited capability of existing methodologies to accurately predict rare but critical events, such as severe TR or battery explosions, remains a notable gap. These events, while infrequent, can have devastating consequences, and the rarity of such events means that there is often insufficient data to train models that could predict their occurrence, thereby impacting the effectiveness of safety measures [73], [74]. Another challenge is the shortfall in longitudinal research that monitors the safety and performance degradation of BEV batteries over their complete lifecycle, which is vital for reliable risk assessments and for designing batteries that remain safe throughout their operational lifespan [75].

The intricate interplay between the electronic and mechanical components of BEVs poses significant challenges when developing comprehensive risk assessment methodologies. Accurately predicting failures and assessing safety in such complex systems requires sophisticated models that account for the interactions between multiple components and operational conditions [80]. This complexity is compounded by the rapid pace of technological change in battery and vehicle technologies, necessitating frequent updates to existing tools and models to address new safety issues and incorporate the latest data, which adds to the challenge of maintaining current and practical risk assessments [71]. Furthermore, varying regulatory requirements across different regions pose challenges for standardizing risk assessments and safety protocols because compliance with international safety standards can be particularly challenging when regulations differ across markets or when new standards are introduced [79].

Finally, conducting comprehensive risk assessments can be resource-intensive and costly, especially involving detailed physical experiments, making it difficult for smaller manufacturers or companies in cost-sensitive markets to implement thorough safety evaluations [74]. In addition, accounting for user behaviors and real-world operating conditions presents significant challenges. The variability in how individuals use and maintain their vehicles, combined with differing road and weather conditions, can significantly affect the performance and safety of BEVs. Predicting and mitigating risks under such variable conditions require adaptable and robust risk assessment tools, which are essential for ensuring the safety and reliability of BEVs as they become more prevalent on roads [72].

4.2. Discussions

The findings of this systematic literature review highlight the significant challenges and opportunities in the development and application of risk assessment methodologies for EVs. While considerable progress has been made in assessing risks related to EV batteries, charging infrastructure, and vehicle operations, the diversity of risk assessment tools and frameworks used in the literature has revealed their strengths and limitations. The implications of these findings extend to improving safety protocols in the BEV industry and shaping future safety policies, particularly regarding new and emerging technologies.

For example, China's dominance in the field of EV safety research reflects its robust manufacturing ecosystem, government-driven initiatives, and concentrated effort to address domestic safety concerns. In contrast, countries such as the United States and Iran make stronger MCP contributions, indicating a higher level of international collaboration. Exploring these regional differences could provide insights into how national priorities influence research trends.

A significant implication for the BEV industry is the need for standardized risk assessment methodologies that can be universally applied across different EV subsystems. Many risk assessment tools are currently isolated in their focus—whether on the battery pack, charging system, or vehicle operation—and often do not account for the complex interdependencies between these components. For instance, methodologies such as fuzzy FMEA and BN are used to assess battery safety and failure modes [76], [78]. However, these approaches are typically applied to specific components without fully integrating them into a broader system-level analysis. Thus, they may miss potential cascading effects from failures in interconnected systems, such as the interaction between the battery and vehicle autonomous driving systems or charging infrastructure. The lack of standardized frameworks across the industry has resulted in inconsistent safety protocols that pose risks to consumers and manufacturers.

Table 2 provides an overview of the reviewed studies, detailing their methodologies, settings, tools, and main findings. The table highlights the diversity of risk assessment approaches applied to BEVs, including quantitative and qualitative methods. Prominent methodologies include clustering algorithms, hybrid neural networks, and bayesian networks, which excel at identifying battery risks and predicting failures. For instance, Fuzzy FMEA studies emphasize the importance of prioritizing risk mitigation strategies for immersion-cooled battery packs, whereas others use postmortem analysis combined with SEM to investigate the physical mechanisms behind TR events.

Table 2. Comparison of risk assessment methods for BEV batteries

No	Method	Effectiveness	Data Requirements	Computational Costs	Key Applications
1	Fuzzy FMEA	High: Systematic prioritization of failure modes	Moderate: Required expert input and data for failure	Low: Manual or semi-automated process	Identifies critical failure modes and supports risk prioritization [76], [78].
2	Hybrid Neural Networks	High: Effective in nonlinear systems	High: Required large training datasets	High: Requires advanced computational resources	Predicting internal resistance and classifying battery safety risks [70].
3	Bayesian Networks	High: uncertainty and expert judgment	Moderate: Required expert input and historical data	Moderate: Computationally intensive for large datasets	Analyzing interdependent risks and ranking key factors in safety scenarios [76].
4	Clustering Algorithms	High: detection of patterns and anomalies in large datasets	High: Extensive operational data are required	Moderate: Efficient with preprocessed data	Identifying outliers in voltage inconsistencies and safety monitoring [27].
5	Binary Logistic Regression	Moderate: Interpretable and effective for linear relationships	Low: Required basic operational data	Low: Minimal computational cost	Assess operational risks like power loss based on temperature and voltage [72].

The evolution of research priorities over time, particularly the increased focus on TR and advanced battery chemistries, highlights the dynamic nature of the field. Understanding how these priorities have shifted because of technological advancements or emerging safety concerns can guide future research and policy development.

For policymakers, these insights emphasize the importance of developing regulations that consider the entire lifecycle of EVs—from design and manufacturing to operation and end-of-life disposal. Research has demonstrated the need for evolving safety standards that are adaptable to new technologies. For example, studies examining the safety of LFP batteries versus NCM batteries reveal important differences in TR characteristics, which should influence policy decisions on battery selection and risk management [26], [81]. As BEVs evolve with the integration of new technologies such as solid-state batteries or autonomous driving systems, policies must remain flexible to address new risk factors.

In addition, there is a growing need for more real-world data to validate the risk models used in EV safety assessments. Many current models rely on experimental or short-term operational data, which can fail to capture long-term usage patterns or diverse real-world conditions. For example, machine learning models that predict battery failures often use data derived from controlled testing environments, which may not accurately reflect the complex operational conditions of EVs in diverse driving scenarios [70]. Therefore, future safety policies should encourage the collection of long-term real-life data to ensure accurate and comprehensive risk models.

The findings also highlight several areas where future research can significantly improve the reliability and effectiveness of risk assessment methodologies. One clear gap is the lack of standardized risk assessment frameworks that can be universally applied across different regions and manufacturers. Research should focus on the development of globally accepted guidelines or models for assessing the risks associated with the use of EV batteries, charging infrastructure, and vehicle operation. These standardized methodologies could enhance safety by ensuring consistency and comparability among various manufacturers and regulatory bodies [74]. Given the increasing complexity of EV systems, particularly with the integration of autonomous technologies and smart charging networks, future studies should aim to create flexible and comprehensive frameworks to accommodate these advancements.

In addition, there is a growing need for integrated risk models that consider the interdependencies between EV subsystems. While current studies often focus on isolated components—such as battery packs, charging stations, and vehicle controllers—there is a need for models that evaluate system-level risks. These models should account for how a failure of one component can trigger a cascade of failures across other subsystems. For example, a BMS failure can compromise the safety and operational integrity of a vehicle [79]. Researchers can provide a more holistic understanding of EV risks by developing integrated models that simulate real-life conditions.

In addition, future risk assessment methodologies should incorporate research on human factors and operational environments. While studies such as those [70], [72] have explored the technical aspects of BEV safety, they often overlook the role of human behavior and external environmental factors in influencing vehicle performance. Human factors such as driver behavior, road conditions, and even local climate can influence the risk profile of an EV. Future research should incorporate these variables into risk models to reflect the diversity of conditions under which BEVs operate.

A remarkably underexplored area in BEV risk assessment is the transportation of BEVs by vessel. Maritime transport introduces unique safety challenges that are increasingly relevant as EVs become more widely distributed globally. The transport of BEVs by sea, for example, presents risks not typically encountered in land-based operations, such as prolonged exposure to high humidity, extreme temperatures, and confined cargo spaces. These conditions can intensify battery risks, including TR and structural degradation. Thus, it is critical to adapt risk assessment methodologies to address these scenarios.

The inclusion of maritime transport in BEV risk assessments must be carefully contextualized. While maritime transport poses unique challenges, such as TR risks due to confined cargo spaces or exposure to extreme environmental conditions, its relevance to the paper's focus on BEV battery risks should be explicitly tied to these factors. For example, thermal management tools like FMEA or real-time monitoring systems can address battery risks during sea transport by detecting early signs of failure [77], [80]. However, expanding this discussion may dilute the focus unless the challenges are directly aligned with BEV safety concerns. Future research could explore maritime-specific adaptations of existing methodologies, but the emphasis should remain on battery-centric risks.

The increasing adoption of EVs and the complexity of their associated technologies necessitate more advanced, integrated, and standardized risk assessment methodologies. By addressing these research gaps, the BEV industry can develop safer, more reliable vehicles, and policymakers can create better regulations to ensure the continued growth and success of the EV market.

5. Conclusion

This systematic literature review has provided valuable insights into the current state of risk assessment methodologies applied to BEVs, focusing on battery safety, risk assessment methods, and the emerging challenges of BEVs. This review highlights the diversity of risk assessment tools employed across different areas of BEV technology, ranging from advanced statistical models and machine learning techniques to traditional methods such as FMEA and BN. These tools directly mitigate BEV battery risks by addressing critical issues such as TR, battery degradation, and operational failures. For instance, FMEA provides a systematic approach to prioritizing failure modes and reducing the probability of catastrophic events, whereas BN assists decision-making under uncertainty by identifying and ranking interconnected risk factors.

One of the key points of this review is the need for standardized risk assessment frameworks that can be universally applied across the BEV industry to ensure consistent safety practices and regulatory compliance. In addition, there is a growing demand for more integrated, system-level risk models that account for the interdependencies between BEV subsystems, such as battery management systems, vehicle control units, and charging infrastructure. The challenges in assessing BEV safety are further compounded by the lack of data that capture diverse real-life operating conditions, which necessitates the collection of long-term real-life usage data to improve the accuracy and relevance of risk models.

Maritime transport introduces unique safety challenges that are increasingly relevant as BEVs become globally distributed. Risks such as prolonged exposure to high humidity, extreme temperatures, and confined cargo spaces can intensify battery safety concerns, particularly TR and structural degradation. Tools like FMEA and real-time monitoring systems can play a critical role in detecting and mitigating these risks during sea transport by providing early warnings and enabling proactive interventions**.** Future studies should focus on developing maritime-specific risk models and safety protocols, potentially incorporating machine learning algorithms and IoT-based monitoring systems to enhance the safety of BEV transport by sea.

Overall, developing advanced, standardized risk assessment methodologies and integrating these models into policy development will play a crucial role in the continued success and growth of the BEV industry. By addressing these gaps, researchers can provide critical insights that will not only enhance the safety of BEVs on the road and during transport but also ensure that the global infrastructure supporting these vehicles is resilient, reliable, and prepared for future challenges.

Author's Declaration

Authors' contributions and responsibilities

The authors made substantial contributions to the study conception and design. The authors take responsibility for data analysis, interpretation, and discussion. The authors have read and approved the final manuscript.

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