Sustainable Futures 11 (2026) 101767

Contents lists available at ScienceDirect

Sustainable Futures

journal homepage: www.sciencedirect.com/journal/sustainable-futures

From minerals to dollars: A scrutiny of lithium-ion battery cost models

Viera Pechancová [a,*], Lucie Hrbáčková [b], Hüseyin Ersoy [c], Manuel Baumann [c], Drahomíra Pavelková [b], Debashri Paul [e], Anna Ivanichenko [a], Jens Buchgeister [c], Manish Kumar [d]

[a] University Institute, Tomas Bata University in Zlín, Nad Ovčírnou IV 3685, 760 01 Zlín, Czech Republic
[b] Faculty of Management and Economics, Tomas Bata University in Zlín, Mostní 5139, 760 01 Zlín, Czech Republic
[c] Institute for Technology Assessment and Systems Analysis (ITAS), Karlsruhe Institute of Technology (KIT), Karlsruhe, Germany
[d] Helmholtz Institute Ulm for Electrochemical Energy Storage (HIU), Karlsruhe Institute of Technology (KIT), Ulm, Germany
[e] Centre of Polymer Systems, University Institute, Tomas Bata University in Zlín, Tr. T. Bati 5678, 760 01 Zlín, Czech Republic

ARTICLE INFO

Keywords:
Lithium-ion battery
Cost model
Battery cost
Battery raw materials
Critical minerals

ABSTRACT

The accelerating growth of electric mobility and stationary storage has intensified demand for lithium-ion batteries, where raw materials represent 50–70% of total cost. Volatility in Ni, Co and Li markets therefore poses major risks for affordability and investment decisions. This study systematically evaluates existing battery-cost models with a specific focus on how raw-material price inputs are represented, standardized and propagated into final $/kWh outputs.

A comparative review of sixteen representative models, including BatPaC, GREET®, EverBatt and CellEST, investigates methodological assumptions, cost-element structure, and transparency of data sources. This work provides the first review that jointly analyses deterministic cost models alongside probabilistic validation using real-world commodity volatility. Robustness is assessed through a 1,000-run Monte Carlo simulation based on historical price distributions of key metals.

Results indicate clear differentiation among chemistries. NMC-111 exhibits the widest 5–95% uncertainty range due to cobalt sensitivity, whereas NMC-811 and NMC-9525 show narrower bands reflecting reduced cobalt exposure. Bottom-up process-based models offer stronger cost traceability and better uncertainty representation than top-down macro forecasts, which often lack explicit linkages to $/kWh outputs. Findings demonstrate that raw-material price treatment strongly influences forecast accuracy, and that scenario-free point estimates systematically under-represent market risk.

To address these gaps, the study proposes a structured multi-source data acquisition strategy integrating public databases, commodity-market feeds and industry publications. The review enhances transparency, establishes reproducible comparison criteria, and quantifies price-volatility effects, offering actionable guidance for researchers, analysts and policymakers aiming to improve reliability and reduce uncertainty in LIB cost assessment.

Abbreviation: ANL, Argonne National Laboratory; ARIMA, Autoregressive Integrated Moving Average; BatPaC, Battery Performance and Cost model; CAM, Cathode Active Material; CAPEX, Capital Expenditure; CellEST, Cell Energy and Cost model; CME, Chicago Mercantile Exchange; Co, Cobalt; DOE, U.S. Department of Energy; EV, Electric Vehicle; ESA, European Storage Association; EverBatt, Closed-loop Battery Recycling model; GREET®, Greenhouse gases, Regulated Emissions, and Energy use in Transportation model; GWh, Gigawatt-hour; IEA, International Energy Agency; kWh, Kilowatt-hour; LCA, Life Cycle Assessment; LCC, Life Cycle Costing; LFP, Lithium Iron Phosphate; LIB, Lithium-ion battery; Li, Lithium; LME, London Metal Exchange; LTSM, Long Short-Term Memory; MCS, Monte Carlo Simulation; Mn, Manganese; Ni, Nickel; NMC, Nickel Manganese Cobalt; NMC-111, Cathode with 1:1:1 Ni:Mn:Co ratio; NMC-811, Cathode with 8:1:1 Ni:Mn:Co ratio; NMC-9525, Cathode with 9.5:0.25:0.25 Ni:Mn:Co ratio; OPEX, Operational Expenditure; PBCM, Process-Based Cost Model; Scopus, Elsevier's Abstract and Citation Database; SHFE, Shanghai Futures Exchange; SiO, Silicon Oxide; S-LCA, Social Life Cycle Assessment; SMM, Shanghai Metals Market; USGS, United States Geological Survey; WoS, Web of Science; $/kWh, U.S. Dollar per Kilowatt-hour.

* Corresponding author.
E-mail address: pechancova@utb.cz (V. Pechancová).

https://doi.org/10.1016/j.sftr.2026.101767
Received 8 June 2025; Received in revised form 22 January 2026; Accepted 19 February 2026
Available online 2 March 2026

1. Introduction

The growing demand for electric vehicles (EVs) has led to a significant expansion of the battery industry, particularly for Lithium-ion batteries (LIBs) such as Nickel Manganese Cobalt (NMC) and Lithium Iron Phosphate (LFP) variants. In the battery market, LFP batteries have gained dominance due to their superior electrochemical properties, including enhanced safety, longevity, and cost-effectiveness [1,2]. LFP cathodes offer a cycle life exceeding 4,000 cycles at 80% depth of discharge, making them highly competitive for stationary storage and EV applications. Meanwhile, demand for higher energy-density LIBs continues to drive research into nickel-rich NMC cathodes, which achieve high specific energy surpassing 900 Wh/kg [3]. The selection of these materials plays an important role in advancing battery performance while controlling costs.

Battery costs are influenced by a range of factors across materials, design, and production. Among these, material costs remain a primary driver, as demonstrated in earlier studies [4–7]. Since raw material costs make up 50–70% of the total cost of LIBs, their fluctuations have a direct impact on battery costs and, consequently, the affordability of EVs [8]. Notably, electrode materials, particularly cathodes, represent nearly 40% of total cell costs, reinforcing their dominant influence on LIB economics [9]. While innovations in pack design, voltage configuration, and electrode additives (e.g., SiO) can influence cost per kWh [10,11], studies consistently confirm that material inputs dominate cost structures [5,13,14]. Geographic factors [15], manufacturing scale, and cell geometry [16] further add complexity to cost estimation and mineral sourcing strategies [17].

The high prices and variability of critical raw materials, especially Nickel (Ni), Manganese (Mn), Cobalt (Co), and Lithium (Li) remain a major challenge for battery manufacturers [18,19], with Li prices in particular showing pronounced volatility [20]. However, the market witnessed a substantial decline in 2024, bringing lithium carbonate prices back to pre-2020 levels. Berckmans et al. [10] project that the $100/kWh cost threshold for NMC batteries will be reached between 2025 and 2030, a milestone expected to accelerate global EV adoption. Additionally, LIB demand is anticipated to grow from 526 GWh in 2020 to over 2,000 GWh by 2030, driven by increasing EV production [21] and energy storage applications [9].

Hence, robust battery cost models are crucial for assessing the impact of raw material price volatility on manufacturing costs. While Berckmans et al. [10] provide projections for LIB costs using silicon-based anode, Lütkehaus [22] highlights the importance of incorporating raw material price fluctuations into cost vulnerability assessments. However, the interchangeable use of "cost" and "price" in battery literature introduces complexity in economic evaluations, necessitating a more standardized approach to cost modeling [22,23]. Prices refer to externally quoted values observed in markets (e.g., commodity exchange prices for Li, Ni, Co, or supplier quotations for battery materials), expressed in units such as $/kg. These prices serve as inputs to the models. Costs, in contrast, refer to internally modeled production or system costs, expressed in $/kWh, which are calculated by aggregating material inputs, processing steps, energy use, labor, overheads, and other cost elements within a defined system boundary.

To address key gaps in battery cost analysis, this study examines the cost structures of LIBs, with a particular emphasis on raw material price inputs. Given the volatility of critical raw material prices, understanding their impact on battery manufacturing costs is essential for improving cost predictability. A comparative evaluation of existing battery cost models, including BatPAC, GREET®, EverBATT, CellEST [7,11], and [24], is conducted to assess how these models incorporate raw material price data. Since these models vary in scope, data structure, and computational complexity, their assumptions shape the cost estimation methodologies. While the models rely on user-inputted material prices, examining how they handle these inputs helps assess their applicability across different market contexts.

The originality of this research lies in its comparative focus on how models handle raw material price inputs and their sensitivity to volatility. By systematically evaluating methodological assumptions and input structures, the study identifies key vulnerabilities in current approaches. The proposed data acquisition framework aims to standardize sourcing practices and enhance reproducibility, providing a foundation for more robust and transparent cost modeling across the LIB value chain.

2. Methodology

This section outlines the methodology employed in the study, comprising three key components: (1) an assessment of how raw material price fluctuations influence LIB costs, (2) a comparative evaluation of existing battery cost models, and (3) the development of a structured data collection strategy to improve the quality and reliability of battery price information.

First, to quantify the impact of raw material price volatility on LIB costs, the study applies a time-series analysis combined with probabilistic cost estimation (Section 3). The analysis focuses on cathode active materials (CAMs), specifically NMC-111, NMC-811, and NMC-9525, due to their sensitivity to Ni, Mn, and Co price fluctuations [10]. The generated cost projections are integrated into the CellEST model [7], allowing for an assessment of two distinct scenarios that highlight market uncertainties and potential cost reduction pathways [25]. To capture uncertainty, the methodology employs a non-parametric Monte Carlo Simulation using historical commodity price data, generating empirical price distributions for each relevant material. These distributions are used to simulate a range of possible CAM cost outcomes. The analysed period ranges from January 2023 to January 2025. Outputs are expressed as median estimates with 5th–95th percentile confidence intervals. To minimize bias from extreme shocks, the model uses pre-2021 price data as training input, excluding the unusually volatile 2021–2022 period caused by pandemic and geopolitical disruptions.

Second, the study conducts a literature-based review (Section 4) to identify relevant battery cost models. A structured systematic literature search was conducted across two scientific databases: Web of Science Core Collection and Scopus. The searches were executed between 12th–14th February 2024 and were limited to peer-reviewed journal articles available in English. The search strategy used Boolean query strings targeting lithium-ion battery cost modelling, calculation methods, and techno-economic assessment frameworks. The exact search queries were as follows:

- Web of Science (searched 12 February 2024) – Topic Search (TS):
  TS = ("lithium batteries" OR "lithium-ion" OR "Li-ion") AND ("cost model" OR "cost modelling" OR "cost calculation" OR "techno-economic" OR "process-based cost") AND ("calculation method" OR "modelling approach");
- Scopus (searched 14 February 2024) – TITLE-ABS-KEY:
  TITLE-ABS-KEY ("lithium batteries" OR "lithium-ion" OR "Li-ion") AND ("cost model" OR "cost modelling" OR "cost calculation" OR "techno-economic" OR "process-based cost") AND ("calculation method" OR "modelling approach").

These searches returned 72 WoS records and 60 Scopus records, yielding 132 total documents prior to screening. After importing all records into the screening dataset and removing duplicates, titles and abstracts were evaluated based on predefined inclusion criteria: (i) relevance to battery cost calculation methodologies, (ii) presence of a cost model, estimation framework, or computational approach, and (iii) publication in a peer-reviewed journal. Studies were excluded if they were non-academic publications, conference abstracts without full text, purely materials-science-focused without modelling content, or lacked methodological transparency. In total, 116 documents were excluded during screening, resulting in 16 studies included in the final review, covering publication years 2007–2024. These values are fully aligned with the PRISMA flow presented in Fig. 1.

A structured comparative analysis is then performed to assess each model's assumptions, input parameters, and methodological frameworks, with a particular focus on how material pricing is handled. To enable cross-model comparison, evaluation criteria are developed based on four key categories described in Section 4.1. This allows the study to explore the models' sensitivity to raw material price inputs and their applicability under varying market conditions. A cost model estimates the costs of an economic activity or business process, including direct costs (such as materials and labour) and indirect costs (such as overhead and administrative expenses) [26].

Finally, informed by the preceding analysis and literature review, the study develops a structured data acquisition strategy aimed at improving the consistency, accessibility, and reliability of battery price data (Section 5). A practical checklist is introduced to guide data acquisition from multiple sources, including battery manufacturers, material suppliers, and industry associations.

3. Analysis of raw material price sensitivity on CAM

The cost of LIB is heavily influenced by fluctuations in raw material prices, particularly cathode chemistries containing metals such as Ni and Co are sensitive to the market price dynamics [27]. As global demand for these materials continues to grow, the need for economic predictability in LIB production becomes more critical compounded with geopolitical uncertainties and supply chain constraints. Despite this volatility, many battery costing models in the literature rely on deterministic pricing (i.e., utilizing static, single-point cost values), which underestimate the financial impact of commodity price fluctuations. To address this shortcoming, probabilistic methods that incorporate uncertainty via confidence intervals offer a more robust framework for forecasting and cost analysis.

One such tool is material price forecasting, which can be used to estimate battery costs under probabilistic conditions based on historical price trends. While advanced forecasting techniques such as Autoregressive Integrated Moving Average (ARIMA) or Long Short-Term Memory (LTSM) networks exist, these models have considerable complexity, often require stationary time series, and are sensitive to hyperparameter tuning and data quality. Moreover, their effectiveness in forecasting material prices influenced by geopolitical and supply chain shocks is limited, particularly when such disruptions are inherently unpredictable.

To provide a more accessible, transparent, and interpretable alternative, this work implements a Monte Carlo Simulation (MCS) based forecast leveraging historical price data without assuming strict statistical distributions. Three representative CAM chemistries (NMC-111, NMC-811, and NMC-9525) were selected for analysis, reflecting varying compositions of Ni, Mn, and Co. The collected commodity prices are incorporated into the CellEST model [7] for estimating the CAM costs based on historical values. The simulation treats each historical material price data point as part of an empirical distribution (i.e., non-parametric bootstrapping) and draws random samples with replacement to generate 1,000 simulated futures over a 2-year forecasting horizon (Jan 2023 – Jan 2025). A fixed random seed was used to ensure reproducibility, and no detrending was applied.

To train the model, we used material price data from before 2021 to avoid price distortions. This training data design intentionally excludes the highly volatile 2021-2022 period, marked by extreme price spike due to pandemic-driven disruptions, war-induced market instability and related supply chain shocks. These price peaks are critical to understanding past short-term risks but considered as outliers for the purpose of long-term cost-estimation.

Due to data access constraints, only the five years of commodity price data were available at high enough temporal resolution (daily granularity) for reliable simulation. Within that period, data prior 2021 were identified as the most representative for constructing price distributions under more typical market considerations. Fig. 2 shows the actual and forecasted costs of the three CAM chemistries over time visualized across two panels. Fig. 2a presents historical price-based CAM cost estimates (dashed lines) alongside the forecast median (solid lines) and probabilistic bands (shaded areas). The forecast band indicate the range between 5^{th} and 95^{th} percentiles derived from the simulations alongside annotated segments (training period, excluded period, and forecasted period). The dashed lines in the plot reveal how CAM costs surged during the excluded peak period before declining near pre-2021 levels. These dynamics show the limitations of single-point forecasts and emphasize the need for probabilistic modelling.

Fig. 22b shows the magnified view of the forecasted estimates for the three CAM chemistries. As it can be observed, NMC-111 with the highest

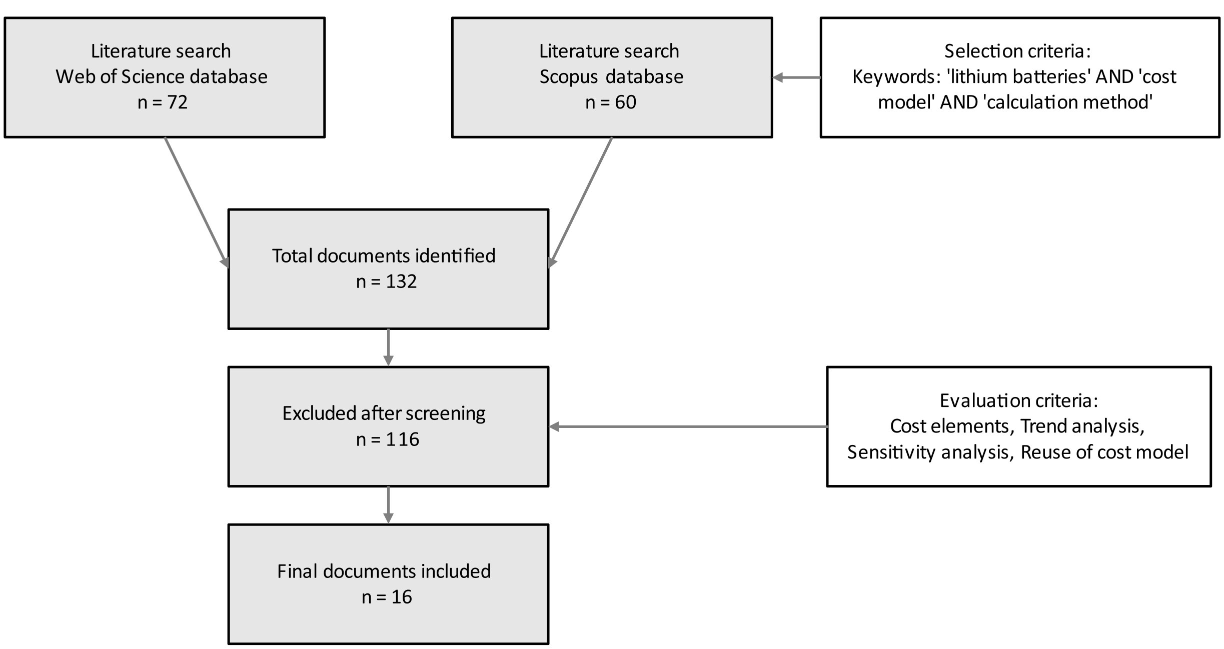

Fig. 1. PRISMA-style flow diagram of literature identification and screening.

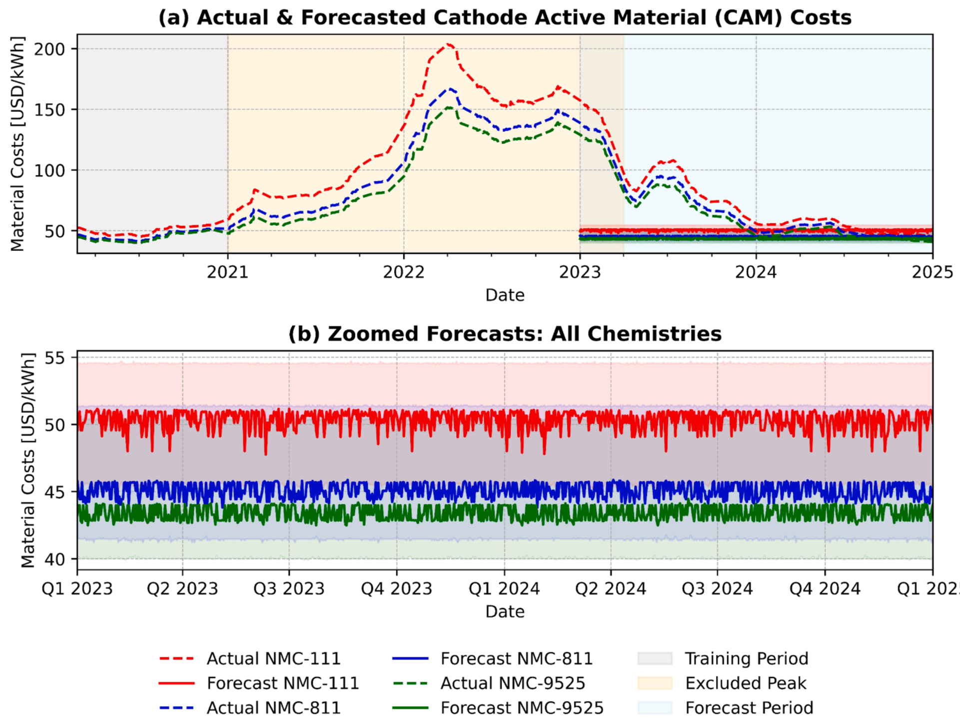

Fig. 2. a) shows the actual material cost evolution and the forecasted probabilistic median (50th percentile) values, along with 5th–95th percentile confidence bands for each CAM chemistry. A visual annotation separates training and forecasting regions, and shaded overlays highlight the excluded volatility period (2021–2022). Fig. 2b) presents a magnified view of the forecasted CAM costs across chemistries, enabling comparative insights into volatility and sensitivity.

Co content, shows the widest uncertainty band reflecting its exposure to volatile Co prices. In contrast, NMC-811 and NMC-9525 show narrower bands mainly due to lover Co content. Hence, the provided example illustrates why incorporation of raw material price uncertainties is important especially for chemistries containing volatile metals.

To benchmark the proposed MCS approach against more detailed forecasting methods, a 12-24-month walk-forward back test was performed using the pre-2021 dataset as the stable reference regime. For each CAM chemistry, ARIMA, LSTM, and MCS were evaluated at each forecast origin. Due to the limited pre-2021 sample length (133 daily observations per chemistry), the maximal feasible walk-forward horizon was approximately 66 days (~2 months) instead of a full annual horizon. Each model was therefore assessed using this rolling 66-days horizon, reporting mean absolute percentage error (MAPE), root mean

Table 1
Pre-2021 walk-forward horizon: 66 days; MCS uses N = 1000, fixed random seed, no detrending.

Cell Chemistry	Horizon	Method	5th	Median	95th	Percentile Width	PI hit rate (5th-95h, pre-2021) [%]
	t_0 (2023-01-01)	MCS	45.51	50.92	54.57	9.06	29.00
		ARIMA	54.06	54.87	55.68	1.61	100.00
		LSTM	53.24	55.08	56.92	3.68	31.90
	t_0 + 6 months (2023-07-01)	MCS	45.61	50.96	54.52	8.90	29.00
		ARIMA	34.40	55.48	76.55	42.16	100.00
		LSTM	57.28	59.12	60.95	3.68	31.90
	t_0 + 12 months (2024-01-01)	MCS	45.51	49.56	54.52	9.01	29.00
		ARIMA	24.70	55.48	86.25	61.55	100.00
		LSTM	57.29	59.13	60.96	3.68	31.90
	t_0 (2023-01-01)	MCS	41.48	44.63	51.32	9.84	24.60
		ARIMA	51.12	51.87	52.62	1.49	98.60
		LSTM	50.72	52.03	53.35	2.64	0.00
	t_0 + 6 months (2023-07-01)	MCS	41.47	44.84	51.39	9.92	24.60
		ARIMA	40.69	51.87	63.05	22.36	98.60
		LSTM	52.67	53.99	55.31	2.64	0.00
	t_0 + 12 months (2024-01-01)	MCS	41.37	44.44	51.39	10.02	24.60
		ARIMA	36.01	51.87	67.73	31.71	98.60
		LSTM	52.67	53.99	55.31	2.64	0.00
	t_0 (2023-01-01)	MCS	40.00	43.28	50.45	10.45	21.70
		ARIMA	50.16	50.92	51.69	1.53	76.80
		LSTM	49.73	50.92	52.10	2.37	0.00
	t_0 + 6 months (2023-07-01)	MCS	40.03	42.68	50.40	10.36	21.70
		ARIMA	39.52	50.92	62.33	22.80	76.80
		LSTM	50.93	52.11	53.30	2.37	0.00
	t_0 + 12 months (2024-01-01)	MCS	39.99	43.98	50.40	10.40	21.70
		ARIMA	34.75	50.92	67.10	32.35	76.80
		LSTM	50.93	52.11	53.30	2.37	0.00

squared error (RMSE), and the empirical prediction-interval (PI) hit rate (5th-95th).

To increase transparency,

Table 1 lists the numerical values of the 5th, median, and 95th forecasts for three critical horizons (t_o, t_o+6 months, t_o+12 months) for each modelling approach (MCS, ARIMA, LSTM), together with the simulation sample size (N=1,000) and random seed. While ARIMA exhibits substantially higher empirical PI hit rates (~77–100%) and the lowest point-forecast errors (MAPE ~3–6%), this should not be interpreted as superior uncertainty representation as per se. As shown in Table 1, ARIMA achieves these high coverage values primarily by producing rapidly widening intervals with increasing forecast horizon. For instance, the 5th-95th percentile width for NMC-111 expands from approximately 1.6 at to t_o over 60 at t_o+12 months, indicating a strong loss of sharpness. Such overly dispersed intervals, although statistically conservative, become increasingly uninformative for techno-economic decision-making.

LSTM yielded moderate point accuracy (MAPE ~7–9%) but systematically under-estimated uncertainty, with near-zero interval coverage. In contrast, MCS exhibits larger point deviations (MAPE ~10–12%), the MCS-based intervals are directly derived from the empirical distribution of historical material price fluctuations and therefore, remain comparatively stable across forecast horizons. This results in narrower and more interpretable uncertainty bands, which better reflect the historical observed variability of the underlying data-generating process. The lover PI hit rates observed for MCS (~20–30%) should therefore not be interpreted as a failure of uncertainty modelling, but rather as a consequence of not artificially inflating interval width to guarantee nominal coverage.

Importantly, deviations beyond the MCS intervals are largely associated with regime shifts and exogenous shocks, which are inherently unpredictable from historical price data alone. Since the goal of this study is not short-term point prediction but long-term techno-economic risk characterization, we prioritize empirically grounded, interpretable, and stable uncertainty estimates over nominal coverage maximation. From this perspective, MCS provides a more suitable uncertainty representation for cost sensitivity than deterministic or strongly model-driven statistical forecasts.

Moreover, the simplicity of MCS makes it ideal for uncertainty modelling, especially when historical data is available but limited in resolution for increasing the robustness of the estimates. It avoids over-simplified assumptions while accounting for the real-world price volatility. While the approach is not intended to predict the next price spike, it effectively captures longer-term probabilistic behaviour, enabling better-informed economic decisions. More granular and extensive datasets could enhance the accuracy of forecasts. In the future, integrating machine learning models or hybrid approaches could further improve robustness, especially when paired with external risk indicators.

4. Battery cost models

The modeling of raw material price inputs represents a key determinant in understanding the battery economics and various cost models have been developed, accounting for material, manufacturing, and other operational factors. In particular, the Battery Performance and Cost (BatPaC) model, developed by Argonne National Laboratory, has emerged as a widely used tool for assessing the cost structure of LIBs. Additionally, the EverBatt model extends cost modeling to closed-loop battery recycling, integrating both economic and environmental considerations. Alongside these, several standalone cost models, such as CellEST, general bottom-up cost models, and process-based cost models (PBCM), offer alternative approaches with varying levels of complexity, transparency, and specificity. Since understanding these battery cost models has been of increased interest, an overview is provided in the following sub-sections.

4.1. Battery cost models: state-of-the-art

Several reviews trace the evolution of battery cost modeling [10,14]. They highlight the dominance of material costs in LIB economics, with recent work stressing the volatility of Li, Ni, and Co [9,28–31]. Leader et al. [31] further demonstrate the economic vulnerability of LIBs to material price spikes, estimating potential cost increases of 13–41%, and advocating for supply risk mitigation in future modeling efforts.

The BatPaC model, developed by Argonne National Laboratory in Microsoft® Excel, represents a state-of-the-art tool for assessing LIB costs, particularly for automotive applications [32]. Originating from long-term R&D and early U.S. Department of Energy (DOE)-commissioned work on battery cost modelling [33,34]. BatPaC has been widely applied to analyse material and energy demand [13,35–37] and also instrumental in evaluating the potential for battery commercialization [38]. The model's breakdown of material consumption enhances understanding of resource needs and cost drivers in battery production [36], while its comparison with independent studies supports validation and benchmarking of cost projections [39].

The EverBatt model addresses both the economic and environmental aspects of closed-loop battery recycling. Its modules integrate inputs such as materials, energy flows, equipment, throughput, and location, and calculate process costs using BatPaC (v3.1, 2018) and a chemical plant cost model [40]. Environmental impacts are assessed with Argonne's GREET® model.

The first version of CellEST presents a standalone model for calculating the performance and cost of electric vehicle LIBs with a specific focus on CAMs [7], such as Li transition metal oxides or metal phosphates. The updated CellEST model provides more detailed evaluation of the performance and cost of pouch LIBs utilizing nickel-rich CAMs and silicon-graphite composite anodes [11]. This assessment involves a detailed analysis of the chemistry and characteristics of the anode, particularly focusing on the utilization of graphite and silicon-graphite composite materials.

Another category of standalone models is general bottom-up cost models, such as those developed by [41] and [15]. Bottom-up models offer greater transparency and detail by incorporating specific characteristics of battery cells and manufacturing processes, along with their associated costs. A specialized subset of bottom-up models are PBCMs, which focus on the granular details of manufacturing processes. By integrating production-specific parameters, PBCMs provide a framework for evaluating cost structures across different battery production scenarios [25,12,16].

4.2. Battery cost models: review parameters for comparison

This chapter presents a comparative analysis of battery cost models based on four key dimensions: (1) scholarly influence and impact, (2) methodological approaches to battery cost estimation, (3) reliability, predictive robustness, and model adaptability of cost models, and (4) data sources and market inputs. These dimensions encompass both academic significance and practical relevance in estimating battery costs. The Table 2 summarizes the hierarchical structure and categorization of the parameters, which were derived from a literature review of major trends shaping cost estimation in the battery and EV sector. Each assessment parameter is operationalised following a structured parametrisation, which specifies the exact definitions, measurement scales, coding rules, and allows value formats for all variables.

(1) **Influence and impact of scholarly contributions:** Indicators include publication year and citation counts (WoS/Scopus), which reflect scholarly visibility. While recent publications may reflect the latest developments in battery technologies and market dynamics, recency alone does not guarantee greater relevance. Both publication year and citation metrics must be interpreted with caution—recent studies may lack temporal

Table 2
Battery cost models' parameters.

Parameter	Indicator	Definition/Measurement Scale/Data Type	Coding	Coding Value Format
Influence and impact of scholarly contributions	Year of publication	Publication year of the model/method	Numerical	Continuous
	Article citations	Number of Web of Science/Scopus citations	Numerical	Continuous
Methodological approaches to battery cost estimation	Calculation method	Type of battery cost calculation method followed	Categorical	Bottom-up, top-down, etc.
	Cost elements groups	Type of main cost element groups included	Categorical	Main cost element groups
	Cell chemistries assessed	Types of cell chemistries assessed	Categorical	Categories of cell chemistries
Reliability, predictive robustness, and model adaptability	Trend analysis	Trend analysis options included or not	Binary	Yes/No
	Sensitivity analysis	Sensitivity analysis options included or not	Binary	Yes/No
	Uncertainty analysis	Confidence intervals range available or not	Binary	Yes/No
	Updates/reuse	Updates, mechanisms for model validation included or not	Binary	Yes/No
Data sources and market inputs	Price data source	Type of data sources listed	Categorical	Supplier information, exchange, studies, etc.
	Transparency of pricing	Availability options of battery cost model/battery pricing data sources	Ordinal	Not Available/Access restricted/ Open Access

maturity for citation uptake, while highly cited works often reflect longer exposure rather than inherently superior scientific value [42]. Therefore, both recency and citation data are considered as complementary indicators of a study's potential contribution to the field [43].

(2) **Methodological approaches to battery cost estimation**: This segment focuses on the calculation methods used in battery cost models, particularly in relation to raw material pricing. Approaches such as bottom-up, top-down, process-based costing, and kilo-costing vary in their level of detail and accuracy. The BatPaC model, for example, includes capital and operating costs during production, including machinery and labour [44]. Operational costs, such as energy losses during charging cycles, must also be modeled to estimate performance and profitability [18, 45]. Separating fixed and variable costs further improves forecasting under different production scenarios [46]. Moreover, evaluating a broad spectrum of cell chemistries, such as LFP and NMC, is essential due to their distinct material compositions and cost structures [47,48–50].

(3) **Reliability, predictive robustness, and model adaptability:** Reviewing battery cost models involves assessing their responsiveness to historical trends, input variations, and uncertainty, as well as their adaptability over time. Trend analysis supports forecasting by identifying past patterns and projecting future costs, with studies tracking metal prices, market shifts, and technological advances [23,51,52] Sensitivity analysis identifies the variables with the greatest cost impact [53], while some models also incorporate uncertainty analysis, providing confidence intervals and scenario variability related to degradation, performance, and market volatility [10]. Long-term relevance further depends on adaptability, including mechanisms for reuse and regular updates [54], in line with ongoing reductions in battery costs driven by improvements in materials and production [55].

(4) **Data sources and market inputs**: Price data can be obtained from diverse sources, including supplier quotes, industry reports, commodity exchanges, and academic literature [56]. Finally, transparency in pricing methodology enables verification and replication of results, particularly when open-access data and assumptions are disclosed [57,58]. According to [59], open access to input variables, model parameters and methodologies increases reliability. Similarly, [60] find that transparency reduces information asymmetries and aligns stakeholder expectations. This approach increases stakeholder confidence in the analyses used to inform policy or industrial investment decisions [61]. In addition, [62] demonstrate the role of accurate pricing data in sensitivity analyses through their work on battery equivalent circuit models.

4.3. Battery cost models: comparative analysis

The parameters selected for the literature review on material cost quantification and battery cost models are summarized in Table 1 (Section 4.2). The further presented parameters include: year of publication, number of citations, calculation method, assessed cell chemistries, incorporation of trend and sensitivity analyses, model updates or reuse, price data sources, and the transparency of pricing information. Table 3 lists the individual authors of the reviewed publications addressing battery cost models.

The Year of Publication ranges from 2007 to 2024, while citations vary from 1 to 2,905, reflecting differing academic impacts (Fig. 3). The Method column classifies models as BatPaC, PBCM, bottom-up, or standalone (see Section 4.1). Examples illustrate this diversity: [63] and [64] introduced unique methods for cost calculation per battery cell; [5,65] and [41] focus on automotive applications; Berg et al. [24] further extended the BatPaC approach by integrating manufacturing process and overhead cost estimates, drawing on empirically validated relationships from Patry et al. [64]; Schmuch et al. [6] used a bottom-up approach; Orangi and Strømman [15] focused on flexible bottom-up cost model based on a cell production process model; and Wentker et al. [7] and Greenwood et al. [11] developed the CellEST model with four main components (Cell Model, Cathode Cost Calculation, Raw Material Costs and Component Costs). Ciez and Whitacre [12] and Berckmans et al. [10] use this cost model to determine the costs for different types of batteries. Duffner et al. [25] use PBCM to estimate current and future costs and Soldan Cattani et al. [16] emphasize the flexibility of this cost model and its adaptability to different production designs.

Across the reviewed studies (Table 4), consistent trends show a long-term decline in LIB costs, with pack prices moving from well above \$200/kWh (~\$240–260/kWh 2023-USD) a decade ago toward the \$100/kWh threshold projected between 2025 and 2030 for NMC chemistries (~\$95–120/kWh normalised), and even earlier for silicon-based designs (Berckmans et al., [10]; Schmuch et al., [6]; Duffner et al., [25]). Cell-level cost ranges are typically reported between \$100–170/kWh (~\$115–185/kWh 2023-USD), while packs are estimated at \$220–250/kWh (~ \$250–285/kWh normalised), with further reductions expected from scale-up (Schmuch et al., [6]; Orangi & Strømman, [15]). Sensitivity analyses consistently identify raw materials as the dominant cost driver, accounting for ~60–70% of total pack cost (Berckmans et al., [10]), with cathode active materials alone contributing ~40%. In particular, cobalt shows the greatest volatility risk: cost spikes can raise NMC-111 CAM costs by over 60% (Wentker et al., [7]), while cobalt-free chemistries such as LFP or LMO remain relatively unaffected. Lithium and nickel prices also exert significant, though less extreme, effects, while labor, location, and manufacturing scale contribute region-specific differences (Orangi & Strømman, [15]). Most studies employ deterministic cost values, yet those incorporating

Table 3
Comparison of battery cost models' parameters.

Authors	Number of citations	Method	Cell Chemistries	Trend Analysis	Sensitivity Analysis	Reuse of cost model	Price data source	Transparency of the pricing information
Kalhammer et al. (2007)	185	Stand-alone	NMC, NCA, LMO, LFP, LCO	No	✓	✗	Manufacturers	NOT AVAILABLE
Nelson et al. (2011)	351	BatPaC	NMC, NCA, LMO, LFP, LCO, LTO	No	✓	✓	Research study; Commodity Market Public organisation - USGS Manufacturers	ACCESS RESTRICTED OPEN ACCESS NOT AVAILABLE
Brodd and Hellou (2013)	92	Stand-alone	NMC	No	✓	✗	Manufacturers	NOT AVAILABLE
Patry et al. (2015)	149 (Scopus)	Stand-alone	NMC, NCA, LMO, LFP	No	✓	✓	Research studies. European project Helios - Suppliers	ACCESS RESTRICTED NOT AVAILABLE
Berg et al. (2015)	221	BatPaC	LCO, LFP, LMO, LNMO, LR-NMC, NCA, NMC, NVPF, SR-NMC, LTO	No	✗	✓	Research studies	ACCESS RESTRICTED
Ciez and Whitacre (2016)	92	PBCM	NMC, NCA, LMO	No	✓	✓	Database BatPac Public organisation - USGS	ACCESS RESTRICTED OPEN ACCESS
Berckmans et al. (2017)	438	PBCM	NMC	Yes	✓	✓	Public organisation - IEA; Organisation - PwC; Manufacturers; Platform - Statista	ACCESS RESTRICTED
Ahmed et al. (2017)	132	BatPaC	NMC	No	✓	✗	Scientific studies; Commodity Markets Expert opinion	ACCESS RESTRICTED NOT AVAILABLE
Vaalma et al. (2018)	2117	BatPaC	NMC, LMO, NMO	Yes	✓	✓	Database BatPac; Public organisation - USGS	ACCESS RESTRICTED
Schmuch et al. (2018)	2905	Bottom-up	NMC, NCA, LMO, LNMO, HE-NMC	Yes	✓	✓	Commodity Markets. Organisation - USGS; Research studies	ACCESS RESTRICTED
Nelson et al. (2019)	419	BatPaC	NMC, NCA, LMO, LFP	No	✓	✓	Commodity Markets; Database BatPaC	ACCESS RESTRICTED
Wentker at al. (2019)	137 (Scopus)	CellEST	NMC, NCA, LR-NMC, LNMO, LMO, LFP	Yes	✓	✓	Database BatPaC Public organisation - USGS	ACCESS RESTRICTED OPEN ACCESS
Greenwood et al. (2021)	65	CellEST	NMC, NCA, LNO	No	✓	✓	Commodity Markets; Database BatPaC; Platform - Alibaba	ACCESS RESTRICTED
Duffner et al. (2021)	103	PBCM	NMC	Yes	✓	✓	Office EU - Eurostat; Research studies Survey	ACCESS RESTRICTED
Orangi and Strømman (2022)	23	Bottom-up	NMC, LFP-G, LMO-G, LMO-LTO, NCA-G	Yes	✓	✓	Commodity Markets; Platform - Alibaba; Provider - ECA International; Platform - Tranding Economics	ACCESS RESTRICTED
Soldan Cattani et al. (2024)	1	PBCM	NMC, NCA, LFP, LMP	No	✓	✓	Research studies	ACCESS RESTRICTED

probabilistic or scenario-based methods demonstrate that supply chain shocks and commodity swings can shift total costs by 20–60%, underscoring the need for models that explicitly capture raw material price volatility. Normalisation to $/kWh requires assumptions on gravimetric energy density, which vary across chemistries, designs, and production scales. Consequently, the resulting $/kWh values are sensitive to these assumptions, and should be interpreted as indicative ranges rather than exact point estimates, particularly when comparing results across studies.

Price data sources include databases, supplier quotes, exchanges, and expert input. Transparency varies significantly: reliance on inaccessible manufacturer or expert data limits verification, undermining reusability [4,63]. Finally, although sensitivity analysis is widespread, none of the reviewed studies conducted a formal uncertainty analysis (e.g. confidence intervals, stochastic variation), leaving a gap in addressing volatility in prices, material supply, and market conditions.

4.4. Battery cost models: cost items

The reviewed studies vary considerably in how they structure cost elements within battery cost models, as illustrated in Fig. 4. While some models provide a detailed breakdown of both variable and fixed costs, others focus narrowly on material inputs. For instance, Nelson et al. [5] employ the BatPaC framework to capture a broad spectrum of cost items, extending beyond material costs to include direct labour, purchased components, overheads, and depreciation. Similarly, Berg et al. [24] provide one of the most comprehensive fixed-cost accounts, encompassing production and logistics, administration, R&D, and equipment. In contrast, several studies (e.g., Vaalma et al. [41], Schmuch et al. [6], Wentker et al. [7], Greenwood et al. [11]) omit explicit treatment of fixed costs, limiting their transparency for long-term investment planning.

Terminology also differs: Nelson et al. [5] use the term investment cost, Brodd and Helou [63] explicitly account for land acquisition and facility construction, while Ahmed et al. [66] refer to capital investment. Across the 16 reviewed studies, materials consistently appear as the dominant variable cost, but the inclusion of additional elements, such as logistics, overheads, administration, R&D, depreciation, energy, and margins, varies substantially. While materials dominate costs, the inclusion of fixed costs largely determines a model's comparability,

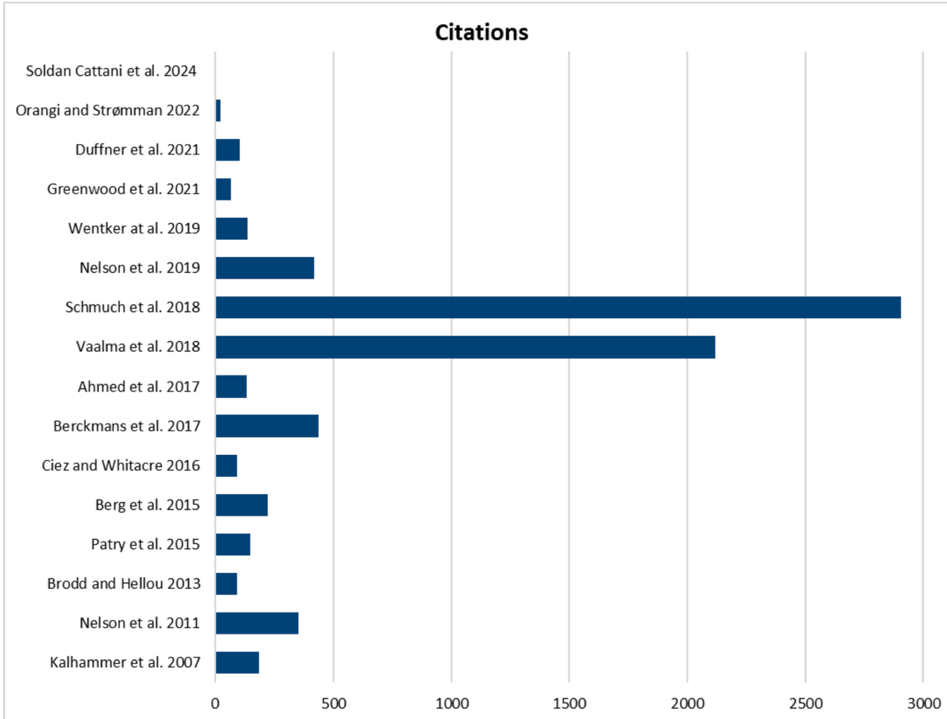

Fig. 3. Number of citations per cost model.

transparency, and policy relevance.

Overall, while CAM costs are a key driver of battery costs, these comparisons highlight that other components (labour, overheads, depreciation, and energy) also play a significant role in cost modelling [10,56]:

- Fixed costs often omitted – Even the two most cited models neglect fixed costs, likely because variable material costs dominate. Yet factory CAPEX can reach $60–100/kWh capacity, so omission skews investment planning.
- No link with publication year – Model sophistication does not follow chronology; scope depends more on institutional purpose than release date.
- BatPaC as benchmark – BatPaC remains the dominant model due to transparency, updates, and DOE support, though it shares the same fixed-cost gaps.
- Material costs as key driver – Cathode active materials consistently represent 30–50% of cell cost; price shifts of Ni/Co/Li can move pack costs by +10–25% ($10–30/kWh). This validates our focus on CAM price volatility.

Despite general agreement on which cost categories matter, studies vary in their granularity and transparency when allocating costs across these categories, which influences comparability and policy relevance [67].

5. Sources for battery prices

Accurate and reliable battery price data are essential for tracking cost trends and developing robust cost models. However, many reviewed approaches, including BatPaC, CellEST, and process-based models, still face challenges in sourcing transparent and up-to-date information [7,14,25,56]. The assumptions about raw material prices often rely on outdated or proprietary sources. As discussed in the review [10,31], the price spikes of critical metals can cause battery cost increases of 13–41%. This reinforces the argument that cost models must be supported by structured, multi-source price data strategies to improve both their accuracy and resilience.

Various sources provide insights into raw material pricing, market trends, and supply chain dynamics, each with distinct advantages and limitations. This chapter categorizes the key sources of battery price data, evaluates their accessibility and reliability, and discusses their implications for industry stakeholders. Fig. 5 and following sub-sections provide a structured comparison of battery price information sources, detailing their accessibility, data coverage, and transparency in raw material prices, to guide users in selecting the most suitable reference for LIB market analysis.

5.1. Market research and consulting groups

Market intelligence firms provide detailed reports on battery materials, including supply chains, pricing, and market trends. These are used by manufacturers, investors, and policymakers for informed decisions on costs and sourcing. Key providers include Benchmark Mineral Intelligence, Deloitte, PwC, and others, though access is often limited by high subscription costs. This restricts transparency and poses challenges for researchers, who must cross-reference multiple sources for reliable data [51].

5.2. Publicly accessible information

Several governmental and international organizations, such as the International Energy Agency (IEA) and The United States Geological Survey (USGS), offer partially accessible data on raw material prices and supply chain trends for key battery materials like Li, Ni, and Co. Eurostat provides broader economic and energy data but lacks detailed battery material pricing. Private platforms like Statista, S&P Global Platts, and Fastmarkets offer specialized market insights, though transparency and update frequency vary. In [68] the authors highlight the challenge posed by limited publicly available data, which often necessitates reliance on proprietary sources. Industry groups like the ESA and International Copper Association contribute sector-specific insights, while platforms

Table 4
Harmonised cost trends and sensitivity findings across reviewed studies (values normalized to USD 2023).

Authors (Year)	Comparative Cost ($/kWh, normalized to 2023)	Key Findings
Ciez & Whitacre (2016)	Lithium price swings of $36–$87/kg would be required to increase cell costs by ~15%, and even extreme lithium cost swings result in <10% impact on cell cost. Normalized to ~$190/kWh baseline equivalent (2023 USD)	Li swings of $36–87/kg → <10% impact
Berckmans et al. (2017)	Projected NMC battery pack costs to drop to $100/kWh between 2025–2030; silicon-based LIBs could reach this earlier, between 2020–2025. Normalized reference ~$118/kWh (2023 USD) from projection range.	Material costs make up about 65% of total pack cost. Roadmap to $100/kWh by 2025–2030
Ahmed et al. (2017)	Li-NMC333 manufacturing requires ~$23 per kg of material, ~4 kWh energy per kg, and ~15 L water per kg.	Provides process-level metrics, not direct $/kWh sensitivity.
Vaalma et al. (2018)	Li & Co demand projections (2016–2050); demand-focused. Only resource + material risk assessment.	Demand-focused, no $/kWh
Schmuch et al. (2018)	Cell: $100–170/kWh; Pack: $220–250/kWh. Normalized to cell $115–196/kWh, pack $253–288/kWh (2023 USD).	Cost target $125/kWh pack by 2022–2025
Nelson et al. (2019) (BatPaC)	Chemistry-dependent model: NMC111 ≈ $146/kWh; LFP ≈$131/kWh (raw 2019 values). Normalized to ~$165/kWh, ~$148/kWh (2023 USD).	Trends differ by chemistry
Wentker et al. (2019)	Reports NMC111 cost increased 63.56% (Jan 2017→Mar 2018). Normalized trend projection →~$208/kWh	Co/Ni volatility drives increase
Greenwood et al. (2021)	Cost projections for UK/Europe; values reported but vary by scenario: €100–120/kWh (~$108–130/kWh 2023 USD after FX + inflation).	Regional variation
Duffner et al. (2021)	Current LIB pack cost ~$106/kWh, projected future cost ~$64/kWh (process-based model). Normalized output $115/kWh → $69/kWh (2023 USD).	Process-based cost modeling
Orangi & Strømman (2022)	NMC111-G: $106.4/kWh (China) vs $153.6/kWh (Norway); scaling to 7.8 GWh → ~31% cost drop. Normalized to China ~$110/kWh; Norway ~$159/kWh (2023 USD).	Labour/location cost differences (~$47.2/kWh) significantly affect total cost.
Soldan Cattani et al. (2024)	Process-based; stresses material cost shares; no single $/kWh headline.	Cost shares, not $/kWh

Note: The monetary values were harmonised to 2023 USD using GDP deflators. Non-USD values were exchanged via annual IMF/World Bank rates prior to inflation correction. Studies reporting costs in €/kg, $/cell or €/module were normalised to $/kWh using mean gravimetric energy densities per chemistry (NMC-811 = 240–260 Wh/kg; NMC-111 = 180–200 Wh/kg; LFP = 150–170 Wh/kg), applying the median where unspecified. Variations in cell design or packing efficiency may shift normalized values without changing underlying material prices or process costs.

like Trading Economics, Investing.com, Mining.com, and Battery News offer market forecasts and industry trends, though consistency remains an issue.

5.3. Metal exchanges

Real-time and historical price data for battery metals are available from major global metal exchanges, including the LME, SHFE, SMM, and CME Group. These platforms are key for market-based price discovery and price forecasting, though access to historical data often requires payment, limiting availability for researchers. Despite this, they remain vital for tracking market trends and supply-demand dynamics [10].

5.4. Other suppliers' data

Battery material suppliers, mining firms, and consultancies such as Umicore, BASF, and LG Chem publish reports on supply chain trends, production costs, and pricing forecasts. However, data from commercial platforms (e.g., Alibaba, Chemall.com, 100PPI.com) are not peer reviewed and may lack transparency or long-term reliability. To strengthen cost modelling, priority should be given to official and verifiable datasets such as those from the US Geological Survey (USGS), International Energy Agency (IEA), and London Metal Exchange (LME). Using these open and standardized sources enhances transparency, reproducibility, and comparability of results, while supplier reports can serve as complementary inputs to capture near-term market dynamics in the rapidly evolving LIB sector [50].

5.5. Implications and strategies for the battery sector stakeholders

The availability and reliability of battery material price data have far-reaching implications across multiple industries:

- Battery manufacturers: Quantified trends show that cell costs have dropped from ~$190/kWh (pack, 2017) to below $120/kWh in recent models, with projections of $64–100/kWh by 2030 [6,14,69]. Such figures directly inform procurement strategies, material selection, and cost optimization efforts.
- Policymakers: Sensitivity analyses demonstrate that raw material swings can shift costs by +20–60% depending on cathode chemistry (e.g., NMC-111 vs LFP) [7]. Incorporating these quantified sensitivities into policy helps stabilize supply chains and incentivize sustainable sourcing [9].
- Investors: Explicit cost differentials, such as $106/kWh (China) vs $154/kWh (Norway) for identical NMC chemistries [52], highlight the financial risk of regional dependencies and inform investment decisions [31].
- Automotive and energy storage sectors: Forecasts toward $100/kWh thresholds are critical for long-term EV affordability and stationary storage competitiveness [25].

Technological advancements (such as solid-state batteries and battery recycling innovations) have the potential to lower costs over time, though they are still accompanied by significant manufacturing and scale-up challenges [70,71]. In parallel, material substitution strategies, such as shifting to sodium-ion or manganese-rich chemistries may reduce dependency on critical raw materials and mitigate exposure to cobalt and nickel price volatility, which in NMC chemistries can drive >+$20/kWh increases from a single raw material fluctuation.

Models should also account for supply chain resilience and regulatory dynamics. Geopolitical risks and raw material constraints directly impact pricing and sourcing strategy [17]. These risks can be mitigated through diversification strategies, long-term supplier agreements, and the use of financial tools such as hedging. For example, Duffner et al. (2021) project future pack costs near $64/kWh, achievable only under stable supply conditions. Regulatory measures, for example the EU's recycled content requirements, will increasingly shape future production costs [72].

To better reflect the economic and environmental realities of battery technologies, cost models could incorporate recycling potential [73] and

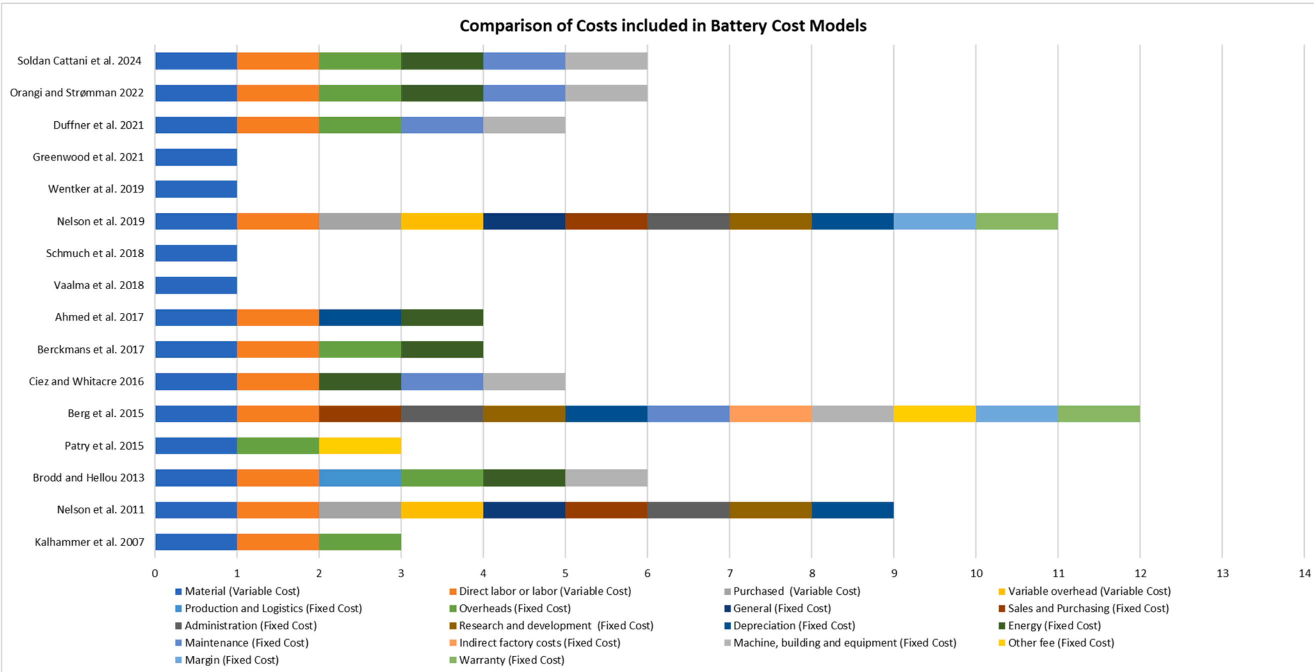

Fig. 4. Fixed and variable costs considered in different battery cost models.

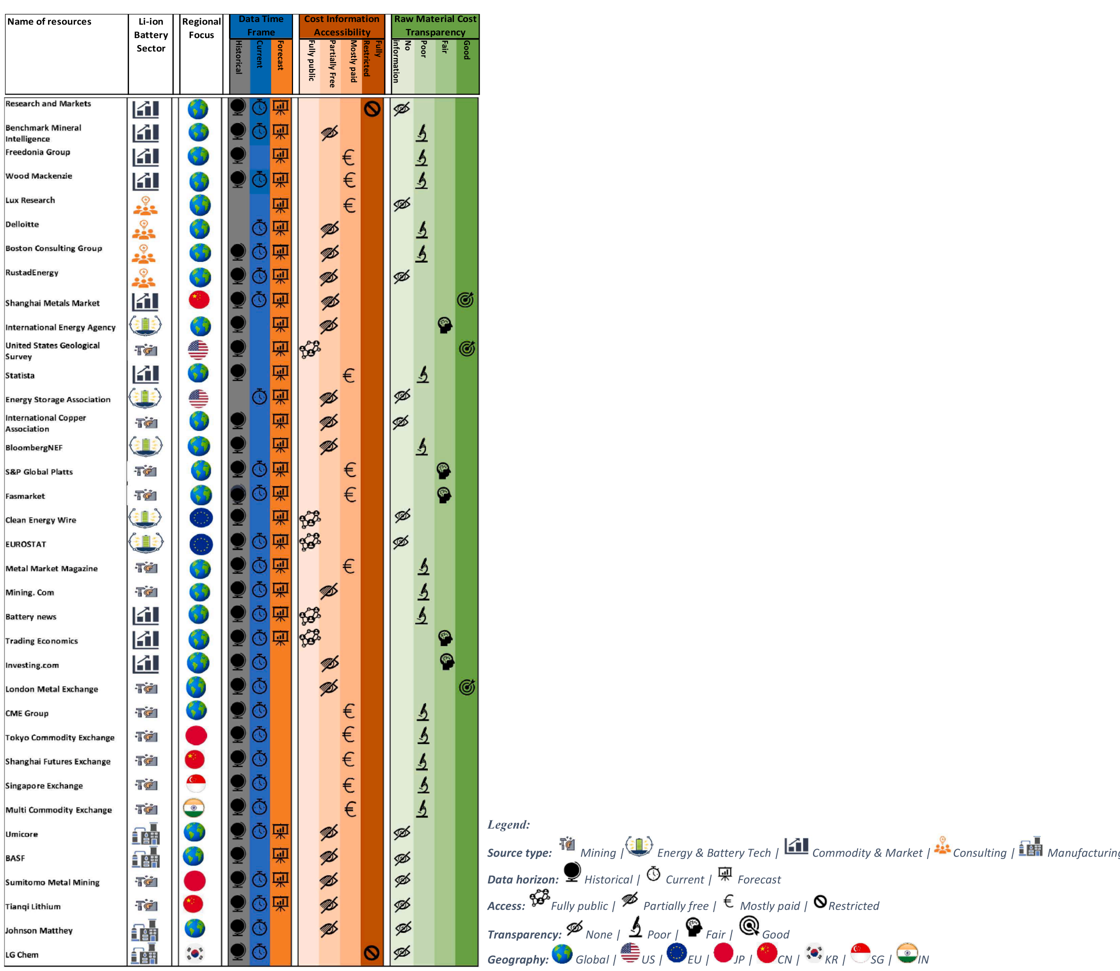

Fig. 5. Analysis of battery price resources.

life cycle cost assessments (LCC). Expanding recycling capacity is crucial for reducing both long-term costs and environmental impacts. Life Cycle Assessment (LCA) methods enable the quantification of emissions, land use, and resource depletion [74], while also capturing social and economic externalities such as health impacts and critical raw material dependencies [75].

To address these gaps, this section further elaborates a straightforward battery price data acquisition strategy aligned with the review findings. It recommends identifying missing data points (e.g., raw material prices, processing costs), integrating multiple data sources (e.g., trading platforms, institutional reports, supplier disclosures), and prioritizing transparency by leveraging open-access and verifiable datasets. This reflects lessons from models that lacked transparency and reusability, such as those relying on expert judgment or proprietary inputs [4,63]. Additionally, the strategy accounts for subscription-based barriers and calls for integrating uncertainty elements, such as market-driven price variability directly into cost model structures.

The fragmented nature of battery price data necessitates a structured approach to data collection with following key steps:

Identify gaps in data availability – evaluate missing price information for key raw materials, processing costs, and manufacturing expenses.

- Integrate multiple sources – combine market reports, trading platform data, supplier disclosures, and institutional reports.
- Assess data transparency – prioritize publicly available and verifiable sources for improved reliability (pedigree matrix).
- Account for subscription barriers – where necessary, allocate resources for premium data sources while cross-referencing with free datasets.
- Incorporate uncertainty factors – address price volatility and supply chain disruptions within cost models.

Despite its contributions, this study has certain limitations. The MCS-based forecasting approach, while effective, is limited by the availability and granularity of historical price data. Additionally, the comparative model evaluation focuses on selected models, leaving room for further exploration of alternative frameworks, such as hybrid cost models that integrate bottom-up and top-down approaches. Moreover, technological advancements, such as the development of solid-state batteries, could introduce new cost dynamics that require further investigation.

Future studies should expand cost modeling frameworks to include emerging battery chemistries and alternative materials, such as sodium-ion and lithium-sulphur batteries, to assess their long-term economic feasibility. Additionally, research should explore the integration of machine learning techniques into cost forecasting to improve prediction accuracy. Further efforts are also needed to standardize cost modeling methodologies by developing open-access datasets and transparent modeling frameworks to enhance cost assessment reliability across industry and academia. Lastly, deeper investigation into policy impacts, circular economy approaches, and life cycle sustainability assessments can provide more holistic insights into battery cost modeling and future market trends.

6. Conclusion

As the battery industry expands in response to growing demand for electric vehicles and stationary energy storage, accurate and adaptable cost modeling becomes essential. This study demonstrates that raw material price volatility is a critical determinant of lithium-ion battery costs, with cathode active materials accounting for up to 40% of cell-level expenditures and driving sensitivities of +20–60% under market shocks. By integrating Monte Carlo simulations and real-world commodity price data into cost analyses, the research illustrates a practical approach to capturing the uncertainty inherent in battery material markets. The study suggests a straight-forward cost estimation, particularly for CAMs such as NMC-111, NMC-811, and NMC-9525.

To address these gaps, we propose minimum disclosure standards, systematic integration of high-volatility scenarios, and the adoption of structured, open-access data acquisition strategies. A comparative evaluation of major battery cost models, including BatPaC, GREET®, EverBATT, and CellEST, reveals that assumptions about raw material pricing play an essential role in shaping battery cost projections. This work advocates for the advancement of cost models that are not only technically rigorous but also responsive to market dynamics. Additionally, the structured data collection strategy developed in this study tackles the fragmentation and limited accessibility of battery price data, enabling more consistent and transparent cost assessments.

Regulators can integrate volatility-adjusted cost robustness metrics when curating models for public programmes or technical standards, thereby promoting methodological consistency across analyses that underpin EV incentive schemes and grid-storage planning. We recommend: (i) establishing minimum disclosure requirements for cost models used in policy contexts, (ii) incorporating high-volatility market scenarios into standardised assessments and (iii) publishing anonymised bill-of-materials splits to enable independent benchmarking and model validation.

Advancing battery cost models depends on integrating diverse and credible data sources, including market analyses, institutional datasets, metal exchanges, and corporate disclosures. Despite ongoing challenges such as data inconsistency, restricted access, and high price volatility, this research suggests the cross-source integration and targeted data acquisition strategy to close existing gaps in cost modeling. By adopting these practices, researchers, policymakers, and industry stakeholders can strengthen decision-making processes and improve the accuracy of future LIB cost forecasts.

CRediT authorship contribution statement

Viera Pechancová: Writing – review & editing, Writing – original draft, Validation, Supervision, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Lucie Hrbáčková:** Writing – review & editing, Writing – original draft, Visualization, Validation, Formal analysis, Data curation. **Hüseyin Ersoy:** Writing – review & editing, Writing – original draft, Visualization, Formal analysis, Data curation. **Manuel Baumann:** Writing – review & editing, Writing – original draft, Formal analysis, Data curation. **Drahomíra Pavelková:** Writing – review & editing, Writing – original draft. **Debashri Paul:** Writing – review & editing, Writing – original draft, Data curation. **Anna Ivanichenko:** Writing – review & editing, Writing – original draft, Visualization, Data curation. **Jens Buchgeister:** Writing – review & editing, Writing – original draft. **Manish Kumar:** Writing – review & editing, Writing – original draft.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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