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Review

Equity Considerations in Public Electric Vehicle Charging: A Review

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Abstract

Public electric vehicle (EV) charging infrastructure is crucial for accelerating EV adoption and reducing transportation emissions; however, disparities in infrastructure access have raised significant equity concerns. This review synthesizes existing knowledge and identifies gaps regarding equity in EV public charging research. Following structured review protocols, 91 peer-reviewed studies from Scopus and Google Scholar were analyzed, focusing explicitly on equity considerations. The findings indicate that current research on EV public charging equity mainly adopts geographic information systems (GIS), network optimization, behavioral modeling, and hybrid analytical frameworks, yet lacks consistent normative frameworks for assessing equity outcomes. Equity assessments highlight four key dimensions: spatial accessibility, cost burdens, reliability and usability, and user awareness and trust. Socio-economic disparities, particularly income, housing tenure, and ethnicity, frequently exacerbate inequitable access, disproportionately disadvantaging low-income, renter, and minority populations. Additionally, infrastructure-specific choices, including charger reliability, strategic location, and pricing strategies, significantly influence adoption patterns and equity outcomes. However, the existing literature primarily reflects the contexts of North America, Europe, and China, revealing substantial geographical and methodological limitations. This review suggests the need for more robust normative evaluations of equity, comprehensive demographic data integration, and advanced methodological frameworks, thereby guiding targeted, inclusive, and context-sensitive infrastructure planning and policy interventions.

Keywords: electric vehicles; public charging infrastructure; systematic review; charging equity; charging behavior; Socioeconomic disparities

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1. Introduction

Electric mobility has rapidly emerged as a cornerstone in the global endeavor to reduce carbon emissions and achieve more sustainable transportation networks. The International Energy Agency (IEA) highlights substantial global disparities in access to EV public charging, emphasizing the importance of equitable infrastructure to enable a widespread shift to electric mobility [1]. Various national governments have intensified efforts to deploy robust EV public charging networks, allocating significant budgetary outlays and incentives for both charging infrastructure and advanced battery technologies. Notably, several

European nations and China continue to pilot large-scale charging infrastructure initiatives. In the United States, recent legislative instruments, alongside directives from agencies such as the U.S. Department of Transportation, aim to catalyze EV adoption through the expansion of public charging access. While public investment and targets accelerate deployment, these benefits are not automatically shared evenly. Prior studies show that charger placement often follows profitability and visibility (e.g., highways, commercial districts), leaving neighborhoods with low home-charging availability, typically affecting renters and residents of multi-unit dwellings, who are dependent on a thinner, less reliable public network [1–3]. In such contexts, policy objectives (adoption, emissions reduction, and mobility inclusion) hinge on whether public charging is equitably distributed and accessible to those who cannot charge at home.

Equity concerns and user behavior are tightly coupled rather than separate topics: the same users who rely most on public charging, such as renters, drivers with smaller battery packs, and those facing longer detours, also exhibit distinct charging preferences and constraints (price sensitivity, range-anxiety hedging, time windows), which shape when and where public infrastructure is actually usable for them [2–16]. Several studies indicate that the widespread deployment of strategically placed charging stations can mitigate range anxiety and encourage broader EV adoption [17,18]. Early efforts in infrastructure expansion often focused on ensuring reliable coverage, with governments and private stakeholders installing chargers along major highways and in city centers to increase consumer confidence in EV usability on inter-city and intra-urban trips [19,20]. However, as EVs expand beyond affluent or early adopters into mainstream markets, researchers and policymakers increasingly recognize that simply achieving coverage is insufficient. Attention must also be paid to whether the infrastructure is evenly distributed, how it caters to different user groups, and how it can be scaled sustainably while meeting evolving mobility and energy demands [21,22]. Research also shows that the lack of equitable and user-centric development could leave traditionally underserved communities, including rural and low-income populations, behind in the shift to electric mobility [23,24]. For instance, wide-ranging accessibility studies in dense urban areas have demonstrated that installing chargers near lucrative commercial centers or affluent residential districts is often more profitable for private operators; however, it frequently results in the unintentional underserving of neighborhoods where residents lack private home charging options, often lower-income communities or areas dominated by multi-unit dwellings. This disparity constitutes a critical equity issue, as those most reliant on public infrastructure face the greatest access barriers. Uneven charger distribution risks limiting EV adoption in these communities, potentially excluding them from the economic and environmental benefits of electric mobility and deepening existing socioeconomic divides [2–6]. Consequently, resolving issues of inclusivity and equitable distribution of charging stations has emerged as a focal challenge not only for municipalities, utilities, and regulators but also for EV manufacturers and prospective investors in charging services.

Beyond equity concerns, a second dimension involves the interplay of user behavior with charging infrastructure design. EV user typologies can be broadly classified into five categories: routine-driven (regular commuting patterns) [7], convenience-oriented (minimal route deviation) [8,9], economic (price sensitivity) [10–12], risk-management (range anxiety mitigation) [13,14], and time-sensitive (scheduling constraints) [15,16]. These patterns directly influence charging decisions through distinct mechanisms. Routine-driven users prefer charging locations that are integrated into their daily routines, while convenience-oriented users prioritize minimal detours. Economically motivated users respond to pricing incentives and time-of-use rates, whereas risk-averse users charge preemptively even when unnecessary. Each typology represents distinct charging behaviors. Table 1 summarizes these charging behaviors across diverse charging typologies.

Table 1. Existing charging behaviors across charging typologies.

Typology ↓/ Charging Behavior →	H1 *	O-L2	L-DC	T-DC
Routine-driven	Medium **	High	Medium	Low–Medium
Convenience-oriented (detour)	Low	High	High	Medium
Economic/price-sensitive	Low–Medium	High	High	Medium
Risk-management (buffer/uptime)	Low–Medium	High	High	High
Time-sensitive	Low	Medium	High	High

* H1 refers to home-dominant and rare public charging, O-L2 refers to opportunity level 2 public charging, denoting charging on work/retail places plus peaks during the day, L-DC refers to local DC fast charging, denoting reliance on frequent public charging on community/metro DC fast chargers, T-DC refers to long-distance DC fast charging, denoting weekend DC fast charging usage for range extension/road trips. ** We evaluated each charging behavior within each charging typology using a range from "Low" to "High" to show how each charging behavior is presented in each typology based on relevant studies' evidence.

Accordingly, infrastructure that is dense but poorly sited for non-home-charging users, or fast but unreliable, can raise time and cost burdens for precisely the populations policy aims to support, weakening the effectiveness of otherwise substantial public investment.

EV public charging decisions consequently hinge on a variety of factors, ranging from cost, time-of-day rates, charging speeds, and trip patterns, to psychological aspects such as range anxiety and perceived station reliability [8,25]. Evidence points to frequent mismatches between the available infrastructure and the actual needs of drivers. For example, while many current deployments favor fast-charging corridors along highways, a substantial portion of EV owners may value slower but more conveniently located chargers, particularly near work sites or shopping malls. In this context, ignoring the heterogeneous behavior of EV users can diminish returns on large-scale infrastructure investments.

The impetus for this review lies at the intersection of two pressing concerns:

First, improving equitable deployment of EV public charging networks through comprehensive equity assessments based on spatial access (SA), cost burden (CB), reliability and usability (RU), user awareness and trust of public charging (AT). Specifically, SA refers to geographic equity asks whether chargers are located close enough for routine use by all groups. GIS studies link higher station density to shorter detours and faster adoption, while highlighting rural and minority "charging deserts" [2,26,27]; CB represents that even where chargers exist, users face heterogeneous out-of-pocket costs, including session fees, detour fuel, or peak-period tariffs. Income-stratified analyses show that low-income and renter households pay a higher share of disposable income for public charging [3,28]; RU means equity also hinges on whether chargers are operational, fast, and easy to use. Field audits reveal that a quarter of public DC fast chargers may be non-functional at a given time, disproportionately discouraging first-time and price-sensitive users [29]; AT denotes that social-psychological access includes knowledge of charger locations and confidence in their reliability. Surveys find lower familiarity and trust among minority and lower-income drivers, compounding physical and financial barriers [30,31]. By systematizing how each dimension is conceptualized and measured, we move beyond one-dimensional notions of "access" and capture the layered barriers facing diverse EV users.

Second, accounting for diverse public charging-related influencing factors such as user socio-economic and demographics, charging behaviors and preferences, public charging infrastructure supply and operations, and system-level plus climate contexts in planning models. Although policy discussions around EV public charging infrastructure continue to expand, particularly in light of the United Nations' Sustainable Development Goals, extant research has only begun to address how equity, accessibility, and technological imperatives converge. Often, location-allocation models (optimization tools that choose station sites and assign demand to them to minimize travel/queuing time or maximize coverage under budget/power constraints) and operational frameworks for EV public charging largely assume homogeneous or idealized EV user charging behaviors, while socio-demographic insights remain under-integrated.

The review aims to answer the following research questions (RQs) to understand how literature measures, what factors matter, where, and with what effects for these factors in the context of EV public charging equity:

- RQ1: What are the main methodological frameworks and analytical approaches used to assess the equity of public charging infrastructure?
- RQ2: What are the key factors influencing the equity of EV public charging at the micro, socio-economic, infrastructure, and system levels?
- RQ3: How do the identified influencing factors affect the equity of EV public charging across SA, CB, RU, and AT dimensions?

Following this introduction, Section 2 elaborates on the systematic methodology employed to gather and analyze the relevant literature on EV public charging. Section 3 distills the findings into thematic clusters, summarizing existing methodologies adopted into public charging equity assessment, listing identified factors categorized into four groups that influence public charging equity, and discussing the implications for those factors' impacts. Section 4 synthesizes key insights, maps out policy-oriented strategies for equitable public charging expansion, and identifies important directions for future research, including the opportunities presented by advanced battery technologies, real-time pricing models, and cross-sector collaborations in mitigating disparities.

2. Materials and Methods

2.1. Material Search and Inclusion Strategy

2.1.1. Resources Search and Identification

We used a systematic review approach to identify and synthesize scholarly works related to EV public charging infrastructure. The database search was conducted in Scopus and Google Scholar, using sets of keywords that combined terms "electric vehicle" OR "EV" with "public charging" OR "publicly accessible charging" OR "non-residential charging" and relevant modifiers ("charging infrastructure" OR "charging station"). Additional keywords captured dimensions of equity and accessibility ("disparity," "inclusi*," "social justice"), user behavior ("travel behavior," "charging behavior," "preference," "adoption"), and socio-economic/demographic factors (workflow showing in Figure 1).

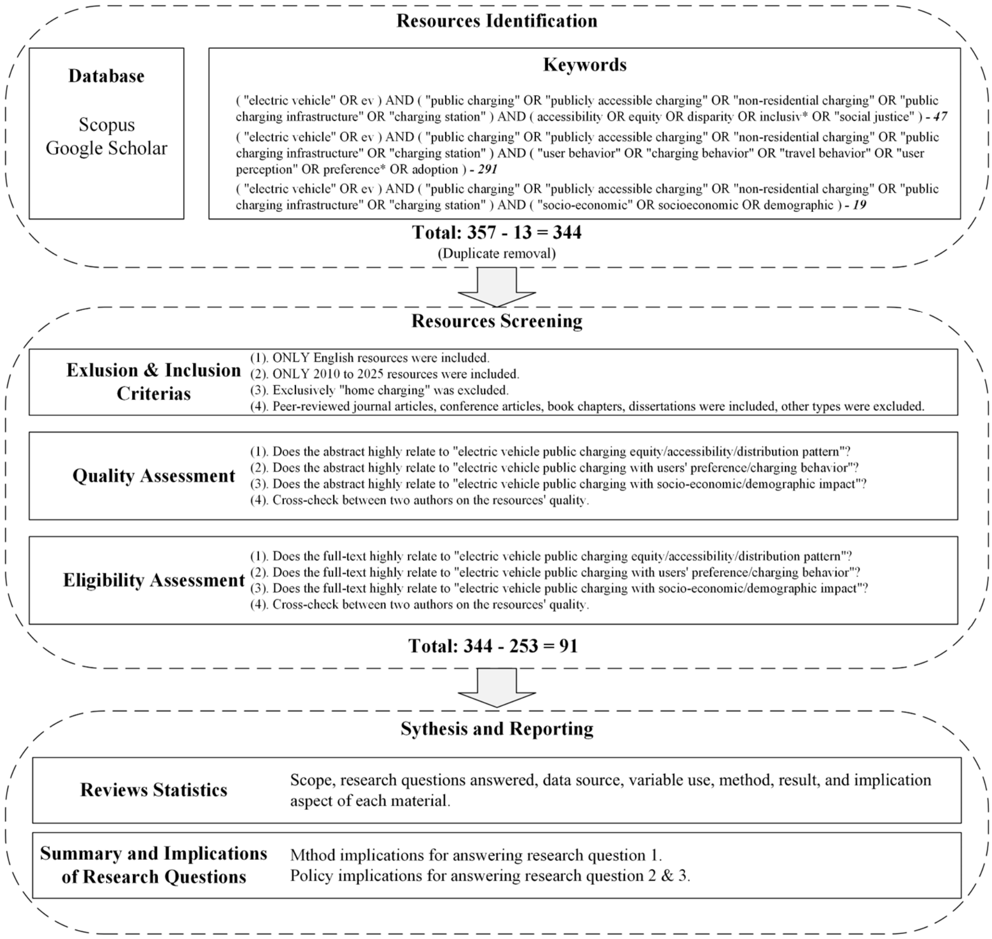

Figure 1. PRISMA search and selection workflow.

2.1.2. Resources Screening, Quality, and Eligibility Assessment

The search yielded a combined total of 357 references from both databases by using pre-defined keyword combinations. Then duplicate records (13 in total) were removed, resulting in 344 unique items. A set of exclusion and inclusion criteria was applied to screen those items, including: (1) Only English-language publications were retained. (2) Only studies published between 2010 and 2025 were considered. Large-scale public-charging roll-outs and the first peer-reviewed equity studies did not appear until the early 2010s, so earlier literature provides little relevant evidence. (3) Studies focusing exclusively on “home charging” were excluded. (4) Peer-reviewed journal articles, conference papers, book chapters, and dissertations were included, while excluding non-peer-reviewed sources such as reports, news articles, or editorials.

We screened titles and abstracts to confirm relevance to at least one of three key review focuses: (1) Equity, accessibility, or distribution aspects of public charging. (2) User preference or charging behavior associated with public charging. (3) Socio-economic or demographic impacts of public charging. Two authors independently conducted this screening to ensure quality and relevance by subjectively selecting an option from “highly related”, “related”, to “not related”, with disagreements resolved through internal discussion based on the options that the two authors selected. When either author selected “highly related” in the context, the material was included. Papers deemed relevant at the abstract level were subject to full-text review to verify their detailed treatment of the same three focus areas. Finally, each full-text was examined by two authors for final eligibility, resolving any discrepancies via consensus following the same process as abstract examinations. Through this iterative screening and assessment process (see Figure 1), we compiled the final set of studies for in-depth synthesis. The subsequent sections elaborate on the synthesis, interpretation, and policy implications derived from these selected materials. One thing worth noting is that to ensure no relevant materials were missed, backward tracking and forward tracking were further conducted for the selected 91 studies by reviewing their reference lists (backward tracking) and inspecting all articles that cite them in Web of Science (forward tracking), following defined inclusion and exclusion criteria; the results remained unchanged.

2.2. Review Statistics

A total of 91 relevant studies were included in this review on equity and charging behaviors in EV public charging infrastructure. Figure 2 provides summaries of the main statistical results, which are discussed in more detail below. First, scholarly output has accelerated sharply since 2021, with publications rising from 4 papers in 2020 to 13 in 2021, 16 in 2022, 15 in 2023, and 20 in 2024. The first quarter of 2025 has already seen 13 studies published, signaling sustained momentum and continued policy relevance. By counting the co-occurrence of keywords that appeared in 91 studies and mapping publication years, Figure 2 illustrates an interesting trend that reflects the growing academic and policy interest in sustainable and equitable transportation solutions, particularly as EV equity becomes more mainstream. Because VOSviewer (v1.6.20) treats singular and plural tokens separately, both 'electric vehicle' and 'electric vehicles' appear as distinct nodes, although they designate the same research theme. Throughout the discussion, we treat them as one concept.

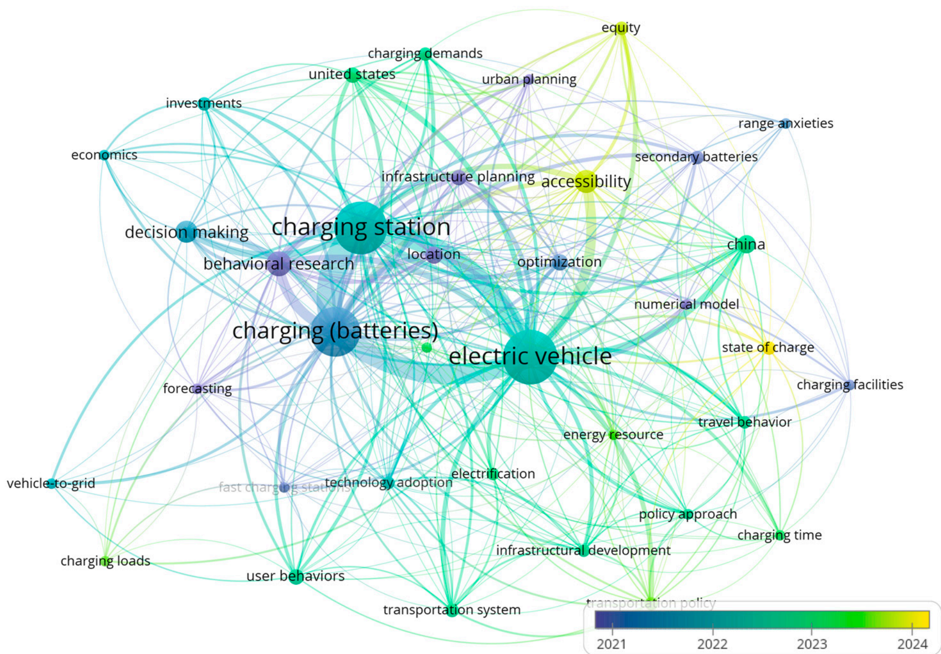

Figure 2. Keywords' co-occurrence networks among observed studies (produced by VOSviewer).

Regarding the study type, the majority of the reviewed papers (76 studies; 83.5%) were published as journal articles, while 15 studies (16.5%) appeared in conference proceedings. With regard to the type of data utilized, the analysis reveals that 52.7% of the studies relied on secondary datasets, whereas 38.5% employed primary empirical data collected through surveys, experiments, or direct measurements. Geographically, the studies covered a wide range of regions. China (23 studies, 25.27%), the United States (23 studies, 25.27%) were the most-analyzed countries, together accounting for almost half of all studies. India, Germany, and the Netherlands followed (6 studies, 6.59%; 6 studies, 6.59%; 4 studies, 4.40%, respectively). A long tail of single- or double-study appearances includes Norway, New Zealand, Kuwait and several sub-national regions (for instance, Ontario, King County). 7 (7.69%) studies adopted a global theoretical scope untethered to real-world locations, signaling an emerging, but still modest, interest in transferable modeling frameworks. This pattern indicates that while the research interest is global, empirical field-based studies remain largely concentrated in high-income countries. This geographical focus also aligns closely with global EV deployment patterns. In 2023, nearly 14 million new electric cars were registered worldwide, bringing the total EV stock to about 40 million, with battery-electric vehicles accounting for approximately 70 percent of that total [1]. New registrations were overwhelmingly concentrated in three markets: China (~60 percent), Europe (~25 percent), and the U.S. (~10 percent) [1]. In the United States, a systematic review of infrastructure needs estimates 13–30 million light-duty EV chargers by 2030, with cumulative investment up to USD 97 billion (vs. about USD 24 billion announced at the time) and an average of 0.8 chargers per vehicle [32]. In the United Kingdom, public support has included GBP 80 million for charging infrastructure and GBP 37 million for innovative charging projects, with some analyses projecting up to 10 million EVs by 2030 [33]. In Turkey, national reviews highlight low but growing adoption and a charging-station density map indicating under-provision in eastern regions, supporting calls to expand coverage beyond the western corridor [34]. Global EV trends continue to develop, as in 2024, EV sales surged past 17 million, surpassing 20 percent of all new car sales [35], mainly with BEVs and PHEVs, but limited on Fuel Cell Electric Vehicles (FCEVs) at this stage [36].

The data sources used in the found literature were highly diverse, encompassing survey-based data, public datasets, corporate data from electric utilities, social media-derived information, and synthesized data generated through simulation models. Survey data and public databases were among the most common sources, although the significant use of synthetic datasets in some studies points to ongoing challenges in accessing comprehensive real-world data.

The distribution of research questions discussed by the reviewed studies provides further insights. 58 studies were observed to primarily focus on behavioral, operational, and usage aspects of EV public charging, making it the most prominent research focus. 49 studies were found to discuss public charging equity assessments and social dimensions. In comparison, 26 studies appeared to relate to public charging spatial distribution, while only 16 studies dealing with systemic barriers and policy implications were the least addressed. Furthermore, an analysis of research focus co-occurrence revealed that operational aspects and equity dimensions are frequently studied together, suggesting an increasing combination of usage behavior analysis with social equity concerns. In contrast, infrastructure planning and systemic barriers are rarely discussed in combination, indicating a potential fragmentation in how infrastructure and policy challenges are conceptualized. Future research would benefit from more integrated frameworks that simultaneously address spatial planning, policy barriers, and equity outcomes.

3. Results and Discussion

Based on 91 studies, this section first surveys the analytical lenses applied to charging equity (Section 3.1 answers RQ1), then synthesizes multi-level factors (Section 3.2 answers RQ2), and finally discusses how those determinants manifest across four equity assessment dimensions in geographic, socio-economic, and climate contexts while highlighting evidence gaps (Section 3.3 answers RQ3).

3.1. Measurement of EV Public Charging Equity

3.1.1. Existing Methodological Frameworks

Within 91 selected studies, 52 were reviewed to have adopted a wide range of methodological frameworks to assess public charging infrastructure accessibility, each with distinct strengths and limitations. Based on (1) how the physical charging network, user demand, and policy levers are abstracted; (2) the mathematical or computational paradigm used to link inputs to outputs; and (3) the equity-related indicators it produces. Table 2 provides a summary of the classifications of existing frameworks proposed in the previous literature. Individual studies may implement a framework with different datasets or solution techniques, but they remain comparable because they operate under the same overarching analytical architecture. Widely used accessibility measures (gravity/2SFCA and kernel density) often assume homogeneous user behavior and static conditions, for instance, identical value of time, uniform trip purposes, and equal ability to substitute between chargers, while omitting reliability and price variability. As a result, they can overstate equity for renters and multi-unit-dwelling drivers who cannot shift to home charging [2–4,6]. Empirical work shows that charging demand is heterogeneous across user types and time windows, challenging these assumptions [10,16,37]. Likewise, siting optimization studies that maximize coverage or flow capture without RU/price inputs risk recommending stations that are dense but functionally inaccessible to non-home-charging users [38–40].

Table 2. Summary of existing adopted frameworks to assess equity in public charging infrastructures.

Framework	Main Idea	Outputs	Strengths	Limitations	Relevant Study Count (%)
Network equilibrium and flow capturing	Treat charging stations as nodes on a multimodal network; jointly optimize travel cost and charging demand.	Optimal station siting, equilibrium flows.	Captures route substitution and queuing effects.	High data and parameterization burden; equilibrium assumptions may break down under stochastic demand.	8 (15.38%)
Spatial accessibility	Measure geographic reach (for instance, coverage radius, 2SFCA, kernel density) relative to population or vehicle stock.	Accessibility scores, hotspot maps.	Intuitive, GIS-friendly; works with sparse data.	May over- or under-estimate access in rural/low-pop-density areas; ignores temporal variation.	16 (30.77%)
Behavioral decision	Embed user heterogeneity (value of time, range anxiety, socio-demographics) in choice or game-theoretic models.	Choice probabilities, elasticities, equity impacts.	Captures distributional effects; aligns with survey evidence.	Sensitive to survey bias and stated-preference artifacts; heavy parameterization.	20 (38.46%)
Hybrid frameworks *	Combine two or more of the above (for instance, equilibrium + behavioral logit, or GIS kernel density feeding a system dynamic adoption loop).	Multi-scale KPIs (coverage, queuing delay, equity index).	Bridges technical and socio-behavioral lenses; better policy realism.	Integration increases data demands and computational complexity.	8 (15.38%)

* In addition to these three core paradigms, a growing body of studies has sought to integrate them, giving rise to hybrid frameworks. These hybrid designs are not a separate paradigm per se but rather combine features of the three to reconcile technical precision with socio-behavioral realism.

Specifically, Network-equilibrium and flow-capturing frameworks treat chargers as nodes on coupled road–power networks and solve mathematical-programming or optimization problems to reach system-wide equilibrium, thereby reproducing routing constraints and queuing dynamics [9,41,42]. Spatial-accessibility frameworks adopt GIS coverage indices, floating-catchment areas, and kernel-density estimates to juxtapose charger supply with population demand, producing intuitive hotspot maps for planners, even though their outputs can be distorted in low-density regions and are sensitive to radius or travel-time thresholds [17,28,38,43,44]. From a user perspective, behavioral-decision frameworks incorporate heterogeneous user preferences, including value of time, range anxiety, and socio-demographics, through discrete choice, Bayesian, or AI estimators, yielding equity-relevant insights at the cost of large, representative survey requirements and potential stated-preference bias [26,39,45–48].

Finally, integrated or hybrid frameworks purposely fuse two or more of the foregoing approaches, for example, Analytic Hierarchy Process (AHP)—entropy—Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) multi-criteria ranking embedded in an equilibrium model or GIS hotspot detection feeding a system-dynamics loop to reconcile engineering precision with social realism, though such syntheses raise data demands and computational complexity [25,49,50].

Overall, these frameworks have broadened the empirical and conceptual base for evaluating EV public charging accessibility, yet network equilibrium remains numerically smaller, largely due to higher demand for rich traffic, power-flow, and socio-economic data, which is similar to the adoption of hybrid frameworks. The choice of these frameworks, therefore, depends on the planning objective and data environment: long-range corridor design favors equilibrium models; cities lacking detailed trip data may start with GIS coverage indices; equity audits or tariff design call for behavioral models; and large public–private programs increasingly adopt hybrids to capture grid constraints and demographic heterogeneity. Framing the approaches along this strategic–tactical–operational spectrum clarifies that they are orthogonal tools in a common toolbox rather than rungs on a maturity ladder. To further investigate what are the current potential methodology gap in measuring EV public charging equity, detailed analytical approaches are discussed for both engagement in 52 studies related to frameworks and adoption frequency among 91 studies.

3.1.2. How Do Analytical Approaches Engage in Existing Frameworks

Analytical approaches to assess public charging accessibility through network-optimization logic employ mathematical programming or flow-capturing models to determine where and how large stations should be located. Corridor-scale studies use mixed-integer and flow-capturing formulations to minimize system-wide travel cost or traveler "inconvenience" [41,42]. More behaviorally rich variants add Bayesian or car-following sub-modules [45,50] and even incorporate equity or dual objectives of efficiency and fairness [51]. Their prescriptive power is high, yet all remain sensitive to congestion-queuing parameters and become computationally prohibitive once national networks or stochastic demand scenarios are introduced [9,52,53]. Meta-heuristic hybrids (genetic algorithms with mathematical programs, for instance) alleviate but do not eliminate scale and calibration issues [54].

A second stream relies on spatial-statistical and GIS techniques to portray how chargers are distributed relative to people, trips, or deprivation scores. Kernel-density estimation, floating-catchment areas, and G2SFCA measures dominate this family, producing intuitive equity maps but often overstating access in low-density tracts [17,27]. Cluster-detection algorithms such as DBSCAN, hierarchical, and K-Prototype approaches sharpen hotspot detection and reveal socio-spatial disparities [4,43,55]. Multi-criteria decision-making (AHP, entropy weighting, improved TOPSIS) is regularly coupled with GIS layers to rank candidate sites [20,25] or to blend efficiency and equity targets [56,57]. Still, these approaches hinge on user-defined buffer radii and survey-derived demand weights, making cross-city transferability weak [21,58].

Machine learning (ML) pipelines wrapped in micro-services forecast temporal demand and feed siting heuristics [46,59], whereas spatial–temporal load-forecasting models link trip chains, Dijkstra routing, and coordinated slow/fast-charge scheduling to anticipate sub-hourly load bursts [60]. Stock-and-flow system dynamics or multi-stakeholder negotiations embed policy feedback and scheduling constraints [49,61], and several studies now propose analytical templates that explicitly fold equity metrics into broader accessibility goals [45,62]. These integrated approaches promise greater realism but demand high-resolution mobility traces, charger-load data, and interdisciplinary calibration, placing large data and computational burdens on researchers.

Table 3 further summarizes six detailed approaches that were frequently used in observed studies. Optimization and mathematical programming models lead the pack with 10 papers (11%). When linking with equity evaluation, such as constraints ensuring minimum service levels in low-income or rural tracts, these models can directly redistribute charging access. Several studies show that adding equity constraints raises costs only modestly while cutting detour distance and waiting times for underserved groups [42,51]. Regression and other econometric tools, as well as spatial-statistical/GIS techniques, follow closely, each with nine studies (9.9%), and together anchor most empirical work on charger use and socio-spatial patterns. From an equity lens, indices such as kernel density or 2SFCA visualize where 'charging deserts' align with disadvantaged communities. However, unless weighted by socio-demographic factors (e.g., renter households, minority populations), these metrics risk describing patterns rather than diagnosing fairness. Studies that integrate deprivation indices or Gini-type measures provide stronger evidence of equity gaps [44,56]. Clustering and other unsupervised methods (eight studies; 8.8%) help uncover latent demand hotspots, while simulation approaches, for instance, trip-chain, agent-based, or power-flow, appear with the same frequency and capture time-varying vehicle-grid interactions. Finally, structured surveys and stated-preference experiments (five studies; 5.5%) and a small but growing group of machine-learning pipelines (four explicit ML-first articles; 4.4%) add behavioral depth and predictive power.

Table 3. Frequently used approaches in assessing public charging infrastructure accessibility.

Approach Class (Keywords)	Studies (N = 91)	% of Corpus [1]	Cum. (%) [1]	Strengths	Assumptions/Cautions
Optimization	10	11%	11.00%	Precise siting and sizing decisions; handles constraints explicitly.	Parameter-sensitive; solution time grows quickly with network size.
Regression	9	9.9%	20.90%	Quantifies utilization drivers; easy statistical inference.	Causal interpretation tenuous if confounders omitted.
Spatial statistics	9	9.9%	30.80%	Hotspot identification, clustering, and Moran's I for equity patterns.	Results hinge on distance thresholds and population weighting.
Clustering and unsupervised learning	8	8.8%	39.60%	Reveals latent usage archetypes without pre-defined classes.	Sensitive to feature scaling; cluster meaning must be interpreted post hoc.

Table 3. *Cont.*

Approach Class (Keywords)	Studies (N = 91)	% of Corpus [1]	Cum. (%) [1]	Strengths	Assumptions/Cautions
Simulation (trip-chain, agent-based, power-flow)	8	8.8%	48.40%	Captures temporal dynamics and vehicle–grid interactions.	Requires granular Origin-Destination (OD), charger, and battery data that are rarely public.
Structured surveys	5	5.5%	53.90%	Direct insight into user willingness-to-pay, equity perceptions.	Sampling bias: stated vs. revealed behavior gap.
Advanced ML	4 *	4.4%	58.30%	High predictive accuracy for demand and dwell time.	Data-hungry black-box models hinder policy transparency.

* ML count reflects only explicit ML-first studies; several optimization papers embed ML modules and are counted above. [1] "% of corpus" refers to (number of studies in that row ÷ 91 total studies) × 100, "Cum. (%)" refers to the cumulative percentage.

Each approach brings clear strengths, precise optimization, transparent regression, intuitive GIS mapping, data-driven clustering, dynamic simulation, or direct behavioral insight, but they also share two concrete gaps. First, only a handful of studies compare their model outputs with observed charger utilization or track equity outcomes over time, so external validity remains limited. Second, the persistence of silos is especially problematic for equity: siting decisions that appear optimal under network constraints may still underserve low-income renters, while GIS equity maps can highlight "charging deserts" without showing whether system-level reliability is maintained. Promising hybrid approaches demonstrate the value of integration. Patil et al. [49] embed behavioral charging behavior into optimization, producing more realistic and equitable siting outcomes. Liu et al. [51] add equity constraints directly into optimization, showing that modest cost increases deliver substantial accessibility gains for disadvantaged tracts. By contrast, Bian et al. [63] illustrate the risks of partial integration: demand forecasting improved, but without socio-demographic features feeding into siting, equity insights remained limited. Beyond technical modularity, practical barriers hinder integration: transportation and energy agencies often operate in silos, privacy restrictions limit the use of household-level data, and policy frameworks frequently prioritize cost recovery over fairness. Addressing these barriers is essential if integrated frameworks are to move from research prototypes to real-world equity planning tools.

3.2. *Multi-Level Influencing Factors of EV Public Charging Equity*

Existing studies have adopted various analytical approaches that involve considering factors into five types of frameworks and have identified multiple factors that can significantly impact public charging infrastructure accessibility and equity across regions and demographic groups.

3.2.1. Micro-Level Factors: User Charging Behavior, Preference, EV Performance

We define micro-level behavior as choices over when, where, and how fast to charge, mediated by travel purposes and perceived costs (time, money, risk). Studies repeatedly document distinct patterns among home-dominant, opportunity L2, local DCFC-reliant, and long-distance DCFC travelers [10,16,37]. These patterns have inequitable consequences when RU (uptime, queues) and CB (tariffs/fees) vary sharply across neighborhoods, even where SA appears adequate [2–4,6,38–40].

User preferences reflect the relative importance individuals place on different charging attributes, with cost sensitivity and convenience being central to infrastructure utilization.

Discrete choice models (infer how users trade off detour, price, and speed from observed or stated choices) consistently show that users value proximity, speed, and reliability in public charging options [28,47,57,64]. Embedding psychological cost terms changes optimal locations and lowers detour kilometers in Sioux Falls [13]. EV performance characteristics refer to the technical specifications of the EV itself, such as battery range and charging speed, which directly influence the frequency and nature of charging needs. Owners of smaller-battery EVs often require more frequent public charging access [4,65]. Integrated models using real-time pricing and mobility patterns illustrate how dynamic pricing structures can interact with user behavior and infrastructure demand [10,16,37].

Charging behaviors then encompass the patterns and decisions EV users make regarding when, where, and how often they charge their EVs. These behaviors are shaped by variables such as the state of charge (SOC), proximity to charging stations, and trip characteristics. Long-distance travelers prioritize fast charging and reduced waiting times [43,66,67], whereas urban users exhibit more varied charging patterns based on location types, such as workplaces and shopping centers, as well as seasonal factors [7,8,15,68,69]. Data-mining work on 189 k Illinois ChargePoint sessions confirms that morning, multifamily or commercial sites, and low start-SOC dominate public use, while workplace sessions are shorter on weekdays [70]. Ride-hailing traces from Nanjing show clear private vs. commercial patterns; a Cumulative Prospect Theory model reveals risk-seeking station choice that cuts waiting time by >10% [71]. Seasonality also matters: winter demand is lowest and autumn highest, with random-forest forecasts yielding MAPE 0.08% [15]. Early work in Amsterdam derived a user-type taxonomy (residents, commuters, taxis, car-sharing, etc.) with distinct temporal-load profiles, providing a foundation for utilization forecasting [72]. Behavioral studies further reveal that range anxiety, trip purpose, and daily routines are key drivers of charging decisions, with users often preferring chargers conveniently located along daily travel routes [6,9,51].

Several approaches implicitly treat users as homogeneous, including equal value of time, identical substitution across charger types/locations, and stable availability—assumptions that conflict with observed differences across H1, O-L2, L-DC, and T-DC users [10,16,37]. Empirical variation in RU and pricing further undermines these assumptions [38–40]. SA metrics (distance/coverage) systematically miss equity losses from RU (downtime/queues) and CB (tariffs/fees), which disproportionately affect O-L2 and L-DC users who depend on public networks [2–4]. Drawing policy implications from static hotspot maps without behavioral inputs or RU/CB terms risks siting that is dense yet unusable for non-home-charging communities [10,16,37,38].

3.2.2. Socio-Economic and Demographic Influences

Socioeconomic and demographic factors, including income, education, and housing status, have a profound influence on EV adoption and infrastructure accessibility. Higher-income and better-educated populations typically enjoy greater access to public charging facilities. However, most income-related studies measure income at the census tract or regional level, which may obscure intra-community variation and risks ecological fallacy. Few studies control for confounding variables such as car ownership rates, housing density, or existing transport services, which can also explain observed inequities. This limits the causal interpretation of income as a driver of inequitable charging access [2,28,38,39,73]. Recent spatial–statistical analyses across ten Chinese cities found significant intra-city inequity in public charging station access [27]. Home ownership and housing type also determine the ability to charge at home, with renters and individuals living in multi-unit dwellings more dependent on public charging networks. While findings are consistent across multiple contexts, most rely on stated-preference surveys rather than revealed behavior, which raises concerns about response bias. Moreover, the emphasis on multi-unit dwellings often overlooks rural renters who may face equal or greater challenges due to sparse public infrastructure [3,40,74]. Furthermore, existing infrastructure often clusters in affluent or commercial areas, exacerbating accessibility barriers for marginalized groups [14,44,75]. Studies have observed that certain nationalities or ethnic groups dominate EV usage in some contexts, indicating uneven participation in the EV transition [22,24,76,77]. These socio-demographic filters determine who must rely on public charging; the next section (Section 3.2.3) examines whether the existing network's availability, siting, and design translate that latent demand into real accessibility.

3.2.3. Infrastructure Supply and Operations: Availability, Siting, Design, and Pricing

Research consistently shows that the availability, strategic placement, and thoughtful design of EV public charging infrastructure play a crucial role in influencing EV adoption rates, user awareness, and utilization patterns across diverse regions and demographic groups. Strategic infrastructure deployment reduces range anxiety and enhances convenience, thereby increasing EV adoption. Yet many siting studies implicitly optimize for utilization rather than equity. By prioritizing traffic density or expected demand, they may inadvertently reinforce advantages for affluent, high-traffic zones. Only a small subset of models [51] explicitly include equity constraints, showing how different methodological assumptions produce different distributional outcomes. Spatial analyses in New Zealand [78] and optimization models in China [54] demonstrate the importance of neighborhood effects, while a bi-level siting model that embeds a range-anxiety cost term shifts the optimal fast-charger set and cuts detour distances [13]. Large-scale trace mining in Nanjing further shows that risk-seeking drivers pick stations that minimize perceived wait time; a Cumulative Prospect Theory engine trims waiting costs by >10% and illustrates how behavior-aware siting can boost perceived accessibility [71]. Similarly, areas with denser and more reliable charging networks consistently show higher EV adoption, as accessible infrastructure improves user confidence and lowers barriers to entry [9,38–40].

Placement strategies that prioritize high-traffic, visible, and convenient locations have been shown to boost user awareness and the perceived viability of EVs for everyday travel [2,44,48]. For instance, clustered stations in Amsterdam [18] and fast-charging hubs along U.S. corridors [41] enhance accessibility and foster adoption through reciprocal effects, where increased infrastructure availability encourages more users. A coordinated load-forecasting framework that links trip-chain demand with home, destination, and en-route charging helps operators proactively avoid local overloads [60]. Theoretical simulations suggest that access to both home and public charging amplifies market share through indirect network effects, highlighting the synergistic benefits of a combined infrastructure strategy [79]. However, current deployments often favor urban and affluent areas, leaving rural and underserved communities with limited access to charging, which restricts adoption potential and perpetuates regional disparities [3,4,75].

Infrastructure design features, including charger type (Level 2 versus DC fast charging), charging speed, pricing models, and user interface design, have significant impacts on utilization and user satisfaction [14,28,47,64]. Studies in Norway [67] and Slovakia [10] reveal diverse user preferences for fast charging and smart charging incentives, which influence how infrastructure is perceived and used. Conversely, experiences of "Charge Point Trauma" in the United Kingdom [29] show that issues such as charger operability, reliability, and complex payment systems can hinder user satisfaction and discourage adoption. High-speed chargers placed along major travel corridors support long-distance EV mobility, especially for drivers lacking reliable home charging options [57,80]. In contrast, poorly maintained or confusingly designed stations deter usage, particularly among first-time

EV drivers or those less familiar with EV technologies [73,74,81]. Beyond physical design, cooperative deep-reinforcement-learning schemes for multi-station networks raise total profit by $\approx$ 24% and smooth loads compared with independent pricing, demonstrating how adaptive tariffs can both entice users and protect the grid [12]. Similar coordinated-behavior load-forecasting models improve network-operation forecasts [60].

Regional variations also play a crucial role in shaping outcomes. In Canada, the "EV Duck Curve" illustrates challenges related to grid stability caused by the clustering of public fast-charger demand [8], while infrastructure scarcity in Kuwait limits EV adoption to wealthier nationals [76]. Cold climates further exacerbate charging needs by reducing battery efficiency, requiring more frequent charging, and impacting infrastructure demand [6,81]. AI-driven design improvements [46] have enhanced user confidence globally, suggesting the potential for technology-driven solutions to improve infrastructure utilization. Despite these advances, several limitations remain, including a reliance on hypothetical scenarios [66], small sample sizes [82], and region-specific data [83], which highlight the need for broader empirical validation across diverse socioeconomic and geographic contexts.

Collectively, these supply-side choices ripple outward, influencing EV adoption patterns, altering peak grid loads, affecting local economic activity, and reshaping emissions footprints. The system-level outcomes are examined next in Section 3.2.4.

3.2.4. System-Level Impacts: Adoption, Grid Loads, Economic and Environmental Outcomes

The socio-economic and environmental impacts of EV public charging infrastructure have been explored through various frameworks and across different geographical contexts. Public charging infrastructure can stimulate local economic growth by attracting businesses, creating new job opportunities, and increasing property values near station locations [3,9,37,74]. However, these benefits are often concentrated in wealthier urban areas, thereby exacerbating existing socio-economic disparities [4,73,75]. Regions with limited infrastructure investment face reduced access to economic opportunities, emphasizing the need for equity-focused planning and deployment strategies [44,84].

On the environmental side, expanding public charging availability encourages EV adoption, leading to reductions in greenhouse gas emissions and urban air pollution [38,40,63,85]. However, the net environmental benefit of public EV infrastructure largely depends on the energy generation mix. Regions powered by renewable energy sources realize greater emission reductions, whereas areas still reliant on fossil fuels may see more limited environmental gains [6,86]. Climatic conditions further influence infrastructure performance and outcomes; colder climates, for example, reduce battery efficiency, necessitating more frequent and prolonged charging, which can stress local electricity grids and potentially increase emissions if clean energy is not available [11,87,88].

Several studies highlight emerging concerns about the resilience of EV public charging networks in the face of extreme weather events associated with climate change, which can disrupt charging availability and reliability [47,80]. Broader social impacts include shifts in transportation habits, land use changes, and urban dynamics, which require integrated and flexible planning approaches [51,89–91]. Tailored regional strategies, such as incentivizing rural charging deployments or integrating charging stations with renewable microgrids, have been shown to promote more equitable and sustainable outcomes [14,58,92,93].

Specific modeling efforts, such as a study using machine learning and microservices-oriented architecture, have demonstrated the potential of smart grid-integrated EV adoption and charging station planning to enhance energy sustainability, although these models often rely on synthetic data, limiting empirical applicability [59]. Similarly, Canadian studies reveal that EV public charging can contribute to new peak electricity loads, posing challenges to grid stability under seasonal variations, though socio-demographic and spatial data gaps remain a limitation [8]. A global panel data study covering 14 countries found that renewable energy availability, education, and population density, rather than GDP alone, influence EV demand [77], though the study did not account for micro-level socio-economic factors.

Without deliberate and inclusive planning, public EV infrastructure risks reinforcing environmental injustices by disproportionately benefiting already advantaged populations [2,5,94]. Innovative policy measures, such as dynamic pricing, public–private partnerships, and community-led planning, are proposed to maximize both the socio-economic and environmental benefits of EV public charging networks. Dynamic pricing could lower off-peak costs for low-income users but risks penalizing those with inflexible schedules (e.g., shift workers). Public–private partnerships may accelerate rollout but often prioritize return-on-investment, raising the risk that underserved communities remain neglected unless subsidies or equity mandates are built in. Community-led planning has strong potential to align siting with local needs, yet implementation faces challenges in data access, funding, and coordination across municipalities. Without explicit mechanisms to incorporate marginalized voices, such approaches may reproduce existing inequalities under the guise of "participation [27,30,61,95,96]. Overall, while EV public charging infrastructure offers substantial societal and environmental benefits, realizing these benefits equitably requires context-sensitive, inclusive, and forward-looking strategies that address regional and climatic differences.

Despite these insights, the effectiveness of the current charging infrastructure is often compromised by overly simplified planning approaches that fail to adequately account for dynamic user behaviors and regional variations [21,49]. Socioeconomic conditions, particularly income, education, and race, interact with geographic factors, resulting in rural, minority, and low-income urban areas facing notably lower charger density [38,56,80,88]. Surveys suggest that minority and lower-income users have lower awareness and trust toward public charging reliability, often feeling marginalized in the shift to electric mobility [6,30,31,97]. Finally, policy and planning practices further complicate equity outcomes. Site selection processes frequently prioritize areas with higher expected utilization, inadvertently reinforcing accessibility advantages for affluent communities [50,91,95]. However, several studies highlight that targeted awareness campaigns and inclusive planning strategies can improve equity outcomes by addressing the needs and barriers faced by diverse user groups [5,64,81,92].

Additionally, Table 4 demonstrates how policy levers explicitly discussed in Section 3 are mapped to the four equity dimensions, including SA (spatial access), CB (cost burden), RU (reliability and usability), AT (awareness and trust), and linked to the system-level outcome categories emphasized in Section 3.2.4 (Adoption, Grid Loads, Economic, Environmental).

Table 4. Policy levers mapped to equity dimensions (SA/CB/RU/AT) and system-level outcomes (adoption, grid loads, economic, environmental).

Policy Lever/Intervention	**SA**	**CB**	**RU**	**AT**	**System-Level Outcomes ****
Availability; Strategic placement (high-traffic, visible sites; corridor hubs)	✓ *			✓	Adoption; Grid; Economic; Environmental
Behavior-aware siting to align supply with observed demand patterns (avoid clustering in underserved regions)	✓		✓	✓	Adoption; Grid; Economic; Environmental

Table 4. *Cont.*

Policy Lever/Intervention	SA	CB	RU	AT	System-Level Outcomes **
Infrastructure design; Station quality (charger type; canopy/lighting; clear wayfinding); Maintenance			✓	✓	Adoption; Economic
Pricing strategies (time-of-day/peak-price tariffs; dynamic pricing)		✓			Adoption; Grid; Economic; Environmental
Payment simplicity (reduce complex payment systems that discourage use)			✓	✓	Adoption
Data-driven operations; Load forecasting (improve network-operation forecasts, e.g., RF forecast error, MAPE)			✓		Grid; Economic
Queue management/scheduling (address waiting and temporal concentration)		✓	✓		Adoption; Grid; Economic

* A ✓ indicates a primary linkage to the specified equity dimension as discussed in Section 3. A blank cell means that dimension was not a primary focus for that lever in these sections. ** Lists the outcome categories (Section 3.2.4) to which each lever is connected in the manuscript: Adoption, Grid Loads, Economic, and Environmental. The table does not assert directionality; see Section 3.2.4 for context (e.g., adoption dynamics, peak-load considerations, and resilience, operational/consumer cost implications, environmental effects conditioned on charging times and grid mix).

3.3. Effects of Identified Factors Across Diverse Contexts

Recent equity in transportation and energy stresses that public charging justice is multi-dimensional; a single metric such as distance to the nearest charger cannot capture the full distribution of benefits and burdens. Building on factors identified from existing studies (see Section 3.2), we evaluate each factor against four dimensions that appear in the literature (see Section 1). By considering the effects of factors on these four dimensions, EV public charging equity could be comprehensively evaluated from physical reachability (SA), direct or indirect user expenditures (CB), functional availability of charging infrastructures (RU), and knowledge of charger locations as well as confidence in their operability (AT), and then further identify potential evidence gaps in geographic, socio-economic, and climate contexts.

Table 5 demonstrates that public EV-charging equity is multidimensional, influenced by diverse factors across spatial access, cost burden, reliability and usability, and awareness and trust. While the four-dimensional evaluations provide a structured way to organize evidence, they necessarily simplify the real-world dynamics. In practice, these factors interact non-linearly: socio-economic constraints (e.g., income, tenure) shape vehicle choice, which feeds into range anxiety; infrastructure reliability influences trust and willingness to use distant chargers; and policy interventions can simultaneously affect multiple dimensions (e.g., pricing schemes altering both cost burdens and spatial access. Micro-level determinants, such as range anxiety and battery size, significantly affect users' reliance on public chargers, often driving increased financial burdens due to more frequent usage or longer detours. This effect is shaped by several mechanisms. Psychologically, uncertainty about the remaining range amplifies perceived risk, leading many drivers—particularly inexperienced or risk-averse users—to prioritize the nearest available charger [13,14]. Informational gaps, such as the lack of reliable real-time data on charger status, further discourage users from venturing to more distant stations. Finally, charging network design plays a role: sparse or unevenly distributed infrastructure raises the penalty of miscalculation, reinforcing the tendency to choose closer, sometimes costlier stations. These mechanisms mean that range anxiety is not just a psychological barrier but an equity issue, as low-income users, who often drive smaller-battery vehicles and have less access to advanced in-car information systems, face sharper trade-offs and higher cumulative costs. Additionally, daily trip purposes such as commuting or retail influence users' habitual charger selection and familiarity, potentially reinforcing existing spatial disparities.

Socio-economic and demographic factors further highlight stark equity issues. Income disparities frequently result in higher charger density in affluent areas, leaving lower-income communities underserved. Renters or individuals living in multi-unit dwellings disproportionately depend on public chargers, incurring higher cumulative costs and experiencing greater inconvenience. Ethnicity and nationality also emerge as critical factors, with marginalized groups often confronting compounded accessibility and trust barriers due to fewer chargers and lower perceived reliability.

Infrastructure supply and operational choices substantially shape user experiences. Higher charger density enhances spatial accessibility, reducing charging deserts, yet placement strategies favoring affluent or high-traffic zones frequently exacerbate inequities. Issues of charger reliability significantly impede usability, notably affecting first-time and financially constrained users, while dynamic pricing and smart scheduling can alleviate cost burdens but require careful implementation to avoid disadvantaging specific user groups.

Finally, broader system-level and climatic considerations have substantial impacts on equity outcomes. Cold climates and increased peak-load demands necessitate more frequent public charging, raising costs and exacerbating inequities in regions without robust infrastructure support. These findings underscore the necessity of comprehensive and integrated planning, emphasizing regional sensitivity, targeted infrastructure deployment, and proactive engagement with underserved communities to effectively address the multi-dimensional nature of EV public charging equity. However, the diversity of study contexts raises caution in generalizing these findings. Evidence from Sioux Falls or Amsterdam reflects urbanized settings with relatively high data availability, while studies in China or Kuwait highlight structural inequities shaped by national policies and cultural factors. Nordic countries and cold US states emphasize climate constraints that may not be adopted elsewhere. Thus, observed impacts are highly context-specific, and equity outcomes are contingent on local governance, regulatory environments, and cultural norms. This context dependency suggests that equity analyses must be interpreted as situational rather than universal. Rather than prescribing one-size-fits-all solutions, comparative frameworks are needed to test whether observed inequities, such as charging deserts, renter disadvantages, or range anxiety, are consistent across contexts or unique to specific policy and cultural environments.

Table 5. Factor evidence on how each impacts the four equity dimensions of EV public charging.

Factor Group	Factor	SA *	SA Impact	CB *	CB Impact	RU *	RU Impact	AT *	AT Impact	Typical Context	References
Micro-level	Range anxiety	↓	Users restrict search radius, choose nearest chargers	↑	Pay a premium to avoid detours	—	—	↓	Lower trust where sites are few	Sioux Falls, USA; national surveys	[6,9,13,51]
	Battery size	↑	Smaller packs require a denser network	↑	More frequent paid top-ups per km	—	—	—	—	Entry-level EVs, CN, and US	[4,65]
	Trip purpose (work/retail/ long-haul)	↓	Workplace sessions cluster at offices; retail at malls	—	—	—	—	↑	Regular commuters learn "home" sites	Amsterdam, NL; Illinois, US; Nanjing, CN	[7,8,70,71]
Socio-economic and demographic	Income level	↑	High-income areas host more chargers	↓	Higher incomes absorb fees; low incomes face ↑ burden	—	—	↑	Affluent users report more trust	10 Chinese cities; US metros	[2,27,28,38,39, 73]
	Housing type (renters, MUDs)	↓	Renters and MUD residents rely on curbside public chargers	↑	Regular public use raises monthly spend	—	—	—	—	US multifamily; CN apartments	[3,40,74]
	Ethnicity/nationality	↓	Minority districts have fewer stations	↑	Longer detours raise cost	—	—	↓	Lower awareness and trust	Kuwait; minority areas US	[22,24,30,31,76, 77,97]

Table 5. *Cont.*

Factor Group	Factor	SA *	SA Impact	CB *	CB Impact	RU *	RU Impact	AT *	AT Impact	Typical Context	References
Infrastructure supply and operations	Network density (stations/km^2)	↑	Higher density shortens the average distance	—	—	—	—	—	—	NZ rollout; CN megacities	[9,38–40,54,78]
	Siting bias to affluent/high-traffic areas	↓	Rural and low-income zones left sparse	—	—	—	—	↑	Visibility boosts perceived access in wealthy zones	Amsterdam, NL; US corridors	[2,18,41,44,48]
	Charger reliability/operability	—	—	↑	Extra fuel/time when units fail	↓	Faults, slow payment apps	↓	Repeat users lose confidence	UK public audit	[29]
	Dynamic pricing/smart scheduling	—	—	↓	Off-peak tariffs cut bills; peak rates ↑ burden	↑	Load balancing shortens queues	—	—	CN multi-station DRL studies	[10,12,16,37,60]
	Charger type (DCFC vs. Level 2)	↑	DCFC extends viable trip range	↑	Higher per-kWh fees at DCFC	↑	Faster sessions; Level 2 is slower	—	—	Norway highways; Slovakia incentives; US	[10,14,28,47,57,64,67]
System-level and climate	Cold-climate battery loss	↓	More stops needed in winter	↑	Extra energy and session fees	—	—	—	—	Nordic and cold US states	[6,11,81,87,88]
	Peak-load/“EV duck curve”	—	—	↑	Peak tariffs or demand charges	↓	Voltage sag slows charging	—	—	Canada winter peaks	[8,59]

* SA = spatial access; CB = cost burden; RU = reliability and usability; AT = awareness/trust. Arrows show direction: ↑ = increases/improves, ↓ = decreases/worsens, — = no observed impact.

4. Conclusions

This review synthesizes extensive findings from 91 peer-reviewed studies examining equity considerations in EV public charging infrastructure across North America, Europe, and Asia. The review points out the emerging trend in EV public charging equity research in recent years, critically compares major methodological frameworks and analytical methods used in prior research, and highlights essential factors influencing equitable access and adoption of EV public charging infrastructure.

This review offers several significant observations to guide future research. Firstly, this review classifies existing theoretical frameworks into three distinct groups, plus their integration usage demonstrated in Figure 3. A significant proportion of adopting spatial and user-related frameworks is observed (a total of 36 studies, accounting for 69.23%), yet few studies have measured EV public charging equity from both spatial and behavioral perspectives by adopting a hybrid framework due to data availability challenges. Findings from the analytical approaches support this distribution. Network-optimization work typically operationalizes equity by embedding minimum service thresholds or dual objectives that balance efficiency with fairness (e.g., minimizing maximum detour distance or waiting time). Spatial-accessibility studies define equity through geospatial indices such as kernel density, 2SFCA, or KDE-plus-Gini, but their results are highly sensitive to buffer radii and weighting assumptions. Behavioral-decision frameworks usually rely on multinomial logit or latent-class choice models to assess how socio-economic attributes (such as income, dwelling type, and range anxiety) shape charger uptake, though these studies are constrained by survey bias and limited transferability. Early hybrid experiments link agent-based demand models with power-flow simulations, measuring equity through multi-criteria indices that couple grid stability with access fairness, but such models remain data- and calibration-intensive. Each framework also carries distinct limitations beyond general data constraints. Optimization assumes equilibrium behavior and often fails to capture stochastic demand or behavioral adaptation. Spatial-accessibility methods are static, rarely validating against real utilization patterns. Behavioral decision approaches depend heavily on stated-preference data, which may not reflect actual usage. Hybrid models, while promising, are computationally demanding and difficult to validate empirically. Since each framework isolates only one side of the problem, including flows, geography, or user choice, comparative tests on a common dataset using standardized equity indicators are now essential. Such head-to-head evaluations would clarify trade-offs, reveal where each framework excels, and guide the design of flexible, context-aware planning tools.

Secondly, this review contributes beyond prior syntheses by offering a multidimensional equity assessment framework that unites SA, CB, RU, and AT, and by examining the effects of identified factors across four dimensions to comprehensively understand EV public charging equity. At the individual-vehicle level, small battery capacity, high range anxiety, and utilitarian trip purposes lengthen detours and raise paid-charging frequency, worsening access and cost. Socio-economic factors such as low income, renting status, and limited digital literacy consistently increase cost burdens and erode trust, with distance effects varying by urban form. On the infrastructure level, higher-power, densely sited, and well-maintained stations reduce access and reliability penalties, although peak-price tariffs can offset these gains. Finally, system-context variables, for instance, cold climate, constrained distribution grids, and uneven policy incentives, shape all four dimensions, especially by amplifying winter demand and voltage sag in underserved regions. Comparative evidence shows that dense urban cores enjoy shorter average distances but face higher tariffs and queueing, whereas rural drivers endure the opposite pattern; low-income renters bear both poor proximity and higher reliance on costly public networks, while owner-occupiers benefit from cheaper home charging despite longer travel. Cold northern cities and regions with weak grids further magnify cost and reliability gaps unless coordinated fast-charger expansion and dynamic pricing are introduced. These findings demonstrate that equitable charging provision cannot be achieved by addressing a single driver; planners could model and monitor all four dimensions and incorporate variables from each analytical level to uncover location- and group-specific interventions that deliver the greatest equity gains. Meanwhile, planners should recognize that these levels and dimensions are not discrete “layers” but interdependent elements. Feedback loops—such as how infrastructure siting affects user trust, or how socio-economic disadvantage amplifies cost burdens through higher public-charging reliance—mean that equity outcomes emerge from complex systems rather than linear hierarchies.

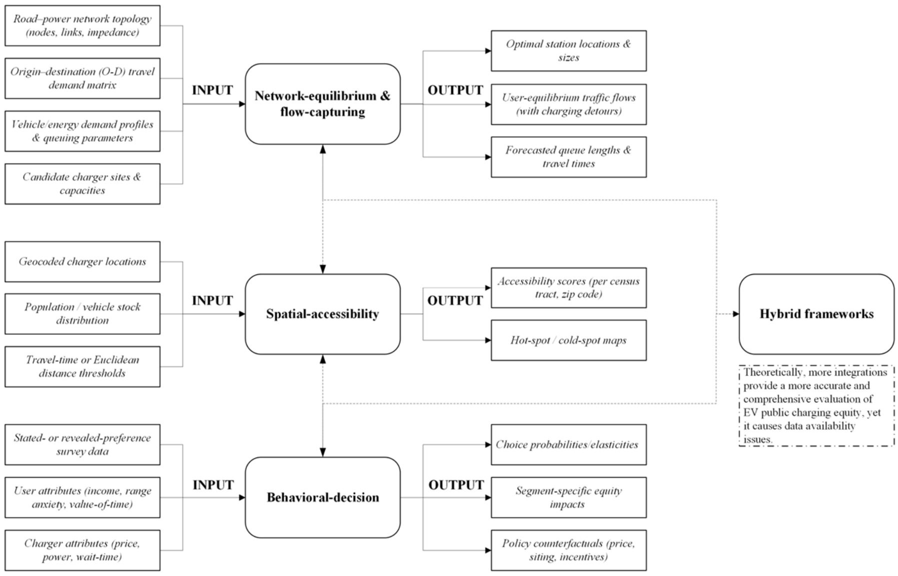

Figure 3. Methodological framework synthesis.

Policy could therefore: (1) institute longitudinal, spatial-temporal monitoring of attitudes and usage, which could be implemented through partnerships with utilities and mobility providers to collect and anonymize high-frequency charging transaction data, GPS traces, and app-based usage logs. Indicators should include not only charger availability and utilization rates, but also wait times, pricing differentials, and disaggregation by socio-economic group or neighborhood. Such monitoring allows agencies to track whether interventions reduce disparities over time, rather than just increasing overall capacity; (2) apply market segmentation to remove financial and access barriers for underserved groups. Effective segmentation requires identifying user clusters (e.g., low-income renters, rural drivers, delivery workers) using socio-demographic, housing, and travel-pattern data. Targeted interventions might include discounted off-peak tariffs for low-income households, priority siting of chargers near multi-unit dwellings, or mobility credits that offset reliance on costly public fast charging. Pilot programs in California and the Netherlands suggest that subsidies tied to user group profiles can significantly reduce access gaps; and (3) tailor charger attributes, including power level, location, and pricing, to local contexts. In addition, comparative research should apply standardized benchmarks—such as spatial access gaps, income-based cost shares, and reliability penalties—to assess the relative merits of competing frameworks in diverse contexts. Future work could consider refining integrated frameworks, comparing them on shared data, and fostering cross-sector collaborations to realize inclusive, equitable, and sustainable charging networks.

However, we acknowledge that this review primarily synthesizes studies from North America, Europe, and Asia, which together represent the largest EV markets and the majority of available peer-reviewed work. Research coverage in Africa, Latin America, and the Middle East remains very limited, reflecting both the nascent nature of EV adoption in these regions and restricted data availability. The scarcity of equity-focused charging studies in emerging EV markets (e.g., Latin America, Africa, the Middle East) highlights a pressing need for future research. These regions often face unique equity challenges, such as limited grid capacity, informal housing, and weaker regulatory frameworks, which are underexplored in the current literature. Also, future research should focus on refining integrated analytical frameworks, conducting comparative studies across methodological approaches, and exploring advanced segmentation strategies to address diverse user needs comprehensively. Such implementation requires standardized comparative exercises across cities or regions, drawing on common datasets that combine travel surveys, socio-demographic information, and charger utilization records. Frameworks should be benchmarked against shared equity indicators, such as (i) average additional travel distance for disadvantaged tracts, (ii) cost burden as a share of household income, and (iii) charger reliability penalties. By grounding evaluations in harmonized benchmarks, researchers can move beyond descriptive comparisons and provide robust evidence of trade-offs across frameworks. Cross-sector collaborations involving policymakers, utilities, communities, and private stakeholders are crucial to promoting inclusive, equitable, and sustainable expansion of EV public charging infrastructure.

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Abbreviations

The following abbreviations are used in this manuscript:

EV	Electric Vehicle
IEA	International Energy Agency
RQ	Research Question
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
GIS	Geographic Information System
AI	Artificial Intelligence
AHP	Analytic Hierarchy Process
TOPSIS	Technique for order preference by similarity to the ideal solution
2SFCA	Two-Step Floating Catchment Area
KPI	Key Performance Indicator
G2SFCA	Gaussian Two-Step Floating Catchment Area
DBSCAN	Density-Based Spatial Clustering of Applications with Noise
ML	Machine Learning
SOC	State of Charge
MAPE	Mean Absolute Percentage Error

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