24th International Conference on Renewable Energies and Power Quality (ICREPQ'26)
Santander (Spain), 10th to 12th June 2026
E&Q Journal - ISSN:2659-8779. Volume 4. July 2026

# Application of Q-Methodology for Characterizing Electric Vehicle Demand Profiles and Governance

F. J. Ramos-Real[1,2], I. Medina-Jiménez[1,2], F. J. Calero-García[1,2], M. G. Rodríguez-Brito[1,2], M. C. Rodríguez-Donate[2,3], I. L. Nieto-González[3], E. Pereda de Pablo[4], J. A. Méndez-Pérez[5], Ó. García-Afonso[4] and B. González-Díaz[4].

[1] Departamento de Economía, Contabilidad y Finanzas, Universidad de La Laguna, 38200 San Cristóbal de La Laguna, Spain.

[2] Instituto Universitario de Investigación Social y Turismo (ISTUR), Universidad de La Laguna, 38200 San Cristóbal de La Laguna, Spain.

[3] Departamento de Economía Aplicada y Métodos Cuantitativos, Universidad de La Laguna, 38200 San Cristóbal de La Laguna, Spain.

[4] Departamento de Ingeniería Industrial, Universidad de La Laguna (ULL). Camino San Francisco de Paula, 19. 38200 La Laguna (Tenerife), Spain, email: bgdiaz@ull.edu.es.

[5] Departamento de Ingeniería Informática y de Sistemas, Universidad de La Laguna (ULL). Camino San Francisco de Paula, 19.38200 La Laguna (Tenerife), Spain.

**Abstract.** The transition to electric mobility involves complex interactions between technological infrastructure and social acceptance. While technical load profiles are critical for grid stability, understanding the "demand profile" from a governance and adoption perspective is equally vital for successful deployment. This paper presents a review of Q-Methodology as a robust tool for identifying and characterizing the subjective demand profiles of stakeholders involved in the electric vehicle (EV) ecosystem. Drawing on recent applications, specifically in isolated energy systems such as the Canary Islands, this review analyses how Q-Methodology systematically groups subjective viewpoints into distinct "demand perspectives" (e.g., Believers, Sceptics, Business-as-Usual). The methodology allows researchers to move beyond traditional surveys by identifying the shared agreements and deep-seated divergences that drive or hinder market demand. We outline the procedural steps—from concourse development to factor analysis—required to construct these profiles. The paper argues that identifying these governance and adoption profiles is a prerequisite for designing effective regulatory frameworks and predicting the success of EV integration strategies.

**Key words.** Electric Vehicle, Q methodology, Demand Assessment, Governance, Energy Transition.

## 1. Introduction

The global shift towards decarbonization has placed Electric Vehicles (EVs) at the forefront of energy policy. However, the integration of EVs is not merely a technical challenge of connecting loads to a grid; it is a socio-technical challenge that requires a deep understanding of the "demand" side—specifically, the willingness of stakeholders to adopt, support, and regulate this technology [1,2].

The EV represents an important pillar of modern decarbonization strategies, serving as a critical technological bridge between the transportation and power sectors. By replacing internal combustion engines, EVs offer a direct pathway to reduce greenhouse gas emissions and local pollutants, while simultaneously providing distributed storage capabilities that can support the integration of intermittent renewable energy sources like wind and solar.

However, the effective capitalization of this potential is hindered by the profound complexity of modelling EV energy demand profiles [3]. Unlike conventional static loads, EV charging demand is inherently stochastic and highly heterogeneous, driven by erratic human behaviours such as variable departure times, daily trip distances, and random connection durations. This unpredictability is further compounded by external factors, including weather conditions, traffic density and the heterogeneous availability of charging infrastructure (Level 1, Level 2 and DC fast charging), making the elaboration of accurate, high□resolution demand curves a significant challenge for grid planners and energy□system modelers.

Establishing a reliable energy demand profile for these vehicles remains a complex technical challenge due to the inherent stochasticity of their usage. In contrast to static municipal loads such as street lighting, which follow fixed schedules, EV demand operates as a probability distribution defined by random user behaviour. This unpredictability introduces a significant "clustering" risk, where the simultaneity of charging events—such as a neighbourhood collectively plugging in at 6:00 PM—can exceed the thermal limits of local transformers. Modelling these risks is frequently hindered by hidden variables and human factors, such as "range anxiety," which drives users to charge batteries that are already 80% full, or price sensitivity, where users delay charging to access cheaper midnight rates. These behavioural nuances create a volatility that is difficult to capture without highly granular data.

Traditional methods for forecasting EV demand often rely on statistical analysis, econometric models or simple surveys to know how the vehicles are used and therefore, to create synthetic profiles to be adopted, reflecting the average usage. However, these methods may fail to capture the complex, subjective, and often conflicting viewpoints of the diverse actors involved (e.g., policymakers, utilities, consumers, recharge infrastructure availability, among other factors). Misalignments in these perspectives can lead to policy failures and slower adoption rates [2].

Recent work EV charging behaviour has demonstrated the value of large data sets and unsupervised learning techniques for identifying empirical user types. For example, a recent statewide study analysed more than 58,000 charging events at public Level□2 stations, applying k□means clustering to 608 frequent users and deriving four distinct user types labelled convenient, gradual, anxious and urgent. These data□driven typologies provide a solid basis for building synthetic charging demand profiles in planning models, but they do not explicitly capture the subjective motives and perceptions that underlie charging decisions [4].

The transition to sustainable energy is a dual challenge necessitating both technological advancement and socio-political adaptation. Despite the maturation of renewable generation and storage technologies, their implementation frequently encounters localized and regulatory resistance. This resistance underscores a critical gap in current energy research: the necessity to rigorously quantify the diverse perspectives of stakeholders, including policymakers, industry experts, and residents. Furthermore, while traditional survey methodologies effectively gauge opinion prevalence, they frequently fail to elucidate the complex value systems and underlying narratives governing the social acceptance of energy infrastructure.

Q methodology offers a complementary approach focused on systematically eliciting and structuring subjectivities. It has been used in transport research to profile travellers in terms of car dependence, attitudes to sustainable modes and the symbolic meanings of car ownership, revealing qualitatively distinct “mobility worldviews” that are not evident from behaviour data alone. This section evaluates the viability of using Q methodology to construct synthetic EV□use profiles and outlines how qualitative Q□factors can be translated into quantitative time□series suitable for modelling charging demand [5].

Originally developed by William Stephenson, Q methodology combines the qualitative richness of interviews with the statistical rigor of factor analysis. Contrasting standard R-methodological approaches that correlate variables across a sample of people, Q methodology correlates people across a sample of variables. By requiring participants to model their viewpoints through a forced-distribution sorting process, the method reveals the distinct clusters of opinion—or "social discourses"—that exist regarding the topic at hand.

This article is a review focused on how it is possible to apply Q methodology as a rigorous research framework for calculating synthetic demand profiles. In comparison with standard qualitative methods, Q methodology combines qualitative inputs with quantitative statistical analysis (Factor Analysis) to reveal distinct clusters of opinion. By understanding these profiles, policymakers can tailor strategies that align with the actual needs and perceptions of the market. This paper analyses how this methodology is able defining EV adoption and usage profiles.

## 2. Methodology

Q methodology is a mixed-method technique designed to uncover shared patterns of subjectivity among stakeholders. Unlike standard “R-methodological” approaches that correlate variables across a sample of people, Q methodology correlates people across a sample of statements (variables). Participants are asked to model their viewpoints by sorting a carefully selected set of statements (the Q-set) into a forced distribution from “most agree” to “most disagree”. The resulting Q-sorts are then analysed using factor analysis to identify distinct clusters of opinion, or social discourses, on the topic at hand [6].

Originally developed in psychology, Q methodology has been successfully adapted to energy and transport research to explore subjective perspectives in a systematic way. The process of calculating a profile involves five main phases [2].

### *A. Definition of the Concourse (Q-Set)*

The first step is to establish the concourse—the sum of all things being said about the topic. In the context of demand for energy technology, this involves gathering statements on regulation, infrastructure, costs, risks, benefits and social participation. From this broad collection, a representative Q-set is selected that covers the main dimensions of debate (e.g., regulatory frameworks, stakeholder participation, usage patterns, implementation mechanisms).

### *B. Selection of Participants (P-Set)*

Unlike random sampling in conventional surveys, Q methodology uses strategic or purposive sampling. The *P-set* consists of key stakeholders whose opinions are relevant to the demand profile, such as public administrators, academics, industry experts and user associations. The goal is to maximize the diversity of viewpoints rather than to achieve statistical representativeness of the whole population.

*C. The Q-Sorting Process*

Participants sort the Q-set statements into a predefined distribution grid (often quasi-normal) ranging from “most disagree” to “most agree”. This forced comparison makes respondents express priorities and trade-offs, revealing the internal structure of their viewpoint. Each completed sort represents one individual’s subjective “profile” with respect to the technology.

*D. Statistical Analysis and Factor Extraction*

All Q-sorts are inter-correlated and subjected to factor analysis (e.g., centroid or principal components). Rotation techniques (such as varimax) are applied to extract a limited number of factors, each representing a shared pattern of sorting across participants.

*E. Interpretation of Profiles*

Each factor is interpreted as a distinct demand perspective or profile. This interpretation is based on the factor array (the idealized Q□sort for that factor), distinguishing and consensus statements, and qualitative comments from participants. Profiles can, for example, be labelled as.

1. Profile A (EV Believers): high demand drivers focused on environmental benefits and urgent action.
2. Profile B (Sceptics): cautious demand, focused on fiscal responsibility and barriers.
3. Profile C (Business as Usual): resistant to change, preferring traditional models.

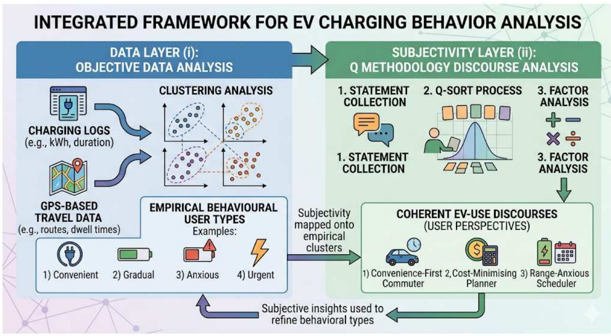


Fig.1. Integrated framework to obtain the synthetic EV usage profile.

Within the broader research framework, these qualitative demand perspectives can be coupled with quantitative data. An integrated framework therefore has two layers: (i) a data layer, where logs or GPS based travel data are clustered into behavioural user types (e.g., convenient, gradual, anxious, urgent [8]), and (ii) a subjectivity layer, where Q methodology identifies coherent usage discourses (e.g., convenience first commuter, cost minimizing planner, range anxious scheduler) that can be mapped onto, or used to refine, the empirical clusters [5]. Synthetic profiles then combine a narrative (from Q) with a calibrated behavioural pattern (from data) (Figure 1).

## 3. Proposed Q□study design for EV□use profiling

This section outlines how Q methodology can be applied specifically to construct synthetic electric vehicle (EV) demand profiles that integrate both behavioural and governance dimensions.

*A. Target population and sampling*

The proposed Q□study would focus on two overlapping groups:
(i) Current EV users, who have regular access to public or semi-public charging infrastructure, analogous to the users represented in charging-log datasets [4].
(ii) Potential EV adopters, to capture latent viewpoints that may shape future charging demand and adoption barriers [9].
Sampling in Q methodology is purposive rather than statistical; the objective is to maximize diversity of viewpoints, not to estimate population shares directly. In practice, the P-set should be structured to cover:

1. Different dwelling types (apartment vs detached house).
2. Access vs lack of access to home charging.
3. Variation in commute distance and trip purposes.
4. Urban, suburban and rural contexts.
5. Known behavioural user roles (residents, commuters, visitors, car sharing users) [10].

*B. Concourse and Q□set development*

In the EV context, the concourse is the comprehensive set of statements about EV use and charging. It should be built from three main sources:

1. Scientific and policy literature on EV adoption, charging behaviour, range anxiety and user typologies, including studies that derive charging patterns and user types from large datasets [8].
2. Existing Q-studies in transport, which provide language on car dependence, modal choice, environmental concern and the symbolic functions of car ownership [4].
3. Qualitative fieldwork, such as interviews or focus groups with EV drivers and prospective users, to capture everyday routines, charging strategies, frustrations and coping mechanisms [11].

From this concourse, a Q-set of around 40–50 statements is selected, balanced across themes relevant for synthetic EV-use profiles:

1. Trip purpose and degree of car dependence.
2. Preferred charging locations (home, work, public slow/fast).
3. Time of day patterns and planning horizon.
4. Range anxiety and SOC thresholds.
5. Sensitivity to tariffs and charging costs.
6. Environmental motives and identity.
7. Experience with EVs and trust in infrastructure.

*C. Q□sorting procedure*

Participants are instructed to sort the statements on a fixed grid (for example, from −4 to +4) according to how well each statement describes their EV use and charging behaviour. Emphasis is placed on daily practice (trip types, where and when they charge, planning strategies) rather than on abstract attitudes to technology.
After sorting, a brief post□sort interview is conducted in which participants explain their reasoning, particularly for statements placed at the extremes of the distribution. These qualitative explanations are later used to enrich the interpretation of the factors.

*D. Factor extraction and interpretation*

Once all Q-sorts are collected, a by-person factor analysis (centroid or principal components, with varimax and/or judgmental rotation) is applied to the correlation matrix of Q-sorts. A small number of factors (for example, three to five) is retained based on eigenvalues, explained variance and interpretability[2].
For each factor, an idealized Q-sort (factor array) is computed, representing the typical ranking of each statement for that viewpoint. Examination of [12]:

1. Distinguishing statements (those ranked very differently across factors),
2. Consensus statements (those ranked similarly across factors), and
3. Post□sort interview material allows each factor to be interpreted and labelled as a coherent EV□use discourse, such as “convenience□first commuter”, “cost□sensitive planner”, “range□anxious scheduler” or “opportunistic charger”.

These discourses form the qualitative backbone of the synthetic EV□use profiles that will later be linked to quantitative charging data.

## 4. From Q□factors to synthetic EV□use profiles

*A. Definition of a synthetic EV□use profile*

In this context, a synthetic EV□use profile is a stylized representation of a typical user type that includes the distribution of daily and weekly trips (e.g., commuting, errands, leisure), the probabilities of charging at different locations (home, work, public Level□2, DC fast) and different times of day, typical SOC at plug□in, duration and energy per session and the charging strategy (top□up vs deep discharge, comfort thresholds for low SOC) [13].
The profile does not describe any specific individual; instead, it represents a coherent behavioural pattern associated with one Q□factor and calibrated against aggregate data.

*B. Mapping Q□factors onto behavioural parameters*

For each factor identified through Q methodology, charging□behaviour parameters can be assigned using results from charging□log and travel□diary studies [4]:

1. A convenience□oriented factor is likely to map onto the most appropriate cluster found in the log□based study, where users charge opportunistically throughout the day without a clear pattern in charge received and rarely fully charge their EVs. The corresponding synthetic profile would feature frequent short sessions, a broad time□of□day distribution and moderate SOC at plug-in.
2. A gradual or procrastinating factor would correspond to the “gradual” users who postpone charging until SOC has decreased to lower ranges, then carry out larger charging events. The profile would contain less frequent, longer sessions triggered at relatively low SOC, possibly supported by DC fast charging for time□constrained users.
3. A range□anxious factor would be aligned with “anxious” users, whose data indicate early charging at high SOC to avoid perceived risk. Their synthetic profile would show high average SOC at plug□in, conservative daily driving distances between charges, and a strong preference for known or trusted charging locations. In this way, existing cluster-based load models can be informed by explicit user discourses, rather than relying solely on statistical clustering of behaviour.
4. An urgent or emergency factor would correspond to “urgent” users, who exhibit charging only when SOC is very low. This profile would include infrequent but deep charging events, often at inconvenient times or locations dictated by necessity.

Behavioural parameters such as hourly charging probabilities, expected energy per event and typical SOC trajectories can then be generated for each factor, comparable to existing methods that create synthetic residential electricity□use profiles from behavioral models and high□resolution monitoring data [14].

*C. Calibration and validation*

Calibration requires linking the Q□factors to observed data, by means of recruiting Q□study participants who are also willing to share their charging□log or GPS data, enabling a direct comparison between each factor’s synthetic parameters and real behaviour. Alternatively, ensuring that the aggregate statistics generated by the synthetic profiles (e.g., distribution of SOC at plug□in, daily energy consumption, peak charging hours) should match those observed in large dataset such as the 58,273□event study [10].
Finally, a validation would test whether simulations using these synthetic profiles can reproduce known aggregate patterns (e.g., proportions of convenient, gradual, anxious and urgent users; peak load periods) and whether the profiles remain robust when applied in different geographic contexts.

## 5. Application of the Q□statements to support synthetic profile construction

The following statements illustrate the types of items that could be included in the Q□set. They are phrased so that respondents can place them on the “most like me” to “least like me” spectrum.

*A. Trip purpose and car dependence*
- “Most of my car trips could not easily be done by public transport or bicycle.”
- “I mainly use my car for commuting to work or study, not for leisure trips.”
- “If public transport were more reliable, I would happily leave the car at home.”

*B. Charging locations and convenience*
- “As long as I can charge at home overnight, I rarely bother with public chargers.”
- “I prefer to charge at work or near my workplace rather than at home.”
- “I often rely on public chargers when I go shopping or run errands.”
- “Fast chargers on highways are essential for how I use my electric car.”

*C. Time□of□day patterns and planning*
- “I plan my charging schedule several days ahead to fit my weekly routine.”
- “I mostly decide to charge at the last minute when I notice the battery is low.”
- “I usually plug in whenever I park somewhere that has a charger, even if I do not strictly need it.”

*D. Range anxiety and SOC thresholds*
- “I start to feel uncomfortable if the battery drops below half full.”
- “Driving with less than 20% charge left makes me nervous, even if a charger is nearby.”
- “I am happy to run the battery down to a low level before I charge.”

*E. Cost and tariffs.*
- “I choose when and where to charge mainly based on price.”
- “I do not pay much attention to charging costs; convenience matters more to me.”
- “I would willingly shift my charging to off□peak hours if prices were lower at night.”

*F. Environmental motives and identity*
- “Reducing my carbon footprint is one of the main reasons I chose an electric car.”
- “As long as it is convenient, I am happy to adapt my charging to help the grid and the environment.”
- “I chose an EV mainly for other reasons (such as performance, technology or incentives), not the environment.”

*G. Experience and trust in infrastructure*
- “Since I started driving an EV, I have changed the way I plan my trips and charging.”
- “At first I worried a lot about finding chargers, but now I rarely think about it.”
- “I still do not fully trust that charging infrastructure will be available when I need it.”

## 6. Conclusions

From a methodological perspective, Q methodology is well suited for identifying distinct EV□use logics that can underpin synthetic profiles, because it is explicitly designed to reveal diversity of viewpoints, including minority discourses such as strong range anxiety or extreme cost sensitivity.
In this paper, the conceptual application and experimental design of the methodology have been presented. It has already proven useful in transport research for profiling travellers in ways that are directly informative for targeted policy measures and communication strategies.
From a governance perspective, each profile (Believers, Sceptics, Business□as□Usual, convenience□first, etc.) implies different needs in terms of tariff design, communication, regulatory pacing and stakeholder□engagement formats. These aspects should therefore be explicitly evaluated within the proposed methodology. Despite these limitations, an integrated framework that combines Q methodology with data□driven clustering is a viable and promising way to construct synthetic EV□use profiles that are both empirically grounded and behaviourally interpretable. Such profiles can improve the realism and policy relevance of planning models for charging infrastructure, distribution grids and broader energy systems that include high EV penetration. Isolated systems that are more sensitive to demand peaks, governance complexity and tourism□related actors will particularly benefit from this method. In this sense, future work will apply the proposed framework in a real Q□study with EV stakeholders in the Canary Islands to derive quantitative profiles and test their impact in power□system simulations.

## Acknowledgement

This work has been supported by the Canary Island Government and by the FEDER funds of the EU under the project grant PROID2025010003 (SOGIED-RI2T).

## References

[1] A.J. Ramírez-Díaz, F.J. Ramos-Real, J. Barrera-Santana, Well-to-Wheels for Light-Duty Vehicle Powertrains by Segments in Isolated Systems, Energies 2023, Vol. 16, 16 (2023). https://doi.org/10.3390/en16031018.

[2] I. Medina-Jiménez, F.J. Ramos-Real, J.E. León Vielma, F. Calero-García, Designing an integrative strategy to introduce electric vehicles in the tourism sector in an outermost region of the European Union, Sustainable Energy Technologies and Assessments 72 (2024) 104071. https://doi.org/10.1016/j.seta.2024.104071.

[3] G.A. Marrero, Y. Perez, M. Petit, F.J. Ramos-Real, F.J. Ramos, Electric vehicle fleet contributions for isolated systems. The case of the Canary Islands, International Journal of Auto-Motive Technology and Management 15 (2015) 171–171. https://doi.org/10.1504/IJATM.2015.068552ï.

[4] M. Khaleghikarahrodi, G.A. Macht, Patterns, no patterns, that is the question: Quantifying users’

electric vehicle charging, Transp. Policy (Oxf). 141 (2023) 291–304. https://doi.org/10.1016/J.TRANPOL.2023.07.020.
[5] M. Cools, E. Moons, B. Janssens, G. Wets, Shifting towards environment-friendly modes: profiling travelers using Q-methodology, Transportation 2009 36:4 36 (2009) 437–453. https://doi.org/10.1007/S11116-009-9206-Z.
[6] F.J. Ramos-Real, S. Escamilla-Fraile, I. Medina-Jiménez, F.J. Calero-García, Engaging governance in electric vehicle adoption: policy implications for an outermost region of the European Union, Transp. Res. Interdiscip. Perspect. 32 (2025) 101552. https://doi.org/10.1016/j.trip.2025.101552.
[7] A.I. Korda, P.A. Asvestas, G.K. Matsopoulos, E.M. Ventouras, N.P. Smyrnis, Automatic identification of oculomotor behavior using pattern recognition techniques, Comput. Biol. Med. 60 (2015) 151–162. https://doi.org/10.1016/J.COMPBIOMED.2015.03.002.
[8] J.R. Helmus, M.H. Lees, R. van den Hoed, A data driven typology of electric vehicle user types and charging sessions, Transp. Res. Part C Emerg. Technol. 2020 (2020). https://doi.org/10.1016/J.TRC.2020.102637.
[9] M.A. Javid, M. Abdullah, N. Ali, S.A.H. Shah, P. Joyklad, Q. Hussain, K. Chaiyasarn, Extracting Travelers' Preferences toward Electric Vehicles Using the Theory of Planned Behavior in Lahore, Pakistan, Sustainability 2022, Vol. 14, 14 (2022). https://doi.org/10.3390/SU14031909.
[10] J.R. Helmus van den Hoed, Unraveling user type characteristics towards a taxonomy for charging infrastructure, in: 28th International Electric Vehicle Symposium and Exhibition, Kintex, Goyang, Korea, Republic Of, KINTEX, 2015. www.hva.nl/urban-technology (accessed April 7, 2026).
[11] J. Bush, Q methodology as a useful method to research transport - The Transport and Health Integrated research NetworK (THINK), (2024). https://think.aber.ac.uk/q-methodology-as-a-useful-method-to-research-transport/ (accessed April 7, 2026).
[12] S. Bamberg, Is a stage model a useful approach to explain car drivers' willingness to use public transportation?, J. Appl. Soc. Psychol. 37 (2007) 1757–1783. https://doi.org/10.1111/J.1559-1816.2007.00236.X;WGROUP:STRING:PUBLICATION.
[13] S. Thorve, Y.Y. Baek, S. Swarup, H. Mortveit, A. Marathe, A. Vullikanti, M. Marathe, High resolution synthetic residential energy use profiles for the United States, Scientific Data 2023 10:1 10 (2023) 76-. https://doi.org/10.1038/s41597-022-01914-1.
[14] P. Berrill, K.T. Gillingham, E.G. Hertwich, Linking Housing Policy, Housing Typology, and Residential Energy Demand in the United States, Environ. Sci. Technol. 55 (2021) 2224–2233. https://doi.org/10.1021/ACS.EST.0C05696.