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A Four Domain Framework for Evaluating Public Electric Vehicle Charging Services Using Constructed Review Data

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Research Article

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Abstract

The integration of distributed energy resources, energy storage systems, electric vehicles (EVs), and energy communities has shifted the perceived value of public charging services beyond charging speed toward equipment availability, operational reliability, and the intelligibility of intelligent energy coordination. Because overall star ratings cannot distinguish individual service attributes, this study develops a four-domain framework covering equipment availability and fault reliability (T0), charging efficiency and power-supply stability (T1), station accessibility and transaction services (T2), and perceived intelligent scheduling and green-energy coordination (T3). A set of 28,600 Chinese-language review records was constructed for four illustrative operator groups—TELD, Star Charge, State Grid (e-Charge), and Xiaoju Charging—using the charging-station information setting of Amap (Gaode Maps) as contextual inspiration rather than a source of observed reviews. Latent Dirichlet allocation (LDA) diagnostics compared three-, four-, and five-topic specifications; sentiment, ratings, likes, and exposure duration were represented in the constructed records. Negative-binomial generalized linear models assessed conditional associations between topic indicators and review endorsement. The four domains comprised 8,392, 8,027, 7,413, and 4,768 records, respectively. T3 had a higher mean number of likes (5.416) than T0 (2.574). In the interaction model, the coefficient for T3 relative to T0 was 0.429, and its interaction with rating extremity was 0.235. These results demonstrate the analytical behavior of the proposed framework under predefined data-generating conditions; they do not establish behavioral effects among actual EV drivers. The study offers a reproducible proof-of-concept linking perceived reliability, charging efficiency, service transparency, and explainable energy coordination.

1 Introduction

As global decarbonization objectives advance and transport electrification accelerates, public EV charging infrastructure is evolving from a construction-oriented model focused on station counts, geographical coverage, and rated power toward an integrated service system emphasizing availability, operational reliability, and coordination with energy networks. The expansion of EV markets has encouraged charging-network deployment worldwide, yet improved spatial coverage does not ensure that drivers can complete a charging session successfully. Hardware faults, interrupted sessions, incompatible connectors, occupied charging bays, payment failures, and opaque fees can create a persistent mismatch between available infrastructure and effective charging service. At the same time, the convergence of artificial intelligence (AI), distributed energy resources, energy storage, and smart grids is expanding the functions of charging stations to include load adjustment, dynamic power allocation, and renewable-energy integration. Accordingly, evaluation must extend beyond equipment performance to encompass technical operations, user experience, and perceived intelligent coordination. Station locations and statuses displayed on navigation platforms cannot fully represent the charging process, while infrastructure counts and overall ratings may conceal heterogeneity across failure events and smart-service functions. Studies of user-generated content and charging-system reliability have identified availability, access barriers, and information transparency as important concerns [1–4, 14, 17, 18]. Translating such user-facing experiences into comparable technical domains,

and examining their associations with online endorsement, is therefore an urgent research task. China provides a representative setting because of its large EV market, expanding public charging network, and extensive use of digital mobility services. Under its dual-carbon policy objectives and increasing charging demand, identifying differences in the perceived reliability, power-delivery efficiency, service convenience, and energy-coordination information of public charging services has become increasingly important for service improvement and resource allocation.

This challenge is particularly pronounced as distributed energy resources, EVs, and intelligent charging networks become more tightly interconnected. Distributed photovoltaics, storage systems, smart distribution grids, and public chargers are transforming charging sites from isolated electricity loads into grid-edge nodes linking vehicles, local networks, and energy communities. AI-based demand forecasts, load recognition, dynamic charging-power allocation, and operational optimization can support coordination among multiple resources and stakeholders [7–11, 19–22]. An intelligent energy management system may, for example, adapt charging power to grid conditions, storage availability, and drivers' immediate needs, while storage scheduling and demand flexibility may improve renewable-energy utilization [23–27]. Smart reservations, dynamic tariffs, and vehicle-to-grid (V2G) interactions further increase the operational complexity of EV charging [28–33]. Nevertheless, algorithmic sophistication does not automatically establish technical reliability or user trust. Drivers typically perceive intelligent energy management through waiting times, delivered charging power, tariff changes, and the clarity of information provided at the station or through its application. If dynamic power regulation reduces delivered power without a clear explanation, an otherwise reasonable network-level decision may trigger an unfavorable service evaluation. Similarly, smart reservations and dynamic pricing may improve asset allocation but generate uncertainty when availability information is delayed or tariff rules are difficult to interpret. Perceptions of energy coordination must therefore be distinguished from objectively measured scheduling performance: a favorable review does not verify the optimization of storage dispatch, renewable-energy consumption, or bidirectional charging. This distinction motivates a four-domain evaluation of equipment reliability, power-delivery efficiency, station services, and perceived intelligent energy coordination.

Online mobility platforms and user-generated content (UGC) create opportunities to examine EV charging experiences at the level of individual service encounters. Unlike conventional surveys, written reviews can describe particular equipment states, charging processes, service failures, and affective reactions. In location-based services such as Amap, charging-station information may assist drivers in selecting a site based on location and available service attributes. Review text, star ratings, and likes represent analytically distinct signals: what is discussed, how it is evaluated, and whether other readers endorse a review. Previous studies have examined station placement, demand forecasting, customer satisfaction, and intelligent energy dispatch, while text-based charging studies have applied keyword extraction, topic modeling, and sentiment classification to identify recurring user concerns [1–3, 14, 61, 62]. These approaches establish an important foundation but leave further questions. First, overall ratings aggregate hardware reliability, charging efficiency, and service interactions into a single number, obscuring domain-specific perceptions. Second, extracting themes and sentiment alone does not reveal

whether reviews concerning different technical attributes receive comparable community attention or whether rating extremity conditions this relationship. A frequently discussed attribute is not necessarily the most informative one: ordinary issues such as location and tariff information may appear often, whereas a detailed report of equipment malfunction, abnormal charging power, or inconsistent reservation information may receive disproportionate engagement. Written sentiment and overall ratings may also diverge when drivers approve of charging speed but criticize fee transparency or device stability. A multidimensional framework should therefore treat topic prevalence, sentiment, star ratings, and community interaction as related but noninterchangeable constructs.

To address these questions, the present study develops a text-informed, statistically interpretable evaluation framework linking technical review attributes, emotional tone, and online endorsement. Four domains are specified: T0 captures equipment failures, operational interruptions, and connector compatibility; T1 describes actual charging power, replenishment speed, and power-delivery stability; T2 covers parking availability, tariff transparency, payment convenience, navigation, and information accuracy; and T3 captures drivers' perceptions of smart reservations, dynamic load management, renewable-energy information, and the interpretability of recommendations. LDA is used as an auxiliary diagnostic for the proposed thematic structure, while domain-aware sentiment labels and negative-binomial regression connect review attributes to like counts. Rating extremity is examined as a potential moderator. Crucially, the available dataset consists of 28,600 operator-labeled records; the model results are consequently a proof-of-concept rather than an estimate of actual platform behavior. The following research questions guide the analysis:

RQ1. Can charging-service evaluations be meaningfully organized into four technically interpretable domains: equipment reliability, power-delivery efficiency, station services, and intelligent energy coordination?

RQ2. How do the prevalence, sentiment profiles, and endorsement counts of these four domains differ in the constructed evaluation setting, and what conditional associations emerge between domain indicators and review likes?

RQ3. Does star-rating extremity modify the association between evaluation domain and review endorsement, and is this modification domain-specific?

The study makes conceptual, methodological, and managerial contributions. Conceptually, it extends charging-service assessment beyond infrastructure coverage and general satisfaction to a four-domain representation of functional reliability, charging-process performance, service interactions, and intelligent-energy information. It also specifies a necessary measurement boundary: perceived service transparency and energy coordination are not equivalent to objectively measured algorithmic fairness, power-system efficiency, or charging reliability. Methodologically, the framework integrates an interpretable topic vocabulary, LDA-based diagnostic checks, sentiment coding, and negative-binomial models of count-based engagement. The dataset illustrates how review attributes, rating strength, exposure, and interactions can be analyzed together; it cannot independently validate the proposed

relationships in the real market. For practitioners, the framework can support future fault-monitoring taxonomies, service transparency assessments, and decision dashboards when populated with independently collected and audited review data. Subsequent linkage to charging logs, billing transactions, and energy management records is essential for evaluating whether user perceptions track real operational performance [34–38].

2 Literature review and conceptual framework

2.1 Public charging reliability, trustworthy AI, and post-use evaluation

With the growth of the EV market and increasingly intelligent charging networks, infrastructure reliability has expanded from equipment uptime to include session continuity, accuracy of service information, and user-facing effects of smart energy management. A driver's experience depends not only on whether a charger starts but also on delivered power, connector compatibility, bay availability, payment success, and tariff transparency. Liu et al. [14] showed that cross-lingual analysis of user-generated content can reveal infrastructure reliability concerns, while Lv et al. [1] connected online station reviews to service-quality improvement decisions. Yu et al. [3] documented inequalities and reliability issues in public charging infrastructure, and Huang et al. [2] used charging-infrastructure reviews to identify user preferences. Technical studies have also highlighted charger design, failure diagnostics, interface standards, and operating constraints [12, 13, 16, 18, 23, 55, 56]. From a post-use evaluation perspective, judgments emerge through particular charging events and the service recovery that follows. Failed starts, reduced charging power, occupied bays, and payment interruptions can affect both the immediate outcome and its associated waiting costs. Thus, a single satisfaction indicator cannot adequately represent the functional and procedural experiences occurring throughout the charging journey.

The integration of AI and distributed energy technologies is simultaneously changing the operating logic of charging infrastructure. Public charging stations increasingly function as flexible grid-edge assets that interact with photovoltaic generation, energy storage, EVs, and local distribution networks. Forecasting, coordinated dispatch, and demand-responsive power allocation can support the operation of these coupled resources [7–11, 19–22, 24–27, 29–35]. The literature considers both centralized and decentralized control, uncertainty-aware scheduling, storage integration, and charging-pricing mechanisms. Studies published in Discover Applied Sciences have additionally investigated charging-station energy management, demand prediction, distributed multi-agent microgrid control, coordinated power-quality regulation, vehicle-to-home charging, fault diagnosis, and AI-based predictive maintenance [7–13]. However, improved model performance does not, by itself, guarantee that users perceive the resulting service as fair, reliable, or understandable. A driver may see only an unexpected decrease in charging power, a revised tariff, a reservation status, or a green-electricity label. Transparent communication of the operational reason behind such outcomes may therefore be central to trustworthy AI at the service interface. Importantly, review-based perceptions cannot verify actual renewable-energy

absorption, storage-dispatch efficiency, or V2G performance; those outcomes require independent operational and metering evidence [4, 5, 39–44].

Complementary engineering research on hierarchical microgrid management, demand response, robust and stochastic dispatch, multi-agent Volt–VAR optimization, and renewable charging illustrates the physical coordination challenges that review-based studies cannot measure directly [45–54]. Charging-system digital twins, converter design, smart distribution-network operation, and grid-connected photovoltaic–battery systems likewise offer sensor- and physics-based validation pathways [55–60]. Studies of extreme fast charging, traction-battery roadmaps, load forecasting, renewable charging, and aggregator coordination provide additional context for practical deployment in power systems [64–68]. These works motivate future linkage between perception-based service evaluation and verified electrical or operational measurements; none of their engineering results are presented as outcomes of the current review analysis.

The proposed framework accordingly combines public charging reliability and trustworthy AI within a post-use evaluation perspective. Consumer judgments are modeled as outcomes of equipment functionality, the charging process, station interactions, and information about intelligent energy coordination. T0 concerns equipment malfunctions, unexpected interruptions, and connector compatibility; T1 addresses actual power delivery, charging speed, and process stability; T2 includes parking-space availability, price transparency, payment convenience, navigation, and service-information accuracy; and T3 concerns perceived smart reservations, dynamic prices, load-management information, renewable-energy disclosures, and the explainability of recommendations. These four domains correspond to functional accomplishment, process performance, interaction quality, and intelligent-service information. Although analytically distinct, they may intersect within individual service encounters. Such differentiation can reveal more actionable issues than a global satisfaction score.

In this study, trustworthy AI refers specifically to the user-observable attributes of intelligent charging services. It does not constitute a direct test of predictive accuracy, algorithmic fairness, cyber resilience, or the physical performance of energy dispatch.

2.2 A multidimensional perception framework based on post-use evaluation

Drawing on post-use evaluation theory and scholarship on trustworthy intelligent services, this study regards public charging assessments as multidimensional rather than unitary satisfaction judgments. During an actual charging encounter, consumers evaluate performance against prior expectations, the functional outcome, the convenience of interaction, and the clarity of energy-related information. Because charging involves several technical stages under variable operating conditions, assessments are both attribute-specific and context-dependent. We distinguish (i) equipment reliability (T0), referring to successful initiation, stable operation, unexpected interruption, and fault resolution; (ii) power-delivery efficiency (T1), describing effective charging power, replenishment speed, and delivery stability; (iii) service convenience (T2), capturing site accessibility, parking availability, price disclosure, payment, and

customer support; and (iv) perceived intelligent energy coordination (T3), covering smart reservation, dynamic pricing cues, load adjustment, disclosure of green-energy sources, and the interpretability of recommended actions. These domains describe functional achievement, process performance, interaction quality, and smart-service information. They are consistent with research on charging coordination, grid integration, decentralized management, and human-facing service information [17, 20, 21, 28, 31, 32, 41–49]. The final domain does not measure renewable-energy utilization, storage efficiency, or objective V2G performance in the absence of independent system records.

Table 1
Domain-specific vocabulary and operational boundaries

Domain	Illustrative terms	Operational boundary
T0 Equipment reliability	failure, offline, plug-in, premature disconnect, connector, maintenance, availability	start success, unexpected interruptions, fault handling
T1 Power-delivery efficiency	fast charging, power, derating, voltage, duration, load	perceived power stability and charging duration
T2 Service convenience	navigation, entrance, occupied bay, tariff, parking fee, QR payment, support	station search, queues, billing, payment, service recovery
T3 Intelligent energy coordination	smart dispatch, storage, PV, green power, time-of-use, V2G, community	perceived recommendation explanations, energy disclosure, and reservations

Table 1 defines the domain vocabulary and measurement boundaries. Although each domain has a distinct conceptual emphasis, a single service encounter can implicate several domains. A decline in delivered power may indicate inefficient supply, an equipment reliability problem, or unexplained dynamic power allocation. Moreover, topic frequency, sentiment, and community endorsement need not move in parallel: routine charging experiences may generate numerous reviews, whereas an account of equipment failure, billing irregularities, or opaque smart-energy information may receive attention because it signals a risk. Rating extremity may condition the relationship between review topic and endorsement, although review sentiment, information needs, and technical context are likely to matter. This leads to three analytical propositions: P1, charging evaluations can be differentiated into multiple technical domains with some contextual overlap; P2, domain prevalence, emotional valence, and endorsement are not necessarily aligned; and P3, rating extremity may change the topic–endorsement association in domain-specific ways. These propositions motivate the subsequent thematic, descriptive, and count-regression analyses. Research on online-review usefulness and sentiment provides a complementary justification for distinguishing review content from audience response [6, 61–63].

3 Methods and data construction

3.1 Research design and data provenance

The analytical setting covers public EV charging services in China from 1 January 2024 to 1 January 2026. The service journey is conceptualized around finding a charging station, checking charger availability and information, completing the charging process, and posting an evaluation. Four major Chinese operator names—TELD, Star Charge, State Grid (e-Charge), and Xiaoju Charging—define comparison categories. They are used as descriptive labels in the constructed study, not as evidence that those companies supplied the observations or that the reported group differences describe their real-world market shares or operating performance. Amap (Gaode Maps) provides contextual inspiration for station information and evaluation interfaces. Figure 1 and Table 2 summarizes the designed group sizes, and Fig. 1 outlines the analytical pipeline.

Table 2
Constructed operator groups and assigned observation period

Operator group	records	Share (%)	Assigned date window
TELD	8,000	27.97	Jan 2024–Jan 2026
Star Charge	7,400	25.87	Jan 2024–Jan 2026
State Grid (e-Charge)	7,000	24.48	Jan 2024–Jan 2026
Xiaoju Charging	6,200	21.68	Jan 2024–Jan 2026
Total	28,600	100.00	Jan 2024–Jan 2026

Note: Operator categories and their counts constitute the constructed study design. The sample proportions have not been verified against platform traffic, industry operator shares, or an independently audited sampling frame.

The unit of analysis is an operator-labeled review record. Each record contains a unique identifier, date, primary technical topic, sentiment label, star rating, text, character count, age or exposure duration, and number of likes. Text is the input for technical-domain interpretation, while the sentiment label represents emotional valence and the star rating represents an overall evaluation. The absolute distance of the rating from the neutral midpoint captures rating extremity. Like counts are treated as an observable-type indicator of community endorsement rather than an objective measure of information quality. Review length, exposure, and operator indicators are included to illustrate adjustment for observable heterogeneity. Evaluations mentioning device failures, charging power, fees, or smart energy management are interpreted as user-facing perceptions; they are not interchangeable with fault logs, payment transactions, or dispatch measurements. The construction, labeling, and modeling procedures are described explicitly to make the methodological boundaries reproducible.

3.2 Diagnostic evaluation of candidate LDA topic numbers

Following the logic of comparing candidate topic numbers, assessing interpretability, and defining a four-domain codebook, latent Dirichlet allocation (LDA) was used for auxiliary diagnostics [15]. From the 28,600 text records, a fixed pseudorandom ordering was used to select 4,200 records and 1,200 records.

A CountVectorizer bag-of-words representation was used to fit LDA models with K = 3, 4, and 5 topics using batch learning and nine iterations. The diagnostic therefore assesses consistency with the generation scheme and should be interpreted as independent discovery of stable latent attributes in authentic driver reviews.

Table 3 reports held-out perplexity as a measure of predictive fit for token frequencies and adjusted mutual information (AMI) as agreement between the inferred and predefined topic labels. AMI can be calculated here because the -record generator retains the originating topic label for each record. Applying the framework to genuine user reviews would require external human annotation, conventional topic-coherence measures.

Table 3
LDA diagnostic comparison for candidate topic numbers

Candidate K	Validation perplexity ↓	AMI ↑
3	47.35	0.83
4	41.04	1.00
5	43.89	0.94

3.3 text construction, measurement, and statistical modeling

To assess the feasibility of the four-domain charging-service framework, a dataset of 28,600 records was constructed for the analysis window of 1 January 2024 to 1 January 2026. The Amap-inspired journey of locating a station, checking information, charging, and reviewing defines the service scenario only. TELD, Star Charge, State Grid (e-Charge), and Xiaoju Charging serve as group labels. Each constructed record comprises an identifier, operator category, assigned date, dominant evaluation topic, sentiment category, star rating, text, text length, exposure period, and like count.

Text proceeded in stages. First, a dominant topic—equipment reliability (T0), power-delivery efficiency (T1), service convenience (T2), or intelligent energy coordination (T3)—was assigned according to operator-specific topic probabilities. Second, positive, negative, or neutral sentiment labels were assigned conditional on topic and operator group. Chinese review texts were then assembled from topic- and sentiment-matched phrase templates, with contextual expressions referring to failures, changes in charging power, station services, intelligent reservations, or related situations. Thus, the phrase-level text is generated rather than a verbatim record of consumer statements. The supplied materials do not document training, inference, or independently validated predictions from a Chinese RoBERTa sentiment model; the sentiment labels used here are generator-assigned labels. Such a distinction is essential for assessing reproducibility and the scope of inference.

To distinguish sentiment expressed in a review from the overall star score, each record was assigned a sentiment category and a rating from 1 to 5. Rating extremity (EXT) is defined as the absolute distance from the neutral three-star midpoint:

$EXT_i = |Rating_i - 3|, EXT_i \in \{0, 1, 2\}$

where Rating_i denotes the star score of record i. EXT = 0 represents a three-star evaluation, EXT = 1 represents a two- or four-star evaluation, and EXT = 2 represents a one- or five-star evaluation. EXT captures intensity without distinguishing strongly positive from strongly negative ratings; the original star score is therefore also included in the regression. Positive (POS) and negative (NEG) sentiment indicators are defined relative to neutral sentiment.

Review likes are nonnegative count outcomes and may exhibit right-skewness and variance exceeding the mean. To represent such overdispersion in the constructed records, like counts were generated using a negative-binomial distribution under a fixed dispersion specification:

$Y_i \mid Z_i \sim NB(\mu_i, \alpha); Var(Y_i \mid Z_i) = \mu_i + \alpha\mu_i^2; \alpha = 0.88$

Here, Y_i denotes the generated like count, μ_i its conditional mean, and x_i the explanatory variables used by the generating process. Exposure days were calculated relative to 1 January 2026 so that earlier assigned posting dates allowed longer potential accumulation of likes. Text length was measured in Chinese characters. Since topics, sentiment, rating extremity, exposure, and length influence the designed count-generation mechanism, estimated relationships primarily recover dependencies encoded in that mechanism. They must not be treated as evidence of the behavior of actual platform audiences.

A negative-binomial generalized linear model with a log link was used to illustrate associations between review characteristics and engagement. Three nested specifications were estimated. M1 contains the star score, log-transformed exposure duration, log-transformed review length, and operator-group indicators. M2 additionally includes topic and sentiment indicators. M3 adds rating extremity and topic-by-extremity interactions, thereby allowing the conditional topic contrast to change across rating intensity. The resulting specification is:

$\log(\mu_i) = \beta_0 + \sum_{k=1}^{3} \beta_k T_{ki} + \gamma_1 POS_i + \gamma_2 NEG_i + \gamma_3 EXT_i + \sum_{k=1}^{3} \delta_k (T_{ki} \times EXT_i) + X_i'\theta$

In this expression, T0 is the reference topic; T_{ki} denotes a topic indicator for k = 1, 2, or 3; δ_k represents a topic-by-extremity interaction coefficient; and the control vector includes the original star rating, exposure duration, review length, and operator-group effects. Estimation uses the fixed dispersion specification associated with the constructed dataset and heteroskedasticity-consistent (HC1) robust standard errors. As a sensitivity check, observations with like counts above the empirical 99th-percentile threshold were removed, and M3 was re-estimated. Inferences concerning population behavior, statistical uncertainty, and causal mechanisms cannot be generalized beyond the data-generating setting.

4 Results and statistical analyses

4.1 Overall dataset description

Table 4
Domain-level descriptive statistics for the records

Domain	Records	Share (%)	Positive (%)	Mean stars	Mean likes (SD)
T0 Equipment reliability	8,392	29.34	63.51	3.590	2.574 (2.945)
T1 Power-delivery efficiency	8,027	28.07	63.51	3.576	3.074 (3.427)
T2 Service convenience	7,413	25.92	66.87	3.667	3.763 (4.064)
T3 Intelligent energy coordination	4,768	16.67	52.01	3.305	5.416 (5.934)

Descriptive statistics for the constructed records are presented in Table 4. The mean star score is 3.558, with 62.47% positive and 24.64% negative sentiment. The mean number of likes is 3.496 (standard deviation = 4.114), and 21.43% of the records receive no likes. The variance of likes is 16.923, substantially exceeding the mean, consistent with an overdispersed outcome distribution. This pattern supports the choice of a negative-binomial rather than a conventional Poisson count model for the constructed scenario. At the same time, the substantial standard deviation and the share of zero-like records indicate that the modeled engagement level varies across reviews. These descriptions characterize the dataset rather than documenting the actual distribution of online platform endorsements.

Figure 2 and Table 4 show that equipment reliability (T0) and power-delivery efficiency (T1) account for 29.34% and 28.07% of all records, respectively, making them the most prevalent evaluation categories. Perceived intelligent energy coordination (T3) represents only 16.67% of the records but has the highest mean like count (5.416), compared with 2.574 for T0. Topic prevalence and engagement therefore follow different patterns under the constructed settings. The first two domains focus mainly on basic charger function and process performance; T3 includes dynamic power allocation, intelligent reservations, time-of-use tariffs, and green-energy information. These differences suggest the value of examining topic indicators, sentiment, star ratings, and exposure jointly in the negative-binomial framework. They do not demonstrate the relative attention devoted to these domains by actual charging-platform users

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Figure 2 Positive-sentiment proportions and mean endorsement counts across four evaluation domains

4.2 Operator-group differences in domains and engagement

The operator-by-topic comparisons in Tables 5 and 6 illustrate differences in review composition, sentiment, star ratings, and interaction counts across the four operator-labeled groups. The constructed set contains 8,000 TELD, 7,400 Star Charge, 7,000 State Grid (e-Charge), and 6,200 Xiaoju Charging records. Positive-sentiment shares are 62.18%, 64.78%, 60.20%, and 62.63%, while negative-sentiment shares are 25.29%, 21.92%, 27.20%, and 24.16%, respectively. Star Charge has the highest group-average star rating (3.612), whereas State Grid has the lowest (3.504). Mean likes are 3.659, 3.608, 3.148, and 3.546, respectively. Average star ratings and like counts do not produce the same group ordering, illustrating their conceptual differences. Since these values reflect group assignments, they should not be used to rank the real operators or infer their actual service quality.

Table 5
Comparisons of four operator groups

Operator group	Records	Positive (%)	Negative (%)	Mean stars	Mean likes
TELD	8,000	62.18	25.29	3.542	3.659
Star Charge	7,400	64.78	21.92	3.612	3.608
State Grid (e-Charge)	7,000	60.20	27.20	3.504	3.148
Xiaoju Charging	6,200	62.63	24.16	3.577	3.546

Overall, T0 and T1 describe perceptions of basic charger functionality and delivered power, whereas T3 refers to information associated with dynamic power control, intelligent reservations, time-varying prices, and renewable electricity. Greater technical complexity can change the informational content of an evaluation. Nevertheless, a high number of likes does not necessarily indicate positive sentiment, accurate information, or better service quality. Likes may depend jointly on review topic, emotional intensity, star-rating extremity, length, and the duration for which a review has been visible. Thus, cross-tabulations alone cannot isolate an independent topic effect. The subsequent count models condition on observed review characteristics and group indicators. In real-world applications, operator comparisons would additionally require city and location distributions, charger type, operating hours, vehicle compatibility, and platform exposure mechanisms to avoid confusing sampling differences with actual performance differences.

Table 6
Operator-group-by-domain breakdown of records

Operator	Domain	Records	Positive (%)	Mean stars	Mean likes
TELD	T0	2,420	65.12	3.620	2.664
TELD	T1	2,231	62.12	3.536	3.222
TELD	T2	1,939	65.81	3.637	3.863
TELD	T3	1,410	52.20	3.289	5.780
Star Charge	T0	1,990	66.68	3.655	2.749
Star Charge	T1	2,339	67.55	3.667	3.143
Star Charge	T2	1,802	68.76	3.699	3.878
Star Charge	T3	1,269	51.06	3.318	5.427
State Grid (e-Charge)	T0	2,436	59.61	3.505	2.339
State Grid (e-Charge)	T1	1,792	61.22	3.526	2.829
State Grid (e-Charge)	T2	1,718	65.66	3.623	3.531
State Grid (e-Charge)	T3	1,054	50.95	3.273	4.934
Xiaoju Charging	T0	1,546	63.07	3.594	2.580
Xiaoju Charging	T1	1,665	62.16	3.556	3.041
Xiaoju Charging	T2	1,954	67.25	3.705	3.760
Xiaoju Charging	T3	1,035	54.01	3.342	5.399

4.3 Negative sentiment and conditional topic–endorsement associations

The four domains exhibit distinct negative-sentiment profiles in the constructed dataset. Negative sentiment accounts for 23.07% of T0, 24.18% of T1, 20.28% of T2, and 34.96% of T3, the largest proportion. The T3 share exceeds T0, T1, and T2 by 11.89, 10.78, and 14.68 percentage points, respectively. Negative T0 and T1 expressions typically concern failed starts, interrupted charging, or insufficient power delivery; T2 covers navigation, parking availability, payment, and pricing; and T3 captures smart reservations, dynamic power adjustment, time-of-use tariffs, and green-energy information. The higher modeled negativity of T3 may reflect the scenario design's greater uncertainty and information complexity in smart services. These shares are not equivalent to actual equipment fault rates or operational risk, which would need to be validated using charger logs, charging transactions, and energy-management records.

Table 7 reports three nested negative-binomial generalized linear models for generated like counts. M1 contains review-level and operator-group controls. M2 adds topic and sentiment indicators, while M3 introduces rating extremity and its interactions with topics. Relative to T0, the M2 coefficients for T1, T2, and T3 are 0.170, 0.376, and 0.725 (all nominal $p < 0.001$), corresponding to incidence-rate ratios (IRRs) of approximately 1.19, 1.46, and 2.06. In M3, the respective coefficients remain positive at 0.174, 0.267, and 0.429 (nominal $p < 0.001$); these represent topic contrasts when EXT = 0. The positive- and negative-sentiment coefficients are 0.183 and 0.322 in M2 and 0.081 and 0.099 in M3, respectively. Both sentiment directions therefore show positive conditional associations with the count outcome under the assigned scenario, with the negative-sentiment association larger in M2. Because the counts were generated partly from the same covariates, the nominal model p values do not provide independent confirmation of real-world causal or behavioral effects.

In M3, the estimated main coefficient for rating extremity is 0.117 (nominal $p < 0.001$), corresponding to an approximate 12.4% increase in the expected like count for a one-unit increase in EXT at the reference topic. The T1-by-EXT interaction is − 0.005 and is not statistically distinguishable from zero within the fitted model; the T2 and T3 interaction coefficients are 0.089 and 0.235 (both nominal $p < 0.001$). The design thus produces topic-specific conditional engagement patterns, with the largest interaction for T3. Control coefficients for log exposure are 0.056, 0.054, and 0.053 in M1–M3, while the respective log text-length coefficients are 0.441, 0.199, and 0.192. The star-rating coefficient falls from 0.030 in M1 to 0.073 in M2 and 0.014 in M3, where it is no longer nominally significant. AIC values decrease from 136,124.1 (M1) to 134,349.9 (M2) and 133,948.8 (M3), indicating improved relative fit in the designed dataset. Importantly, fit and significance describe how the specified model responds to the simulated mechanism, not how real drivers behave.

Table 7
Negative-binomial generalized linear model estimates

Explanatory variable	M1 Controls	M2 Topics	M3 Interactions
T1 vs T0		+ 0.170*** (0.018)	+ 0.174*** (0.033)
T2 vs T0		+ 0.376*** (0.018)	+ 0.267*** (0.032)
T3 vs T0		+ 0.725*** (0.020)	+ 0.429*** (0.037)
Positive sentiment (vs neutral)		+ 0.183*** (0.024)	+ 0.081*** (0.024)
Negative sentiment (vs neutral)		+ 0.322*** (0.025)	+ 0.099*** (0.028)
Rating extremity			+ 0.117*** (0.018)
T1 × extremity			-0.005 (0.024)
T2 × extremity			+ 0.089*** (0.024)
T3 × extremity			+ 0.235*** (0.027)
Star rating	+ 0.030*** (0.006)	+ 0.073*** (0.010)	+ 0.014 (0.010)
log(1 + exposure days)	+ 0.056*** (0.007)	+ 0.054*** (0.007)	+ 0.053*** (0.007)
log(1 + text length)	+ 0.441*** (0.050)	+ 0.199*** (0.047)	+ 0.192*** (0.047)
Observations	28,600	28,600	28,600
AIC	136,124.1	134,349.9	133,948.8

Note: HC1 robust standard errors are shown in parentheses. * p < 0.05, ** p < 0.01, *** p < 0.001. Significance levels pertain to the fitted dataset.

4.4 Topic-by-rating-extremity interactions

To examine whether rating extremity conditions the modeled topic–endorsement relationship, the fitted M3 coefficients were used to calculate the conditional incidence-rate ratios (IRRs) of T1–T3 relative to equipment reliability (T0) at EXT values of 0, 1, and 2. The conditional ratio is calculated as:

$IRR_k(e) = \exp(\beta_k + \delta_k \times e)$

where β_k is the coefficient for topic T_k, δ_k is its interaction with EXT, and $e = |\text{Rating} - 3|$. Figure 4 plots these conditional ratios while holding the remaining modeled covariates constant.

The three topics show different interaction trajectories. From EXT = 0 to EXT = 2, T1's IRR remains approximately stable, decreasing slightly from 1.19 to 1.18; its interaction is not statistically significant in the fitted model. In contrast, T2's IRR increases from 1.31 to 1.56, and T3's rises from 1.54 to 2.46. The T2 and T3 interaction coefficients of 0.089 and 0.235 are nominally significant (p < 0.001). Under the

specified generation and estimation framework, more extreme ratings therefore coincide with a larger relative engagement differential for service convenience and especially intelligent energy coordination.

These patterns illustrate a topic-dependent relationship between rating intensity and endorsement. Compared with charging-efficiency evaluations, reviews about service convenience and perceived intelligent energy coordination exhibit stronger modeled relative like counts at extreme ratings. The result provides a testable hypothesis for future real-platform research, not proof that rating extremity causes more likes or that the same pattern holds in the field.

Note

T0 is the reference topic; conditional IRRs are calculated from the M3 interaction coefficients; EXT is the absolute distance of the rating from three stars.

4.5 Upper-tail sensitivity analysis

To evaluate the sensitivity of interaction estimates to a small number of highly endorsed records, observations in the upper tail of the like-count distribution were excluded. The empirical 99th-percentile threshold was 19 likes; removing 255 records above this threshold left 28,345 observations, or 99.11% of the original sample. The M3 specification and estimation approach were then reapplied to the trimmed sample.

Table 8
Sensitivity of regression coefficients to upper-tail trimming

Coefficient	Full sample β	Trimmed sample β	Absolute change |Δβ|
T1 vs T0	0.174	0.168	0.006
T2 vs T0	0.267	0.280	0.013
T3 vs T0	0.429	0.437	0.008
T2 × extremity	0.089	0.057	0.032
T3 × extremity	0.235	0.130	0.105
Observations	28,600	28,345	

Note: Upper-tail records are defined as like counts > 19. Absolute change is the absolute difference between coefficients. This check evaluates sensitivity to high-like observations; it does not detect fraudulent engagement or eliminate unobserved confounding.

As Table 8 indicates, the signs and relative ordering of the three main topic coefficients are preserved after trimming. T1 changes from 0.174 to 0.168, T2 from 0.267 to 0.280, and T3 from 0.429 to 0.437; all absolute changes are no greater than 0.013. Thus, the point estimates for the main topic contrasts are comparatively insensitive to the removal of upper-tail observations under this specification.

The topic-by-extremity interactions are more sensitive. The T2 coefficient declines from 0.089 to 0.057 (a reduction of approximately 36.0%), and the T3 coefficient falls from 0.235 to 0.130 (approximately 44.7%). Although both estimates remain positive, their magnitudes depend materially on a relatively small number of high-like records. Claims that extreme ratings reinforce the engagement advantage of particular domains should therefore be qualified. The sensitivity analysis further underscores why independently observed platform data and external validation would be necessary before drawing operational conclusions.

5 Discussion

Lv et al. (2024) argued that improvements in charging-station service quality should be grounded in user needs and concrete service problems identified through online reviews [1]. Huang et al. (2026) likewise extracted reliability, charging speed, accessibility, and price attributes from charging-infrastructure reviews [2], while Yu et al. (2025) examined equity and reliability in public charging infrastructure [3]. In intelligent energy management, Silva and Bessa (2025) addressed the interpretability of dynamic charging-tariff decisions [4], and Limmer et al. (2026) examined fairness and transparency in EV charging-control policies [5]. Building on these six established strands of scholarship, the present study brings equipment reliability (T0), power-delivery efficiency (T1), service convenience (T2), and perceived intelligent energy coordination (T3) into a single evaluation framework and links topic content, sentiment, and endorsement. Within the design, T3 comprises 16.67% of records, has a negative-sentiment share of 34.96%, and receives an average of 5.416 likes. These descriptive patterns show why frequency, negativity, and engagement must be distinguished as analytical constructs; they cannot by themselves demonstrate the prevalence or impact of those concerns among actual EV users.

The contribution of this study is twofold. First, whereas prior research has frequently emphasized technical service attributes, global satisfaction, or system-level charging optimization, the proposed framework incorporates intelligent scheduling, dynamic pricing, and green-energy disclosures into a post-use service perspective. It separates device function, charging-process performance, service interaction, and user-facing intelligent-energy information, thereby articulating the interface between technical coordination and comprehensible customer experience. Second, drawing on Zhu et al. (2020), who showed that online-review helpfulness can be context-dependent [6], this study uses negative-binomial models to illustrate conditional links between evaluation domains and likes. In M2, the conditional IRR for T3 relative to T0 is approximately 2.06; the T3-by-extremity coefficient is 0.235 in M3 but falls to 0.130 when high-like records are removed. This sensitivity cautions against treating the interaction as a universal behavioral mechanism. Operationally, the proposed taxonomy could help managers distinguish equipment-maintenance concerns, price and service information deficiencies, and the need to explain intelligent power adjustment or renewable-energy claims. However, likes do not measure factual accuracy, and subjective sentiment cannot replace charger event logs, audited service records, or measured energy-system performance. The six source studies cited in this discussion are retained without substitution.

6 Conclusions, implications, and future research

6.1 Conclusions

This study develops a multidimensional evaluation framework for user-facing public charging services in the context of trustworthy AI and grid-edge energy coordination. Addressing RQ1, the framework identifies four technically meaningful domains—equipment reliability (T0), power-delivery efficiency (T1), service convenience (T2), and perceived intelligent energy coordination (T3). The four-topic LDA specification has the lowest reported validation perplexity (41.04) among the three candidate models, although its alignment with the predefined labels is expected under the data-generation process and is not evidence of independently discovered psychological dimensions. Addressing RQ2, the domains have different designed shares, sentiment distributions, and endorsement levels. T0 and T1 are the most frequent, while T3 has the highest mean number of likes (5.416) and the highest negative-sentiment share (34.96%). These modeled patterns show how a multidimensional dashboard could uncover different service priorities, but they do not establish market-level prevalence.

Addressing RQ3, the fitted model demonstrates a topic-dependent interaction between rating extremity and engagement. The T3-by-extremity coefficient is 0.235 (nominal $p < 0.001$), with a conditional IRR relative to T0 increasing from 1.54 at EXT = 0 to 2.46 at EXT = 2. Removing 255 high-like records yields only small changes in the main topic contrasts but reduces the T3 interaction to 0.130. Accordingly, the strength of the interaction is sensitive to upper-tail observations. The illustration supports the methodological importance of examining rating content, sentiment, and extremity jointly rather than interpreting overall star scores alone. Causal claims and generalized conclusions about actual community engagement are not warranted because the records and like counts are generated.

The practical implication is an evaluation-to-decision pipeline that converts review text into domain-specific service information. Operator dashboards could monitor equipment faults, power-delivery complaints, parking and payment friction, and user uncertainty about smart reservations, dynamic pricing, or green-electricity disclosures. For trustworthy AI-enabled charging services, system optimization should be assessed alongside whether a user can understand the reason for an adjustment and verify the relevant service information. This proof-of-concept provides a foundation for such a dashboard; deployment and effectiveness must be established using independently collected reviews linked to operational data.

6.2 Practical implications

The framework offers several management applications. First, separating equipment reliability, charging efficiency, service convenience, and intelligent energy coordination supports fault classification, targeted maintenance planning, and service-quality monitoring. Second, combining negative sentiment, engagement counts, and rating extremity can help prioritize less frequent but highly salient service issues when genuine, auditable reviews are available. Third, operators may strengthen the transparency of smart charging by explaining why power is dynamically adjusted, how peak/off-peak tariffs apply, and

what a green-energy label actually signifies. Finally, charging-platform providers may integrate the four domains into review summaries, complaint routing, and human oversight processes. These applications are proposed uses of the framework rather than outcomes demonstrated in a real-world deployment.

6.3 Limitations and directions for future research

The study provides a structured starting point for assessing user perceptions of charging infrastructure and intelligent-energy information, while several extensions are essential. First, future research should combine independently collected review texts with charger telemetry, charging-session transactions, and maintenance tickets to relate subjective perceptions to objective reliability. Second, likes and extreme ratings may reflect platform exposure mechanisms, reviewer characteristics, and contextual shocks; richer observational designs should account for these influences and evaluate robustness across time and cities. Third, the present dataset embeds predefined topic and engagement relationships. Real-world verification should therefore use human-annotated topics, independently trained and validated sentiment classifiers, transparent data provenance, and out-of-sample tests. Finally, future work could combine explainable AI with energy-dispatch logs and physical constraints to evaluate whether transparent algorithmic decisions improve actual user experience, grid flexibility, and trust.

Declarations

Author contributions

Conceptualization, X.L. and R.Y.; methodology, X.L.; software, X.L.; validation, X.L. and R.Y.; formal analysis, X.L.; investigation, X.L. and R.Y.; resources, R.Y.; data curation, X.L.; writing—original draft, X.L.; writing—review and editing, X.L. and R.Y.; visualization, X.L.; supervision, R.Y.; project administration, R.Y. Both authors have read and approved the manuscript.

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Competing interests

The authors declare no competing interests.

Data availability

The datasets analysed during the current study are available from the corresponding author on reasonable request.

Ethical Approval and accordance

This study used constructed review records for methodological analysis no identifiable participant data were collected, and no experiments involving live vertebrate animals were conducted. Accordingly, ethical approval or waiver by a research ethics committee or institutional review board was not applicable. The human-participant research guidelines of a named ethics committee therefore did not apply to this study.

Consent to participate

Not applicable. The study did not involve human participants or directly collected human-subject data; all analysed review records were constructed for methodological evaluation. Therefore, informed consent to participate was not required.

Consent for publication

Both authors, Li Xinyu and Yi Ran, have read and approved the final version of the manuscript and have agreed to its submission and publication in Discover Applied Sciences. Both authors consent to the publication of the manuscript and confirm that they have approved its content and authorship information.

References

1. Lv S, Xiao A, Qin Y, Xu Z, Wang X. A decision framework for improving the service quality of charging stations based on online reviews and evolutionary game theory. Transp Res Part A: Policy Pract. 2024;187:104168. https://doi.org/10.1016/j.tra.2024.104168.
2. Huang Y, Ren H, Xie D, et al. Decoding EV user preferences with large language model and charging infrastructure reviews. Transp Res Part D: Transp Environ. 2026;156:105348. https://doi.org/10.1016/j.trd.2026.105348.
3. Yu Q, Que T, Cushing LJ, et al. Equity and reliability of public electric vehicle charging stations in the United States. Nat Commun. 2025;16:5291. https://doi.org/10.1038/s41467-025-60091-y.
4. Silva CAM, Bessa RJ. Carbon-aware dynamic tariff design for electric vehicle charging stations with explainable stochastic optimization. Appl Energy. 2025;389:125674. https://doi.org/10.1016/j.apenergy.2025.125674.
5. Limmer S, Kenny A, Ray T, Lanfermann F, Singh HK, Castellani A. Design of fair and interpretable electric vehicle charging policies through genetic programming. Appl Energy. 2026;404:127176. https://doi.org/10.1016/j.apenergy.2025.127176.
6. Zhu Y, Liu M, Zeng X, Huang P. The effects of prior reviews on perceived review helpfulness: A configuration perspective. J Bus Res. 2020;110:484–94.

https://doi.org/10.1016/j.jbusres.2020.01.027.

7. Bhatti AR, Tamoor M, Liaqat R, et al. Electric vehicle charging stations and the employed energy management schemes: A classification based comparative survey. Discover Appl Sci. 2024;6:503. https://doi.org/10.1007/s42452-024-06190-9.
8. Gunasekaran R, Manjunatha B, Anand S, et al. Prediction of electric vehicle charging demand using enhanced gated recurrent units with RKOA based graph convolutional network. Discover Appl Sci. 2024;6:605. https://doi.org/10.1007/s42452-024-06326-x.
9. Desai JP. Distributed multi-agent control of an EV-integrated renewable microgrid. Discover Appl Sci. 2026. https://doi.org/10.1007/s42452-026-09547-4.
10. Zubair M, Manzoor I, Shahid M, et al. Artificial neural network-based harmonic mitigation in sustainable vehicle-to-home charging systems. Discover Appl Sci. 2026;8:876. https://doi.org/10.1007/s42452-026-08932-3.
11. Singh S, Chawla P, Singh B. Coordinated control and harmonic mitigation in hybrid energy systems with electric vehicle park integration for enhanced power quality. Discover Appl Sci. 2026;8:793. https://doi.org/10.1007/s42452-026-08778-9.
12. Kumar MP, Velpula S, Saiprakash C, et al. Advancements in fault detection and diagnosis methods for electric vehicles: A review. Discover Appl Sci. 2025;7:1235. https://doi.org/10.1007/s42452-025-07758-9.
13. Mahale Y, Kolhar S, More AS. A comprehensive review on artificial intelligence driven predictive maintenance in vehicles: Technologies, challenges and future research directions. Discover Appl Sci. 2025;7:243. https://doi.org/10.1007/s42452-025-06681-3.
14. Liu Y, Francis A, Hollauer C, et al. Reliability of electric vehicle charging infrastructure: A cross-lingual deep learning approach. Commun Transp Res. 2023;3:100095. https://doi.org/10.1016/j.commtr.2023.100095.
15. Blei DM, Ng AY, Jordan MI. Latent Dirichlet allocation. J Mach Learn Res. 2003;3:993–1022. https://www.jmlr.org/papers/v3/blei03a.html.
16. Richardson DB. Electric vehicles and the electric grid: A review of modeling approaches, impacts, and renewable energy integration. Renew Sustain Energy Rev. 2013;19:247–54.
17. Chakraborty P, Parker R, Hoque T, et al. Addressing the range anxiety of battery electric vehicles with charging en route. Sci Rep. 2022;12:5588.
18. Choi H, Lee J, Koo Y. Value of different electric vehicle charging facility types under different availability situations: A South Korean case study of electric vehicle and internal combustion engine vehicle owners. Energy Policy. 2023;174:113436.
19. Thompson AW, Perez Y. Vehicle-to-Everything (V2X) energy services, value streams, and regulatory policy implications. Energy Policy. 2020;137:111136.
20. Bhatti AR, Salam Z, Aziz MJBA, Yee KP, Ashique RH. Electric vehicles charging using photovoltaic: Status and technological review. Renew Sustain Energy Rev. 2016;54:34–47.

21. Wang Z, Wang S. Grid power peak shaving and valley filling using vehicle-to-grid systems. IEEE Trans Power Delivery. 2013;28(3):1822–9.
22. Pang C, Dutta P, Kezunovic M. BEVs/PHEVs as dispersed energy storage for V2B uses in the smart grid. IEEE Trans Smart Grid. 2011;3(1):473–82.
23. Das HS, Rahman MM, Li S, Tan CW. Electric vehicles standards, charging infrastructure, and impact on grid integration: A technological review. Renew Sustain Energy Rev. 2020;120:109618.
24. Elsayed AT, Mohamed AA, Mohammed OA. DC microgrids and distribution systems: An overview. Electr Power Syst Res. 2015;119:407–17.
25. Wu Y, Wang Z, Huangfu Y, Ravey A, Chrenko D, Gao F. Hierarchical operation of electric vehicle charging station in smart grid integration applications—An overview. Int J Electr Power Energy Syst. 2022;139:108005.
26. Wu Y, Ravey A, Chrenko D, Miraoui A. Demand side energy management of EV charging stations by approximate dynamic programming. Energy Conv Manag. 2019;196:878–90.
27. Tian A, Li W, Li Z, Sun Y. Network security-aware charging of electric vehicles. Int J Electr Power Energy Syst. 2018;100:42–9.
28. Domínguez-Navarro JA, Dufo-López R, Yusta-Loyo JM, Artal-Sevil JS, Bernal-Agustín JL. Design of an electric vehicle fast-charging station with integration of renewable energy and storage systems. Int J Electr Power Energy Syst. 2019;105:46–58.
29. Deb S, Gao XZ, Tammi K, Kalita K, Mahanta P. A novel chicken swarm and teaching learning based algorithm for electric vehicle charging station placement problem. Energy. 2021;220:119645.
30. Khalkhali H, Hosseinian SH. (2020) Multi-class EV charging and performance-based regulation service in a residential smart parking lot. Sustainable Energy, Grids and Networks 22:100354.
31. Al Wahedi A, Bicer Y. Techno-economic optimization of novel stand-alone renewables-based electric vehicle charging stations in Qatar. Energy. 2022;243:123008.
32. Park SW, Cho KS, Hoefter G, Son SY. Electric vehicle charging management using location-based incentives for reducing renewable energy curtailment considering the distribution system. Appl Energy. 2022;305:117680.
33. Arias NB, Franco JF, Lavorato M, Romero R. Metaheuristic optimization algorithms for the optimal coordination of plug-in electric vehicle charging in distribution systems with distributed generation. Electr Power Syst Res. 2017;142:351–61.
34. Tushar W, Yuen C, Huang S, Smith DB, Poor HV. Cost minimization of charging stations with photovoltaics: An approach with EV classification. IEEE Trans Intell Transp Syst. 2015;17(1):156–69.
35. Mouli GRC, Schijffelen J, van den Heuvel M, Kardolus M, Bauer P. A 10 kW solar-powered bidirectional EV charger compatible with CHAdeMO and COMBO. IEEE Trans Power Electron. 2018;34(2):1082–98.
36. Monteiro V, Pinto JG, Afonso JL. Experimental validation of a three-port integrated topology to interface electric vehicles and renewables with the electrical grid. IEEE Trans Industr Inf.

2018;14(6):2364–74.
37. Chaudhari K, Ukil A, Kumar KN, Manandhar U, Kollimalla SK. Hybrid optimization for economic deployment of ESS in PV-integrated EV charging stations. IEEE Trans Industr Inf. 2017;14(1):106–16.
38. Zhang Y, You P, Cai L. Optimal charging scheduling by pricing for EV charging station with dual charging modes. IEEE Trans Intell Transp Syst. 2018;20(9):3386–96.
39. Sortomme E, Hindi MM, MacPherson SJ, Venkata SS. Coordinated charging of plug-in hybrid electric vehicles to minimize distribution system losses. IEEE Trans Smart Grid. 2010;2(1):198–205.
40. Clement-Nyns K, Haesen E, Driesen J. The impact of charging plug-in hybrid electric vehicles on a residential distribution grid. IEEE Trans Power Syst. 2009;25(1):371–80.
41. Tulpule PJ, Marano V, Yurkovich S, Rizzoni G. Economic and environmental impacts of a PV powered workplace parking garage charging station. Appl Energy. 2013;108:323–32.
42. Kerscher S, Arboleya P. The key role of aggregators in the energy transition under the latest European regulatory framework. Int J Electr Power Energy Syst. 2022;134:107361.
43. Zheng Y, Wang Y, Yang Q. Two-phase operation for coordinated charging of electric vehicles in a market environment: From electric vehicle aggregators' perspective. Renew Sustain Energy Rev. 2023;171:113006.
44. Li D, Zouma A, Liao JT, Yang HT. An energy management strategy with renewable energy and energy storage system for a large electric vehicle charging station. eTransportation. 2020;6:100076.
45. Tookanlou MB, Kani SAP, Marzband M. An optimal day-ahead scheduling framework for E-mobility ecosystem operation with drivers' preferences. IEEE Trans Power Syst. 2021;36(6):5245–57.
46. Liu L, Zhou K. Electric vehicle charging scheduling considering urgent demand under different charging modes. Energy. 2022;249:123714.
47. Gholami K, Karimi S, Anvari-Moghaddam A. Multi-objective stochastic planning of electric vehicle charging stations in unbalanced distribution networks supported by smart photovoltaic inverters. Sustainable Cities Soc. 2022;84:104029.
48. Knezović K, Marinelli M, Zecchino A, Andersen PB, Træholt C. Supporting involvement of electric vehicles in distribution grids: Lowering the barriers for a proactive integration. Energy. 2017;134:458–68.
49. Zhang W, Gandhi O, Quan H, Rodríguez-Gallegos CD, Srinivasan D. A multi-agent based integrated volt-var optimization engine for fast vehicle-to-grid reactive power dispatch and electric vehicle coordination. Appl Energy. 2018;229:96–110.
50. Xiong L, Tang Y, Mao S, et al. A two-level energy management strategy for multi-microgrid systems with interval prediction and reinforcement learning. IEEE Trans Circuits Syst I Regul Pap. 2022;69(4):1788–99.
51. Ren H, Zhang A, Wang F, et al. Optimal scheduling of an EV aggregator for demand response considering triple level benefits of three-parties. Int J Electr Power Energy Syst. 2021;125:106447.

52. Zhu R, Kondor D, Cheng C, et al. Solar photovoltaic generation for charging shared electric scooters. Appl Energy. 2022;313:118728.
53. Jiao F, Zou Y, Zhang X, Zhang B. Online optimal dispatch based on combined robust and stochastic model predictive control for a microgrid including EV charging station. Energy. 2022;247:123220.
54. Zhang X, Wang Z, Lu Z. Multi-objective load dispatch for microgrid with electric vehicles using modified gravitational search and particle swarm optimization algorithm. Appl Energy. 2022;306:118018.
55. Mahmud K, Town GE, Morsalin S, Hossain MJ. Integration of electric vehicles and management in the internet of energy. Renew Sustain Energy Rev. 2018;82:4179–203.
56. Naseri F, Gil S, Barbu C, et al. Digital twin of electric vehicle battery systems: Comprehensive review of the use cases, requirements, and platforms. Renew Sustain Energy Rev. 2023;179:113280.
57. Yilmaz M, Krein PT. Review of battery charger topologies, charging power levels, and infrastructure for plug-in electric and hybrid vehicles. IEEE Trans Power Electron. 2012;28(5):2151–69.
58. Yan Z, Gao Z, Navesi RB, Jadidoleslam M, Pirouzi A. Smart distribution network operation based on energy management system considering economic-technical goals of network operator. Energy Rep. 2023;9:4466–77.
59. Hota AR, Juvvanapudi M, Bajpai P. Issues and solution approaches in PHEV integration to smart grid. Renew Sustain Energy Rev. 2014;30:217–29.
60. Badawy MO, Sozer Y. Power flow management of a grid tied PV-battery system for electric vehicles charging. IEEE Trans Ind Appl. 2016;53(2):1347–57.
61. Wang M, Craig MT. The value of vehicle-to-grid in a decarbonizing California grid. J Power Sources. 2021;513:230472.
62. Zheng L. The classification of online consumer reviews: A systematic literature review and integrative framework. J Bus Res. 2021;135:226–51. https://doi.org/10.1016/j.jbusres.2021.06.038.
63. Furtado FS, Reutterer T, Schröder N. The carrot and the stick in online reviews: Determinants of un-/helpfulness voting choices. J Bus Econ. 2022;92:565–90. https://doi.org/10.1007/s11573-021-01044-x.
64. Srdic S, Lukic S. Toward extreme fast charging: Challenges and opportunities in directly connecting to medium-voltage line. IEEE Electrification Magazine. 2019;7(1):22–31.
65. Hao H, Cheng X, Liu Z, Zhao F. China's traction battery technology roadmap: Targets, impacts and concerns. Energy Policy. 2017;108:355–8.
66. Yin W, Ji J, Wen T, Zhang C. Study on orderly charging strategy of EV with load forecasting. Energy. 2023;278:127818.
67. Sujitha N, Krithiga S. RES based EV battery charging system: A review. Renew Sustain Energy Rev. 2017;75:978–88.
68. Harsh P, Das D. Optimal coordination strategy of demand response and electric vehicle aggregators for the energy management of reconfigured grid-connected microgrid. Renew Sustain Energy Rev.

2022;160:112251.

Figures

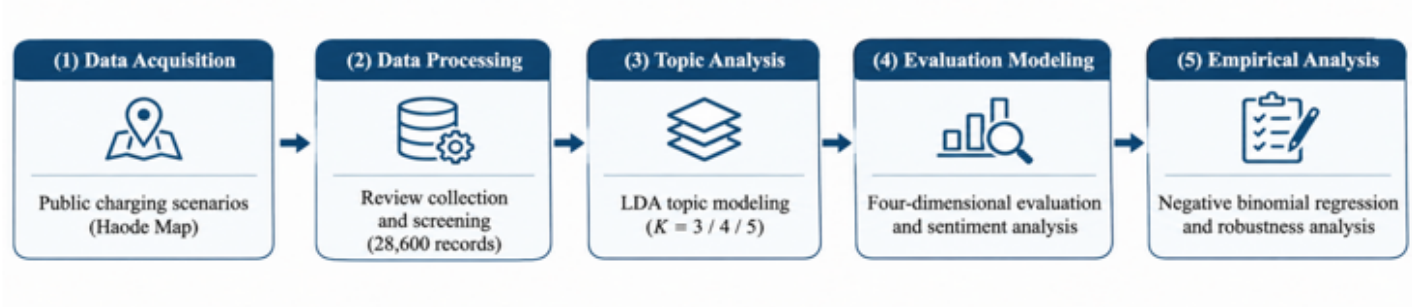

Figure 1

Analytical framework and data-construction pipeline

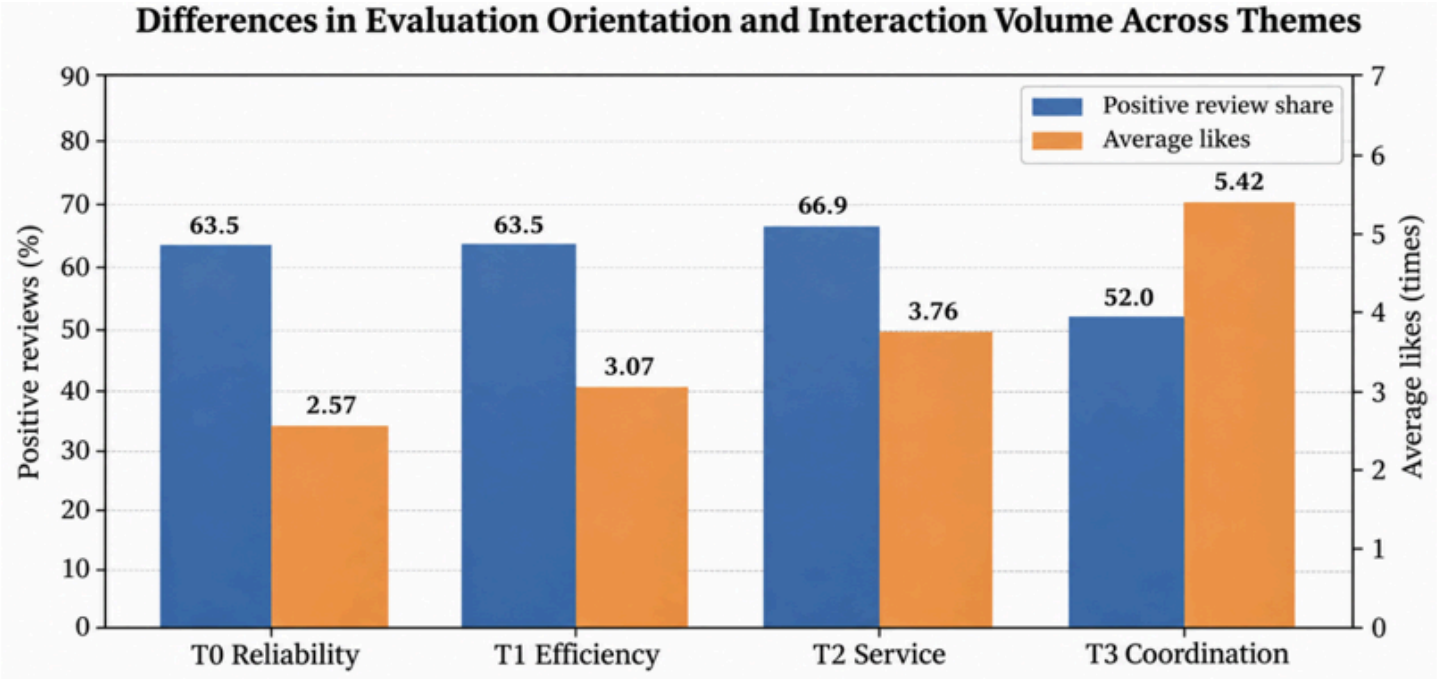

Figure 2

Positive-sentiment proportions and mean endorsement counts across four evaluation domains

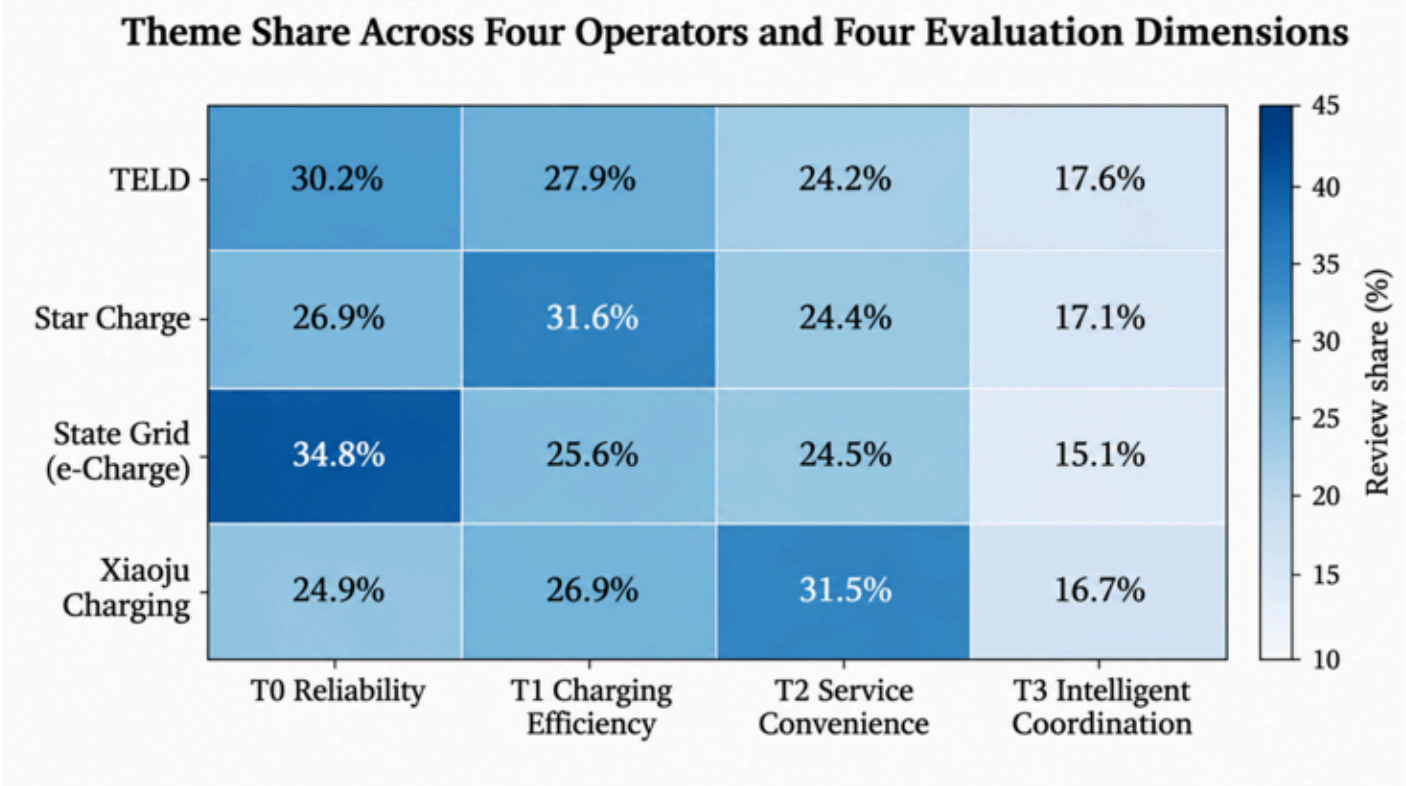

Figure 3

Within-operator topic proportions for four illustrative operator groups

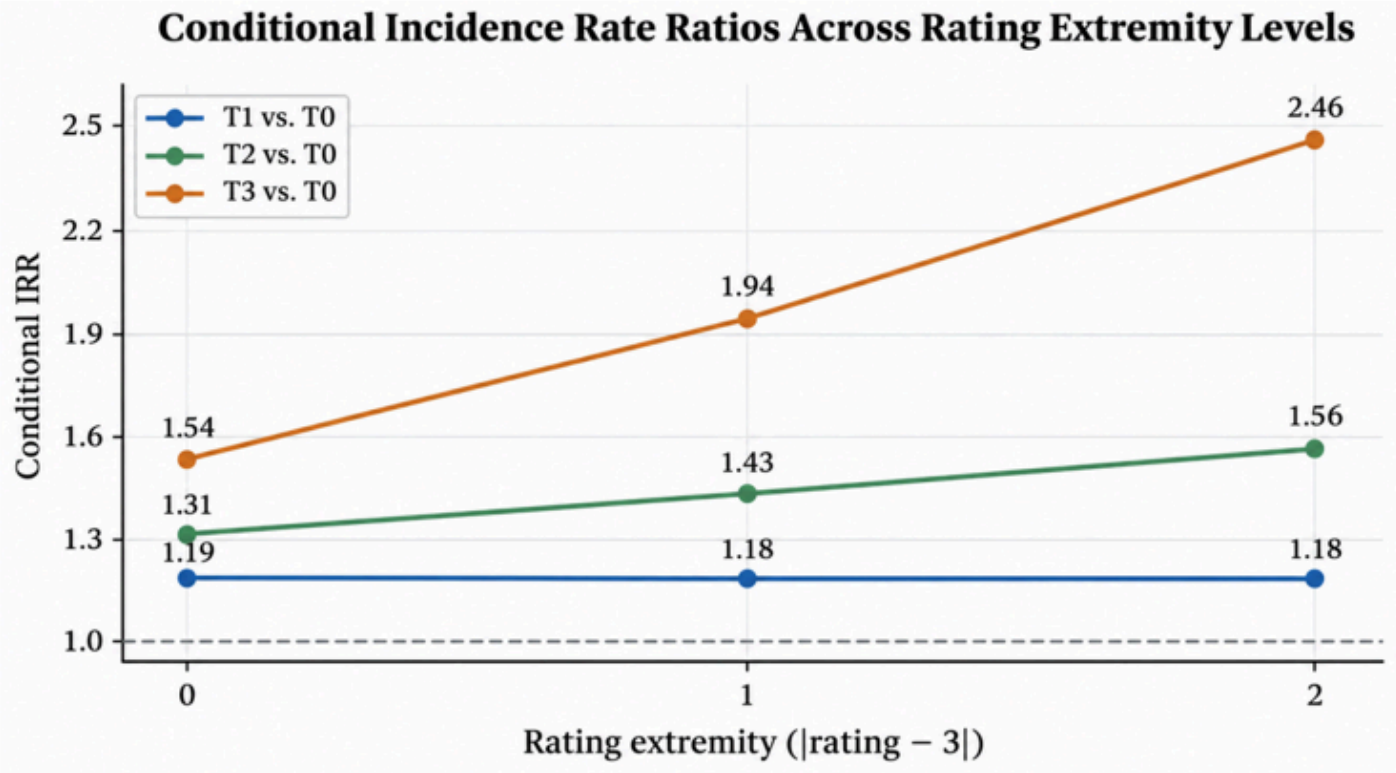

Figure 4

Conditional incidence-rate ratios for topic contrasts across rating-extremity levels

Note: T0 is the reference topic; conditional IRRs are calculated from the M3 interaction coefficients; EXT is the absolute distance of the rating from three stars.