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Evaluating construction strategies for EV charging infrastructure to support electric vehicle adoption

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Abstract

The transition to electric mobility requires charging systems that are not only physically available but also perceived as reliable, convenient, and compatible with everyday travel. This exploratory study combines survey evidence from 94 respondents with a province- and NUTS-2-level assessment of electric vehicle (EV) charging infrastructure in Türkiye. Four perception dimensions—charging station availability, home charging availability, charging time, and battery range—were examined using descriptive statistics, reliability analysis, one-way analysis of variance, and ordered logistic regression. Respondents assigned high importance to all four dimensions, with home charging availability receiving the highest mean score. ANOVA results showed that statistically significant differences were concentrated mainly in home charging availability, charging station availability, and charging time, particularly across marital-status, employment-status, and occupational groups. Charging station availability showed the strongest positive association with near-term vehicle purchase readiness and approached the conventional 5% significance threshold ($\beta = 0.588$, $p = 0.051$); however, the overall model was not significant, and the outcome was a general vehicle-purchase measure rather than a direct EV-purchase intention item. The spatial assessment showed that charging provision was concentrated in metropolitan and western regions and was not distributed proportionally to regional population or land area. Taken together, the findings support user-centred, phased, and equity-sensitive infrastructure planning, while the regression evidence is interpreted as exploratory rather than as proof of EV-adoption determinants.

1. Introduction

Electric vehicles (EVs) have become a central component of transport decarbonization, energy transition, and sustainable mobility policy. Their adoption, however, depends on more than vehicle technology or financial incentives. Users must also be able to integrate charging into everyday travel, residential conditions, and longer-distance mobility. Charging infrastructure therefore operates simultaneously as a physical service network and as a source of confidence in the practical usability of EVs [1-6].

Türkiye provides a rapidly changing context for examining this issue. According to the Otomotiv Distribütörleri ve Mobilite Derneği, 1,084,496 new automobiles were sold in 2025; electric automobiles accounted for 17.7% of sales and hybrid automobiles for 27.2%, giving these two categories a combined share of 44.9% [7]. This market share does not demonstrate that most prospective buyers considered a battery-electric vehicle, nor does it imply that every hybrid vehicle depends on external charging. It does show, however, that electrified powertrains are no longer marginal alternatives in the new-vehicle market. Individuals preparing to purchase a vehicle in the near term therefore constitute a relevant group for exploring whether charging-related considerations are associated with purchase readiness, provided that this outcome is not misrepresented as direct EV purchase intention.

For prospective EV users, infrastructure adequacy is not determined by charger counts alone. Objective accessibility may differ from perceived accessibility, and a station shown on a map may provide little practical value if it is unavailable, unreliable, difficult to use, or poorly located. Home charging access, charging duration, public-station availability, and battery range consequently shape the perceived convenience and behavioural feasibility of electric mobility [8-15]. These dimensions are also directly relevant to infrastructure

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planning because they influence station siting, residential integration, capacity requirements, and service-quality priorities.

Previous research has examined EV adoption factors, charging accessibility, residential charging barriers, public-charger reliability, spatial inequality, and policy support across different national settings [16-22]. Türkiye-focused studies have likewise addressed market development, technology acceptance, adoption intentions, taxation, charging accessibility, future vehicle growth, and operational challenges at charging sites [23-28]. Nevertheless, perception-based evidence and regional infrastructure provision are often examined separately, and the translation of these two forms of evidence into implementation-oriented planning remains comparatively limited.

Against this background, the present study examines four charging-infrastructure perceptions—charging station availability, home charging availability, charging time, and battery range—and evaluates how they vary across socio-demographic and mobility groups. It also explores their association with near-term vehicle purchase readiness and assesses the regional distribution of charging infrastructure across Türkiye. The purchase-readiness item concerns any vehicle and is therefore used only as an exploratory adoption-related outcome, not as a direct measure of EV intention. The study contributes by combining a user-centred survey perspective with regional spatial evidence and by translating the findings into cautious recommendations for demand-responsive deployment, residential charging integration, phased investment, spatial equity, and risk-aware project delivery.

2. Literature Review

2.1. The role of charging infrastructure in EV adoption

Charging infrastructure is one of the principal conditions shaping the perceived practicality of EV ownership. Consumers evaluate not only purchase price, operating cost, environmental benefits, and vehicle performance, but also whether charging is available, accessible, reliable, and compatible with their mobility routines [5, 6, 8, 12, 15]. Infrastructure can therefore influence adoption through both objective provision and users' interpretation of that provision.

Objective accessibility refers to measurable conditions such as charger density, distance, network coverage, or the number of charging points within a defined area. Perceived accessibility concerns whether users believe that charging is easy to find, convenient, and available when required [8, 9]. The two are related but not identical: calculated accessibility may show only a modest association with perceived convenience and may not explain perceived availability. This distinction means that infrastructure expansion should be assessed through both physical provision and user experience.

Public, workplace, and residential charging perform complementary functions. Public fast charging supports corridor and long-distance travel, while destination charging can be integrated into periods of parking at workplaces, commercial areas, and public facilities [11, 12]. The usefulness of these systems depends on location, charging speed, waiting time, payment performance, connector compatibility, safety, and session reliability. A charger that is broken, blocked, or unable to complete a session may increase "charge anxiety" even where nominal network coverage appears adequate [15, 22, 29, 30].

Home charging is particularly important because it allows charging to be incorporated into long residential parking periods and reduces dependence on public stations [11-13]. Evidence from Sweden indicates that both private and public charging close to home and work increase the likelihood of choosing a chargeable vehicle, with private charging access exerting a stronger influence than public charging density [12], and respondents with private parking and uncomplicated private charging report higher willingness to purchase an EV than those relying on street or shared parking [13]. Access is nevertheless uneven. Apartment residents, renters, households without private parking, and users dependent on on-street parking may face physical, financial, managerial, electrical-capacity, and regulatory barriers [14]. These constraints connect charging feasibility to housing type, parking access, income, and household circumstances, making residential charging both a technical provision issue and an equity concern [13, 14, 31].

Spatial adequacy also depends on where and for whom chargers are constructed. Road-level analysis in the Tokyo metropolitan area found that more than 60% of roads in selected cities may face insufficient charging infrastructure, although targeted rapid-charging expansion can substantially reduce this insufficiency [17]. Studies of Michigan cities further show that charging-infrastructure growth follows different patterns depending on city size, metropolitan density, and high-traffic road ratios [18], while a census-tract model in Maryland identified fast-charging access, workplace charging, and teleworking as key factors associated with EV ownership and suggested higher EV growth in suburban and high-income areas [19]. Consistent with this, public-charger deployment in Washington State increased battery-electric-vehicle adoption, but the estimated gains were concentrated in higher-income counties [16]. These findings indicate that aggregate charger totals can conceal weak route coverage or unequal access [31, 32], and that infrastructure following only existing commercial demand may reinforce regional and socio-economic inequalities. Accordingly, planning should combine demand efficiency with minimum accessibility, corridor continuity, and provision in underserved areas.

Policy and market maturity influence how these infrastructure conditions affect adoption. Financial incentives, charging investment, consumer information, and reliable service can operate jointly rather than independently [4, 20-22, 33]. In Türkiye, Gönül et al. [23] assessed the national EV market, charging infrastructure, regulations, and industrial capacity, emphasizing that charging provision should be expanded particularly in eastern Türkiye and supported by public awareness and incentives. Technology-acceptance and machine-learning studies have identified charging-infrastructure accessibility, perceived cost, and EV knowledge as leading predictors of stated adoption intention [24, 25], while an ordinal-logit policy comparison found that abolishing the special consumption tax produced the largest estimated increase in switching intention, whereas simply increasing the number of charging stations had a positive but statistically non-significant effect [26]. Forecasts also project substantial growth in electric and hybrid vehicles by 2030 [27], and a simulation of converting a conventional fuel station to EV charging showed that such conversion can increase queueing and reduce operational capacity, underlining that charging deployment is also a question of site planning and service capacity [28]. This literature confirms the relevance of charging access while also showing that its effect varies with economic conditions, user knowledge, housing, and policy design.

Despite this growing body of work, two gaps remain. First, most EV-adoption studies focus on consumer intention, incentives, or vehicle attributes, and fewer translate user perceptions into concrete infrastructure-planning and construction strategies. Second, in the Turkish context, perception-based evidence and objective regional provision have largely been examined separately, so the connection between perceived charging adequacy and implementation-oriented, spatially differentiated planning remains underdeveloped. The present study addresses these gaps by examining charging station availability, home charging availability, charging time, and battery range as related but distinct dimensions of perceived practicality. It does not claim that these perceptions alone determine EV adoption. Instead, it evaluates their distribution across respondent groups, explores their limited association with near-term vehicle purchase readiness, and considers how user perceptions may complement objective regional evidence in infrastructure planning.

2.2. Theoretical framework

The selection and interpretation of the four perception variables are guided by the Technology Acceptance Model (TAM) and the Theory of Planned Behaviour (TPB). TAM emphasizes perceived usefulness and perceived ease of use, whereas TPB explains behavioural intention through attitudes, subjective norms, and perceived behavioural control [24, 34, 35]. Within this framework, charging station availability and charging time relate to the perceived practicality and ease of EV use, while home charging availability and battery range relate to perceived control over charging and travel. These theories justify treating charging perceptions as adoption-related conditions, but they do not make a general vehicle-purchase item equivalent to direct EV purchase intention.

This interpretation is consistent with technology-acceptance research in Türkiye, where perceived usefulness, ease of use, compatibility, charging access, and range concerns have been associated with intention to use EVs [24]. In the present study, the framework is used primarily to organize the perception variables and interpret their planning relevance. The ordered logistic regression is therefore an exploratory test of association with near-term vehicle purchase readiness rather than a confirmatory model of EV adoption.

2.3. Spatial distribution of EV charging infrastructure in Türkiye

As contextual background for the user-centred analysis that follows, this subsection summarizes the national distribution of EV charging infrastructure, compiled by the authors from publicly available records. A spatial assessment was conducted at both the province and NUTS-2 levels to evaluate the geographic distribution of EV charging infrastructure across Türkiye. At the province level, the dataset distinguishes among AC-only charging points, DC-only charging points, locations offering both AC and DC charging, and total charging points. This classification makes it possible to assess not only overall infrastructure provision, but also charger-type composition and the relative balance between slower destination-oriented charging, faster corridor-oriented charging, and mixed-format provision.

At the national scale, the province-level dataset sums to 14,808 charging points. The distribution is strongly concentrated in the largest metropolitan and economically active provinces. In total charging points, İstanbul, Ankara, and Antalya form the dominant group, followed by a second tier that includes İzmir, Bursa, Muğla, Kocaeli, Konya, Kayseri, Balıkesir, and Mersin. This spatial pattern indicates that charging infrastructure is concentrated primarily in metropolitan areas, tourism-oriented provinces, and provinces located along major national transport corridors.

A similar concentration is observed for AC-only charging points, which are especially prominent in the largest urban centers. By contrast, the distribution of DC-only charging points appears somewhat more corridor-sensitive, reflecting not only metropolitan demand but also the role of intercity mobility and route-based fast charging. Locations offering both AC and DC charging are considerably fewer in number, but they are likewise concentrated in provinces with more developed charging ecosystems. Overall, the province-level results suggest that infrastructure expansion has not occurred uniformly across charger types: AC-only charging appears especially concentrated in larger urban markets, whereas DC charging shows a stronger connection to intercity accessibility and corridor-based mobility. Mixed AC/DC locations remain comparatively limited and clustered in provinces with more mature or diversified charging networks.

At the other end of the distribution, several eastern and peripheral provinces remain weakly supplied in absolute terms. In these provinces, both AC-only and DC-only provision are limited, and mixed-format charging locations are often absent or nearly absent. This points to a marked east–west imbalance in infrastructure rollout and indicates that peripheral and less densely developed provinces continue to face comparatively weak charging availability. The provincial data also reveal variation in charger composition, with some provinces exhibiting relatively balanced AC and DC provision and others showing a stronger orientation toward one charging type. This suggests that infrastructure adequacy should be evaluated not only in terms of total charger counts, but also in relation to charger mix and provincial mobility context.

To complement the province-level assessment, a second stage of analysis was conducted at the NUTS-2 level. This level of aggregation was selected because NUTS defines Level 2 as the basic regional scale for socio-economic analysis and regional policy [36]. In the Turkish context, the corresponding İBBS/NUTS framework comprises 26 Düzey-2 regions [37]. Province-level charging-point totals were therefore aggregated to the NUTS-2 level in order to identify broader regional disparities in infrastructure provision. The detailed province-level ranking of the largest charging-point concentrations is presented in Table 1. The infrastructure provision is dominated by İstanbul and Ankara, followed by a smaller group of metropolitan, tourism-oriented, and corridor-linked provinces.

To improve comparability across regions with different demographic and spatial characteristics, the regional totals were normalized in two ways: by population and by land area. Population-normalized availability was calculated as charging points per 100,000 inhabitants using the 2024 ADNKS provincial population data [38]. Area-normalized density was calculated as charging points per 1,000 km² using the official province-area dataset [39]. Based on 14,808 mapped charging locations, a national population of 85,664,944, and a land area of 780,043 km², the corresponding national averages are approximately 17.29 charging points per 100,000 inhabitants and 18.98 charging points per 1,000 km² [38-40].

Province-level charging-point data were compiled from the Energy Market Regulatory Authority's Şarj@TR platform [40]. The dataset was accessed on 30 April 2026, and the counting unit was a mapped charging location rather than an individual socket. Population-normalized availability was highest in Ankara, Antalya, Balıkesir, Aydın, and İstanbul, whereas lower values were concentrated in eastern and southeastern regions such as Ağrı, Van, Hatay, Gaziantep, and Mardin. Area-normalized density was highest in compact metropolitan regions, particularly İstanbul, Ankara, İzmir, Kocaeli, and Bursa, while large eastern regions remained comparatively sparse. Fig. 1. summarizes the strongest and weakest NUTS-2 regions under both normalization approaches.

Because the dataset aggregated to the NUTS-2 level contains only one observation per region, conventional group-based inferential procedures such as ANOVA or Kruskal–Wallis are not statistically appropriate. To evaluate whether the regional allocation of charging infrastructure corresponded to the spatial distribution of population, a chi-square goodness-of-fit test was performed using regional population shares as the expected distribution. The results indicated a highly significant deviation between observed and expected charging-point totals, $\chi^2(25) = 3241.43$, $p < 0.001$, demonstrating that EV charging infrastructure is not distributed across NUTS-2 regions in proportion to population size. Examination of standardized residuals revealed that İstanbul (TR10), Ankara (TR51), Antalya (TR61), İzmir (TR31), and Kocaeli (TR42) were characterized by substantially higher charging-point totals than expected under a population-proportional distribution. In contrast, Hatay (TR63), Gaziantep–Adıyaman–Kilis (TRC1), Şanlıurfa–Diyarbakır (TRC2), Mardin–Batman–Şırnak–Siirt (TRC3), and Van–Muş–Bitlis–Hakkâri (TRB2) exhibited marked deficits relative to population-based expectations. A parallel chi-square goodness-of-fit test based on regional area shares likewise yielded a highly significant result, $\chi^2(25) = 162114.83$, $p < 0.001$, indicating that the spatial distribution of charging infrastructure is also highly uneven when evaluated relative to land area.

Table 1. Top 10 provinces in Türkiye by total number of charging points and charger-type composition

Rank	Province	AC-only	DC-only	AC+DC	Total
1	İstanbul	2,401	1,014	543	3,958
2	Ankara	1,067	443	288	1,798
3	Antalya	484	274	106	864
4	İzmir	349	223	94	666
5	Bursa	339	245	75	659
6	Muğla	208	157	41	406
7	Kocaeli	186	150	44	380
8	Konya	171	126	41	338
9	Kayseri	98	86	130	314
10	Balıkesir	108	164	34	306

Source: Authors' compilation from the EPDK Şarj@TR platform [39], accessed 30 April 2026. In this table, a "charging point" denotes a mapped charging location/station classified as AC-only, DC-only, or mixed AC/DC; individual sockets are not counted separately.

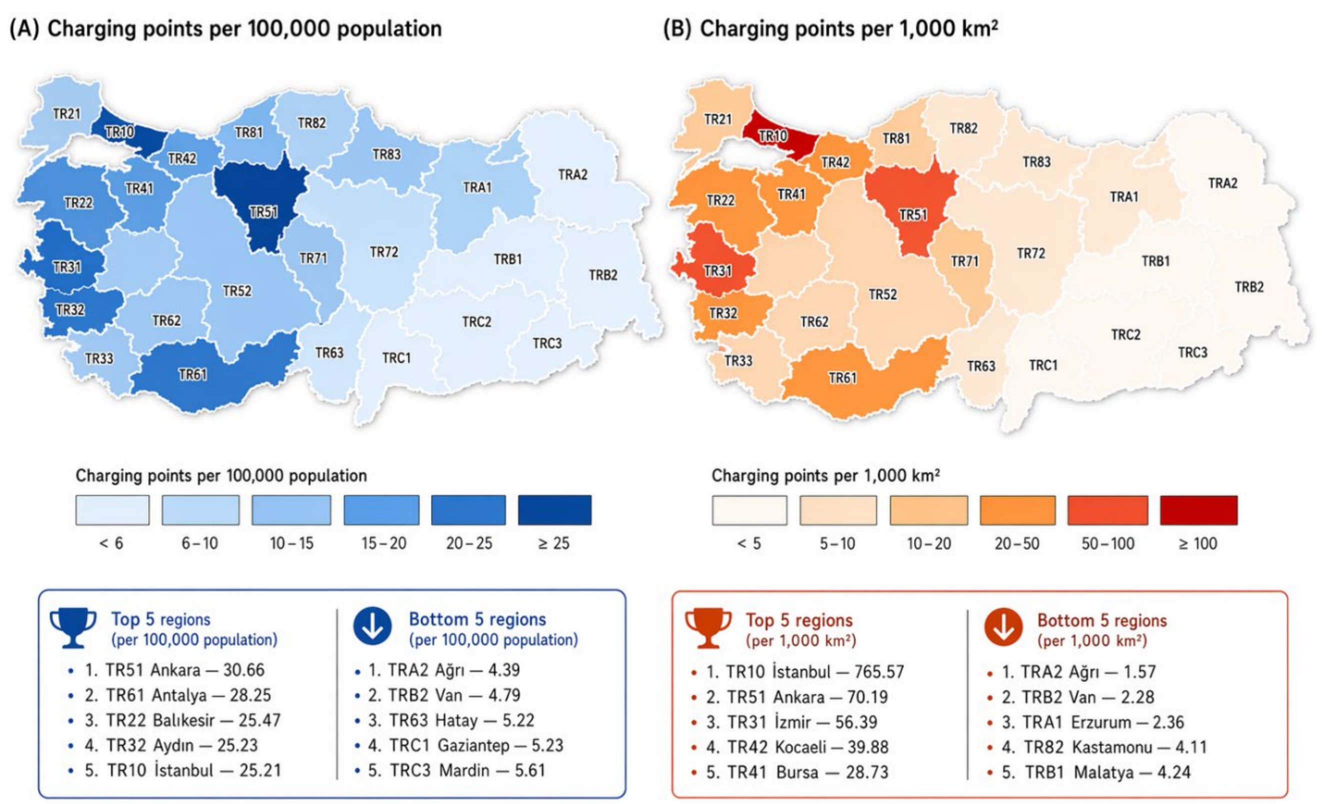

Fig. 1. Regional distribution of EV charging points in Türkiye at the NUTS-2 level: Charging points per 100,000 population and per 1,000 km²

These spatial results establish the objective regional context for the survey-based analysis. Their implications for differentiated regional investment, corridor coverage, and minimum service standards are discussed in Section 5.2 rather than repeated in this subsection.

3. Methodology

3.1. Research design, survey instrument, and data collection

This study employed a survey-based quantitative design to examine individuals' perceptions of EV charging infrastructure and to assess how these perceptions relate to near-term vehicle purchase readiness and infrastructure-planning considerations. A structured questionnaire was developed from the relevant literature and informed by field observations. The survey was conducted online using Microsoft Forms as part of a master's thesis study, enabling standardized data collection across different locations.

The survey data were collected in March 2026. Based on the available recorded start and completion times, the average survey completion time was approximately 10 minutes. The questionnaire consisted of 47 questions in total, and the present article focuses on the subset of variables required for the analyses reported in this manuscript.

The analysed questionnaire items covered four groups of variables. The first group consisted of socio-demographic characteristics, including age, gender, marital status, number of children, education level, household income, employment status, and occupation. The second group covered mobility and vehicle-use characteristics, including daily travel distance, vehicle ownership, driving experience, main transport mode, vehicle-use intensity, vehicle age, vehicle replacement interval, and fuel type. The third group measured near-term vehicle purchase readiness and previous EV purchase experience. The fourth group consisted of the charging-infrastructure perception items used in the main analyses: charging station availability, home charging availability, charging time, and battery range.

The charging-infrastructure perception items were measured using five-point Likert-type scales ranging from 1 = Strongly Disagree to 5 = Strongly Agree. These items were used to evaluate whether respondents considered public charging availability, home charging feasibility, charging duration, and driving range to be important practical conditions for EV use.

A total of 94 respondents completed the questionnaire. Their age, gender, education, income, vehicle ownership, and near-term purchase-readiness characteristics are reported in Section 4.1. The sample included varied socio-demographic and mobility profiles but was predominantly male and university educated. It was considered suitable for exploratory descriptive and group-based analyses, while its size and composition limit broader generalization.

Overall, this approach enabled the collection of standardized data on attitudes, perceptions, and behavioral tendencies, while also allowing comparisons across respondents with different demographic, socio-economic, and mobility characteristics. The collected responses are suitable for descriptive statistical analysis, including frequency distributions, percentages, mean values, and standard deviations. In addition, the structure of the questionnaire allows further inferential analyses, such as analysis of variance (ANOVA) and chi-square tests, to evaluate whether socio-demographic characteristics lead to statistically significant differences in perceptions of electric vehicle charging infrastructure and adoption-related factors. In this way, the methodological framework was designed to generate user-centered empirical evidence relevant to EV charging infrastructure planning and development. Recent articles in this journal have applied related quantitative methods, including Welch's one-way ANOVA and Games-Howell post-hoc testing to operational rail-delay data [41], survey and Relative Importance Index methods to environmental-sustainability awareness in the Turkish construction sector [42], and questionnaire-based stepwise multiple regression to construction safety and health performance [43].

Several important sample characteristics should be acknowledged at the outset and borne in mind throughout the interpretation of all findings. With 94 respondents recruited through a convenience and snowball approach, the sample is moderate in size and is not representative of the Turkish population as a whole. Among the 91 respondents with valid gender data, 67 were male (73.6%), and the sample was predominantly composed of individuals with higher education qualifications, with a substantial proportion holding bachelor's or postgraduate degrees. Although income groups are relatively balanced and a range of employment and occupational backgrounds is represented, these demographic skews mean that the perceptions and stated intentions reported in this study reflect, first and foremost, those of a specific, relatively educated, predominantly male segment of potential EV adopters. Accordingly, the findings should not be generalized beyond this specific profile, and any group-level comparisons within the sample should be interpreted with caution given the small cell sizes that result from subdividing an already limited sample.

3.2. Variables and measures

The analytical framework distinguished among an ordinal outcome, four core charging-infrastructure perception variables, and socio-demographic and mobility-related grouping variables. The variables were selected in line with research on EV adoption, charging accessibility, perceived convenience, and user behaviour.

The ordinal outcome was the survey item asking whether respondents planned to buy a vehicle within the next two years, coded as no, undecided, and yes. It is described throughout this study as near-term vehicle purchase readiness. The item did not ask whether the intended vehicle would be electric; consequently, it is not a direct measure of EV purchase intention. Its use is motivated by the changing Turkish automobile market, in which electric and hybrid vehicles together represented 44.9% of new automobile sales in 2025 [7], making near-term purchasers a relevant transition group. Nevertheless, market shares cannot establish that a specific respondent considered an EV, and the regression is therefore interpreted only as an exploratory adoption-related analysis. Supplementary items on previous EV purchase and willingness to purchase an EV again were used descriptively for respondents with prior EV experience.

The core independent variables were respondents' perceptions of charging infrastructure, measured using Likert-scale items. These variables focused on dimensions directly related to the perceived practicality of EV use, namely charging station availability, home charging availability, charging time, and battery range or driving range perception. More specifically, these measures captured the perceived adequacy and accessibility of public charging stations, the feasibility of charging at home or in residential settings, concerns related to charging duration and waiting time, and perceptions regarding whether EV range is sufficient for daily and long-distance travel.

To support group-based comparisons, the survey also collected a range of socio-economic and household characteristics, including age, gender, income level, education level, employment status, marital status, household composition, number of children, and vehicle ownership status. Vehicle ownership was treated as particularly relevant because access to a private vehicle may influence both EV familiarity and charging expectations. Household composition was also included, given its potential influence on travel needs and vehicle purchase decisions. In addition, several travel behavior variables were incorporated as contextual measures, including daily travel distance, driving experience, primary transportation mode, and level of car use.

3.3. Data analysis

The survey data were analyzed using descriptive and inferential statistical methods. The analytical strategy summarized respondent characteristics and perceptions, assessed the internal consistency of the four charging-related measures, tested group differences in those perceptions, and explored their association with near-term vehicle purchase readiness.

In the first stage, descriptive statistics were used to characterize the sample and provide an overall profile of respondents' attitudes and perceptions. Frequency distributions and percentage values were reported for categorical variables such as gender, income level, education level, employment status, and vehicle ownership. For Likert-scale items related to charging infrastructure perceptions, mean scores and standard deviations were calculated in order to identify general patterns in the data.

Internal consistency was assessed using Cronbach's alpha for the four related perception items: charging station availability, home charging availability, charging time, and battery range. The coefficient, reported in Section 4.1, was used to assess their degree of overlap; the items remained separate in the subsequent ANOVA and regression analyses.

One-way ANOVA was used to examine whether the four charging-infrastructure perceptions differed across socio-demographic and mobility groups. Statistical significance was evaluated primarily at $p < 0.05$. Results between $p = 0.05$ and $p = 0.10$ were reported as exploratory patterns and interpreted using their exact p-values rather than treated as conclusive findings.

Homogeneity of variances was assessed prior to post hoc analysis [44].

When the assumption of homogeneity of variances was violated, the Games-Howell procedure was used for post hoc pairwise comparisons. This test does not require equal variances or equal group sizes and is therefore more appropriate under heteroscedastic conditions. For each pair of groups, the comparison is based on

$$q_{ij} = \frac{\left|\bar{X}_i - \bar{X}_j\right|}{\sqrt{\frac{s_i^2}{n_i} + \frac{s_j^2}{n_j}}} \tag{1}$$

where $\bar{X}_i$ and $\bar{X}_j$ are the sample means, s_i^2 and s_j^2 are the sample variances, and n_i and n_j are the respective group sample sizes. The significance of the comparison is then evaluated using the Welch–Satterthwaite approximation to determine the effective degrees of freedom, accounting for unequal variances between groups. Accordingly, the Games-Howell procedure provides a robust post hoc method under conditions of heteroscedasticity and unequal group sizes [45].

Because near-term vehicle purchase readiness had three naturally ordered categories (no, undecided, yes), an ordered logistic regression model was estimated. Ordered logistic regression is appropriate when category ranking is meaningful but intervals between categories are not assumed to be equal. Letting Y denote purchase readiness and X_k denote the four infrastructure-perception variables, the model is specified as:

$$log\left(\frac{P(Y > j)}{P(Y \leq j)}\right) = \alpha_j - \sum_{k=1}^{4} \beta_k X_k\,, \qquad j = 1,2 \tag{2}$$

where α_j are threshold parameters and β_k are regression coefficients in Equation 2. Parameters were estimated by maximum likelihood. Model adequacy was assessed using the log-likelihood, a likelihood-ratio test against the intercept-only model, McFadden, Cox & Snell, and Nagelkerke pseudo-R^2 statistics, and the Akaike and Bayesian information criteria (AIC and BIC). Possible multicollinearity was examined using a Pearson correlation matrix and variance inflation factors (VIF). Positive coefficients indicate higher odds of being in a stronger purchase-readiness category, whereas negative coefficients indicate lower odds. Odds ratios were calculated as e^{β} [46, 47].

This framework separates the direct descriptive and group-comparison evidence from the more limited exploratory regression evidence.

4. Results

4.1. Sample characteristics and descriptive findings

The dataset comprised 94 respondents who completed the online questionnaire. Age information was available for 90 respondents, with a mean age of 30.08 years (standard deviation, SD = 12.89) and a range of 18 to 71 years. For group-based analyses, age was categorized as 18–24 years (n = 42), 25–34 years (n = 27), and 35 years and over (n = 21). Table 2 presents age, gender, education, income, vehicle ownership, and near-term vehicle purchase readiness.

Table 2. Socio-demographic characteristics of the survey respondents

Variable	Category	Frequency (n)	Percentage (%)
Age	18–24 years	42	46.70
	25–34 years	27	30.00
	35 years and over	21	23.30
Gender	Male	67	73.60
	Female	24	26.40
Education	Pre-university	9	10.00
	University degree	62	68.90
	Graduate	19	21.10
Income	Low-income	34	38.20
	Middle-income	35	39.30
	High-income	20	22.50
Vehicle Ownership	Personal vehicle	44	46.80
	Company vehicle	1	1.10
	No vehicle	49	52.10
Vehicle Purchase Readiness	Yes (Planning)	35	37.20
	No (Not planning)	31	33.00
	Undecided	28	29.80

Gender data were available for 91 respondents, of whom 73.6% were male and 26.4% were female. The sample was highly educated: among valid responses, 68.9% reported a university degree, 21.1% had graduate-level education, and 10.0% had pre-university education. Income distribution was relatively balanced across categories, with 38.2% in the low-income group, 39.3% in the middle-income group, and 22.5% in the high-income group.

Vehicle ownership patterns indicated a relatively even split in direct vehicle access. While 52.1% of respondents reported not owning a vehicle, 46.8% owned a personal vehicle and 1.1% reported access to a company vehicle. For analytical purposes, vehicle ownership was also recoded into a binary distinction between respondents with vehicle access and those without vehicle access. Regarding near-term purchase readiness, 37.2% stated that they planned to buy a vehicle within the next two years, 33.0% reported no such plan, and 29.8% were undecided.

Overall, the sample may be characterized as relatively young, male-dominated, and highly educated, with a fairly balanced distribution across income groups and a near-even division between respondents with and without direct vehicle access. These characteristics should be considered when interpreting the representativeness and broader generalizability of the findings [48].

The indicators provide further insight into respondents' current vehicle characteristics, near-term purchase readiness, and previous EV experience. As shown in Fig. 2, gasoline vehicles represented the largest share of reported fuel types (47.7%), followed by diesel vehicles (36.4%), while electric and hybrid vehicles accounted for smaller shares (11.4% and 4.5%, respectively). Regarding near-term vehicle purchase readiness, 37.2% of respondents stated that they planned to buy a vehicle within the next two years, whereas 33.0% reported no such plan and 29.8% were undecided. The results also show that previous EV purchase experience was very limited, with 94.4% of respondents reporting no previous EV purchase and only 5.6% reporting prior EV purchase experience. Overall, these findings indicate that although direct EV ownership experience remains limited within the sample, a meaningful share of respondents reported near-term vehicle purchase readiness. Because valid response counts differed across items, percentages in Fig. 2. are based on valid responses for each corresponding variable.

Fig. 3. presents the driving and vehicle-use profile of the respondents. The sample includes a considerable proportion of experienced drivers, with 45.5% reporting more than 15 years of driving experience, 29.5% reporting 6–15 years, and 25.0% reporting 0–5 years. Most respondents reported having no children (77.7%), while one and two children each accounted for 9.6%, and three children accounted for 3.2%. Daily travel distances were generally moderate: 55.7% of respondents reported travelling 0–15 km per day, 28.6% travelled 15–30 km, and 15.7% travelled more than 30 km. Vehicle ownership was almost evenly divided between respondents without a vehicle (52.1%) and those with a personal vehicle (46.8%), while company vehicle access was reported by 1.1%. Private car use was the dominant main transport mode (69.0%). The remaining responses were distributed across public transport-related categories, including public transport (16.7%), bus (4.8%), and metro (4.8%), while walking and scooter use each accounted for 2.4%.

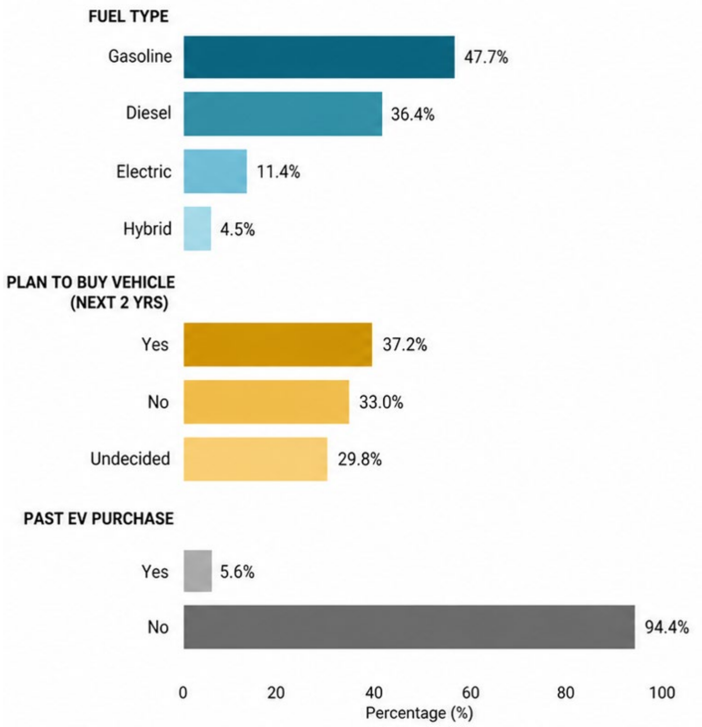

Fig. 2. Distribution of vehicle- and EV-Related indicators among respondents (%)

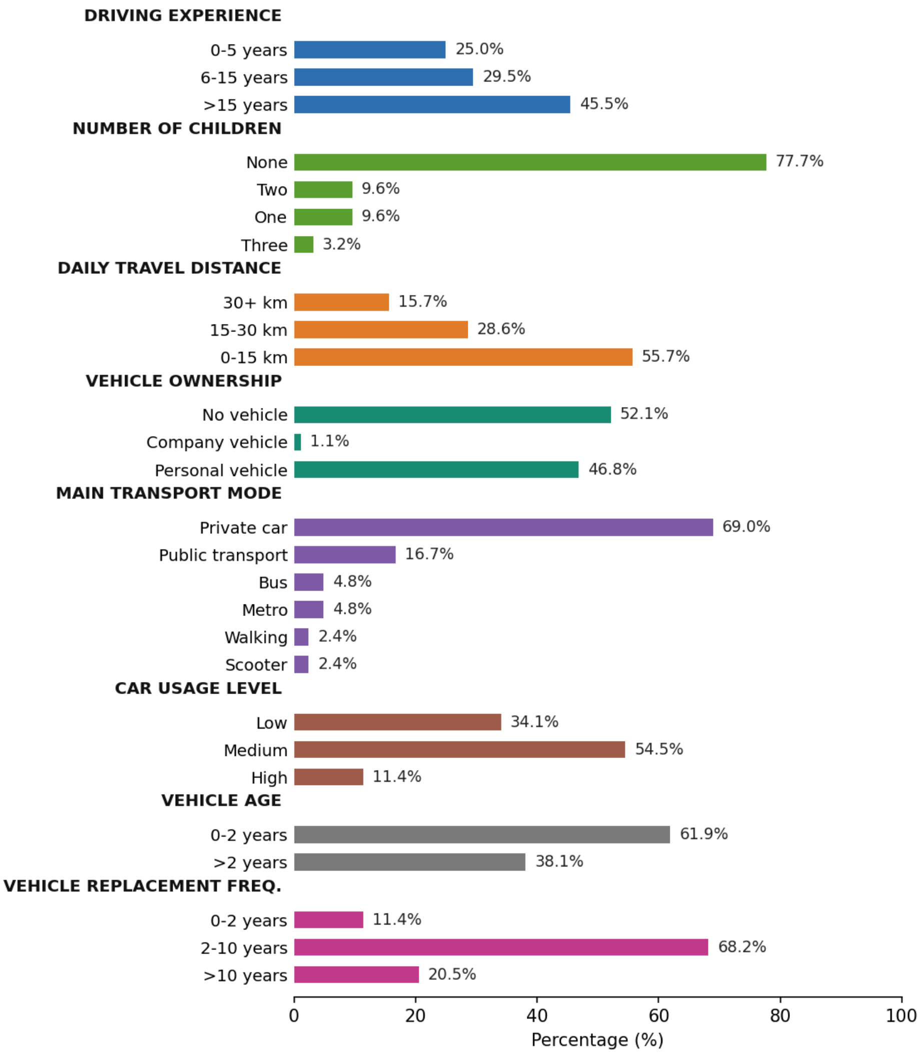

Fig. 3. Driving and vehicle-use profile of respondents (%)

In terms of car use intensity, medium-level use was the most common category (54.5%), followed by low (34.1%) and high use (11.4%). The results also indicate that most reported vehicles were relatively new, with 61.9% being 0–2 years old, and the most common vehicle replacement interval was 2–10 years (68.2%). Overall, these patterns show that the sample is strongly connected to private vehicle use, while also including respondents with relatively short daily travel distances, which is relevant for evaluating the practical feasibility of EV use and charging infrastructure expectations. Because valid response counts differed across travel and vehicle-use variables, percentages in Fig. 3. are based on valid responses for each item.

Respondents assigned consistently high importance to all four charging-related attributes (Table 3). Home charging availability received the highest mean rating (M = 4.57, SD = 0.69), followed by charging station availability (M = 4.53, SD = 0.68), charging time (M = 4.51, SD = 0.69), and battery range (M = 4.38, SD = 0.87). The narrow range of these high means indicates that the practical conditions of charging were widely regarded as important within the sample.

Table 3. Descriptive statistics of EV charging infrastructure perception variables

Perception Variables	Mean (M)	Std. Deviation (SD)	Min.	Max.
Home charging availability	4.57	0.69	2	5
Charging station availability	4.53	0.68	3	5
Charging time	4.51	0.69	2	5
Battery range	4.38	0.87	1	5
Range anxiety	3.91	1.14	1	5
Charging infrastructure concern	3.89	1.03	1	5

Two broader concern variables were also examined. Range anxiety had a mean score of 3.91 (SD = 1.14), while charging infrastructure concern had a mean score of 3.89 (SD = 1.03). Although these values were somewhat lower than the ratings assigned to the four specific infrastructure attributes, they nevertheless indicate elevated concern regarding the practical conditions of EV use.

The descriptive pattern therefore shows that charging infrastructure was not a peripheral consideration for respondents. At the same time, the concentration of ratings near the upper end of the scale suggests a possible ceiling effect, which may reduce the ability of these variables to distinguish between purchase-readiness groups.

The four perception items yielded a Cronbach's alpha of 0.716 based on 89 complete observations, indicating moderate internal consistency among related aspects of charging practicality.

Item–rest correlations were strongest for charging station availability (r = 0.612), charging time (r = 0.574), and home charging availability (r = 0.524), while battery range showed a weaker positive relationship (r = 0.356). These values indicate meaningful overlap without showing that the items are interchangeable; they were therefore retained as separate variables in the subsequent analyses.

4.2. Group differences in charging infrastructure perceptions

A series of one-way ANOVA tested 16 socio-demographic and mobility variables across four perception dimensions—charging station availability, charging time, home charging availability, and battery range—producing 64 omnibus comparisons. The primary significance threshold was $p < 0.05$.

Across the majority of the tested variables, no statistically significant group differences were identified. Specifically, 12 of the 16 independent variables yielded no significant differences across any of the four charging perception dimensions. Variables such as age, gender, education level, number of children, daily driving distance, vehicle ownership status, duration of holding a driver's license, primary transportation mode, vehicle usage frequency, and vehicle age did not significantly affect how respondents evaluated charging station availability, charging time, home charging, or battery range. This pattern suggests a relatively broad baseline consensus regarding the importance of EV charging infrastructure across much of the sample.

Although income did not reach the conventional significance threshold, a marginal pattern was observed for charging time sensitivity ($F = 2.63$, $p = 0.078$). Descriptively, the high-income group reported the highest concern regarding charging time (M = 4.80), followed by the low-income group (M = 4.45) and the middle-income group (M = 4.37). Although the result was not statistically conclusive, the descriptive pattern within this sample suggests that respondents in the high-income group may place greater importance on charging time. This interpretation should be regarded as exploratory and should not be generalized beyond the present sample.

Despite the overall pattern of similarity, several statistically significant differences did emerge. Marital status was significantly associated with perceptions of home charging availability ($p = 0.026$). Married respondents assigned greater importance to home charging availability (M = 4.79) than single respondents (M = 4.47). This pattern may reflect differences in household and residential circumstances; prior studies show that home-charging feasibility is closely related to dwelling type, parking access, and constraints in multifamily housing [12-14].

Employment status also had a significant effect on two infrastructure dimensions. Significant differences were observed for both charging station availability ($p = 0.025$) and charging time ($p = 0.016$). Employed respondents assigned higher importance to charging station availability (M = 4.71) and charging time (M = 4.74) than students (M = 4.41 for both variables). This pattern may reflect greater sensitivity to time efficiency and public charging access among employed respondents; however, commuting routines were not measured directly, and this explanation should therefore be treated as exploratory.

Occupational category was significantly associated with home charging availability in the omnibus one-way ANOVA ($F(14, 54) = 2.42$, $p = 0.010$), indicating that at least two occupational groups differed. Because Levene's test indicated heterogeneity of variances ($W = 3.15$, $p = 0.004$), the Games-Howell procedure was applied for post hoc pairwise comparisons; categories represented by a single respondent were excluded from these comparisons. Several occupational groups rated home charging at the scale maximum (lawyers, civil servants, workers, and police/military officers, all M = 5.00), whereas engineers/architects (M = 4.38) and self-employed respondents (M = 4.40) gave somewhat lower ratings. The Games-Howell comparisons identified the engineer/architect group, which was both the largest subgroup (n = 26) and the only one with appreciable rating dispersion, as differing significantly from lawyers, civil servants, workers, and police/military officers (mean difference = 0.62, $p = 0.004$ for each pair); no other pairwise contrast reached significance (all $p > 0.50$). These differences should be read with caution given the small and uneven occupational subgroup sizes.

Overall, the ANOVA results indicate that perceptions of battery range and public charging station availability were relatively consistent across the sample, whereas practical aspects of charging feasibility, particularly home charging availability and charging time, showed greater variation across specific socio-economic groups. As shown in Table 4, the clearest sources of variation were associated with household structure, employment status, and occupational background.

Table 4. Statistically significant differences in EV charging infrastructure perceptions by socio-demographic groups

Socio-Demographic Variable	Perception Dimension	Mean (Group 1)	Mean (Group 2)	p-value	Interpretation
Marital Status	Home Charging Availability	Married: 4.79	Single: 4.47	0.026	Married individuals place higher importance on home charging
Employment Status	Charging Station Availability	Employed: 4.71	Student: 4.41	0.025	Employed individuals are more sensitive to station availability
Employment Status	Charging Time	Employed: 4.74	Student: 4.41	0.016	Employed individuals are more sensitive to charging time
Occupation (Job)	Home Charging Availability	Civil servant/ Legal profession 5.00	Engineer/Architect 4.38	0.010	Occupation affects perceived importance of home charging

Overall, significant differences were confined to a small subset of the 64 comparisons. For 12 of the 16 grouping variables—including age, gender, education, income, vehicle ownership, and daily travel distance—no p-value below 0.05 was detected for any of the four perceptions. This should not be interpreted as proof that the groups are equivalent; within this sample, it indicates only that the available data did not identify clear differences. The detected variation was concentrated mainly in home charging and charging time, suggesting that residential feasibility and time sensitivity may be more context-dependent than the general importance assigned to public charging.

4.3. Infrastructure perceptions and near-term vehicle purchase readiness

An ordered logistic regression explored the relationship between the four infrastructure perceptions and near-term vehicle purchase readiness. The outcome was ordered as no, undecided, and yes, and the model used 89 complete observations. Because the item concerned the purchase of any vehicle rather than an EV specifically, the estimates are interpreted as adoption-related exploratory associations. The pre-specified threshold was $p < 0.05$; exact p-values close to that boundary are reported as borderline evidence rather than forced into a sharp substantive distinction [49]. The estimated coefficients are presented in Table 5.

Table 5. Ordered logistic regression coefficients: Infrastructure perceptions and near-term vehicle purchase readiness (Standardized predictors, n = 89)

Predictor	β	OR	p
Charging station availability	0.588	1.800	0.051†
Home charging availability	−0.454	0.635	0.089†
Charging time	−0.353	0.703	0.213
Battery range	0.198	1.220	0.384
Threshold τ_1	−1.148	—	—
Threshold τ_2	0.137	—	—

β = standardized regression coefficient; OR = odds ratio ($e\beta$, the multiplicative change in the odds of being in a higher purchase-readiness category per 1 SD increase in the predictor); p = two-tailed p-value. †$p < 0.10$. Predictors are z-standardized. Thresholds (τ) are intercept parameters of the proportional-odds model.

Charging station availability produced the largest positive coefficient (β = 0.588, OR = 1.80) and approached the conventional 5% threshold ($p = 0.051$). Substantively, this is a borderline positive association rather than a result that should be dismissed as wholly uninformative or reported as formally significant at $p < 0.05$. Home charging availability had a negative exploratory coefficient (β = −0.454, OR = 0.64, $p = 0.089$), which may reflect respondents emphasizing home charging because its absence is perceived as a barrier [12-14]. Charging time (β = −0.353, $p = 0.213$) and battery range (β = 0.198, $p = 0.384$) showed weaker evidence. These coefficients describe associations, not causal effects or confirmed predictors of EV choice [49]. The full model-fit diagnostics are presented in Table 6, and the multicollinearity diagnostics in Table 7.

Table 6. Goodness-of-Fit statistics for the ordered logistic regression model

Fit measure	Value
Observations (n)	89
Log-likelihood (full model)	−94.00
Log-likelihood (null model)	−97.23
Likelihood-ratio χ^2 (df = 4)	6.46
p-value (LR test)	0.167
McFadden pseudo-R^2	0.033
Cox & Snell pseudo-R^2	0.070
Nagelkerke pseudo-R^2	0.079
AIC	200.00
BIC	214.93

To assess the adequacy of the ordered logistic regression model, several goodness-of-fit measures were examined, as reported in Table 6. The likelihood-ratio test comparing the full model with the intercept-only (null) model was not statistically significant (LR $\chi^2(4) = 6.46$, $p = 0.167$), indicating that the four infrastructure-perception predictors, taken together, did not significantly improve model fit at the 5% level. Consistent with this, the pseudo-R^2 values were low (McFadden = 0.033; Cox & Snell = 0.070; Nagelkerke = 0.079), and the information criteria (AIC = 200.00; BIC = 214.93) likewise indicate only modest explanatory power. These diagnostics confirm that the regression results should be interpreted with appropriate caution.

Table 7. Pearson correlations and Variance Inflation Factors (VIF) among the charging-infrastructure perception predictors (n = 89)

Variable	Station	Home	Time	Range	VIF
Charging station availability	1.00	0.47	0.64	0.31	1.84
Home charging availability	0.47	1.00	0.46	0.31	1.40
Charging time	0.64	0.46	1.00	0.26	1.78
Battery range	0.31	0.31	0.26	1.00	1.15

Possible multicollinearity among the four predictors was examined using a Pearson correlation matrix and variance inflation factors (VIF), as reported in Table 7. The correlations were low to moderate, the strongest being between charging station availability and charging time ($r = 0.64$). All VIF values were well below the conventional threshold of 5 (and the more conservative threshold of 10), ranging from 1.15 for battery range to 1.84 for charging station availability. These results indicate that multicollinearity is not a material concern and does not undermine the interpretation of the individual coefficients, although the moderate overlap among the predictors—consistent with the scale's internal consistency (Cronbach's $\alpha = 0.716$)—suggests that the four constructs represent related facets of a broader charging-infrastructure perception.

5. Discussion

5.1. Interpretation of findings and comparison with prior literature

The survey and spatial analyses offer two complementary findings. First, respondents rated all four charging dimensions highly, with home charging receiving the highest mean. Second, charging infrastructure was distributed unevenly across Türkiye when normalized by population and land area. These results place user-perceived practicality and regional provision at the centre of the planning problem, while the limited sample requires an exploratory interpretation.

Near-term vehicle purchasers are relevant to the EV transition because they are approaching an actual choice point in a market where electric and hybrid automobiles together accounted for 44.9% of new automobile sales in 2025 [7]. This market context strengthens the rationale for examining purchase readiness, but it does not show that every prospective purchaser considered an EV. The dependent variable therefore captures readiness to enter the vehicle market, not direct EV intention or the composition of an individual's consideration set.

The high means for charging station availability, home charging, charging time, and battery range are consistent with literature showing that consumers evaluate EVs through practical access, reliability, residential feasibility, and travel flexibility [8-15, 22, 30]. Because the means ranged only from 4.38 to 4.57, a ceiling effect is plausible: charging may be regarded as important by most respondents regardless of whether they plan to purchase a vehicle soon. This helps explain why strongly rated infrastructure attributes did not necessarily separate the three purchase-readiness categories.

Group differences were limited and concentrated mainly in home charging and charging time. This pattern is compatible with evidence that residential charging depends on dwelling type, parking, electrical capacity, household arrangements, and management conditions [12-14]. For occupation, Games-Howell post-hoc comparisons showed that engineers/architects rated home charging significantly lower than several maximally rating groups (lawyers, civil servants, workers, and police/military officers), although the small and uneven subgroup sizes limit the weight that can be placed on these specific contrasts. The absence of detected differences for many other variables likewise does not establish population-wide equivalence.

Beyond these group differences, the relationship between the four perceptions and purchase readiness was examined directly through the regression model. The regression provides a more nuanced result than a simple significant/non-significant label. Charging station availability had the strongest positive coefficient and $p = 0.051$, which is almost indistinguishable substantively from a value just below 0.05. Because $p < 0.05$ was specified in advance, the coefficient is reported as borderline rather than formally significant. More importantly, the overall likelihood-ratio test was not significant ($p = 0.167$) and the pseudo-R^2 values were low. The model therefore does not establish that charging perceptions predict EV adoption.

One plausible reason for the weak overall model is imperfect alignment between the predictors and outcome. Charging access, time, and range are expected to influence whether an EV is selected, whereas the outcome asked whether any vehicle would be purchased. Some respondents may have planned to buy an internal-combustion vehicle without seriously evaluating an EV; others may have considered an EV and rejected it because of charging, price, or another factor. General purchase timing may also depend more strongly on income, financing, household need, or the condition of the current vehicle. The questionnaire did not identify EV consideration sets or reasons for rejecting an EV, so these explanations remain hypotheses for future research.

The spatial analysis adds a stronger objective planning result. Metropolitan and western regions had higher provision, while several eastern and southeastern regions remained below population- and area-based expectations. Read together, the survey identifies attributes valued by respondents and the spatial analysis identifies where objective provision is comparatively weak. This supports an equity-oriented planning interpretation, but not a directly tested regional relationship because the survey was not geographically representative.

5.2. Implications for infrastructure planning and delivery

The following implications are planning recommendations derived from the combined evidence; they are not effects demonstrated directly by the regression model.

Public charging investment should be demand-responsive and service-oriented. Deployment should account for trip generation, dwell time, corridor demand, network visibility, uptime, waiting conditions, payment reliability, and real-time information rather than relying only on aggregate charger totals [8, 9, 11, 15, 30, 32]. Metropolitan regions with high demand still require additional capacity, but the priority there should increasingly be performance, reliability, fast-charging capacity, and closure of subregional gaps.

Residential charging should be treated as a core construction and building-management issue. New developments can incorporate EV-ready electrical capacity and parking design, while existing apartment stock may require shared charging systems, retrofit guidance, financing support, and clearer approval procedures. Workplace, public-parking, curbside, and neighbourhood charging can complement home charging where private parking is unavailable [12-14].

Regional investment should combine efficiency with territorial equity. Population-deficit regions such as TRC2, TR63, TRC1, TRB2, and TRC3 require catch-up provision, while geographically large and sparse regions require corridor continuity and strategically spaced fast chargers rather than dense urban saturation. Planning should therefore move from raw province totals toward service standards such as charging points per 100,000 inhabitants, maximum distance to a fast charger, corridor spacing, and minimum regional coverage obligations.

Construction should be phased and scalable. Modular layouts, pilot deployment, and staged capacity expansion can reduce demand and technology risk while preserving the ability to add chargers without major reconstruction. Early coordination with electricity distribution companies, grid-capacity assessment, land-use integration, standardized municipal permitting, and site-level operational analysis are necessary to address grid, land, financial, and implementation risks [18, 20, 28, 32].

Delivery will require coordination among national authorities, municipalities, distribution companies, developers, building managers, and private charging operators. Public support can be targeted toward locations where commercial returns are weak but accessibility needs are high, while private operators can provide investment and technical capacity.

6. Conclusions

This exploratory study examined charging-infrastructure perceptions and regional charging-point distribution in Türkiye. The survey results showed that respondents assigned high importance to all four charging dimensions: charging station availability, home charging availability, charging time, and battery range. This indicates that charging-related conditions are central to the perceived practicality of electric mobility rather than secondary considerations.

The ANOVA results showed that statistically significant differences were limited to a small subset of comparisons. The clearest differences were observed in home charging availability by marital status and occupation, and in charging station availability and charging time by employment status. These findings suggest that residential charging feasibility and time sensitivity are more socially differentiated than battery range or the general importance assigned to public charging. However, the absence of significant differences for most grouping variables should be interpreted cautiously and should not be treated as evidence of full group equivalence.

The ordered logistic regression provided only limited evidence. Charging station availability showed the strongest positive association with near-term vehicle purchase readiness and approached the conventional significance threshold. However, the overall model was not statistically significant and had low explanatory power. In addition, the outcome measured intention to purchase any vehicle rather than direct EV purchase intention. Therefore, the regression findings should be interpreted as exploratory associations rather than confirmed determinants of EV adoption.

The spatial analysis produced a clearer infrastructure-planning result. Charging infrastructure in Türkiye is strongly concentrated in metropolitan and western regions and is not distributed proportionally to either regional population or land area. This indicates a spatial equity problem in the current charging network. Planning should therefore not rely only on total charger counts or market-led deployment in high-demand provinces. Corrective investment is needed for underserved eastern, southeastern, and peripheral regions, together with corridor-based fast-charging coverage and minimum regional service standards.

Overall, the findings support a user-centred and spatially differentiated approach to EV charging-infrastructure planning. Public charging reliability, residential charging integration, phased construction, and regional equity should be considered together. The main limitations are the small and non-representative sample, the predominance of male and highly educated respondents, small subgroup sizes, possible ceiling effects in perception scores, and the absence of a direct EV purchase-intention measure.

Declarations

Conflict of Interests

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Author Contributions

M. Y. Kahveci: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data Curation, Writing – Original Draft, Writing – Review & Editing, Visualization, Project administration. A. S. Kesten: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data Curation, Writing – Original Draft, Writing – Review & Editing, Visualization, Project administration, Supervision.

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Data Availability Statement

The data presented in this study are available from the corresponding author upon reasonable request.

Ethics Committee Permission

The authors acquired ethics committee permission for the surveys implemented in this paper from Gebze Technical University Ethics Committee (Date: 18.03.2026; File No: 244970).

Use of Generative AI and AI-assisted Technologies

The author(s) used Claude (Anthropic) to improve the language and readability of the manuscript and have reviewed and take full responsibility for the final content.

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