EVtools

Public EV Charging Station Infrastructure Perfomance

A Model-Based Evaluation of Roll-out Strategies

MSc Thesis, Delft University of Technology

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TUDelft

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by

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Acknowledgements

Dear reader,

With this thesis, I complete my master's journey, during which I have been immersed in the world of public charging station infrastructure, governance models, and data-driven planning. Over the past year, I have worked with large operational datasets, clustered urban contexts, and analysed how different roll-out strategies perform across urban, suburban and rural areas. This process has not only deepened my understanding of EV infrastructure planning but has also taught me a great deal about working systematically with data, collaborating with practitioners, and dealing with the inevitable detours of research.

This work would not have been possible without the support of many people. I would first like to thank my university supervisors, Jan Anne Annema and Linda Kamp, for their guidance, critical questions and encouragement throughout the entire process. Their feedback helped me sharpen my research design, interpret the results more carefully, and keep the bigger picture in mind when I was lost in the details.

I would also like to express my appreciation to EVTools, especially Tim and Guus, as the professionals who contributed to the practical side of this thesis. The opportunity to work with real-world data, tools and insights from the EV infrastructure field has been invaluable. In particular, I am thankful for access to operational charging data, the opportunity to learn from EV planning practices, and the many informal conversations that helped me understand how governance models, concessions, and open markets play out beyond the theoretical level.

A special thanks goes to my friends and fellow students, who were always there for coffee breaks, shared frustrations over LaTeX and statistics, and celebrated the small milestones along the way. Their support made the process lighter and more enjoyable. I am equally grateful to my family for their patience, interest and constant encouragement. Their belief in me has been an essential source of motivation, especially during the more stressful phases of writing and revising.

Looking back, I hope that this thesis will contribute in a small way to the ongoing development of fair, efficient and future-ready public charging networks. Suppose the framework and findings presented here can support practitioners, policymakers or researchers in making more informed decisions about roll-out strategies and spatial contexts. In that case, the effort has been worthwhile.

I wish you an insightful and enjoyable read.

P.G.L. Palazzi
Delft, 2025

Executive Summary

The accelerating transition toward electric mobility represents a cornerstone of global efforts to decarbonise transport systems and achieve long-term climate goals. As electric vehicle (EV) adoption expands, the demand for accessible, reliable, and efficient public charging station infrastructure (PCSI) grows. Public charging networks not only enable the practical use of EVs but also play a pivotal role in supporting the integration of renewable energy, reducing greenhouse gas emissions, and promoting equitable access to sustainable transport.
In the Netherlands, early policy support and public–private cooperation have led to one of the most advanced EV charging ecosystems in the world. Yet, as the market matures, local authorities face increasingly complex decisions about how to plan and manage charging infrastructure. The deployment of PCSI has become a multidimensional challenge that intersects spatial planning, energy management, and mobility policy. Stakeholders such as local authorities and charging point operators (CPOs) must align diverging objectives — public accessibility, economic viability, and system efficiency — while operating under differing governance models and local conditions.
Despite growing experience and the availability of digital planning tools, substantial uncertainty remains about how various roll-out strategies perform in practice. Local authorities adopt a wide range of approaches — from reactive, request-based models to proactive, data-driven or strategic planning frameworks — but limited empirical evidence exists on which strategies deliver the most effective outcomes under different urban contexts. As a result, opportunities to optimise infrastructure performance and ensure equitable, context-sensitive deployment remain underexploited.

While the Netherlands has made significant progress in deploying PCSI, the process remains fragmented and uneven across local authorities. Local authorities apply diverse roll-out strategies without clear evidence of which combinations perform best in different urban contexts. This lack of systematic evaluation makes it difficult for decision-makers to select strategies that effectively balance accessibility, utilisation, and operational efficiency.
The heterogeneity of local environments further complicates PCSI deployment. Urban, suburban, and rural areas differ substantially in population density, spatial structure, and socio-economic composition, all of which influence charging demand and infrastructure feasibility. Existing research often overlooks these contextual variations, focusing instead on optimisation or simulation models that assume uniform conditions. As a result, there is limited empirical understanding of how real-world strategy choices interact with local characteristics to shape infrastructure performance.
Moreover, most prior studies simplify planning approaches into broad binary distinctions—such as “push versus pull” or “reactive versus strategic” — which fail to capture the nuanced governance and planning styles observed in practice. This absence of a detailed, data-driven framework for evaluating PCSI performance across contexts has created a knowledge gap. Without such insight, opportunities to improve deployment efficiency, equity, and transparency remain constrained, limiting the potential contribution of charging infrastructure to the wider transition toward sustainable mobility.

The objective of this research is to evaluate how different PCSI roll-out strategies perform across diverse urban-infrastructural contexts. By combining empirical operational data with spatial and socio-economic indicators, the study develops a model-based framework that systematically links deployment strategies to measurable performance outcomes.
The goal is not to prescribe a single optimal strategy, but to provide evidence-based insight into how the effectiveness of various approaches depends on the characteristics of local authority environments. This understanding can help policymakers and practitioners select strategies that align with their specific urban conditions and policy objectives.
Accordingly, the central research question guiding this thesis is:

> **How do different roll-out strategies for public EV charging station infrastructure perform across varying urban-infrastructural profiles, as measured by key performance indicators?**

To address this main question, the research examines:

1. How local authorities can be classified into meaningful urban profiles based on socio-economic and spatial characteristics;
2. How governance model and planning style can systematically categorise real-world roll-out strategies;
3. Which performance differences emerge across these context-strategy combinations;
4. How these differences can inform more context-sensitive PCSI planning and policy design.

This research adopts a constructive, quantitative, multiple-case study approach to evaluate the performance of different PCSI roll-out strategies across diverse urban-infrastructural contexts in the Netherlands. The methodological framework integrates empirical data analysis with model-based evaluation, enabling a systematic comparison of strategy effectiveness across varying local conditions.
The study is structured into four main steps:

1. **Urban profiling through clustering:** Local authorities are classified into urban-infrastructural profiles using neighbourhood-level data from the Dutch Central Bureau of Statistics (CBS). A two-step *k*-means clustering process groups neighbourhoods based on variables such as income, address density, and land area, and then aggregates these results to classify local authorities.
2. **Strategy allocation:** Real-world roll-out strategies are identified from open-source policy documents and industry data and categorised by governance model (concession-based or open-market) and planning style (reactive, strategic, or data-driven). These are mapped onto the classified local authorities to create a structured context–strategy framework.
3. **Performance evaluation:** Three key performance indicators (KPIs) - charging station utilisation (utilisation rate), energy throughput (kWh delivered), and user reach (number of unique users) - are derived from the NDW LINDA 2024 dataset. These KPIs reflect operational effectiveness and accessibility across local authorities.
4. **Comparative performance assessment:** The KPI results are combined into a composite performance index (CPI) and statistically validated using analysis of variance (ANOVA) and Tukey Honest Significant Difference (HSD) tests. This analysis reveals how strategy effectiveness varies across urban profiles, highlighting which combinations of strategy and context yield the highest infrastructure performance.

This structured, data-driven approach enables the systematic evaluation of PCSI roll-out strategies under real-world conditions. It bridges the gap between theoretical planning frameworks and empirical performance evidence, providing an analytical foundation for more informed and context-sensitive infrastructure decision-making.

The analysis demonstrates that the PCSI roll-out strategies vary across different urban-infrastructural contexts. Distinct performance patterns emerge when comparing urban, suburban, and rural local authority profiles, reflecting the influence of socio-economic and spatial characteristics on infrastructure performance.
Across all contexts, data-driven and strategic planning approaches consistently outperform purely reactive models in terms of utilisation rate and delivered energy. These approaches benefit from proactive siting and continuous monitoring, resulting in a more balanced spatial coverage. In contrast, request-driven strategies tend to stay behind, particularly in dense urban areas where reactive deployment struggles to keep pace with demand growth.

When considering governance models, open-market frameworks show competitive performance in high-density environments, where multiple CPOs stimulate network expansion and innovation. However, in lower-density suburban and rural contexts, concession-based models achieve higher stability and more equitable coverage, due to coordinated planning and clearer long-term investment horizons. The statistical validation confirms that these differences are significant across two of the three selected KPIs: utilisation rate and energy throughput. The CPI further highlights that the most effective strategy–context combinations integrate data-driven planning within structured governance models adapted to local infrastructural and socio-economic conditions.
Overall, the results indicate that there is no single universally optimal roll-out strategy. Instead, strategy

effectiveness is context-dependent: the alignment between governance approach, planning style, and local urban profile determines infrastructure performance. These findings provide a robust empirical foundation for tailoring PCSI roll-out strategies to the specific characteristics of local authorities.

The results of this research provide actionable insights for policymakers, local authorities, and CPOs involved in planning and managing PCSI. They highlight the need for policy frameworks and operational strategies that are both data-informed and context-specific.
For local authorities, the findings demonstrate the value of adopting data-driven and strategic planning approaches to anticipate charging demand and optimise infrastructure placement. Integrating empirical performance indicators into decision-making processes can enhance transparency, enable proactive expansion, and ensure that infrastructure development keeps pace with EV adoption. Local authorities should leverage open data sources and analytical tools to monitor utilisation patterns and adjust deployment strategies accordingly continuously.
From a governance perspective, the research suggests that strategy effectiveness depends on matching governance models to local conditions. Open-market models can stimulate innovation and responsiveness in dense urban contexts. At the same time, concession-based approaches may be better suited to suburban and rural areas where coordinated planning and stable partnerships are essential for ensuring equitable access.
At the national level, policymakers can support this process by establishing standardised evaluation frameworks for comparing the performance of PCSI roll-out strategies across regions. Such frameworks would enable evidence-based growing, facilitate best-practice sharing, and guide funding or regulatory interventions toward strategies that deliver results.
More broadly, the study underscores the importance of treating PCSI as a socio-technical system — one in which, governance, and user behaviour interact dynamically. Strengthening collaboration between public and private stakeholders, improving data transparency, and aligning policy objectives across governance levels will be critical for accelerating the efficient, equitable, and sustainable expansion of public charging infrastructure.

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Nomenclature

Abbreviations

Abbreviation	Definition
AHP	Analytic Hierarchy Process
ANOVA	ANalysis Of VAriance
CBS	Central Agency of Statistics
CCS	Combined Charging System
CDRpy	Computational Data-driven Roll-out in Python
CoSEM	Complex Systems Engineering and Management
CI	Confidence Interval
CPI	Composite Performance Index
CPO	Charging Point Operator
DBSCAN	Density-Based Spatial Clustering of Applications with Noise
EV	Electric Vehicle
FDR	False Discovery Rate
GHG	Greenhouse Gas
GIS	Geographic Information Systems
HSD	Honest Significant Difference
ICEV	Internal Combustion Engine Vehicle
KPI	Key Performance Indicator
LINDA	Charging Station Infrastructure Data
MCDA	Multi-Criteria Decision Analysis
NACS	North American Charging Standard
NDW	National Road Traffic Data Portal
PCSI	Public Charging Station Infrastructure
POI	Points of Interest
SOM	Self-Organising Map
TOPSIS	Technique for Order Preference by Similarity to Ideal Solution
V2G	Vehicle-to-Grid

Symbols

Symbol	Definition	Unit
c	Cluster	Dimensionless
k	value for number of clusters	Dimensionless
$\dot{k}$	KPI	Dimensionless
n	Sample size	Dimensionless
s	Sample standard deviation	Dimensionless
st	Strategy	Dimensionless
x	Raw KPI value	% OR kWh OR users
$\bar{x}$	Sample mean of the KPI	Dimensionless
z	z-score normalisation	Dimensionless
$z_{\alpha/2}$	critical value for a 95% two-sided confidence interval	Dimensionless

Symbol	Definition	Unit
$\frac{s}{\sqrt{n}}$	Standard error of the mean	Dimensionless
μ	Mean value	Dimensionless
σ	Standard diviation	Dimensionless

1 Introduction

1.1. Assessing public charging infrastructure roll-out strategies

The global shift towards electric mobility is gaining momentum, driven by climate ambitions, evolving policy frameworks, and advances in vehicle and energy technologies. This transition is evident in the rapid uptake of electric vehicles (EVs), which, in turn, is driving a growing demand for accessible and reliable public charging station infrastructure (PCSI). Stakeholders in this system — such as local authorities and charging point operators (CPOs) — face the complex task of coordinating priorities, navigating regulatory frameworks, and managing logistical and technical constraints (Rienks 2023; Helmus and Hoed 2016).

Although national policies and public–private initiatives have supported early PCSI deployment in the Netherlands (Helmus, Spoelstra, et al. 2018), new challenges have emerged. These include the absence of uniform roll-out strategies, limited transparency around procedural performance, and a lack of standardised frameworks to evaluate strategy effectiveness (Wolbertus, Hoed, et al. 2021; P. P. Singh et al. 2023). In response, digital tools such as EVTools have been introduced to support stakeholders in managing the full process — from infrastructure siting to operational monitoring (EVTools.nl 2025). This research is conducted in collaboration with EVTools, leveraging their platform, datasets, and operational insights regarding the roll-out and performance of public charging stations.

Despite the growing availability of such possibilities, a gap persists in systematically assessing how different deployment strategies perform across varying urban conditions. Without such evaluation, opportunities for targeted improvements remain unexplored (Wolbertus, Jansen, and Kroesen 2020). This study aims to address this gap by analysing how combinations of urban-infrastructural profiles and roll-out strategies are associated with high-performing charging stations, as measured by key performance indicators (KPIs), using a model-based evaluation approach.

1.2. Electric mobility as a driver of sustainable development

The shift towards electric mobility is driven by the need to reduce greenhouse gas (GHG) emissions and dependence on fossil fuels. As the transport sector contributes nearly 15% of global CO_2 emissions, electrification plays a central role in achieving long-term sustainability targets. However, the potential of electric mobility extends beyond emission reduction alone. PCSI, in particular, offers opportunities to support the broader transformation of energy and urban systems.

Charging stations can contribute to energy system flexibility by shifting charging to periods of surplus electricity, thereby balancing grid demand. Bidirectional charging technologies enable electric vehicles to supply energy back to the grid when needed, while smart charging allows alignment with renewable energy generation. In this way, charging stations can function as decentralised energy storage units and support local energy resilience. Moreover, when embedded in urban development strategies, PCSI can enhance the functionality of smart cities by integrating with dynamic energy systems and mobility services (Wolbertus, Jansen, and Kroesen 2020).

Despite these possibilities, the full realisation of these benefits depends on the adequate availability, distribution, and utilisation of charging infrastructure. In many cities, the pace of PCSI deployment lags behind EV adoption, leading to congestion at charging points, unequal access across neighbourhoods, and grid inefficiencies (Wolbertus, Jansen, and Kroesen 2020). Furthermore, effective deployment is hindered by stakeholder misalignment: while local authorities prioritise social accessibility and long-term planning, private operators often focus on demand concentration and profitability (Meheden et al. 2021). These structural tensions undermine the scalability and equity of EV infrastructure development, ultimately slowing progress toward broader climate and mobility goals.

To address these challenges, this study explores how public charging strategies perform under different local conditions. By comparing infrastructure performance across local authorities' contexts, the research provides an empirical basis for better aligning strategy choices with urban-infrastructural characteristics.

1.3. Problem statement

Despite the growing policy momentum and technological progress supporting electric mobility, the effective deployment of PCSI remains a challenge. Local authorities are primarily responsible for developing charging networks on public land, yet they face uncertainty in selecting the most appropriate roll-out strategy for their local context. In practice, local authorities adopt a range of approaches — ranging from concession-based to open-market models, and from reactive to proactive planning — without evidence of which strategies yield the best performance outcomes.

The diversity of urban environments intensifies this challenge. Local authorities' control of land varies widely in terms of spatial form, socio-economic composition, and infrastructure capacity, all of which influence both the demand for charging and the feasibility of specific deployment models. At the same time, stakeholder misalignment between local authorities and CPOs adds further complexity: while municipalities aim for equitable access and long-term planning, CPOs are guided by commercial viability and operational efficiency. The absence of a consistent framework to evaluate strategy effectiveness across these varying conditions hinders decision-making and successful, coordinated PSCI growth.

As a result, the roll-out of public charging infrastructure often lacks coherence, transparency, and measurable performance benchmarks. This research addresses this problem by systematically analysing how different roll-out strategies perform across diverse urban-infrastructural profiles, using KPIs derived from real-world operational data. The findings aim to provide empirical insight to support more informed and context-sensitive decision-making for future PCSI planning.

1.3.1. Research scope

This research focuses on the evaluation of PCSI deployed on public land in the Netherlands, which is under the responsibility of different local authorities. The study is limited to publicly accessible charging stations and therefore excludes private, semi-public, and fast-charging stations.

The performance of different PCSI roll-out strategies is assessed across various local authority contexts, which are classified based on selected urban-infrastructural characteristics. For this study, variables such as income, address density, and land area — derived from Central Statistical Office (CBS) neighbourhood-level data (Central Bureau of Statistics 2024) - are used. The model is flexible and allows for the inclusion of other indicators if desired.

Local authorities are clustered into urban profiles using a two-step k-means clustering approach. First on a neighbourhood level after which the local authorities are clusters based on their neighbourhood composition.

The evaluation is based on three selected key performance indicators (KPIs): station utilisation (occupancy rate), energy throughput (kWh), and user reach (number of unique users). These indicators were chosen for this study, although the evaluation model allows for the inclusion of other KPIs if desired. These KPIs are derived from NDW LINDA 2024 station-level operational data (Nationale Databank Wegverkeersgegevens (NDW) 2024). The roll-out strategies under comparison are extracted from open-source policy documents and categorised by governance model (concession or open market) and planning style (reactive, data-driven, or strategic).

The scope of this study is analytical and exploratory: it does not provide prescriptive recommendations but aims to generate insights into how roll-out strategies perform across different types of local contexts.

1.4. Knowledge gap

While the growth of electric mobility has spurred substantial academic work on charging infrastructure deployment, an area to explore is how PCSI roll-out strategies are evaluated across diverse urban contexts. Existing studies have focused on the technical, economic, or spatial optimisation of PCSI deployment (X. Zhang et al. 2025; Sayarshad, Soltani, and Asad 2024), or the simulation of policy scenarios to assess network performance (Wolbertus, Hoed, et al. 2021). For example, Helmus, Spoelstra, et al. (2018) compared demand-driven and strategic roll-out strategies using transaction-level data, while Wolbertus, Hoed, et al. (2021) used agent-based modelling to test the effects of planning intensity and feedback loops. These studies have made significant contributions, yet they offer limited insight into how actual strategy choices perform under varying urban conditions.

More specifically, the literature falls short in two areas. First, few studies systematically analyse how different roll-out strategies perform across empirically derived urban-infrastructural contexts. While some work considers the role of socio-demographic or spatial variables (Rienks 2023), there is little evidence of how strategy effectiveness varies in practice between, for instance, high-density inner-city areas and low-density suburban environments. This limits the applicability of existing findings to stakeholders, who must tailor strategies to complex, varied local conditions.

Second, evaluations simplify the landscape of planning approaches into binary categories such as “push” versus “pull” or “reactive” versus “strategic” (Helmus, Spoelstra, et al. 2018; Wolbertus, Hoed, et al. 2021). In reality, a broader spectrum of governance models exists, including concession-based and open-market frameworks, and adopt varying levels of planning proactivity and data usage (Meheden et al. 2021; P. P. Singh et al. 2023). These nuances are rarely captured or compared in ways that support evidence-based decision-making across contexts.

Moreover, a large portion of the existing literature adopts a technical or optimisation-driven lens, focusing on idealised placement models or network simulations (X. Zhang et al. 2025; Sayarshad, Soltani, and Asad 2024). As a result, limited academic attention has been given to developing practical, context-sensitive evaluation frameworks that link roll-out strategies to measurable performance outcomes using real-world operational data (Mandolakani et al. 2024).

This study addresses these gaps by empirically examining how different PCSI roll-out strategies perform across the Netherlands, using real operational data from NDW LINDA (Nationale Databank Wegverkeersgegevens (NDW) 2024) and urban-infrastructural variables derived from CBS neighbourhood statistics (Central Bureau of Statistics 2024). Specifically, it combines:

1. a classification of local authorities based on urban-infrastructural profiles,
2. a categorisation of real-world roll-out strategies based on planning style and governance model, and
3. a set of selected KPIs that reflect both public and private stakeholder interests.

By linking strategy types to empirically defined urban contexts, this research creates a data-driven framework for evaluating context-dependent performance. Unlike prescriptive optimisation models, the aim is to generate actionable insights that inform more effective, place-sensitive PCSI planning. The study thus contributes both academically and practically by filling a gap in comparative, context-aware strategy evaluation using real deployment data.

1.5. Research objective and questions

The main objective of this research is to evaluate how different PCSI roll-out strategies perform across varying urban-infrastructural contexts in the Netherlands. This evaluation aims to provide empirical insight into which strategies are more effective in which types of local authority environments, based on measurable performance outcomes.

In doing so, the research contributes to both the academic understanding of context-sensitive infrastructure planning and to the practical decision-making for PCSI deployment. The analysis is structured around three core components: (1) the classification of local authorities into urban-infrastructural profiles based on CBS neighbourhood-level data, (2) the categorisation of real-world roll-out strategies by governance and planning style, and (3) a set of performance indicators reflecting operational effectiveness and accessibility.

The study does not aim to prescribe universally optimal strategies. Instead, it seeks to create a context-strategy-performance tool that can guide better-aligned and more informed decision-making for PCSI development.

Main research question:

> *How do different roll-out strategies for public EV charging station infrastructure perform across various urban-infrastructural profiles, as measured by key performance indicators?*

Sub-questions:

1. How can local authorities be classified into meaningful urban-infrastructural profiles based on relevant spatial and infrastructural characteristics?
2. Which roll-out strategies can be applied by local authorities?
3. Which performance differences emerge across roll-out strategies and urban-infrastructural profiles based on station-level operational data?
4. How can these differences be interpreted to better understand the alignment between strategy type and urban context?

1.6. Research approach

This study adopts a constructive, quantitative multiple-case study design to evaluate how different PCSI roll-out strategies perform across varying urban-infrastructural contexts. The aim is not to test a specific hypothesis, but to develop a data-driven evaluation framework that can be reused by stakeholders involved in EV infrastructure planning. The research design follows a scenario-based logic: observed roll-out strategies are systematically combined with empirically derived urban profiles, and their performance is assessed using a set of operational KPIs. The result is an exploratory framework that enables structured comparison between different strategy–context combinations.

The approach consists of four main steps:

1. **Urban profiling through clustering**
   Local authorities are first classified into urban-infrastructural profiles using a two-step k-means clustering procedure. Neighbourhood-level socio-economic and spatial data from the Central Agency of Statistics (CBS) are used, specifically land area, income per inhabitant and surrounding address density for 2022. After data cleaning and standardisation, neighbourhoods are clustered for a range of k values; silhouette scores are used to select the preferred number of clusters. Next, local authorities are characterised by the distribution of these neighbourhood types within their boundaries, and a second k-means model is run on these distributional profiles to obtain local-authority clusters. All steps -variables, preprocessing operations, k-range and cluster assignment - are implemented in Python and documented so that the clustering can be replicated or adapted with alternative variables.
2. **Strategy allocation**
   Following the classification of local authorities, a typology of PCSI roll-out strategies is constructed that combines two governance models - mono-/multi-concession and open market - with three planning styles (request-driven, strategic, data-driven). This typology is derived from academic literature, EVTools documentation and practical planning procedures. For each local authority, open-source policy documents, tender texts and planning reports are collected and qualitatively assessed. Based on the dominant characteristics of its approach, every local authority is assigned to one of the six strategy types. The resulting mapping links each case to both an urban-infrastructural cluster and a roll-out strategy, forming the context–strategy framework used in the performance analysis.
3. **KPI evaluation**
   Performance is measured using charging-station KPIs from the NDW LINDA (Laadpaal INfrastructuur DAta) dataset for the year 2024. For the public, AC charging points on public land, three indicators are extracted: (i) utilisation rate (%), (ii) average daily energy delivered (kWh/day/charging point), and (iii) average number of unique users per day. These KPIs were selected based on the literature and short exploratory interviews with both public and private stakeholders to capture utilisation, accessibility, and economic potential. Monthly station-level KPIs are aggregated

to annual averages per local authority, and then merged with the context–strategy framework, yielding a complete dataset at local authority level.

4. **Performance assessment**
   The final step evaluates how each roll-out strategy performs within each urban profile. First, a coverage matrix is constructed to show the number of local authorities available in every cluster–strategy cell. Next, KPI values are averaged per context–strategy combination to obtain a performance matrix. To synthesise results, a Composite Performance Index (CPI) is calculated by normalising the three KPIs and applying stakeholder-informed weights that differentiate public and private perspectives. Finally, differences between strategies and clusters are statistically examined using analysis of variance (ANOVA) and post-hoc Tukey HSD tests for both individual KPIs and the CPI. This provides an empirically validated comparison of which strategy–context combinations are associated with relatively higher infrastructure performance.

This multi-step approach enables a transparent and reproducible analysis of PCSI deployment strategies, grounded in publicly available datasets, clearly specified clustering and coding procedures, and standard statistical tests. It reflects a socio-technical perspective by jointly considering governance arrangements, planning practices and operational performance within a single comparative framework.

1.7. Research objective related to Complex Systems Engineering and Management

This study fits within the CoSEM framework by addressing the technical, institutional, and economic complexities of PCSI development. CoSEM research focuses on designing interventions that balance technological feasibility with societal and policy considerations, making it an appropriate lens for analysing the PCSI. By examining PCSI deployment, this study aims to develop an analytical tool that clarifies how different urban-infrastructural profiles may influence the effectiveness of various roll-out strategies. This reflects a systems engineering approach in which a socio-technical system — the PCSI — is analysed not only through its technical components, but also its institutional dynamics, stakeholder coordination, and governance structures. In doing so, the study contributes to the CoSEM objective of designing interventions for complex environments by offering a structured method for evaluating PCSI roll-out processes.

2
Background

In the previous chapter, the research objectives, corresponding research questions, and the approach of this thesis were outlined. This chapter will delve deeper into these issues by examining the broader context of electric mobility, its significance for sustainable development, and the essential role that stakeholder collaboration plays in shaping effective deployment strategies.

2.1. The Global Transition to Electric Mobility

The global transition towards electric mobility is increasingly recognised as a vital step in achieving long-term sustainability and mitigating climate change. The transportation sector, responsible for nearly 15% of global CO_2 emissions, is a key area for reducing GHG emissions, particularly through the adoption of EVs (IEA 2025). The electrification of vehicles, including electric cars, buses, and two-wheelers, plays a central role in decreasing reliance on fossil fuels, contributing to global sustainability goals (Udendhran et al. 2025).

The widespread adoption of EVs is a crucial part of efforts to decarbonise the transportation sector. As countries strive to meet climate targets, such as those outlined in the Paris Agreement, the transition to electric mobility has gained momentum. National policies, technological innovations, and environmental awareness are driving this shift. For example, the European Union has committed to ensuring that all new cars sold by 2035 will be zero-emission vehicles, providing a clear regulatory framework for EV adoption (Rani and Jayapragash 2024). This global push is supported by advancements in battery technologies, particularly lithium-ion batteries, which have reduced costs and improved energy densities, making EVs more affordable and accessible to consumers (Ogunnowo, Ezeanochie, and Akinsooto 2025).

Despite the technological progress, the transition to electric mobility is not without challenges. One of the most pressing issues is the deployment of sufficient PCSI. As the number of EVs on the road increases, there is an urgent need for a reliable and widespread charging network to support their operation. Without an adequate charging infrastructure, concerns such as range anxiety could hinder the broader adoption of EVs. Studies have shown that one of the main barriers to EV adoption is the limited availability of public charging stations, particularly in rural or underserved urban areas (WSN 2025). The expansion of PCSI is therefore essential to alleviate these concerns and ensure that EVs can be effectively integrated into the mainstream transportation system.

The transition also faces geographic and socio-economic disparities. While many developed countries, such as those in Europe and North America, have made substantial progress in deploying EVs and the necessary infrastructure, other regions, particularly in Africa and parts of Asia, continue to face challenges. The availability of charging stations, regulatory frameworks, and financial incentives vary widely between countries and regions. Addressing these gaps is crucial to achieving a global transition to electric mobility that is equitable and accessible to all (Okafor et al. 2025).

Urban planners face the task of integrating PCSI into city layouts, ensuring that stations are strategically located to meet demand while maintaining system efficiency (Udendhran et al. 2025). This dynamic requires careful coordination to ensure the successful and sustainable deployment of PCSI.

2.2. The Role of Public Charging Infrastructure

The availability and distribution of PCSI directly influence consumer confidence, charging convenience, and ultimately, the success of the electrification of transportation systems (Yu et al. 2025; Burra, Al-Khasawneh, and Cirillo 2024).

PCSI plays a role in addressing one of the key barriers to EV adoption: range anxiety. Range anxiety refers to the fear of running out of battery power before reaching a charging station, which can discourage potential EV owners from transitioning to electric mobility (Nasri et al. 2025). A well-distributed, reliable charging network can mitigate this issue by ensuring EV drivers have access to convenient charging stations, thereby boosting consumer confidence. Additionally, PCSI can contribute to the reduction of GHGs by supporting the broader shift away from ICEVs (Udendhran et al. 2025).

As the number of EVs continues to grow globally, the need for efficient and sustainable charging infrastructure has intensified. Cities and local authorities face the challenge of deploying charging stations that meet users' needs while balancing operational costs, environmental considerations, and equitable access. Furthermore, integrating renewable energy sources into the charging infrastructure is essential to reducing EVs' carbon footprint and supporting sustainable energy systems. Solar-powered charging stations, for example, can provide a clean energy source while also reducing grid dependency (Nasri et al. 2025; An et al. 2025).

Moreover, the role of PCSI extends beyond simply providing physical charging stations. It encompasses the design and deployment of smart charging systems that optimise energy distribution, reduce grid congestion, and enable bidirectional energy flow. Such systems enable vehicles to not only draw power from the grid but also contribute energy back to the system during peak demand periods, enhancing grid stability and supporting energy storage (Yu et al. 2025; Burra, Al-Khasawneh, and Cirillo 2024). This feature, known as vehicle-to-grid (V2G) technology, is significant in balancing supply and demand as the global energy system transitions to renewable energy sources (Rani and Jayapragash 2024).

In many regions, governments and private entities are investing in the development and expansion of PCSI to support the shift towards sustainable transportation. National and local governments have introduced policies and incentives to promote EV infrastructure development, including tax credits, subsidies, and funding for installing public charging stations. For instance, in the United States, federal and state-level programs have facilitated the growth of a public charging network, which is critical for accelerating EV adoption (WSN 2025; Rani and Jayapragash 2024). However, despite these efforts, significant gaps remain in the accessibility, affordability, and reliability of charging stations. To ensure equitable access to charging infrastructure, it is essential to address disparities in infrastructure deployment, ensuring that all communities, regardless of location or socioeconomic status, have access to charging stations (Yu et al. 2025).

The ongoing development of PCSI must also account for technological advancements in EV charging speeds, user-friendly interfaces, and payment systems. Fast-charging stations are essential to reducing the time required to recharge an EV, making it more convenient for drivers to use electric mobility as a practical alternative to traditional ICEVs (Yu et al. 2025; Nasri et al. 2025).

Overall, PCSI is pivotal to the successful transition to electric mobility. It not only supports EV operational needs but also contributes to sustainability, grid stability, and equitable access. As the adoption of EVs accelerates, the continued expansion and innovation of PCSI will be essential to realising the environmental and economic benefits of electric mobility.

2.3. Challenges in Deploying Public Charging Infrastructure

The large-scale roll-out of PCSI remains one of the most critical bottlenecks in the global transition to electric mobility. Although EVs have seen rapid adoption in recent years, the expansion of supporting infrastructure continues to face substantial technological, financial, spatial, and governance-related challenges (Ghani et al. 2025; R. Singh, Malarkey, and MacKenzie 2024). These challenges limit both the accessibility and reliability of charging networks, which in turn influence user confidence and the overall rate of EV uptake (Knittel and Tanaka 2025).

A major challenge concerns the uneven geographical distribution of charging infrastructure. Studies have shown that charging networks are disproportionately concentrated in high-income and urban areas, leaving rural or disadvantaged communities behind (Khan et al. 2022; Lou et al. 2024). This spatial imbalance not only reinforces existing inequalities in mobility access but also, as stated, perpetuates range anxiety among potential users in peripheral regions. For example, Lou et al. (2024) demonstrated that low-income and minority populations in U.S. metropolitan areas have significantly fewer public charging stations per capita and often face longer travel distances to reach them. Similarly, Khan et al. (2022) found that dense urban areas, such as New York City, exhibited clear spatial inequities, with low-income neighbourhoods having markedly lower charging access than affluent districts. Such disparities underscore the need for planning frameworks that integrate equity metrics into PCSI roll-out strategies.

Technological limitations further constrain the effectiveness of current public charging networks. Interoperability issues between different charging standards — such as the Combined Charging System (CCS), and the emerging North American Charging Standard (NACS) — hinder cross-network compatibility and reduce user convenience (H. Wang et al. 2025). Additionally, the availability of fast-charging technologies remains limited in many regions, leading to long waiting times and congestion at high-demand locations (R. Singh, Malarkey, and MacKenzie 2024). These operational bottlenecks are compounded by grid integration issues, which can overload local distribution networks during peak charging. Research highlights that as EV penetration increases, unmanaged charging demand may significantly strain existing grid capacity, requiring advanced load management and smart-charging solutions (Ghani et al. 2025; H. Wang et al. 2025).

Beyond technology, economic and policy challenges continue to slow PCSI expansion. The high capital cost of establishing public chargers, coupled with uncertain profitability due to fluctuating utilisation rates, discourages private investment (Knittel and Tanaka 2025). Although government subsidies and incentive schemes have proven effective in accelerating deployment in early-adopting regions, the absence of consistent, long-term policy frameworks remains a key barrier in many markets (Ghani et al. 2025). Conrad, Hehmeyer, and Cain (2024) report that even in leading regions such as California, bureaucratic delays, permitting complexities, and grid-connection obstacles have significantly slowed the roll-out of charging stations despite strong policy ambitions.

Moreover, user experience and reliability remain central concerns. Public charging stations often suffer from maintenance issues, inconsistent pricing, and unreliable service, which collectively undermine user confidence (R. Singh, Malarkey, and MacKenzie 2024; Yu et al. 2025). These reliability problems discourage repeated use and hinder the public's perception of charging convenience. In response, some studies suggest that monitoring uptime, service frequency, and spatial coverage as formal KPIs could improve network accountability (Yu et al. 2025).

Finally, the governance of public–private collaboration presents persistent challenges. Effective coordination between local authorities and private CPOs is often lacking, resulting in fragmented planning and inefficient resource allocation (Knittel and Tanaka 2025; Conrad, Hehmeyer, and Cain 2024). Addressing this requires integrated frameworks that align commercial incentives with public objectives, ensuring that deployment strategies serve both accessibility and operational efficiency goals.

2.4. Stakeholder Coordination in PCSI Deployment

Stakeholder coordination in the PCSI roll-out is a critical element in the transition to electric mobility. As the electrification of transportation increases globally, a multitude of stakeholders become involved in both planning and operationalising the infrastructure necessary to support EVs. These stakeholders include public local authorities, private CPOs, regulatory bodies, and end-users of EV charging services. Each of these parties has differing priorities, making effective coordination both challenging and essential for successful infrastructure roll-outs.

Local authorities are often tasked with managing the PCSI, yet they face significant challenges in balancing public satisfaction, equity, and the long-term sustainability of the deployment. These local authorities must ensure that PCSI meets local needs while adhering to regional and national policy frameworks. Coordination among stakeholders is critical to ensure that public charging stations are accessible, reliable, and cost-effective. However, local authorities may find themselves at odds with CPOs, who are driven by profit motives and operational efficiency rather than social equity and long-term urban planning objectives. This dual focus creates a complex governance challenge, as both parties must collaborate to create a balanced and effective deployment strategy (LaMonaca and Ryan

2022; Y. Zhang et al. 2024).
Private stakeholders, such as charging point operators, face their own challenges in managing the economic aspects of PCSI deployment. While the demand for charging stations increases with the adoption of EVs, operators must balance profitability with customer needs. In urban environments, this becomes particularly challenging as operators seek to install charging points in high-demand locations that maximise their financial returns, but may not necessarily align with broader accessibility goals. CPOs must also coordinate with local authorities to navigate zoning laws, public space usage, and other regulatory hurdles that can delay deployment (Anadón Martínez and Sumper 2023; LaMonaca and Ryan 2022).
Regulatory bodies also play an essential role in fostering stakeholder coordination. Local authorities play a critical role in providing clear policies and incentives that align the interests of both public and private stakeholders. Policies such as subsidies, tax breaks for EV manufacturers, and financial incentives for infrastructure development can encourage private investment in charging stations. Still, they must be carefully tailored to meet local needs. For example, Das (2024) emphasises the role of government policies in facilitating the viability of charging infrastructure development in cities by modelling various policy scenarios. Effective regulatory frameworks can also ensure that there is equity in access to charging stations across different income groups and geographic regions (Ghani et al. 2025).
However, challenges persist in achieving equitable access to charging infrastructure. Studies show that underserved communities, particularly low-income areas, often experience inequitable access to public charging stations. This is a significant issue because equitable access to charging is vital for encouraging widespread EV adoption. Khan et al. (2022) point out that the inequitable distribution of charging stations can underline existing social inequalities and prevent communities from fully benefiting from the transition to electric mobility. To address these challenges, governments and private operators must work together to ensure that charging stations are distributed equitably, especially in regions with low EV adoption rates.
The collaboration among stakeholders is also influenced by their varying levels of engagement in the infrastructure's planning and operational phases. Local authorities, which are often responsible for urban planning, tend to focus on the long-term sustainability and environmental impacts of PCSI. In contrast, CPOs may prioritise operational efficiency, demand generation, and return on investment. This divergence in priorities underscores the need for integrated planning frameworks that allow for the effective collaboration of both public and private stakeholders in deploying PCSI (Y. Zhang et al. 2024; LaMonaca and Ryan 2022; González-Salas et al. 2025).

To summarise this chapter, the successful deployment of PCSI is essential for the widespread adoption of EVs and the transition to a sustainable transport system. The chapter highlights the importance of addressing challenges such as range anxiety, uneven infrastructure distribution, and technological limitations while ensuring effective stakeholder coordination. As the EV market continues to grow, overcoming these barriers and fostering collaboration among stakeholders will be crucial to providing an equitable, reliable, and efficient charging infrastructure that supports both environmental and societal goals.

2.5. Thesis Structure

The remainder of this thesis is structured as follows. Chapter 2 provides background on the global transition to electric mobility and the role of public charging infrastructure, outlining key deployment challenges and stakeholder coordination issues. Chapter 3 reviews the academic literature on spatial and socio-economic determinants of PCSI, roll-out strategies, and performance evaluation methods, and synthesises these into the conceptual foundation for this study. Chapter 4 presents the methodological framework, detailing the constructive quantitative multi-case study design, the clustering of local authorities, the mapping of roll-out strategies, the selection of KPIs, and the performance assessment procedure. Chapter 5 describes the data used in the analysis and the preprocessing steps for clustering, strategy mapping, and KPI construction. Chapter 6 reports the empirical results, including the identified urban-infrastructural clusters, the distribution of roll-out strategies, and the KPI and composite performance outcomes across context–strategy combinations. Chapter 7 discusses these findings in relation to the research questions, reflects on methodological limitations, and elaborates on strategic and policy implications. Finally, Chapter 8 concludes the thesis by summarising the main findings, answering the research questions, reflecting on the research objective, and outlining directions for future research.

3
Literature Review

This chapter presents a review of the existing literature on the deployment of the PCSI in the context of the global transition to electric mobility. The aim is to critically analyse and synthesise the current body of research on the strategies, performance, and methodologies associated with PCSI deployment. By reviewing the academic discourse on infrastructure planning, stakeholder coordination, and technological advancements, this chapter identifies research gaps and provides a foundation for the proposed research methods. The insights garnered from this review will help contextualise the study's objectives and refine the methodological framework for evaluating PCSI deployment strategies.

3.1. Spatial and Socio-Economic Determinants of Public Charging Station Infrastructure

3.1.1. Inequality in Public Charging Station Infrastructure Access

Inequality in access to public charging stations has emerged as a significant barrier in the global transition to electric mobility. As EV adoption grows, disparities in the distribution and accessibility of PCSI become more evident, especially across different geographic and socio-economic contexts. The uneven deployment of charging stations can underline existing social inequalities, making it harder for marginalised communities to access reliable, affordable charging options. This inequality is particularly noticeable in low-income neighbourhoods and rural areas, where infrastructure investment is often limited due to lower demand and perceived profitability.

Several studies highlight spatial disparities in PCSI distribution, noting that charging stations are often concentrated in wealthier, urban areas, while rural and underserved communities have limited or no access to charging infrastructure. Ermagun and Tian (2024) conducted a national study in the United States, revealing that socio-economic and environmental factors play a crucial role in determining where charging stations are installed. Areas with higher incomes, better infrastructure, and more active environmental policies tend to have greater access to EV charging facilities. In contrast, disadvantaged areas, such as lower-income and minority neighbourhoods, often have insufficient charging options. This issue is exacerbated in rural areas, where lower population densities reduce the business case for deploying charging stations.

Furthermore, the technological and operational quality of charging stations often varies between regions, further deepening inequality. Roy and Law (2022) used machine learning techniques to examine spatial disparities in EV charging station placements and found that stations in high-demand areas, particularly those in affluent urban centres, are more likely to offer faster, more reliable charging solutions, while stations in less accessible regions often suffer from maintenance issues and inconsistent service. These operational disparities lead to unequal charging experiences for users, discouraging the adoption of electric vehicles in underserved areas and hindering the shift to more sustainable mobility options.

M. Wang, Liang, and Li (2024) employed a multidimensional framework to assess the spatial distribution of EV charging infrastructure in Nanjing, China, and highlighted the impact of both socio-economic and environmental factors on charging station accessibility. The study found that spatial inequalities in PCSI deployment are not limited to income and urban density, but are also influenced by local energy infrastructure and the prioritisation of certain neighbourhoods in urban planning. These findings emphasise the need for a more comprehensive understanding of the factors contributing to the unequal distribution of charging stations, as well as the importance of integrating equity considerations into infrastructure planning.

Addressing these disparities is crucial for ensuring equitable access to electric mobility. Jiao, Choi, and Nguyen (2024) examined public charging access disparities in Austin, Texas, and proposed strategies to improve accessibility, including targeted infrastructure investments in underserved areas and integrating equity metrics into transportation electrification plans. The study highlighted that government policies and regulations must prioritise equitable distribution and accessibility of charging infrastructure, ensuring that marginalised communities are not left behind in the transition to electric vehicles.

Inequality in PCSI access is a significant challenge that requires targeted interventions to ensure that all communities have equal access to the benefits of electric mobility. Addressing these spatial and socio-economic disparities is essential to the widespread adoption of EVs, particularly in regions where a lack of accessible, reliable charging infrastructure hinders the transition to electric mobility. Effective policy frameworks, strategic planning, and collaboration between public and private stakeholders will be key to overcoming these challenges and achieving a fair and equitable transition to sustainable transportation systems. Furthermore, establishing a performance framework that enables the analysis and comparison of PCSI performance across different types of local authorities could help define strategies that lead to well-performing charging stations.

3.1.2. Urban-infrastructural characteristics in PCSI planning

The deployment and efficiency of PCSI are heavily influenced by various urban-infrastructural characteristics, such as population density, income distribution, transport networks, energy infrastructure, and land use patterns. These factors not only determine the demand for EV charging stations but also affect the feasibility and effectiveness of deploying these stations across different local authorities. Understanding how these urban characteristics impact PCSI is critical for developing efficient and equitable deployment strategies.

Urban density, for example, plays a significant role in determining the number of charging stations needed in a given area. In densely populated urban environments, the demand for public charging stations is typically higher due to a larger number of EV owners. However, the available space for station installation is often limited, requiring innovative solutions to integrate charging infrastructure into existing urban landscapes. For instance, strategic planning for curbside charging is increasingly becoming a key method for addressing space limitations in densely built areas, as it allows for the utilisation of public streets for station installation without disrupting other urban functions (X. Zhang et al. 2025).

Income distribution within urban areas also impacts access to PCSI. Wealthier neighbourhoods tend to have greater access to charging infrastructure due to higher investments in electric vehicle ownership and infrastructure development. Conversely, lower-income neighbourhoods may experience significant barriers to accessing charging stations, exacerbating social inequalities in EV adoption. Several studies have highlighted these disparities, suggesting that socioeconomic factors must be considered when planning the deployment of PCSI to ensure equitable access for all community members (Bwire 2025).

Transport networks are another essential urban characteristic influencing the distribution and accessibility of charging infrastructure. Areas with well-developed transportation networks often provide easier access to charging stations, as the infrastructure can be integrated into existing transit corridors. However, regions with fragmented or underdeveloped transport networks may face challenges in ensuring adequate access to EV charging stations, as the lack of connectivity can limit the effectiveness of station placement (Sheng et al. 2025).

Moreover, regional energy infrastructure plays a crucial role in PCSI performance. The capacity of local energy grids to support the increased demand from EVs is often a limiting factor in areas with older or less developed energy systems. As demand for charging stations rises, especially in regions with high EV adoption rates, local grids may experience strain during peak charging times. Integrating smart grid technologies and improving load management strategies can help mitigate these issues, but it requires coordination between PCSI developers, local authorities, and energy providers (Sheng et al. 2025).

Lastly, land use patterns and zoning regulations influence where charging stations can be installed.

Urban planning policies, such as zoning laws and land use restrictions, often dictate the feasibility of deploying public charging stations in certain areas. For example, in residential areas, ensuring charging stations are easily accessible can be challenging, especially for renters or individuals without private parking (Wolbertus 2024). Integrating PCSI into mixed-use developments or public spaces, such as parking lots and retail areas, can help address these challenges, ensuring charging stations are more evenly distributed across both high-demand urban and underserved suburban areas.
Thus, urban-infrastructural characteristics are crucial for understanding how different local authorities perform in terms of PCSI deployment and its operational performance. By considering factors such as population density, income distribution, and land area, planners can develop strategies that optimise charging station placement, ensure equitable access, and enhance the overall performance of the PCSI. Addressing these issues will be essential for achieving a sustainable and efficient transition to electric mobility.

3.1.3. Classification Frameworks in Urban Environments

In urban planning and the deployment of PCSI, classification frameworks can help categorise local authorities into meaningful groups that support tailored infrastructure strategies. Such frameworks commonly rely on clustering methods that combine socio-economic, spatial, and infrastructural variables to identify distinct urban typologies. By grouping cities or neighbourhoods based on shared characteristics, these methods help determine where infrastructure investments are most effective and where accessibility or performance gaps are most pronounced (J. Wang and Biljecki 2022; Rodrigues et al. 2025; Reibel 2011; Kilani and Dhaher 2024).
Unsupervised machine learning techniques, particularly clustering algorithms, have attracted increasing attention for their ability to handle large, complex datasets in urban analysis. J. Wang and Biljecki (2022) provided a systematic review of how unsupervised methods, including K-means, Self-Organising Maps (SOMs), and DBSCAN, are used to detect hidden spatial structures in high-dimensional urban data. These approaches enable the identification of zones based on indicators such as density, land use, and socio-economic characteristics. Similarly, Kilani and Dhaher (2024) highlighted how K-means and related techniques can effectively reveal latent spatial relationships and clustering patterns across cities, supporting applications ranging from land-use classification to infrastructure allocation. These methods are particularly valuable in PCSI planning because they reduce the complexity of multidimensional data and allow for the systematic identification of distinct urban profiles that influence charging demand and accessibility.
Despite its popularity, K-means clustering has limitations. Its reliance on Euclidean distance makes it less flexible in handling mixed-type data (categorical and continuous variables), and its outcomes depend on the initial selection of cluster centroids. Moreover, determining the optimal number of clusters (k) can affect classification accuracy and interpretability. However, Rodrigues et al. (2025) demonstrated that such challenges can be mitigated by combining K-means with a multi-stage clustering design, integrating socio-economic and Points of Interest (POI) data to enhance the robustness and interpretability of results.
Alternative clustering methods, such as Density-Based Spatial Clustering of Applications with Noise (DBSCAN) and fuzzy clustering, have been proposed to address some of K-means' weaknesses. DBSCAN performs well in identifying clusters of irregular shape and is robust to outliers. Still, it struggles with datasets containing clusters of varying densities — a common feature of urban environments where dense city centres and sparsely populated regions coexist (J. Wang and Biljecki 2022). Its performance is also susceptible to parameter choices - ε, which defines the maximum distance between two points to be considered neighbours, and MinPts, which specifies the minimum number of points required to form a dense region - making it less reliable for (inter)national-scale analyses of heterogeneous local authorities. Fuzzy clustering methods, as discussed by Reibel (2011), allow for partial cluster membership and provide nuanced representations of spatial phenomena. Still, they require complex calibration and yield results that are less easily interpretable for policy use. These limitations make them less suitable for studies that require both computational efficiency and policy applicability, such as the classification of local authorities for PCSI deployment.
Further methodological advancements have improved clustering accuracy and spatial coherence. Integrating Geographic Information Systems (GIS) with clustering techniques, as demonstrated by Rodrigues et al. (2025), enhances classification granularity by incorporating spatial dependencies, such as land-use proximity, connectivity, and accessibility. This integration enables more context-aware

groupings of urban areas, which is essential for PCSI planning, where charging demand is influenced by both spatial form and socio-economic activity. Kilani and Dhaher (2024) similarly emphasise that combining clustering algorithms with spatial attributes strengthens the interpretive power of classifications, allowing urban typologies to reflect not only statistical similarity but also spatial functionality.
In weighing the strengths and weaknesses of available clustering methods, the reviewed literature consistently identifies K-means as a particularly effective approach for urban classification tasks requiring interpretability, scalability, and efficiency (J. Wang and Biljecki 2022; Rodrigues et al. 2025; Kilani and Dhaher 2024). While it assumes convex clusters and requires numerical data, its performance can be optimised through normalisation techniques and validation tools. The use of silhouette analysis, as proposed by **rousseeuw87**, provides a robust measure of clustering quality and an objective way to determine the optimal number of clusters. This combination balances methodological rigour with computational practicality, ensuring that classifications are both meaningful and reproducible.

3.2. PCSI Roll-Out Strategies

The deployment of PCSI plays a role in the transition to electric mobility, and the strategies adopted for its roll-out are critical in determining the charging network's accessibility, efficiency, and long-term sustainability. Roll-out strategies encompass the planning and implementation approaches that dictate where, when, and how charging infrastructure is developed. The academic literature identifies a range of such strategies, from data-driven and optimisation-based models to more traditional push-and-pull frameworks. However, a consistent and unified framework for categorising these approaches remains absent. This lack of standardisation often results in strategies that are insufficiently tailored to the specific spatial, social, and infrastructural contexts of different urban environments, thereby limiting their overall effectiveness.

3.2.1. Push and Pull Strategies

Push-and-pull strategies are two fundamental approaches to promoting EV adoption and deploying PCSI. In a "push" strategy, government or regulatory bodies play a dominant role by providing incentives, such as subsidies for installing charging infrastructure or public funding for charging points in underserved areas. The "pull" strategy, on the other hand, relies on market-driven approaches, where the expansion of PCSI is guided by demand from users and private operators (Helmus, Spoelstra, et al. 2018).
The case of the Netherlands provides a valuable insight into the effectiveness of these strategies. In their assessment of push-and-pull roll-out strategies, Helmus, Spoelstra, et al. (2018) argue that a balanced combination of both approaches is necessary to overcome challenges related to the uneven distribution of charging stations. A push strategy is particularly effective in the early stages of EV adoption, where the market is not yet mature enough to generate significant private-sector investment. However, as the market matures, pull strategies become more relevant, allowing market forces to guide infrastructure expansion efficiently.

3.2.2. Data-Driven and Optimisation Approaches

In recent years, data-driven approaches have gained significant attention for their ability to optimise the placement and performance of PCSI. These strategies utilise large datasets, often involving traffic patterns, demographic data, and energy consumption information, to identify areas with high demand and ensure that infrastructure is deployed where it is most needed.
A prominent example is the work of Farhadi et al. (2023), who employed a multi-objective optimisation framework to develop a data-driven approach for EV charging infrastructure. By integrating multiple objectives, such as minimising the cost of infrastructure deployment while maximising accessibility, their method allows planners to optimise the roll-out process based on real-world data. This approach not only improves efficiency but also ensures that charging stations are deployed to align with urban mobility patterns and energy demands.
Similarly, Fischer, Michalk, and Bogenberger (2024) developed the Computational Data-driven Roll-out in Python (CDRpy) tool to support data-driven roll-out of charging infrastructure in urban areas. This tool supports strategic planning for charging networks by integrating factors such as population density, traffic flow, and land-use patterns. The tool is designed to help policymakers and infrastructure planners

identify optimal locations for new charging stations, ensuring a more balanced and efficient deployment process.

3.2.3. Agent-Based Simulation and Dynamic Planning

Another valuable strategy explored in the literature is agent-based simulation, which offers a dynamic and flexible approach to planning the roll-out of PCSI. Wolbertus, Hoed, et al. (2021) utilised agent-based models to simulate the effects of different roll-out strategies for large-scale EV adoption in urban areas. This method enables modelling of various stakeholder behaviours, including those of local authorities, CPOs, and EV users. The simulation provides insights into how different policy interventions and strategies can affect the speed and effectiveness of PCSI expansion, helping to identify the most efficient pathways for infrastructure deployment.

Agent-based models also allow for the consideration of feedback loops and stakeholder interactions, which are crucial for understanding how market dynamics and regulatory policies can influence the overall success of PCSI roll-out. According to Wolbertus, Hoed, et al. (2021), agent-based simulation offers a powerful tool for evaluating the impacts of different governance structures and coordination mechanisms, which are essential for effective PCSI deployment.

3.2.4. Concluding Thoughts on PCSI Roll-Out Strategies

Across the literature, a multitude of roll-out approaches have been proposed, ranging from traditional policy-led frameworks to advanced, data-driven optimisation models (Helmus, Spoelstra, et al. 2018; Wolbertus, Hoed, et al. 2021; Farhadi et al. 2023; Fischer, Michalk, and Bogenberger 2024). However, these strategies are often described in isolation, with no unified framework for categorising the various approaches available to policymakers and practitioners. This absence of standardisation limits the comparability of planning outcomes and makes it difficult for local authorities to select strategies that best fit their specific urban-infrastructural contexts.

Drawing from both the academic literature and insights from EVTools.nl (2025) practice, this study proposes a structured framework for understanding and categorising PCSI roll-out strategies (Figure 3.1). The framework is designed to guide local authorities and other stakeholders in selecting an appropriate approach based on governance model and planning style.

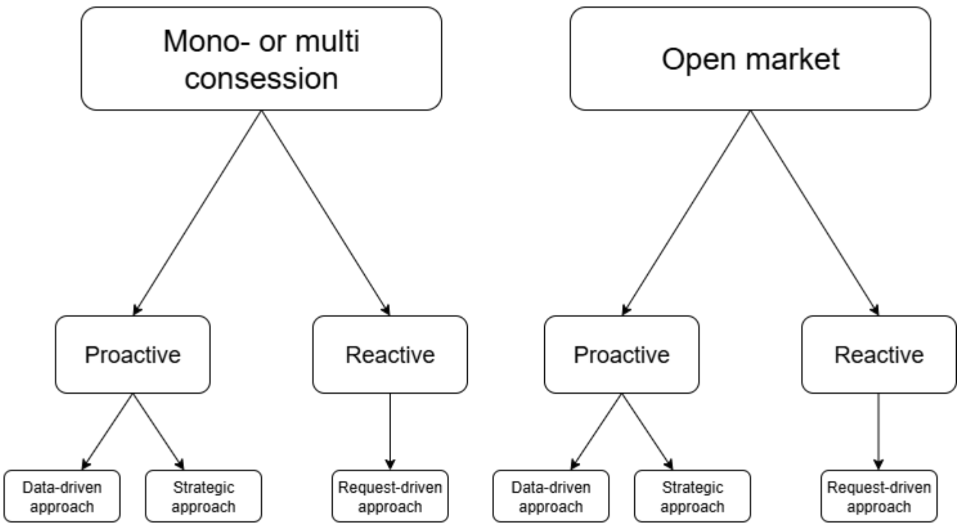

Figure 3.1: PCSI roll-out strategies

At the highest level, roll-out strategies can be divided into two governance models: Concession-based models, where one or more CPOs are granted exclusive or shared contracts to deploy and operate charging stations within a defined area; and open-market models, where multiple CPOs can freely propose and install charging stations — subject to local authority approval — without exclusive territorial rights (EVTools.nl 2025). Within each governance model, three primary planning approaches can be distinguished: request-driven, strategic, and data-driven. These represent different approaches to determining when and where to install new charging stations. All assessed roll-out strategies could be traced back to one of the three proposed and distinguished methods.

Request-Driven Approach

The request-driven approach is typically associated with the early stages of EV market development, where citizen requests guide infrastructure deployment. Under this model, residents who lack private parking or home charging can apply for a public charging point near their home. Local authorities then coordinate with the contracted or licensed CPO to install the charger once sufficient demand is demonstrated. This bottom-up process ensures that charging infrastructure is directly aligned with user demand, but tends to result in uneven spatial coverage and slower expansion rates. Studies of the Netherlands' early concession-based roll-outs demonstrate that request-driven strategies were effective for initial market stimulation but insufficient for large-scale, equitable coverage (Helmus, Spoelstra, et al. 2018; Wolbertus, Hoed, et al. 2021).

Strategic Approach

In contrast, strategic approaches rely on predefined siting plans. Charging stations are deployed in batches at locations identified as strategically important for network accessibility, visibility, or equity. Site selection is often informed by expert judgement, policy priorities, and existing mobility infrastructure, rather than direct user requests. Helmus, Spoelstra, et al. (2018) note that strategic placement can accelerate infrastructure growth and improve spatial balance, especially in areas where EV ownership is expected to rise. However, this approach depends heavily on accurate forecasting and may lead to underutilisation if siting assumptions do not reflect actual charging behaviour.

Data-Driven Approach

The data-driven approach is a more advanced, adaptive planning strategy that leverages empirical data and modelling to determine optimal charging station locations. In this model, charging demand is monitored continuously, and new stations are added once defined performance thresholds — such as utilisation rates, energy throughput, or user requests — are exceeded. Farhadi et al. (2023) developed a multi-objective optimisation framework integrating cost, accessibility, and energy efficiency. In contrast, Fischer, Michalk, and Bogenberger (2024) introduced the CDRpy tool, which supports continuous, data-driven decision-making by integrating spatial, socio-economic, and traffic data. These approaches enable more responsive, efficient infrastructure deployment, aligning the roll-out pace with actual usage patterns and urban development dynamics.

Integrating Governance and Planning Approaches

The combination of governance models (concession-based or open-market) with planning approaches (request-driven, strategic, or data-driven) provides a structured way to describe and compare roll-out strategies. Under a concession model, CPOs operate within exclusive contractual zones. A reactive, request-driven approach may be suitable in early phases, while more proactive, strategic or data-driven approaches support mature markets. In an open-market context, multiple CPOs compete to install and operate chargers. Here, proactive data-driven strategies can foster innovation and efficiency, while maintaining equitable access through regulatory oversight. This integrated framework provides a practical tool for policymakers and researchers to classify and assess different roll-out strategies according to their institutional, spatial, and technological contexts. It also bridges the conceptual gap in the literature by presenting a coherent typology of PCSI deployment approaches that balances theoretical insights with real-world practice.

3.3. Mapping PCSI Performance

Understanding PCSI's performance helps optimise its planning, operations, and future expansion. For instance, Netherlands Enterprise Agency (RVO) (2020) states that the PSCI should be evaluated every two years. Performance measurement allows policymakers, local authorities, and CPOs to assess how effectively existing infrastructure supports EV adoption and where interventions are required to enhance efficiency, accessibility, or business viability. The literature identifies a range of KPIs to assess the success of PCSI deployment, often focusing on utilisation, energy throughput, user accessibility, and reliability (Wolbertus 2024; Helmus and Hoed 2016; Borlaug et al. 2023; Maase et al. 2018).

3.3.1. Quantitative Indicators of PCSI Performance

Several studies propose quantitative frameworks for evaluating PCSI based on measurable station-level data. Helmus and Hoed (2016) suggest that utilisation rate, measured as the ratio of time or energy a charging port is actively used relative to its total availability, is one of the most informative indicators of performance. This metric provides direct insight into how effectively the installed infrastructure is being used and whether supply matches demand in a given area. Similarly, Maase et al. (2018) highlight energy throughput (kWh per station) and session frequency as key performance metrics that can reveal differences in charging behaviour between residential, commercial, and transit-oriented locations.

Adding to this empirical foundation, Borlaug et al. (2023) conducted a large-scale analysis of over 3,700 public charging stations and 1.4 million charging sessions across the United States. Their study established utilisation, expressed in kilowatt-hours per port per day, as a standardised metric for assessing station performance. The authors identified local EV adoption rate, pricing models, and charger type (Level 2 or DC Fast Charging) as significant determinants of utilisation. Importantly, they introduced the concept of charge idling — periods when a vehicle remains plugged in but is no longer charging — as a key source of operational inefficiency. This finding underscores that the actual capacity and effectiveness of charging stations cannot be assessed solely by installation counts; they must also consider the dynamic usage patterns of EV drivers. These insights are particularly relevant for performance evaluations in Europe, where data availability and urban density patterns often differ but where similar utilisation-based benchmarks can be applied to monitor the efficiency of PCSI networks.

3.3.2. Determinants of PCSI Performance

The literature also highlights that PCSI performance is influenced by contextual factors related to a region's physical, socio-economic, and infrastructural characteristics. Wolbertus (2024) demonstrate that local income levels, population density, and proximity to transport corridors significantly affect charging station utilisation. Stations located in high-income, mixed-use urban areas tend to experience higher usage rates. At the same time, those in low-density or peripheral zones often underperform due to lower vehicle turnover and weaker demand. Additionally, the authors argue that the availability of complementary infrastructure — such as parking spaces and grid capacity — further determines the operational success of charging facilities.

Similarly, Maase et al. (2018) identify grid connectivity, accessibility, and station reliability as critical determinants of PCSI performance. Poor grid integration can lead to charging delays or reduced energy throughput, while limited accessibility — caused by inadequate signage, parking restrictions, or malfunctioning equipment — negatively impacts user satisfaction and station turnover. These findings collectively emphasise that PCSI performance is not only a function of technological capability but also of spatial equity and operational management.

3.3.3. Towards a Comprehensive Performance Evaluation Framework

Synthesising insights from these studies, it becomes evident that PCSI performance must be evaluated through a multidimensional framework incorporating both quantitative and qualitative indicators. Quantitative measures — such as utilisation rate, energy throughput, and charging frequency — offer objective benchmarks for system efficiency, while qualitative aspects — such as accessibility, equity, and user experience — capture the social and behavioural dimensions of infrastructure performance (Helmus and Hoed 2016; Borlaug et al. 2023; Wolbertus 2024). Furthermore, longitudinal data analysis enables tracking of station performance over time, revealing patterns of growth, saturation or under-utilisation that may inform future siting decisions. In Table 3.1, a schematic overview of the discussed performance metrics and their definition is provided.

The reviewed literature demonstrates that measuring PCSI performance requires moving beyond installation counts towards an integrated evaluation framework that accounts for utilisation, efficiency, and contextual determinants. By combining operational KPIs with socio-spatial analysis, local authorities and policymakers can better assess the effectiveness of existing charging networks and design adaptive roll-out strategies that respond to evolving patterns of EV demand and urban development. Such a performance-driven approach ensures that public charging infrastructure not only meets current mobility needs but also supports the long-term sustainability and equity goals of the electric mobility transition (Borlaug et al. 2023; Maase et al. 2018; Wolbertus 2024).

Table 3.1: KPIs for evaluating PCSI performance.

KPI	Definition	Key References
Utilisation Rate	Proportion of time or energy a charging port is in active use relative to its total available operational time. Often expressed as kWh per port per day or hours in use per day. Indicates infrastructure demand and efficiency of resource use.	(Borlaug et al. 2023; Helmus and Hoed 2016; Maase et al. 2018)
Energy Throughput	Total amount of electrical energy (in kWh) delivered by a charging station over a defined period. Reflects charging intensity and operational load on the network.	(Maase et al. 2018; Wolbertus 2024)
Session Frequency	Average number of charging sessions per charging port or per day. Serves as a proxy for demand and user engagement, complementing energy-based metrics.	(Helmus and Hoed 2016; Borlaug et al. 2023)
Charge Idling	Percentage of time a vehicle remains connected to the charger after active charging has finished. High idling rates indicate inefficiencies and reduced system turnover.	(Borlaug et al. 2023; Maase et al. 2018)
Accessibility Index	Measure of physical and spatial access to charging stations, accounting for proximity, density, and availability of public parking. Often linked to equity and spatial justice.	(Wolbertus 2024; Helmus and Hoed 2016)
Reliability / Uptime	Percentage of time that charging stations are operational and available for use. A key determinant of user satisfaction and network trust.	(Maase et al. 2018; Helmus and Hoed 2016)
Equity of Distribution	Evaluates how evenly charging infrastructure is distributed across different socio-economic or geographic areas, addressing inclusion in access.	(Wolbertus 2024; Borlaug et al. 2023)

3.4. Analysing Performance Differences Across PCSI Strategies

The evaluation of PCSI performance could become an increasingly important research focus within the broader field of transport electrification. Once sufficient operational data are available — covering local authority characteristics, roll-out strategies, and KPIs — the challenge lies in identifying methods to analyse and compare performance across contexts. The academic literature presents a broad spectrum of analytical approaches, ranging from descriptive assessments to composite indices and inferential statistical testing. Each method contributes distinct insights, yet their suitability varies depending on the multidimensional nature of PCSI systems.

3.4.1. Approaches to Performance Evaluation in PCSI Research

Early studies of PCSI performance primarily relied on single-metric indicators such as charger utilisation, energy throughput, or uptime reliability. These measures provided valuable descriptive overviews but offered limited capacity for comparing infrastructure effectiveness across different spatial or strategic contexts (Helmus and Hoed 2016; Borlaug et al. 2023). As charging networks expanded, scholars began to employ statistical and econometric analyses to identify the drivers of performance variability. For instance, Wolbertus (2024) applied regression models to examine how demographic, spatial, and operational factors influence public charging station performance, finding that utilisation is best predicted by nearby station activity levels, income, and paid parking—indicators of dense urban contexts. Such approaches enhanced understanding of performance determinants but remained largely unidimensional, focusing on individual KPIs rather than overall system efficiency.

To address this limitation, researchers in energy and transport systems have increasingly adopted composite indicator methodologies. The foundational guidelines established by Economic Co-operation, OECD, and EUJRC (2008) provide a comprehensive methodological framework for constructing composite indicators through systematic procedures of normalisation, weighting, and aggregation. Saisana and Saltelli (2011) further emphasise the importance of transparency, uncertainty, and robustness testing to ensure that methodological assumptions do not distort outcomes. These principles render composite indicators particularly suitable for evaluating complex socio-technical systems such as PCSI, where performance arises from the interplay of operational, spatial, and social dimensions.

Complementary perspectives from the multi-criteria decision analysis (MCDA) literature offer additional methodological depth. Techniques such as the Analytic Hierarchy Process (AHP) and the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) provide systematic frameworks for weighting and ranking criteria based on stakeholder or expert preferences (Saaty 2022; Greco, Figueira, and Ehrgott 2016). While these approaches contribute valuable theoretical insight, they also introduce subjectivity through expert-driven weighting schemes. In operational infrastructure studies — such as PCSI deployment — more straightforward, transparent methods, including equal weighting or data-derived weighting via principal component analysis, are generally preferred to enhance reproducibility and minimise bias in performance assessment.

3.4.2. Comparing Performance Across Contexts

Once key performance metrics or composite indices are established, determining whether observed differences across strategies or local contexts are statistically significant becomes crucial. Analysis of Variance (ANOVA) remains the standard method for assessing mean differences across multiple groups. In evaluating PCSI, this enables researchers to test whether average performance differs significantly between rollout strategies (e.g., request-driven, strategic, or data-driven models) or across distinct urban profiles. When the assumption of homogeneity of variances is violated — a frequent issue in heterogeneous urban datasets — the Welch ANOVA provides a robust alternative (Welch 1951).

After establishing that overall differences exist, post-hoc testing is required to identify which specific group means differ. Among various available methods, Tukey's Honestly Significant Difference (HSD) test remains one of the most robust and interpretable for pairwise mean comparisons, balancing statistical power with strong control of error (Tukey 1949). These features make Tukey's HSD particularly appropriate in applied research where clear, statistically validated group comparisons are required to inform decision-making.

For non-normal data distributions or ordinal indicators, non-parametric alternatives such as the Kruskal–Wallis test and Dunn's post-hoc procedure provide robust options (Kruskal and Wallis 1952; Dunn 1964). In hierarchical data structures — where individual charging stations are nested within local authorities — mixed-effects models offer a means to capture both fixed (e.g., strategy type) and random (e.g., local variation) effects (Pinheiro and Bates 2000). Moreover, resampling-based approaches such as bootstrap or permutation tests can enhance robustness when sample sizes are small or unbalanced (Good 2005). To mitigate false-positive findings in large-scale comparisons, false discovery rate (FDR) adjustments are recommended (Benjamini and Hochberg 1995).

3.4.3. Synthesising the Literature for PCSI Evaluation

A synthesis of the reviewed literature indicates that while multiple quantitative frameworks exist for analysing infrastructure performance, their suitability for PCSI evaluation depends on analytical objectives and data availability. Regression-based methods, such as those applied by Wolbertus (2024), are effective for identifying explanatory drivers of station performance but less appropriate for holistic, multi-criteria comparison across strategies or spatial contexts. Conversely, multi-criteria decision analysis (MCDA) offers structured approaches for incorporating stakeholder preferences yet often introduces methodological complexity and subjectivity that can limit replicability in empirical data studies.

Composite indicator methods bridge these extremes by integrating multiple KPIs into a single interpretable measure while maintaining transparency and data-driven robustness (Economic Co-operation, OECD, and EUJRC 2008; Saisana and Saltelli 2011). When combined with inferential techniques such as ANOVA and Tukey's HSD, this approach supports both comprehensive performance assessment and statistically validated group comparison. Confidence intervals further enhance interpretability by quantifying uncertainty in mean differences, ensuring that observed variations reflect genuine performance disparities rather than sampling noise.

Consequently, the integrated use of a Composite Performance Index (CPI) with statistical validation through ANOVA and Tukey's HSD offers a balanced and rigorous framework for evaluating PCSI performance differences. The CPI consolidates multi-dimensional operational indicators into a transparent, comparable metric. At the same time, inferential testing provides robust evidence of significant variation across roll-out strategies or urban contexts—thereby aligning analytical rigour with the empirical and policy-oriented aims of PCSI research.

4

Methodology

This chapter presents the methodological framework applied in this study to evaluate the performance of PCSI roll-out strategies across varying urban-infrastructural contexts. Building upon the literature review presented in the previous chapter, this study adopts a constructive, scenario-based, and quantitative case study design. The overarching goal is to develop a context–strategy evaluation matrix that can support stakeholders in making informed decisions about EV infrastructure planning.

To achieve this, a structured four-step methodology is employed. First, local authorities are grouped into distinct urban-infrastructural profiles using a two-step k-means clustering approach, supported by silhouette analysis to validate the choice for k. Next, a framework of roll-out strategies is constructed based on EVTools data, existing literature, and local authorities' documentation. These strategies are then assigned to the local authorities within each cluster to create a comprehensive context–strategy matrix. Subsequently, quantitative KPIs are collected from the NDW database for each local authority to complete the created context-strategy matrix with results. Lastly, the performance of each strategy is evaluated within its respective cluster context using these KPIs, enabling cross-contextual comparisons of effectiveness.

This methodology enables systematic identification of which roll-out strategies perform best in which types of urban environments. It contributes not only to academic understanding of PCSI deployment but may also offer practical guidance for policy and planning in the rapidly evolving field of e-mobility.

4.1. Constructive Quantitative Case Study

This study adopts a constructive quantitative case study methodology. The constructive element lies in the development of a scenario-based decision-support tool — the context–strategy performance matrix — which is built from empirical data rather than theoretical modelling. The quantitative element is grounded in the use of numerical KPIs and statistical techniques, which will be explained in this chapter. The case study dimension allows for detailed exploration of variation in PCSI outcomes across the real-world practices of local authorities.

This method was selected for three reasons:

- **Applicability:** A constructive approach is well-suited for producing actionable outcomes in infrastructure planning (Lukka 2003).
- **Comparability:** Quantitative analysis enables structured cross-case comparison across multiple urban contexts (Mahoney and Goertz 2006).
- **Context sensitivity:** The case study design captures the real-life implementation conditions of PCSI roll-out strategies (Yin 2014; Crowe et al. 2011).

4.2. Step 1: Clustering local authorities

The first step of this research involves classifying local authorities into urban-infrastructural profiles using an unsupervised machine learning approach. The rationale for this step stems from insights

from EVTools, where forecasts of the number of required public charging stations are typically made per neighbourhood within each local authority's jurisdiction and projected across future time horizons (e.g., 2028 or 2030). Given that such planning processes operate on a neighbourhood scale, this study adopts a data-driven clustering approach to identify groups of similar neighbourhoods.
Neighbourhood-level data were obtained from the *Core Numbers of Districts and Neighbourhoods* dataset published by the Central Bureau of Statistics (CBS) (Central Bureau of Statistics 2024). This open-access database offers comprehensive indicators for all neighbourhoods in the Netherlands, including spatial, demographic, and socio-economic characteristics. For this study, three variables were selected based on their relevance to PCSI planning and demand estimation: average income, address density, and land area. This selection is supported by previous research, which identifies socio-economic status, urban density, and land availability as key determinants of EV charging needs (Jabbari and Mohammadian 2022). Together, these variables represent three urban dimensions — affluence, intensity, and magnitude — each of which plays a distinct role in shaping the demand and feasibility for PCSI (J. Wang and Biljecki 2022).

- **a_lan_ha** — land area (in hectares), representing the spatial extent of development;
- **g_ink_pi** — average income per inhabitant, indicating socio-economic capacity and EV mobility potential;
- **ste_oad** — address density, serving as a proxy for urban form and built-environment intensity.

To prepare the dataset for clustering, irrelevant columns were filtered out and the remaining values — `gwb_code` (local authority code), `gm_name` (local authority name), `a_lan_ha` (land area), `ste_oad` (address density), and `g_ink_pi` (income) — were standardised using the RobustScaler method. Robust scaling reduces the influence of outliers by centring the data around the median and scaling it according to the interquartile range, thereby improving clustering stability for non-normally distributed urban data (Huber 1981; Iglewicz and Hoaglin 1993).
A k-means clustering algorithm was then applied to the neighbourhood dataset to identify distinct urban types. K-means is an unsupervised learning algorithm that partitions observations into k non-overlapping groups by minimising intra-cluster variance and maximising inter-cluster separation, and is widely applied in urban research for distinguishing spatial-economic profiles due to its scalability, simplicity, and interpretability (Reibel 2011; J. Wang and Biljecki 2022). To determine the optimal number of clusters k, silhouette scores were calculated for values ranging from 2 to 10. The silhouette coefficient assesses clustering quality by comparing intra-cluster tightness and inter-cluster separation (Rousseeuw 1987).
These neighbourhood clusters form the basis for the second step in the clustering procedure: the classification of local authorities. Although EVTools makes prognoses at the neighbourhood level, local authorities govern multiple neighbourhoods, each with a unique composition. It is therefore essential to characterise local authorities based on the distribution of neighbourhood types within their jurisdiction.
To accomplish this, each local authority was mapped to its corresponding neighbourhood composition, and a distributional profile was generated. These profiles were then fed into a second k-means clustering algorithm to group local authorities that share similar internal compositions. The resulting clusters are not labelled a priori but interpreted ex post based on their average values for address density, land area, and income, together with the internal composition of neighbourhood types within each local authority. In line with common distinctions in Dutch spatial planning practice, these empirically derived profiles are subsequently referred to as urban, suburban, and rural clusters.

4.3. Step 2: Mapping Roll-Out Strategies

As established in the previous chapter, the existing literature does not provide a comprehensive, standardised mapping of all PCSI roll-out strategies currently in use. To address this gap, a typology of three distinct strategy types in two contracting models was developed based on insights from the academic literature, EVtools documentation, and practical planning approaches. This typology serves as a conceptual framework to categorise the diversity of roll-out strategies observed across municipalities:

- **Mono- or Multi-Concession:**

- *Proactive:*
  - Data-driven approach
  - Strategic approach
- *Reactive:*
  - Request-driven approach

- **Open Market:**
  - *Proactive:*
    - Data-driven approach
    - Strategic approach
  - *Reactive:*
    - Request-driven approach

The next step involves systematically identifying which of these strategies each local authority applies. This was achieved by collecting and reviewing open-source policy documents from local authorities and official planning reports. Each local authority's approach to PCSI development was analysed in detail and manually assigned to one of the predefined categories based on its dominant characteristics. The full overview of this mapping — including justifications for each strategy assignment — is presented in Appendix B. This appendix includes the complete cluster–context–strategy matrix, which links each local authority to both its urban-infrastructural cluster (as established in Step 1) and its assigned roll-out strategy. The accompanying notes detail the interpretation of municipal plans and explain why specific strategic classifications were made. Through this process, each local authority is now situated within a dual framework: a contextual cluster based on its neighbourhood composition and a strategic category based on its policy orientation and implementation practices. This combined framework provides the analytical foundation for evaluating PCSI performance across different context–strategy pairings in the next step of the methodology. A sample of the data

4.4. Step 3: KPI Selection

This study uses performance data from the LINDA dataset (Laadpaal INfrastructuur DAta), a component of the National Road Traffic Data Portal (NDW). LINDA is a government-managed platform developed to support the roll-out, monitoring, and evaluation of PCSI in the Netherlands. It provides a standardised and validated overview of public charging station usage, collected from CPOs. The platform ensures data reliability through rigorous quality control, enabling its use for policy, planning, and research applications. LINDA offers access to a range of KPIs relevant to EV charging infrastructure, including:

- **Occupancy Rate (%)** — the percentage of time a charging station is in use;
- **Average Number of Unique RFID Users per Day** — a proxy for user reach and public accessibility;
- **Average Energy Delivered per Day (kWh)** — indicating throughput and usage intensity.

To determine which KPIs to include in the performance evaluation, short exploratory interviews were conducted with key stakeholders: representatives from MRA-Elektrisch (MRA-e), Vattenfall, and Park 'n Charge. MRA-e is a government-funded organisation that centrally coordinates PCSI planning across municipalities in the provinces of Noord-Holland, Flevoland, and Utrecht. It organises joint tenders, provides process support for municipalities, and applies a multi-criteria placement logic based on user requests, data insights, and policy goals. MRA-e was selected as an interview partner due to its broad regional scope, which includes municipalities from all urban-infrastructural profiles identified in the clustering analysis.

According to MRA-e representatives, municipalities prioritise public satisfaction and equitable access. As such, occupancy rate and unique user count were seen as the most relevant KPIs, reflecting station coverage and community engagement. These insights are supported by previous research, which finds that public authorities often rank accessibility and geographic fairness above financial KPIs (Koogh et al. 2023). In contrast, the market-driven stakeholders — CPOs Vattenfall and Park 'n Charge — were more interested in average energy delivery, as this directly relates to revenue potential. This preference aligns with literature that highlights the importance of kWh throughput and financial return for private operators (Wolbertus 2024).

Based on these insights, this study adopts a three-KPI framework to reflect the diverse priorities of public and private stakeholders. Data for these KPIs were collected from LINDA for all charging stations in the Netherlands for the year 2024. Monthly charging station data were aggregated to calculate annual averages for each local authority. These averages were then integrated into the existing dataset, which already contained each local authority's cluster classification and assigned roll-out strategy, resulting in a complete context–strategy–performance matrix.

Appendix B provides a detailed overview of the dataset used, including the KPIs for each local authority.

4.5. Step 4: Performance Assessment

With the entire dataset in place — including local authorities, their assigned cluster, roll-out strategy, and corresponding KPIs — the final methodological step is to evaluate strategy performance across urban-infrastructural contexts. This evaluation is structured around a matrix that enables direct comparison of different strategy–context combinations based on measurable charging station outcomes.

4.5.1. Matrix Construction

The first step is to assess data coverage by generating a pivot table that shows the number of observations per *cluster–strategy* combination. This step provides a transparent overview of the number of local authorities represented in each cluster–strategy combination, allowing for a clear assessment of data availability and the robustness of the subsequent performance evaluation. In Table 4.1, a simplified visualisation is represented with dummy data for a better understanding of the described concept. The actual results will be presented in the following chapters.

Table 4.1: Illustrative Data Coverage: Number of Local Authorities per Cluster–Strategy Combination

Strategy	Urban	Suburban	Rural
Request	14	9	3
Strategic	6	17	5
Data-Driven	3	8	10

Next, a performance matrix is constructed by aggregating the KPIs for each combination of cluster and roll-out strategy. Each value is computed by taking the year average across all charging stations within each local authority belonging to a given cluster–strategy pair. The resulting matrix provides an interpretable overview of how different roll-out strategies perform across different local contexts, based on real-world KPI data. This matrix enables stakeholders to identify which roll-out approaches yield the most favourable infrastructure performance for each urban-infrastructural profile per KPI. In Table 4.2, a simplified visualisation is depicted with dummy data for a better understanding of the described concept. The actual results will be presented in the following chapters.

Table 4.2: Illustrative Performance x Cluster x strategy matrix: Values per Cluster–Strategy Combination

Cluster	Strategy	Occupancy Rate (%)	Avg kWh / station / day	Avg Unique users / station / day
Urban	Strategy A	23.18	22.87	3.18
	Strategy B	24.21	23.58	3.18
	Strategy C	21.28	24.66	3.30
Suburban	Strategy A	14.50	25.37	3.22
	Strategy B	20.62	24.06	3.11
	Strategy C	16.93	24.79	3.18
Rural	Strategy A	15.34	21.57	2.69
	Strategy B	17.93	24.52	3.01
	Strategy C	18.53	24.64	3.24

4.5.2. Composite Performance Index (CPI)

To synthesise the three KPIs into a single interpretable value, a Composite Performance Index (CPI) is developed. The CPI allows for a general performance score while preserving the underlying KPI-level detail for nuanced interpretation. Each KPI is first standardised using z-score normalisation to ensure comparability across indicators with different units and scales. This prevents any single KPI from dominating the composite index due to its magnitude and allows for a fair aggregation of performance metrics (**oecd2005**; Wu et al. 2018; Ghorbani, Liu, and Z. Wang 2022). The normalisation is as follows:

$$z_{c,st,\dot{k}} = \frac{x_{c,st,\dot{k}} - \mu_{\dot{k}}}{\sigma_{\dot{k}}}$$

Where:

- $x_{c,st,\dot{k}}$: raw KPI value for cluster c, strategy st, and KPI $\dot{k}$,
- $\mu_{\dot{k}}$: mean of KPI $\dot{k}$ across all groups,
- $\sigma_{\dot{k}}$: standard deviation of KPI $\dot{k}$ across all groups.

Unlike equal weighting, the CPI in this study adopts a stakeholder-specific weighting approach, recognising that different actors - local authorities and CPOs - prioritise different performance criteria. Local authorities typically focus on public service delivery, accessibility, and equitable coverage. Therefore, for local authorities' decision-making, greater weight is assigned to occupancy rate - reflecting system utilisation - and unique user count - indicating reach and inclusivity. A smaller weight is given to energy throughput, as revenue generation is not the primary concern. Based on the weighting logic outlined in Bonilla, Fernández, and González (2022) and the focus on usage and accessibility in Kaiser, Angenendt, and Sauer (2023), the following weights are used:

$$\text{CPI}_{\text{local authority}} = 0.4 \cdot z_{\text{occupancy}} + 0.4 \cdot z_{\text{users}} + 0.2 \cdot z_{\text{energy}}$$

In contrast, commercial CPOs prioritise operational efficiency and financial performance. For this stakeholder group, energy throughput serves as a direct proxy for revenue and, therefore, receives the highest weight. Occupancy rate also matters for network efficiency, while the number of users is typically less critical unless it impacts load balancing or market expansion. Reflecting these priorities and supported by Kaiser et al. (Kaiser, Angenendt, and Sauer 2023), the weights for the CPO-focused CPI are:

$$\text{CPI}_{\text{CPO}} = 0.6 \cdot z_{\text{energy}} + 0.3 \cdot z_{\text{occupancy}} + 0.1 \cdot z_{\text{users}}$$

Where:

- $z_{\text{occupancy}}$, z_{users}, and z_{energy} are the standardised (z-score) values of the KPIs
- The weights sum to 1 in both cases, ensuring comparability

This stakeholder-sensitive CPI formulation allows a performance analysis that reflects real-world objectives. It follows best practices in multi-criteria infrastructure evaluation, as demonstrated in the work of Bonilla, Fernández, and González (2022) and Kaiser, Angenendt, and Sauer (2023).

4.5.3. Statistical Validation

To ensure that the differences observed in the performance of roll-out strategies are statistically significant, a comprehensive statistical validation process is applied. This process is carried out because conclusions can be drawn from KPI results, but the availability of charging station data and sample sizes per cluster-strategy combination may vary significantly. Therefore, the differences in CPI, as measured through the KPIs, are subjected to statistical evaluation. This analysis assesses the relevance and reliability of the results, accounting for varying sample sizes and data characteristics. The purpose of this validation is not to evaluate the robustness of each individual KPI before aggregation into the CPI, but to determine the statistical significance of the insights derived from the dataset used. The statistical validation process consists of multiple steps that aim to quantify the uncertainty and importance of observed differences in KPI performance. These steps include:

1. **Confidence Intervals (CIs):** For each KPI, 95% CIs are computed to assess the precision of the observed KPI values. The CI provides a range in which we believe the true population parameter (i.e., the true mean KPI value) is likely to fall. A narrower CI suggests that the mean is estimated with greater precision, while a wider CI indicates greater uncertainty. For each KPI, the 95% CI is computed using the formula:

   $$CI = \bar{x} \pm t_{\alpha/2,n-1} \cdot \frac{s}{\sqrt{n}}$$

   Where:

   - $\bar{x}$: The sample mean of the KPI, which represents the average value of the KPI across all local authorities in a given cluster–strategy combination. For instance, for the occupancy rate KPI, $\bar{x}$ would be the average occupancy rate across all municipalities in a particular cluster and strategy.
   - s: The sample standard deviation of the KPI values. This quantifies how spread out or variable the KPI values are across the municipalities within the given cluster-strategy combination. A higher standard deviation means there's greater variation in the values.
   - n: The sample size — the number of local authorities within the given cluster-strategy combination. Larger sample sizes provide more reliable estimates of the population parameter.
   - $t_{\alpha/2,n-1}$: The t-critical value, which corresponds to the desired confidence level (95% in this case) and is derived from the t-distribution. This value varies depending on the sample size n.
   - $\frac{s}{\sqrt{n}}$: The standard error (SE) of the mean, which quantifies how much the sample mean ($\bar{x}$) is likely to vary from the true population mean. Smaller standard errors suggest that the mean is a more accurate estimate of the true value.

   After calculating the 95% CIs, the results are presented visually. For each KPI, the mean value is plotted alongside the lower and upper bounds of the 95% confidence interval. This visualisation provides an intuitive way to understand the range of possible true values for the KPI. The results are displayed using a bar chart, where each bar represents the mean value for a specific cluster-strategy combination, and the whiskers represent the 95% CI. The whiskers show the range within which the true value of the KPI is likely to fall with 95% confidence. This type of visualisation allows for easy comparison of the performance of different strategies within each cluster, providing insights into which strategy performs best for each KPI. By visualising the data in this way, we can clearly observe which strategy yields the most consistent results (i.e., the smallest CI) and which have greater performance variation.

2. **Tukey's HSD Test:** In addition to CIs, Tukey's Honest Significant Difference (HSD) test is applied to determine which strategy–cluster combinations differ significantly from one another. This post-hoc test follows an Analysis Of Variance (ANOVA) and is particularly suitable for comparing multiple groups with unequal sample sizes, as is the case in this study. The Tukey's HSD test helps identify whether any of the observed differences between the groups — in terms of KPI performance — are statistically significant. The Tukey's HSD test compares the means of all possible pairs of cluster–strategy combinations and calculates the minimum significant difference between them. If the observed difference between any two combinations exceeds this threshold, the difference is deemed statistically significant. This ensures that the observed performance differences are not due to random fluctuations or chance but are genuinely indicative of different performance outcomes. In this study, Tukey's HSD test is applied to the results of each KPI. By performing the test, we can determine which strategies in each cluster significantly outperform others. The results of the Tukey's HSD test are displayed alongside the 95% CIs for each KPI, providing a robust statistical comparison that accounts for both the magnitude of the differences and their statistical significance.
The results of Tukey's HSD test are used to identify which strategy-cluster combinations significantly outperform others for each KPI. For each pair of strategies within a cluster, the test calculates a p-value to determine whether the observed difference in means is statistically significant. If the p-value is less than the alpha level - set at 0.05 - this indicates that the difference in performance is not due to random chance and can be considered a real difference. The 0.05 alpha level in Tukey's HSD test is chosen because it is a balanced and widely accepted threshold for detecting statistically significant differences while minimising the risk of false positives. It's widely used across disciplines, making it a standard approach in statistical testing. In the context of this study, Tukey's HSD test helps to clarify which strategies deliver the best performance in each cluster. For example, suppose two strategies have non-overlapping confidence intervals (CIs) and the p-value from the Tukey test is less than 0.05. In that case, the difference in performance between the two strategies is statistically significant. The test results are displayed alongside the 95% Confidence Intervals (CIs) for each KPI, with the statistical significance indicated by stars ($*$) next to the best-performing strategy. A star denotes that a strategy has a significant performance advantage over other strategies in that particular cluster. The stars visually highlight the superior strategies, making it easy to identify the most effective approaches in each cluster.

3. **The Difference Between Confidence Intervals (CIs) and Tukey's HSD Test**: While both (CIs) and Tukey's HSD Test provide valuable insights into the differences between strategy-cluster combinations, they serve different purposes in the analysis. CIs give a range of possible values for the KPI's true mean. They provide a sense of the precision of the observed mean and help assess the uncertainty around the mean. A narrow CI suggests that the sample mean is a precise estimate of the true population mean, while a wider CI indicates greater uncertainty. The CI gives us the range within which the true average KPI value is likely to fall, thus showing the variability of each strategy's performance within a cluster. Tukey's HSD Test, on the other hand, is a post-hoc test that evaluates explicitly whether the differences between pairs of strategies within each cluster are statistically significant. While CIs show the potential range of the mean, Tukey's HSD test helps to identify which specific strategy-cluster combinations significantly outperform others. It compares all possible pairs of strategies and calculates the minimum significant difference between them, ensuring that observed differences are not due to random chance. The combination of both CIs and Tukey's HSD test offers a comprehensive statistical approach. CIs provide the reliability of the estimates, while Tukey's HSD identifies which differences between strategies are truly meaningful. This dual approach ensures that the conclusions drawn from the study are robust: we are not only confident in the accuracy of our estimated means but can also validate

whether the observed differences in performance are statistically significant. The combination of these two measures strengthens the study by providing both a confidence range for each mean and a rigorous test for comparing the effectiveness of different strategies within each cluster.

The process of applying CIs and Tukey's HSD test to each KPI ensures that insights drawn from individual KPIs, as well as the aggregated CPI, are statistically sound and not affected by any inconsistencies in the data. These statistical techniques ensure that the conclusions drawn from the performance matrix are not only interpretable but also statistically robust. The application of CIs and Tukey's HSD test increases the reliability of the results, providing policy-makers with robust evidence on which to base decisions. The validation process accounts for varying sample sizes and differing data characteristics and ensures the integrity of the analysis by addressing potential sources of variability.

4.6. Summary of the Methodology

This chapter outlines the methodological framework for evaluating the performance of PCSI roll-out strategies across different urban contexts in the Netherlands. The overarching aim is to develop a *context-strategy evaluation matrix* that enables stakeholders to identify which implementation approaches perform best under specific urban conditions. The study employs a constructive quantitative case study design, integrating empirical data, scenario-based analysis, and statistical validation.

The methodology consists of four main steps.

Step 1: Clustering Local Authorities. A two-stage k-means clustering approach was used to classify local authorities based on neighbourhood-level socio-economic and spatial variables obtained from CBS data: income, address density, and land area. Silhouette analysis guided the choice of the number of clusters. Three distinct urban-infrastructural profiles emerged — *urban*, *suburban*, and *rural* — that served as the basis for subsequent comparisons.

Step 2: Mapping Roll-Out Strategies. PCSI deployment strategies were categorised into proactive (data-driven or strategic) and reactive (request-based) approaches, across two contracting models: mono-/multi-concession and open market. Policy documents and EVTools data were reviewed to assign each municipality to one of these categories, producing a comprehensive context–strategy matrix.

Step 3: Selecting KPIs. Quantitative performance data were obtained from the LINDA dataset, part of the NDW. Based on literature and consultations with public and private stakeholders, three KPIs were selected: (1) Occupancy Rate (%), representing utilisation; (2) Average Number of Unique Users per Day, reflecting accessibility; and (3) Average Energy Delivered per Day (kWh), capturing intensity of use and economic potential. These KPIs represent both public and private performance priorities and were aggregated annually per local authority.

Step 4: Performance Assessment. The collected data were used to evaluate each roll-out strategy within its respective cluster. A performance matrix was constructed to summarise KPI outcomes per cluster-strategy pair. A CPI was then developed to combine the three KPIs into a single performance measure, using stakeholder-specific weighting schemes. For local authorities, greater emphasis was placed on occupancy and accessibility, while for CPOs, energy throughput was prioritised. Statistical validation through confidence intervals and Tukey's HSD tests ensured that differences in KPI and CPI values between strategies were statistically significant.

Overall, this structured four-step methodology combines machine learning, policy analysis, and quantitative evaluation to link urban context with PCSI roll-out performance systematically. It not only advances academic understanding of EV infrastructure deployment but also provides a practical, data-driven decision-support tool for planners and policymakers in e-mobility. In Figure 4.1, the total step-by-step overview of the methodology is provided.

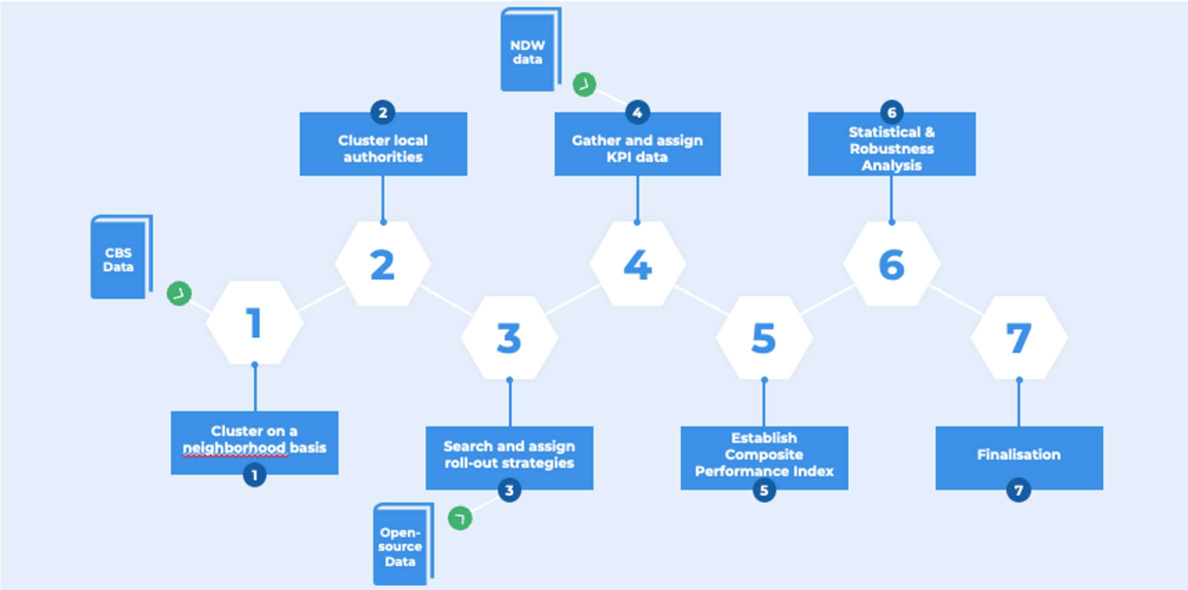

Figure 4.1: Methods step-by-step overview. This scheme visualises the sequential steps of the methodological framework, including data sources (CBS, open-source, NDW) and analytical stages from clustering to statistical validation.

5

Data Exploration

5.1. Data Exploration

Chapter 4 outlined the methodological framework used to address the research questions of this study. This chapter examines the dataset that was collected and prepared for analysis. The purpose of this exploration is to understand the data's structure and characteristics and to generate insights that inform subsequent analytical stages. First, the dataset will be evaluated based on its sources, variables, and coverage. Subsequently, descriptive analyses are conducted to assess the distribution, completeness, and relationships among the selected indicators. This exploration provides the empirical foundation for the clustering, strategy mapping, and performance assessment presented in the following chapters.

5.2. Data used for clustering local authorities

The clustering analysis was conducted using data from the CBS, specifically the *Key Figures for Districts and Neighbourhoods 2004–2025* dataset (Central Bureau of Statistics 2024). This dataset provides the necessary socio-economic and spatial indicators for all Dutch neighbourhoods and serves as the basis for the clustering process described earlier. The datasets for 2023 to 2025 were either incomplete, inconsistent, or provisional regarding income data. Consequently, the 2022 dataset was selected to ensure analytical completeness and reliability.
Figure 5.1 presents a sample of the raw data to be processed, illustrating the structure of the neighbourhood-level indicators used for clustering. Variables not used in the analysis were removed from this sample to maintain focus on the relevant attributes. Although the CBS dataset is available only in Dutch, an explanatory reference table clarifies the variable definitions and their corresponding English descriptions, as provided by Statistics Netherlands (CBS) (2025).

- **gwb_code** = CBS coding
  - Local authority code has 4 positions, preceded by 'GM'.
  - District code has 6 positions: local authority code (4) + district code (2), preceded by 'WK'.
  - Neighbourhood code has 8 positions: local authority code (4) + district code (2) + neighbourhood code (2), preceded by 'BU'.
- **regio** = Regional designation of the geographical unit.
- **gm_naam** = Official name of the local authority.
- **recs** = The chosen regional classification refers to: local authority, District, or Neighbourhood.
- **a_lan_ha** = Land area [ha]
  - The land area is determined by combining the most recent digital Land Use file with the digital file of local authority, district, and neighbourhood boundaries.
  - The land and water areas for the year 2022 are based on Land Use File 2017 (BBG2017).
  - For 2020 and 2021, the data are based on Land Use File 2015 (BBG2015).
  - Both BBG2017 and BBG2015 take into account the boundary changes between the Netherlands

and Belgium near Maastricht and Eijsden as of 1 January 2018.
- The land area is expressed in whole hectares (ha).

- **g_ink_pi** = Average income per inhabitant [x 1 000 euro]
  - The arithmetic mean income per person based on the total population in private households.
  - The value is reported only for regions with at least 2,500 persons in private households.
- **ste_oad** = The surrounding address density [per km^2]
  - The surrounding address density (OAD) of a neighbourhood, district, or local authority is the average number of addresses per square kilometre within a circle with a radius of one kilometre, measured on 1 January.
  - The OAD indicates the degree of concentration of human activities (living, working, schooling, shopping, leisure, etc.).
  - CBS uses the OAD to determine the level of urbanisation of an area.
  - For this calculation, the OAD is first determined for each address, then the mean is taken of all addresses in the area.
  - Addresses are sourced from the Geographical Base Register (definitive version) of the relevant year, which includes all Dutch addresses with a postcode, local authority code, and district/neighbourhood code.

gwb_code_10	gwb_code_8	regio	gm_naam	recs	gwb_code	ind_wbi	g_ink_pi	a_lan_ha	ste_oad
NL00	0000	Nederland	Nederland	Land	NL00	.	30,8	3364723	2039
GM0014	0014	Groningen	Groningen	Gemeente	GM0014	1	28,2	18553	3373
WK001400	001400	Centrum	Groningen	Wijk	WK001400	1	24,4	228	6501
BU00140000	00140000	Binnenstad-Noord	Groningen	Buurt	BU00140000	1	22,7	37	6712
BU00140001	00140001	Binnenstad-Zuid	Groningen	Buurt	BU00140001	1	23,1	55	6417
BU00140002	00140002	Binnenstad-Oost	Groningen	Buurt	BU00140002	1	22,9	27	6151
BU00140003	00140003	Binnenstad-West	Groningen	Buurt	BU00140003	1	26,4	10	6369
BU00140004	00140004	Noorderplantsoen	Groningen	Buurt	BU00140004	1	.	19	6311
BU00140005	00140005	Hortusbuurt-Ebbingekwartier	Groningen	Buurt	BU00140005	1	28,0	43	6786
BU00140007	00140007	UMCG	Groningen	Buurt	BU00140007	1	.	24	6513
BU00140008	00140008	Stationsgebied	Groningen	Buurt	BU00140008	1	22,4	13	5751
WK001401	001401	Oud-Zuid	Groningen	Wijk	WK001401	1	28,0	369	4178
BU00140100	00140100	De Meeuwen	Groningen	Buurt	BU00140100	1	34,3	22	4369
BU00140101	00140101	Oosterpoort	Groningen	Buurt	BU00140101	1	27,4	40	4348
BU00140102	00140102	Herewegbuurt	Groningen	Buurt	BU00140102	1	32,0	16	4308
BU00140103	00140103	Rivierenbuurt	Groningen	Buurt	BU00140103	1	27,4	55	4220
BU00140104	00140104	Grunobuurt	Groningen	Buurt	BU00140104	1	29,1	22	3693
BU00140105	00140105	Badstratenbuurt	Groningen	Buurt	BU00140105	1	25,9	6	5526
BU00140106	00140106	Zeeheldenbuurt	Groningen	Buurt	BU00140106	1	23,9	33	4008
BU00140107	00140107	Laanhuizen	Groningen	Buurt	BU00140107	1	31,1	21	3495
BU00140108	00140108	Stadspark	Groningen	Buurt	BU00140108	1	.	129	2220
BU00140109	00140109	Martini Trade Park	Groningen	Buurt	BU00140109	1	.	25	2790
WK001402	001402	Oud-West	Groningen	Wijk	WK001402	1	28,4	112	5404
BU00140200	00140200	Oranjebuurt	Groningen	Buurt	BU00140200	1	30,8	26	5470
BU00140201	00140201	Noorderplantsoenbuurt	Groningen	Buurt	BU00140201	1	29,2	25	6307
BU00140202	00140202	Schildersbuurt	Groningen	Buurt	BU00140202	1	27,2	36	5488
BU00140203	00140203	Kostverloren	Groningen	Buurt	BU00140203	1	26,9	25	3760
WK001403	001403	Oud-Noord	Groningen	Wijk	WK001403	1	23,9	178	5206
BU00140300	00140300	De Hoogte	Groningen	Buurt	BU00140300	1	22,4	55	5230
BU00140301	00140301	Indische buurt	Groningen	Buurt	BU00140301	1	22,8	69	5067
BU00140302	00140302	Professorenbuurt	Groningen	Buurt	BU00140302	1	26,5	53	5392
WK001404	001404	Oosterparkwijk	Groningen	Wijk	WK001404	1	26,7	149	4291
BU00140400	00140400	Gorechtbuurt	Groningen	Buurt	BU00140400	1	27,4	38	5320
BU00140401	00140401	Vogelbuurt	Groningen	Buurt	BU00140401	1	25,5	35	4236
BU00140402	00140402	Bloemenbuurt	Groningen	Buurt	BU00140402	1	23,5	23	3534

Figure 5.1: The raw dataset from the CBS used for clustering local authorities

Prior to clustering, as can be verified in Appendix A 01-standardisation, neighbourhood data was filtered, relevant columns were selected, the dataset was cleaned and standardised to be ready for the k-means clustering algorithm. A sample of the processed data is provided in Figure 5.2

gwb_code	gm_naam	std_g_ink_pi	std_ste_oad	std_a_lan_ha
BU00140000	Groningen	-1,826086957	3,277663027	-0,08045977
BU00140001	Groningen	-1,663043478	3,103570375	0,126436782
BU00140002	Groningen	-1,673913043	2,946591915	-0,195402299
BU00140003	Groningen	-1,423913043	3,075243435	-0,390804598
BU00140005	Groningen	-1,336956522	3,321333727	-0,011494253
BU00140008	Groningen	-2,141304348	2,710534081	-0,356321839
BU00140100	Groningen	-0,554347826	1,894954264	-0,252873563
BU00140101	Groningen	-1,239130435	1,882561228	-0,045977011
BU00140102	Groningen	-0,945652174	1,858955444	-0,32183908
BU00140103	Groningen	-1,27173913	1,807022721	0,126436782
BU00140104	Groningen	-1,043478261	1,496016524	-0,252873563
BU00140105	Groningen	-1,467391304	2,577751549	-0,436781609
BU00140106	Groningen	-1,717391304	1,681912068	-0,126436782
BU00140107	Groningen	-0,880434783	1,379167896	-0,264367816

Figure 5.2: Processed dataset, ready for clustering

The clustering procedure followed the two-step approach outlined in Chapter 4. In the first step, neighbourhoods were grouped according to selected urban and socio-economic characteristics to reveal spatial patterns at the sub-local-authority level. In the second step, local authorities were clustered based on the composition of their neighbourhoods, thereby capturing intra-local-authority level heterogeneity while establishing a nationally comparable typology. The K-means algorithm was applied owing to its interpretability and scalability for large datasets, with the optimal number of clusters (k) determined through silhouette analysis (Rousseeuw 1987; Rodrigues et al. 2025).

The resulting local authority clusters represent distinct urban-infrastructural profiles, ranging from dense, high-income urban cores to lower-density suburban and rural contexts. Each cluster displays unique combinations of demographic, spatial, and infrastructural attributes that are expected to influence both charging demand and the performance of applied roll-out strategies. The next step links these clustered local authorities to their respective deployment strategies, enabling a structured comparison of performance outcomes across different contextual environments.

5.3. Data Used for Strategy Mapping

After clustering the local authorities into distinct urban-infrastructural profiles, the next step was to identify and categorise the roll-out strategies implemented across local authorities. The objective of this process was to establish a consistent, data-based classification of deployment approaches that could be linked to each local-authority cluster. Information was obtained from open-source policy documents, procurement tenders, and operational data provided by EVTools. Together, these sources enabled the construction of a verified dataset connecting each local authority to a predefined roll-out strategy type within the framework introduced in Chapter 3, comprising the dimensions of *governance model* and *planning style* (Helmus, Spoelstra, et al. 2018; Wolbertus, Hoed, et al. 2021; Farhadi et al. 2023; Fischer, Michalk, and Bogenberger 2024; Netherlands Enterprise Agency (RVO) 2020).

The governance model dimension differentiates between *concession-based* and *open-market* approaches. In the concession-based model, local authorities contract one or more CPOs to install, operate, and maintain charging infrastructure under defined conditions and contract durations. In the open-market model, multiple CPOs may install charging stations independently, subject to local authorities' permitting and regulatory oversight.

The planning-style dimension reflects the degree of proactivity and data dependency in the siting process. Three principal categories were identified: *request-driven*, *strategic*, and *data-driven*. Request-driven strategies rely on citizen applications, typically supporting residents without access to private parking. Strategic approaches involve periodically deploying charging stations at predefined candidate sites to ensure spatial coverage and policy consistency. Data-driven approaches utilise demand indicators to trigger new installations dynamically and continuously.

Local authorities' roll-out strategies were classified by systematically reviewing available local-authority documents, including public tenders, contract specifications, and mobility or sustainability plans. These were cross-checked with operational records from EVTools to confirm correspondence between stated policy frameworks and observed implementation patterns. Where ambiguities were identified, classifications were validated against the latest EVTools deployment. It should be noted that the strategy framework applied in this study was developed by the author, drawing on both EVTools documentation and the academic literature discussed in Chapter 3. Therefore, the reviewed policy documents did not explicitly state which of the established roll-out strategy was in use; however, they provided sufficient information on local objectives, procedural structures, and governance arrangements to enable classification. Each local authority was therefore assigned to one of the defined strategy types through informed interpretation of these policy descriptions. The rationale for each classification is detailed in the final dataset sample presented in Appendix B. The resulting dataset links each clustered local authority to its respective roll-out strategy, providing an analytical foundation for comparative performance assessment.

5.4. KPI Data

Now that the local authorities have been clustered according to their neighbourhood-level characteristics and assigned to their respective roll-out strategies, the final data requirement involves linking the KPI data to the urban–infrastructural–strategy matrix. Once the KPI data are integrated, the dataset becomes complete for analysis and performance assessment. The performance analysis in this study is based on operational data describing the utilisation of public charging stations in the Netherlands. These data were obtained from the NDW, specifically from the LINDA database, which consolidates transaction-level records from multiple CPOs. The dataset contains anonymised information on individual charging sessions, including start and end times, energy delivered, and session identifiers. These records form the empirical basis for the KPIs defined in Chapter 3: occupancy, energy throughput, and unique users (Helmus and Hoed 2016; Maase et al. 2018; Wolbertus 2024).

The LINDA dataset represents the most comprehensive national-level source of charging data currently available. For this research, the dataset was filtered to include only public-access stations operating within the local authorities covered by the clustering analysis. Sessions with missing or inconsistent time or energy records were excluded to ensure data integrity. The LINDA portal does not include data from all CPOs in every region of the Netherlands; therefore, only the local authorities for which reliable data were available were included — resulting in coverage for 314 of the 342 Dutch local authorities. Table 5.1 provides an overview of the available LINDA KPI data.

Table 5.1: Overview of CPOs included in the LINDA dataset

CPO	Available since	Regions
Allego	01–2024	Gelderland, Overijssel, Arnhem, Amsterdam
Equans (Greenflux)	06–04–2023	Groningen, Drenthe, Amsterdam, Utrecht (city)
Equans (LMS)	26–03–2023	Zuid-Holland, Gelderland
Qwello	21–06–2024	National coverage
Total Energies	01–2023	MRA-e, Friesland
Ubitricity	07–2023	MRA-e
Vattenfall	01–01–2023	Amsterdam, Gelderland-Overijssel, Brabant-Limburg, MRA-e, Utrecht (city), The Hague
WeDriveSolar (LMS)	26–03–2023	Utrecht (city)

LINDA receives data from the CPOs with which it maintains contractual agreements, as shown in Table 5.1. These data are reported per local authority and per month. The next step involved aggregating all available monthly observations for each KPI and local authority. This process produced the monthly averages for the following KPIs: `averageKwhPerDay`, `averageNumberOfUniqueRfidPerDay`, and `OccupancyRate`.

Table 5.2 presents a sample of the collected LINDA data, illustrating three charging stations located in Amsterdam and their corresponding monthly KPI values used in this study. Table 5.3 provides the official NDW documentation describing the definition and calculation of these KPIs (Nationale Databank

Wegverkeersgegevens (NDW) 2024).

Year	Month	City	Address	District	CBS District	CBS Neighbourhood	ChargeStationID	uniqueRfidCount	occupancyRate	averageKwhPerDay
2024	3	Amsterdam	Letelierstraat 2	Nieuw-West	De Aker	Middelveldsche Akerpolder	NL*GFX*EACE0526130	22	57,74	27,389
2024	2	Amsterdam	Letelierstraat 2	Nieuw-West	De Aker	Middelveldsche Akerpolder	NL*GFX*EACE0526130	19	55,19	25,292
2024	4	Amsterdam	Letelierstraat 2	Nieuw-West	De Aker	Middelveldsche Akerpolder	NL*GFX*EACE0526130	23	57,92	28,721
2024	7	Amsterdam	Letelierstraat 2	Nieuw-West	De Aker	Middelveldsche Akerpolder	NL*GFX*EACE0526130	27	66,75	20,183
2024	1	Amsterdam	Letelierstraat 2	Nieuw-West	De Aker	Middelveldsche Akerpolder	NL*GFX*EACE0526130	21	55,7	27,068
2024	12	Amsterdam	Letelierstraat 2	Nieuw-West	De Aker	Middelveldsche Akerpolder	NL*GFX*EACE0526130	24	59,61	24,834
2024	6	Amsterdam	Letelierstraat 2	Nieuw-West	De Aker	Middelveldsche Akerpolder	NL*GFX*EACE0526130	19	63,07	19,832
2024	5	Amsterdam	Letelierstraat 2	Nieuw-West	De Aker	Middelveldsche Akerpolder	NL*GFX*EACE0526130	19	57,1	24,002
2024	8	Amsterdam	Letelierstraat 2	Nieuw-West	De Aker	Middelveldsche Akerpolder	NL*GFX*EACE0526130	26	60,16	21,44
2024	10	Amsterdam	Letelierstraat 2	Nieuw-West	De Aker	Middelveldsche Akerpolder	NL*GFX*EACE0526130	18	64,15	24,368
2024	9	Amsterdam	Letelierstraat 2	Nieuw-West	De Aker	Middelveldsche Akerpolder	NL*GFX*EACE0526130	26	67,43	19,344
2024	11	Amsterdam	Letelierstraat 2	Nieuw-West	De Aker	Middelveldsche Akerpolder	NL*GFX*EACE0526130	24	62,19	24,579
2024	1	Amsterdam	Meeuwenlaan 108	Noord	Noordelijke IJ-oevers-Oost	Hamerstraatkwartier-West	NL*GFX*EEVB*P1529004	55	54,09	21,859
2024	4	Amsterdam	Meeuwenlaan 108	Noord	Noordelijke IJ-oevers-Oost	Hamerstraatkwartier-West	NL*GFX*EEVB*P1529004	58	57,54	24,55
2024	5	Amsterdam	Meeuwenlaan 108	Noord	Noordelijke IJ-oevers-Oost	Hamerstraatkwartier-West	NL*GFX*EEVB*P1529004	49	42,61	19,447
2024	12	Amsterdam	Meeuwenlaan 108	Noord	Noordelijke IJ-oevers-Oost	Hamerstraatkwartier-West	NL*GFX*EEVB*P1529004	54	48,67	20,523
2024	6	Amsterdam	Meeuwenlaan 108	Noord	Noordelijke IJ-oevers-Oost	Hamerstraatkwartier-West	NL*GFX*EEVB*P1529004	56	37,95	20,2
2024	7	Amsterdam	Meeuwenlaan 108	Noord	Noordelijke IJ-oevers-Oost	Hamerstraatkwartier-West	NL*GFX*EEVB*P1529004	57	38,17	19,703
2024	8	Amsterdam	Meeuwenlaan 108	Noord	Noordelijke IJ-oevers-Oost	Hamerstraatkwartier-West	NL*GFX*EEVB*P1529004	40	26,81	16,965
2024	2	Amsterdam	Meeuwenlaan 108	Noord	Noordelijke IJ-oevers-Oost	Hamerstraatkwartier-West	NL*GFX*EEVB*P1529004	57	52,13	21,565
2024	3	Amsterdam	Meeuwenlaan 108	Noord	Noordelijke IJ-oevers-Oost	Hamerstraatkwartier-West	NL*GFX*EEVB*P1529004	55	59,81	23,615
2024	10	Amsterdam	Meeuwenlaan 108	Noord	Noordelijke IJ-oevers-Oost	Hamerstraatkwartier-West	NL*GFX*EEVB*P1529004	50	40,21	20,53
2024	9	Amsterdam	Meeuwenlaan 108	Noord	Noordelijke IJ-oevers-Oost	Hamerstraatkwartier-West	NL*GFX*EEVB*P1529004	36	44,64	23,383
2024	11	Amsterdam	Meeuwenlaan 108	Noord	Noordelijke IJ-oevers-Oost	Hamerstraatkwartier-West	NL*GFX*EEVB*P1529004	53	44,77	18,275
2024	11	Amsterdam	Schoenerstraat 30	Noord	Banne Buiksloot	Banne-Zuidwest	NL*TCB*ETNLP011056	21	48,07	25,861
2024	8	Amsterdam	Schoenerstraat 30	Noord	Banne Buiksloot	Banne-Zuidwest	NL*TCB*ETNLP011056	10	22,57	35,211
2024	1	Amsterdam	Schoenerstraat 30	Noord	Banne Buiksloot	Banne-Zuidwest	NL*TCB*ETNLP011056	13	20,76	34,4
2024	2	Amsterdam	Schoenerstraat 30	Noord	Banne Buiksloot	Banne-Zuidwest	NL*TCB*ETNLP011056	20	29,8	30,796
2024	5	Amsterdam	Schoenerstraat 30	Noord	Banne Buiksloot	Banne-Zuidwest	NL*TCB*ETNLP011056	20	26,07	30,74
2024	3	Amsterdam	Schoenerstraat 30	Noord	Banne Buiksloot	Banne-Zuidwest	NL*TCB*ETNLP011056	18	49,56	29,17
2024	7	Amsterdam	Schoenerstraat 30	Noord	Banne Buiksloot	Banne-Zuidwest	NL*TCB*ETNLP011056	21	29,57	30,672
2024	10	Amsterdam	Schoenerstraat 30	Noord	Banne Buiksloot	Banne-Zuidwest	NL*TCB*ETNLP011056	23	46,75	34,469
2024	4	Amsterdam	Schoenerstraat 30	Noord	Banne Buiksloot	Banne-Zuidwest	NL*TCB*ETNLP011056	15	44,43	29,138
2024	6	Amsterdam	Schoenerstraat 30	Noord	Banne Buiksloot	Banne-Zuidwest	NL*TCB*ETNLP011056	16	23,14	31,559
2024	12	Amsterdam	Schoenerstraat 30	Noord	Banne Buiksloot	Banne-Zuidwest	NL*TCB*ETNLP011056	20	33,73	20,649
2024	9	Amsterdam	Schoenerstraat 30	Noord	Banne Buiksloot	Banne-Zuidwest	NL*TCB*ETNLP011056	23	33,09	27,518

Table 5.2: Sample of the collected data imports from the LINDA portal.

Table 5.3: NDW description of the collected KPIs

KPI (per month – year)	Description
`averageKwhPerDay`	Monthly average energy delivered (kWh) per charging station. Calculated as the total energy (kWh) divided by the number of charge points. This indicator is meaningful primarily at aggregation levels higher than individual stations.
`averageNumberOfUniqueRfidPerDay`	Average number of unique RFID users per day. Represents the mean count of distinct users initiating charging sessions per charging point.
`OccupancyRate`	Share of occupancy per charging point, computed as the total minutes occupied divided by the total minutes available during the observation period.

The aggregated KPI data were then matched to the urban–infrastructural–strategy matrix developed in the previous stages. The resulting integrated dataset enables the analysis of PCSI performance across distinct urban-infrastructural profiles, each linked to its corresponding roll-out strategy and KPI outcomes over 2024. Appendix B provides a sample of the completed dataset.

6
Results

This chapter presents the empirical outcomes of the research and provides a structured overview of how Dutch local authorities differ in their charging infrastructure contexts, strategic approaches, and performance outcomes. Building on the methodological framework described in Chapter 4, the results are organised into four main parts: the identification of urban-infrastructural clusters, the distribution of roll-out strategies across these contexts, the corresponding KPI outcomes, and the statistical validation of observed patterns. Together, these analyses establish the quantitative foundation for the interpretive discussion that follows in Chapter 6.

6.1. Clustering Results

This section presents the outcomes of the clustering procedure applied to the 2022 CBS dataset. The aim is to identify distinct groups of local authorities with comparable socio-economic and spatial characteristics relevant to PCSI planning. First, all Dutch neighbourhoods were clustered based on three variables: income, address density and land area. To validate the choice of the number of clusters (k), a silhouette analysis was performed. The calculated silhouette scores are depicted in Figure 6.1. As shown in Figure 6.1, the silhouette score peaked at $k = 2$, suggesting a natural binary grouping. However, to enable more nuanced comparisons between context–strategy combinations, and following recommendations from urban clustering literature (Kilani and Dhaher 2024), a 3-cluster solution was chosen. This decision allowed the identification of three interpretable urban-infrastructural profiles:

- **Cluster 0: Urban Areas**;
- **Cluster 1: Suburban Areas**;
- **Cluster 2: Rural Areas**.

After choosing $k = 3$, the k-means algorithm was applied to the CBS dataset. The results are depicted in Figure 6.2.

Figure 6.1: Silhouette scores for neighbourhood-level clustering.

Silhouette scores per k:

$k = 2$: 0.8522 $k = 3$: 0.7969 $k = 4$: 0.7848
$k = 5$: 0.7549 $k = 6$: 0.6767 $k = 7$: 0.5672
$k = 8$: 0.3639 $k = 9$: 0.4305 $k = 10$: 0.4195

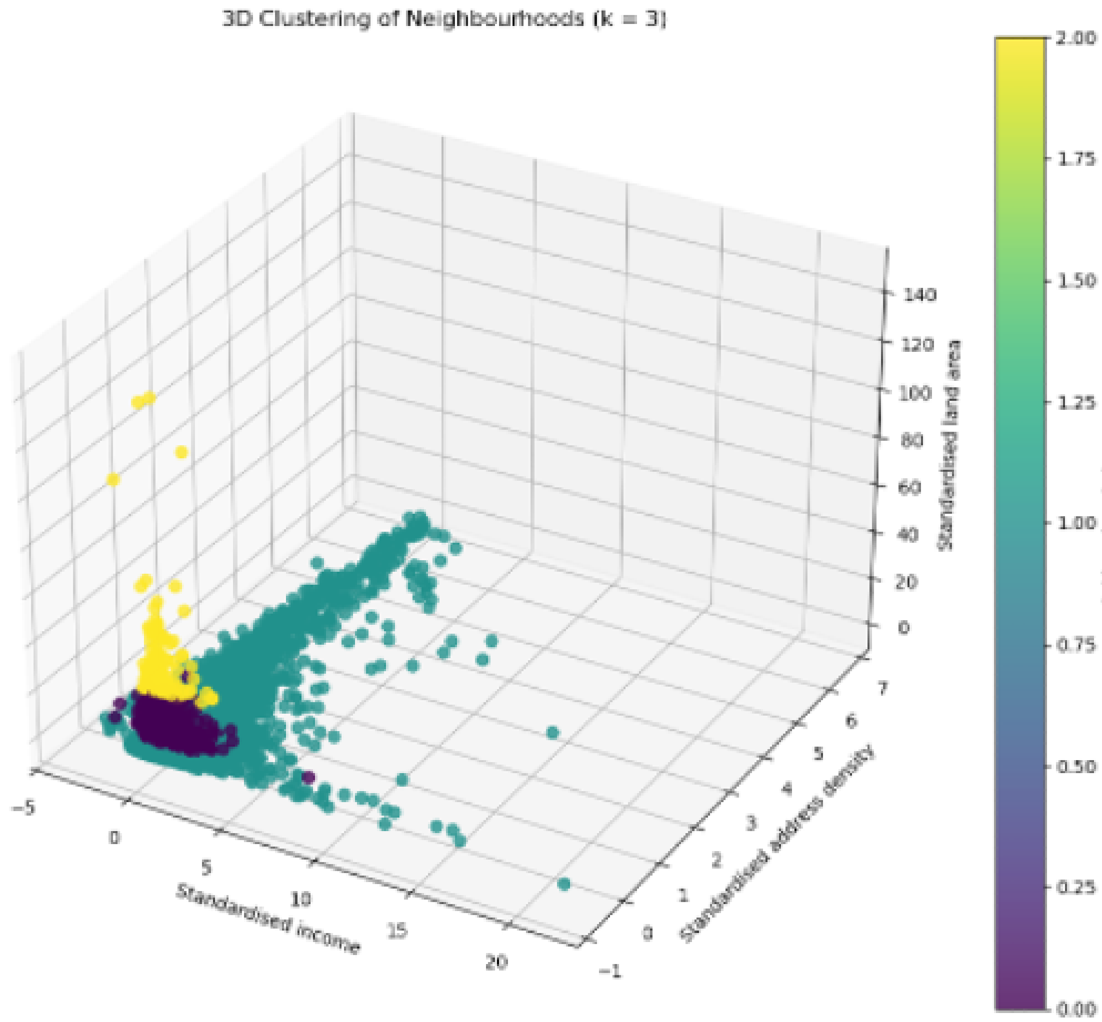

Figure 6.2: 3D visualisation of neighbourhood clusters ($k = 3$).

Now that neighbourhoods are clustered based on their socio-economic characteristics, the local authorities can be grouped based on their neighbourhood composition. Again, silhouette analysis was used to determine the optimal value of k for this second-level clustering. As shown in Figure 6.3, $k = 2$ achieved the highest silhouette score, with $k = 10$ and $k = 9$ following. Nonetheless, a 3-cluster solution was chosen for both analytical consistency and interpretability, particularly given the Dutch planning context, which often distinguishes between urban, suburban, and rural typologies. The marginal differences between $k = 2$, $k = 3$, $k = 9$ and $k = 10$ are also all less than 0.05 (Reibel 2011; J. Wang and Biljecki 2022).

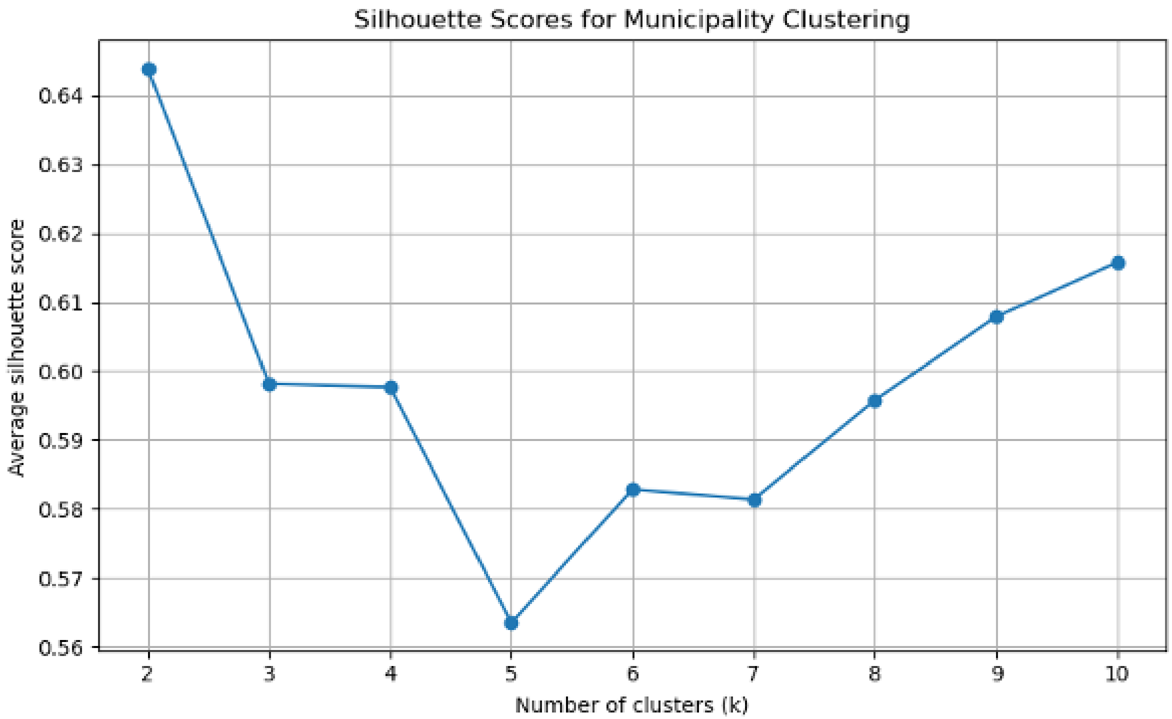

Figure 6.3: Silhouette scores for local authority-level clustering.

Silhouette scores per k (Local Authorities):
$k = 2$: 0.6439 $k = 3$: 0.5982 $k = 4$: 0.5976
$k = 5$: 0.5634 $k = 6$: 0.5828 $k = 7$: 0.5813
$k = 8$: 0.5958 $k = 9$: 0.6079 $k = 10$: 0.6158

This second clustering phase yielded three local authority profiles based on their internal neighbourhood composition. The outcome is a hierarchical classification in which local authorities are grouped by the relative prevalence of urban, suburban, and rural neighbourhoods in their jurisdiction. This refined classification serves as the foundation for the next analytical steps, where real-world PCSI roll-out strategies are mapped onto these clusters to evaluate their relative performance in context. The composition of neighbourhoods within each cluster is shown in Table 6.1, and the complete codebase and results are attached in Appendix A.

Table 6.1: Distribution of neighbourhood clusters within local authority clusters

Local Authority Cluster	Neighbourhood Cluster 0	Neighbourhood Cluster 1	Neighbourhood Cluster 2
Urban	0.0230	0.9722	0.0048
Suburban	0.1681	0.7991	0.0328
Rural	0.3763	0.5923	0.0314

The labels “urban”, “suburban”, and “rural” were assigned to the clusters ex post, based on their indicator profiles and neighbourhood composition. As shown by the average standardised values of address

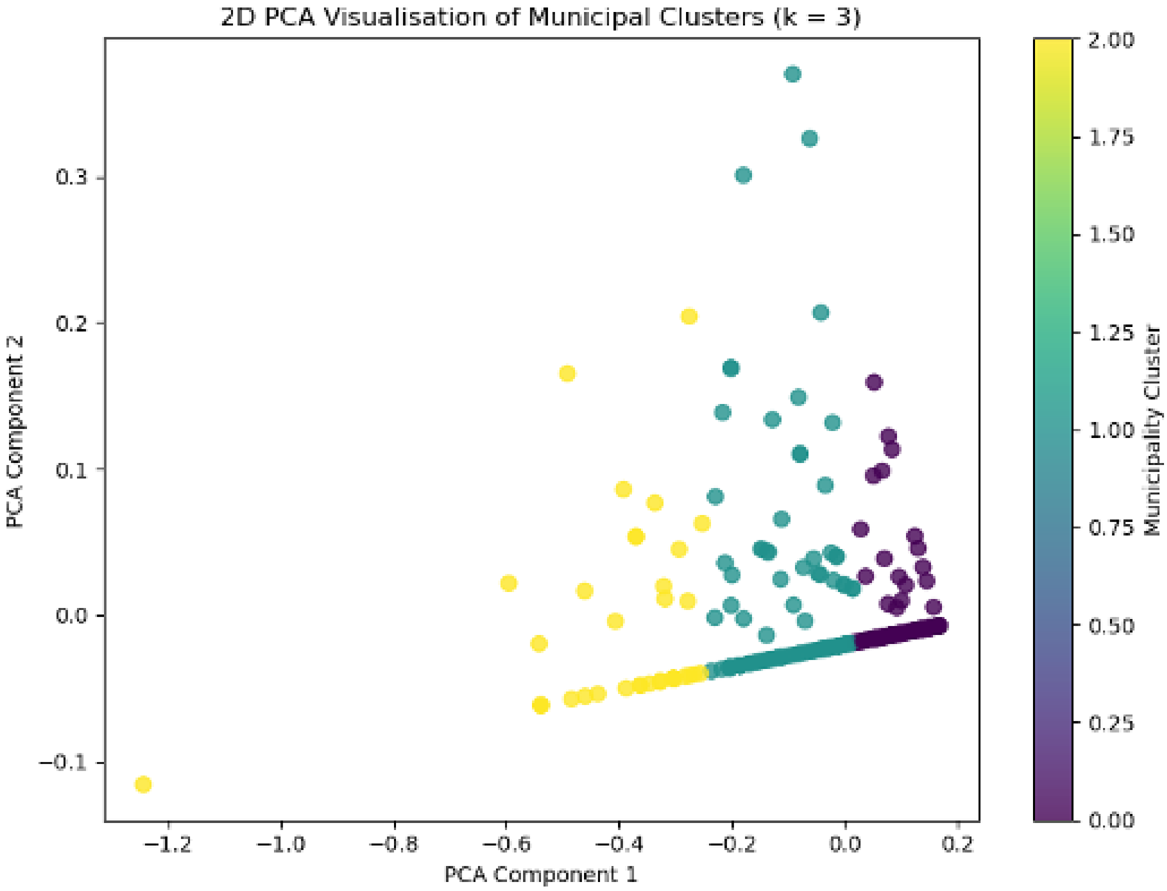

Figure 6.4: 2D visualisation of local authority clustering.

Number of local authorities per cluster:

Cluster 0: 199
Cluster 1: 106
Cluster 2: 40

density, land area, and income, one cluster is characterised by very high address density, relatively small land areas and higher incomes, which corresponds to what is typically understood as an urban environment in the Dutch planning context. A second cluster shows intermediate densities, larger land areas and middle-income levels, which align with a suburban profile. The third cluster combines low address densities with expansive land areas and comparatively lower average incomes, reflecting a more rural character. Table 6.1 confirms these patterns at the local-authority level by showing systematic differences in the mix of neighbourhood types within each cluster. For clarity and interpretability, these three empirically derived profiles are therefore referred to as the Urban, Suburban, and Rural clusters in the remainder of this study.

6.2. Roll-Out Strategy Distribution

Building on the clustering outcomes, this section examines how the identified local authorities are distributed across the defined roll-out strategies. Each local authority was assigned to a strategy according to the governance and planning-style framework introduced in Chapter 3, combining the dimensions of *governance model* (concession or open market) and *planning style* (reactive request-based, proactive data-driven, or proactive strategic).

Table 6.2: Coverage by cluster and strategy

Strategy	Urban	Suburban	Rural	Total
Concession reactive request-based	39	18	6	63
Concession proactive data-driven	92	45	14	151
Concession proactive strategic	31	25	17	73
Open market reactive request-based	14	4	0	18
Open market proactive data-driven	2	0	0	2
Open market proactive strategic	4	2	1	7
Total	182	94	38	314

Table 6.2 shows the coverage of Dutch local authorities across the six identified roll-out strategy types, differentiated by their urban-infrastructural cluster. In total, 314 local authorities were classified, corresponding to the 314 for which KPI data were available in the LINDA dataset. The majority of local authorities operate under *concession-based* frameworks, reflecting the dominant governance model in the Dutch PCSI landscape. Within this group, the *proactive data-driven* approach accounts for nearly half of all local authorities (151 out of 314), indicating a growing trend toward adaptive, evidence-based planning practices among concession-based systems.

By contrast, *open-market* models are relatively scarce, with only 27 local authorities following this governance arrangement. Among them, the *reactive request-based* variant is most common, suggesting that market-led charging expansion often remains dependent on user demand rather than systematic network planning.

Across all governance models, the majority of implementations occur within urban clusters, while rural local authorities represent only a small fraction of the total (38 out of 314). This pattern mirrors broader spatial trends in EV adoption and public charging deployment, where denser urban areas offer greater utilisation potential and more favourable investment conditions. Overall, the distribution in Table 6.2 provides an overview of how different roll-out strategies intersect with local infrastructural contexts, forming the basis for the comparative performance analysis presented in the next section.

6.3. KPI Results

This section presents the KPI results derived from the LINDA dataset for 2024. The aggregated KPIs — occupancy rate, average energy throughput per station, and average number of unique users per station — were matched with the urban–infrastructural–strategy matrix developed in the previous stages. The results are presented cluster by cluster, illustrating how KPI outcomes vary across the identified urban, suburban, and rural contexts. Some configurations, particularly within open-market categories, show incomplete or limited data coverage, reflecting their smaller representation in the LINDA dataset and warranting cautious interpretation of comparative results.

6.3.1. Cluster: Urban Profiles

Table 6.3 summarises the average KPI values for urban local authorities across the six roll-out strategy types. Within this urban cluster, concession-based models are more prevalent, while open-market configurations are less common. However, this pattern may also reflect the availability of operational data within the LINDA dataset rather than the actual absence of open-market arrangements. As data coverage is not entirely uniform across CPOs, particularly in competitive or fragmented markets, the observed dominance of concession-based cases should be interpreted with some caution.

Table 6.3: Average KPI values for urban local authorities over 2024

Strategy	**Occupancy** (%)	**Energy** (kWh/day/charging point)	**Users** (/day/charging point)
Concession — reactive request-based	23.19	22.87	3.18
Concession — proactive data-driven	24.21	23.58	3.18
Concession — proactive strategic	21.28	24.66	3.30
Open market — reactive request-based	16.05	19.88	3.05
Open market — proactive data-driven	13.70	20.23	3.16
Open market — proactive strategic	14.81	19.83	3.25

The KPI values in Table 6.3 indicate that urban local authorities operating under concession-based frameworks generally achieve higher occupancy and energy throughput than those under open-market arrangements. Among the concession-based approaches, the *proactive data-driven* strategy records the highest occupancy rate (24.21%), closely followed by the *reactive request-based* model (23.19%). The *proactive strategic* approach shows slightly lower occupancy but achieves the highest energy throughput (24.66 kWh/day/charging point) and the greatest average number of unique users (3.30/day/charging point).

Open-market strategies exhibit lower KPI values across all indicators. The *reactive request-based* model records an occupancy rate of 16.05% and 19.88 kWh/day/charging point, while the *proactive* variants perform marginally lower on both indicators. Nevertheless, these differences may partly stem from the incomplete representation of open-market data in the LINDA dataset, rather than from inherent performance disparities. Overall, the results suggest that in dense urban contexts, charging points under concession-based governance tend to exhibit higher utilisation. However, further validation would be needed to confirm whether this reflects actual strategic effects or data coverage patterns.

6.3.2. Cluster: Suburban Profiles

Table 6.4 presents the average KPI values for suburban local authorities across the six roll-out strategy types. As with the urban cluster, concession-based strategies account for the majority of recorded cases. However, this predominance may also reflect the availability of operational data in the LINDA database, as information for several open-market configurations was not reported or incomplete.

Table 6.4: Average KPI values for suburban local authorities over 2024

Strategy	**Occupancy** (%)	**Energy** (kWh/day/charging point)	**Users** (/day/charging point)
Concession — reactive request-based	14.50	25.37	3.22
Concession — proactive data-driven	20.62	24.06	3.11
Concession — proactive strategic	16.93	24.79	3.18
Open market — reactive request-based	17.56	21.42	3.15
Open market — proactive data-driven	x	x	x
Open market — proactive strategic	15.34	21.57	2.69

The suburban cluster displays lower overall occupancy rates than the urban group, though average energy throughput remains comparable across several concession-based strategies. The *proactive data-driven* approach records the highest occupancy level within this cluster (20.62%), followed by the *reactive request-based* strategy (14.50%). Energy throughput values for these concession-based models range between 24 and 25 kWh per charging point per day, suggesting consistent utilisation despite lower density contexts.

Data coverage for open-market strategies in suburban areas is limited. The *reactive request-based* and *proactive strategic* variants show moderate occupancy and user levels, yet their results should be interpreted cautiously given the incomplete representation in the LINDA dataset. Consequently, while concession-based models appear to dominate in suburban contexts, this may partly reflect the availability of reliable operational data rather than a definitive governance pattern. The results nonetheless indicate that where concession frameworks are implemented, charging points in suburban areas maintain steady usage across all three KPI indicators.

6.3.3. Cluster: Rural Profiles

Table 6.5 presents the average KPI values for rural local authorities across the six roll-out strategy types. Similar to the suburban and urban clusters, concession-based frameworks constitute the majority of recorded observations. However, this pattern may also be partly attributable to the limited availability of data for open-market models in the LINDA dataset. Several open-market configurations were not represented, likely reflecting incomplete coverage from certain CPOs rather than their absence in rural practice.

Table 6.5: Average KPI values for rural local authorities over 2024

Strategy	**Occupancy** (%)	**Energy** (kWh/day/charging point)	**Users** (/day/charging point)
Concession — reactive request-based	17.93	24.52	3.01
Concession — proactive data-driven	18.53	24.64	3.24
Concession — proactive strategic	13.66	24.80	3.03
Open market — reactive request-based	x	x	x
Open market — proactive data-driven	x	x	x
Open market — proactive strategic	22.66	25.53	2.73

The results in Table 6.5 show that rural local authorities record generally lower occupancy levels than suburban or urban areas, though energy throughput remains relatively stable across concession-based strategies. Among these, the *proactive data-driven* approach achieves the highest occupancy rate (18.53%) and user count (3.24/day/charging point), whereas the *proactive strategic* strategy shows a lower occupancy rate (13.66%) despite comparable energy delivery.
For open-market strategies, the available data are highly limited. Only a single observation was available for the *proactive strategic* variant, which displays higher energy throughput (25.53 kWh/day/charging point) but lower user frequency (2.73/day/charging point). Given the incomplete representation of open-market cases in rural contexts, these results should be treated with caution. Overall, the data suggest that concession-based governance remains more visible in rural charging infrastructure. However, this apparent dominance may partly result from the restricted scope of available LINDA records rather than a definitive absence of alternative governance models.

6.3.4. Composite Performance Index

To provide an integrated perspective on network performance, a Composite Performance Index (CPI) was constructed for each cluster and roll-out strategy. The index combines the three KPI dimensions after normalisation to a common 0–1 scale. Two variants were derived to reflect distinct perspectives: the CPI_{LA} representing the local authority viewpoint (emphasising balanced accessibility and utilisation) and the CPI_{CPO} representing the charging point operator perspective (emphasising operational and throughput efficiency). A simple average (CPI_{AVG}) is also reported to have an equal KPI weight reference. Table 6.6 presents the results across all clusters and strategies.

Table 6.6: Composite Performance Index (CPI) results by cluster and strategy

Cluster	Strategy	Occupancy	Energy (kWh/day/ charging point)	Users (users/day/ charging point)	N	Norm. Occ.	Norm. Energy	Norm. Users	CPI_{AVG}	CPI_{LA}	CPI_{CPO}
0	Concession – Reactive (request-driven)	23.19	22.87	3.18	39	0.90	0.63	0.50	0.68	0.69	0.70
0	Concession – Proactive (data-driven)	24.21	23.58	3.18	92	1.00	0.78	0.50	0.76	0.76	0.82
0	Concession – Proactive (strategic)	21.28	24.66	3.30	31	0.72	1.00	1.00	0.91	0.89	0.92
0	Open market – Reactive (request-driven)	16.05	19.88	3.05	14	0.22	0.01	0.00	0.08	0.09	0.07
0	Open market – Proactive (data-driven)	13.70	20.23	3.16	2	0.00	0.08	0.44	0.18	0.10	0.09
0	Open market – Proactive (strategic)	14.81	19.83	3.25	4	0.11	0.00	0.81	0.31	0.21	0.10
1	Concession – Reactive (request-driven)	14.50	25.37	3.22	18	0.00	1.00	1.00	0.67	0.60	0.70
1	Concession – Proactive (data-driven)	20.62	24.06	3.11	45	1.00	0.67	0.79	0.82	0.85	0.78
1	Concession – Proactive (strategic)	16.93	24.79	3.18	25	0.40	0.85	0.93	0.73	0.70	0.72
1	Open market – Reactive (request-driven)	17.56	21.42	3.15	4	0.50	0.00	0.88	0.46	0.55	0.24
1	Open market – Proactive (data-driven)	x	x	x	0	0.50	0.50	0.50	0.50	0.50	0.50
1	Open market – Proactive (strategic)	15.34	21.57	2.69	2	0.14	0.04	0.00	0.06	0.06	0.07
2	Concession – Reactive (request-driven)	17.93	24.52	3.01	6	0.47	0.00	0.55	0.34	0.41	0.20
2	Concession – Proactive (data-driven)	18.53	24.64	3.24	14	0.54	0.12	1.00	0.55	0.64	0.33
2	Concession – Proactive (strategic)	13.66	24.80	3.03	17	0.00	0.28	0.58	0.29	0.29	0.23
2	Open market – Reactive (request-driven)	x	x	x	0	0.50	0.50	0.50	0.50	0.50	0.50
2	Open market – Proactive (data-driven)	x	x	x	0	0.50	0.50	0.50	0.50	0.50	0.50
2	Open market – Proactive (strategic)	22.66	25.53	2.73	1	1.00	1.00	0.00	0.67	0.60	0.90

The CPI results show clear differences across clusters, governance types, and planning styles. In the urban cluster, the highest overall composite scores are observed for concession-based strategies, with both CPI_{LA} and CPI_{CPO} exceeding 0.75. Within this group, the proactive, data-driven variants show the strongest performance, while reactive approaches also perform relatively well. Open-market strategies, by contrast, show substantially lower composite values, mostly below 0.30, and exhibit greater variability between the local authority and operator indices.
In the suburban cluster, composite performance remains high for concession-based configurations, with most strategies ranging from 0.70 to 0.85. The CPI_{CPO} and CPI_{LA} scores are closely aligned but not identical, with minor differences observed between reactive and proactive approaches. Open-market cases record notably lower composite scores and include several instances of missing or incomplete data.
In the rural cluster, results display greater variation across strategies. Concession-based models generally register moderate composite values, with CPI_{LA} scores between 0.29 and 0.64 and CPI_{CPO} values ranging from 0.20 to 0.33. The single open-market observation within this cluster shows a relatively high operator index (CPI_{CPO} = 0.90) alongside a lower local authority value (CPI_{LA} = 0.60).
Overall, the CPI results present consistent ranking patterns across clusters. Concession-based and proactive strategies generally appear at the top of each cluster's range. At the same time, open-market configurations occupy the lower end and exhibit greater variability and data incompleteness.

6.4. Statistical Validation

This section provides statistical validation of the KPI results to assess whether observed performance differences between roll-out strategies and urban-infrastructural clusters are statistically meaningful. For each KPI—occupancy, delivered energy, and unique users—mean values and 95% confidence intervals were calculated to evaluate variability and reliability across strategy types. Subsequently, Tukey's Honest Significant Difference (HSD) post-hoc tests were applied to identify statistically significant pairwise differences between groups at the 95% confidence level. Together, these analyses strengthen the robustness of the findings by distinguishing genuine performance effects from variations arising due to sample size or data dispersion.

6.4.1. Occupancy

This subsection presents the statistical validation of occupancy results across the identified clusters and roll-out strategies. Mean occupancy rates and 95% confidence intervals were calculated for each strategy within every cluster to assess the variability and reliability of observed utilisation levels. These descriptive statistics provide the empirical basis for subsequent performance comparisons. Figure 6.5 visualises the mean occupancy values and their corresponding confidence intervals. The 95% confidence intervals represent the range within which the true mean occupancy is expected to fall with 95% probability; non-overlapping intervals suggest statistically meaningful differences between strategy groups.

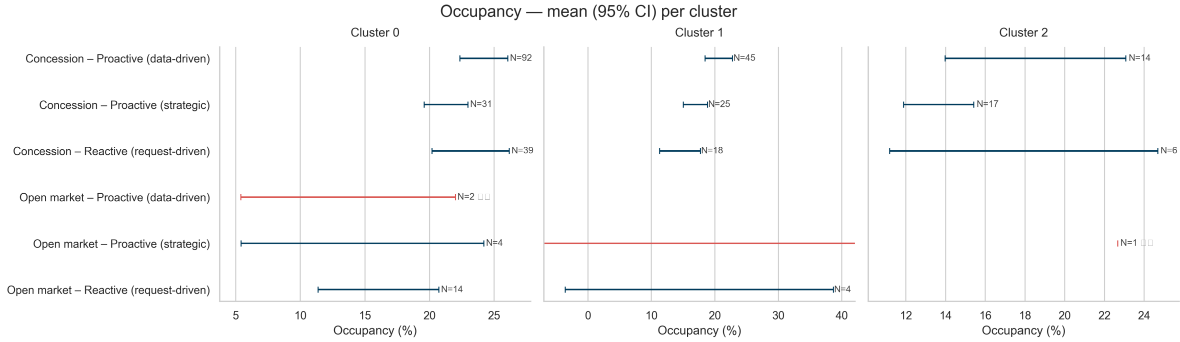

Figure 6.5: Mean occupancy (%) with 95% confidence intervals per cluster and roll-out strategy.

To complement the graphical representation, Table 6.7 presents the underlying descriptive statistics used for the confidence interval calculations. For each strategy-cluster combination, the table reports the mean occupancy, lower and upper confidence bounds, sample size (N), standard deviation (SD), and standard error (SE). The final column flags cases with particularly low observation counts ($N < 4$), where confidence intervals may be unreliable. Including this summary provides transparency into how the confidence intervals were derived and highlights variation in data availability across strategy types, especially for open-market approaches.

Table 6.7: Summary statistics for occupancy by cluster and roll-out strategy (LINDA 2024)

Cluster	Strategy	Mean (%)	95% CI (low–high)	N	SD	SE	Low N flag
0	Concession – Reactive (request-driven)	23.2	20.2–26.2	39	9.2	1.47	
0	Concession – Proactive (data-driven)	24.2	22.4–26.1	92	8.9	0.93	
0	Concession – Proactive (strategic)	21.3	19.6–23.0	31	5.9	1.06	
0	Open market – Reactive (request-driven)	16.1	11.4–20.7	14	8.1	2.06	
0	Open market – Proactive (data-driven)	13.7	5.4–22.0	2	0.9	0.65	△
0	Open market – Proactive (strategic)	14.8	5.4–24.2	4	5.9	2.95	△
1	Concession – Reactive (request-driven)	14.5	11.3–17.7	18	6.5	1.42	
1	Concession – Proactive (data-driven)	20.6	18.5–22.8	45	7.1	1.07	
1	Concession – Proactive (strategic)	16.9	15.0–18.8	25	4.6	0.92	
1	Open market – Reactive (request-driven)	17.6	–3.6–38.7	4	12.2	6.13	△
1	Open market – Proactive (strategic)	15.3	–94.7–125.4	2	0.9	0.65	△
2	Concession – Reactive (request-driven)	17.9	11.2–24.7	6	6.4	2.63	
2	Concession – Proactive (data-driven)	18.5	14.0–23.1	14	7.9	2.11	
2	Concession – Proactive (strategic)	13.7	11.9–15.4	17	3.4	0.83	
2	Open market – Proactive (strategic)	22.7	n/a	1	–	–	△

Across the three clusters, concession-based strategies generally record higher and more stable occupancy rates, while open-market configurations display greater variability and wider confidence intervals, linked to smaller sample sizes. In **Cluster 0 (Urban)**, the *concession – proactive data-driven* (24.2%) and *concession – reactive request-based* (23.2%) models achieve the highest mean occupancies, both supported by narrow confidence intervals and relatively large samples ($N = 92$ and $N = 39$ respectively). Open-market approaches in this cluster show lower mean occupancies — ranging between 13.7% and 16.1% — and greater uncertainty due to fewer observations.
Within **Cluster 1 (Suburban)**, the *concession – proactive data-driven* strategy again records the highest occupancy (20.6%), followed by the *open-market reactive request-based* (17.6%) and *concession – proactive strategic* (16.9%) variants. Confidence intervals for open-market cases are wide, indicating

limited data availability. The lower mean for the *concession – reactive request-based* model (14.5%) corresponds with a smaller sample size ($N = 18$).
In **Cluster 2 (Rural)**, occupancy levels are more dispersed and overall lower. The *concession – proactive data-driven* (18.5%) and *concession – reactive request-based* (17.9%) strategies present overlapping confidence intervals, suggesting comparable utilisation. In contrast, a single open-market observation (*proactive strategic*, 22.7%) prevents meaningful comparison.

To further assess these differences, a Tukey HSD post-hoc test was conducted to determine whether mean occupancy values across strategy types differ significantly at the 95% confidence level. The results are summarised in Table 6.8, where the “$\star$” symbol indicates statistically significant pairwise differences ($p < 0.05$).

Table 6.8: Tukey HSD results for occupancy across clusters and strategies (95% CI)

Cluster	Strategy	Occupancy (%)	95% CI	N	Sig. ($p < 0.05$)
0	Concession – Proactive (data-driven)	24.2	22.4–26.1	92	
0	Concession – Reactive (request-driven)	23.2	20.2–26.2	39	
0	Concession – Proactive (strategic)	21.3	19.6–23.0	31	
0	Open market – Reactive (request-driven)	16.1	11.4–20.7	14	$\star$
0	Open market – Proactive (strategic)	14.8	5.4–24.2	4	
0	Open market – Proactive (data-driven)	13.7	5.4–22.0	2	
1	Concession – Proactive (data-driven)	20.6	18.5–22.8	45	
1	Open market – Reactive (request-driven)	17.6	–3.6–38.7	4	
1	Concession – Proactive (strategic)	16.9	15.0–18.8	25	
1	Open market – Proactive (strategic)	15.3	–94.7–125.4	2	
1	Concession – Reactive (request-driven)	14.5	11.3–17.7	18	$\star$
2	Open market – Proactive (strategic)	22.7	n/a	1	
2	Concession – Proactive (data-driven)	18.5	14.0–23.1	14	
2	Concession – Reactive (request-driven)	17.9	11.2–24.7	6	
2	Concession – Proactive (strategic)	13.7	11.9–15.4	17	

6.4.2. Delivered Energy

This subsection examines the statistical validation of delivered energy (kWh/day/charging point) across the identified clusters and roll-out strategies. Mean energy throughput values and their 95% confidence intervals were computed for each strategy within every cluster to assess variation in charging activity and the reliability of observed differences. Figure 6.6 displays these mean values with their corresponding confidence intervals. The 95% confidence intervals indicate the range within which the true mean energy throughput is expected to fall with 95% probability; non-overlapping intervals therefore suggest statistically meaningful differences between strategy groups.

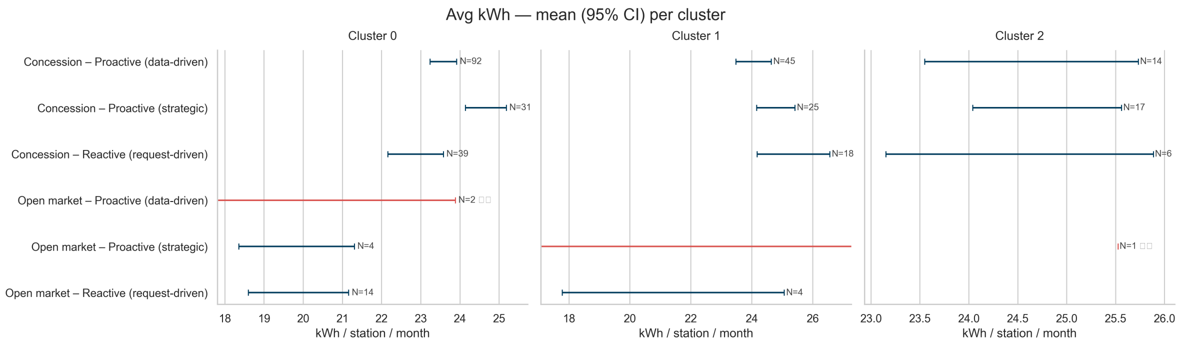

Figure 6.6: Mean delivered energy (kWh/day/charging point) with 95% confidence intervals per cluster and roll-out strategy.

To complement the visualisation, Table 6.9 reports the descriptive statistics that underlie the confidence interval calculations. For each cluster and strategy, it provides the mean delivered energy, the lower and upper confidence bounds, the sample size (N), the standard deviation (SD), and the standard error (SE). The final column flags cases with fewer than four observations ($N < 4$), for which the reliability of the confidence interval is limited. Including this table enhances transparency in the analytical process and clarifies how data variability affects confidence intervals—particularly in open-market strategies, which tend to have smaller datasets.

Table 6.9: Summary statistics for delivered energy by cluster and roll-out strategy (LINDA 2024)

Cluster	Strategy	**Mean** (kWh/day/ charging point)	**95% CI (low–high)**	N	SD	SE	Low N flag
0	Concession – Reactive (request-driven)	22.9	22.2–23.6	39	2.19	0.35	
0	Concession – Proactive (data-driven)	23.6	23.2–23.9	92	1.65	0.17	
0	Concession – Proactive (strategic)	24.7	24.2–25.2	31	1.83	0.33	
0	Open market – Reactive (request-driven)	19.9	18.7–21.0	14	2.88	0.77	
0	Open market – Proactive (data-driven)	20.2	19.7–20.8	2	0.41	0.29	△
0	Open market – Proactive (strategic)	19.8	18.9–20.7	4	0.93	0.46	△
1	Concession – Reactive (request-driven)	25.4	24.2–26.6	18	2.84	0.57	
1	Concession – Proactive (data-driven)	24.1	23.5–24.6	45	1.45	0.29	
1	Concession – Proactive (strategic)	24.8	24.2–25.4	25	1.52	0.30	
1	Open market – Reactive (request-driven)	21.4	19.0–23.7	4	3.68	1.14	△
1	Open market – Proactive (strategic)	21.6	13.0–30.1	2	1.88	1.34	△
2	Concession – Reactive (request-driven)	24.5	23.5–25.6	6	1.83	0.53	
2	Concession – Proactive (data-driven)	24.6	23.6–25.6	14	1.89	0.51	
2	Concession – Proactive (strategic)	24.8	24.1–25.5	17	1.48	0.36	
2	Open market – Proactive (strategic)	25.5	n/a	1	–	–	△

Across the three clusters, delivered energy levels follow a broadly similar pattern to occupancy, with concession-based strategies showing higher and more stable mean values. In **Cluster 0 (Urban)**, the *concession – proactive strategic* strategy records the highest mean energy throughput (24.7 kWh/-day/charging point), followed closely by the *concession – proactive data-driven* (23.6 kWh/day/charging point) and *concession – reactive request-based* (22.9 kWh/day/charging point) models. Open-market strategies display considerably lower means (19.8–20.2 kWh/day/charging point) and wider confidence intervals, reflecting small sample sizes ($N \leq 4$).
Within **Cluster 1 (Suburban)**, all concession-based variants again exhibit high and consistent mean values, ranging from 24.1 to 25.4 kWh/day/charging point, while open-market approaches perform markedly lower, with mean values near 21 kWh/day/charging point and extremely broad confidence intervals. This variation suggests that open-market results in suburban areas should be interpreted cautiously, as small-N samples yield unstable estimates.
In **Cluster 2 (Rural)**, all concession-based approaches cluster closely together around 24.5–24.8 kWh/-day/charging point, indicating stable and relatively homogeneous utilisation levels. A single open-market observation (*proactive strategic*, 25.5 kWh/day/charging point) was recorded in this cluster, but the absence of additional data precludes reliable comparison.

To determine whether the observed differences between strategy types are statistically significant, a Tukey HSD post-hoc test was conducted at the 95% confidence level. The results are shown in Table 6.10, where the symbol "$\star$" denotes statistically significant pairwise differences ($p < 0.05$).

Table 6.10: Tukey HSD results for delivered energy across clusters and strategies (95% CI)

Cluster	Strategy	Energy (kWh/day/ charging point)	95% CI	N	Sig. ($p < 0.05$)
0	Concession – Proactive (strategic)	24.7	24.1–25.2	31	
0	Concession – Proactive (data-driven)	23.6	23.2–23.9	92	⋆
0	Concession – Reactive (request-driven)	22.9	22.2–23.6	39	⋆
0	Open market – Proactive (data-driven)	20.2	16.6–23.9	2	⋆
0	Open market – Reactive (request-driven)	19.9	18.6–21.2	14	⋆
0	Open market – Proactive (strategic)	19.8	18.4–21.3	4	⋆
1	Concession – Reactive (request-driven)	25.4	24.2–26.6	18	
1	Concession – Proactive (strategic)	24.8	24.2–25.4	25	
1	Concession – Proactive (data-driven)	24.1	23.5–24.6	45	
1	Open market – Proactive (strategic)	21.6	–33.9–77.1	2	
1	Open market – Reactive (request-driven)	21.4	17.8–25.1	4	⋆
2	Open market – Proactive (strategic)	25.5	n/a	1	
2	Concession – Proactive (strategic)	24.8	24.0–25.6	17	
2	Concession – Proactive (data-driven)	24.6	23.5–25.7	14	
2	Concession – Reactive (request-driven)	24.5	23.2–25.9	6	

6.4.3. Unique Users

This subsection presents the statistical validation of unique user counts (users/day/charging point) across the identified clusters and roll-out strategies. Mean values and 95% confidence intervals were computed for each strategy within every cluster to assess user engagement patterns and sampling variability. Figure 6.7 illustrates the mean number of unique users per charging point, along with their confidence intervals. The 95% confidence intervals represent the range within which the true mean user count is expected to fall with 95% probability; non-overlapping intervals therefore suggest meaningful differences between strategy types.

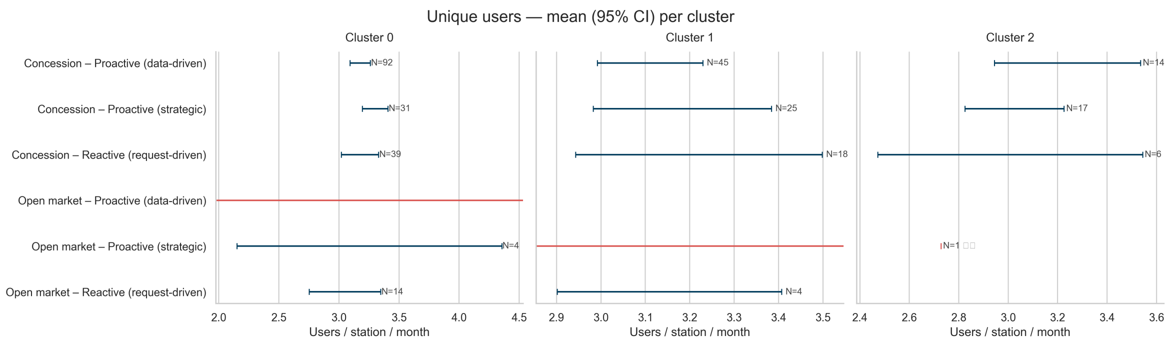

Figure 6.7: Mean number of unique users (users/day/charging point) with 95% confidence intervals per cluster and roll-out strategy.

To complement the graphical representation, Table 6.11 reports the descriptive statistics underlying the confidence interval calculations. For each cluster–strategy combination, the mean, lower and upper confidence bounds, sample size (N), standard deviation (SD), and standard error (SE) are shown. A flag symbol (△) marks cases with particularly low sample sizes ($N < 4$), where estimates may be less reliable. Including this summary enhances transparency and clarifies how confidence intervals were derived across varying data densities, particularly between concession-based and open-market strategies.

Table 6.11: Summary statistics for unique users by cluster and roll-out strategy (LINDA 2024)

Cluster	Strategy	Mean (users/day/ charging point)	95% CI (low–high)	N	SD	SE	Low N flag
0	Concession – Reactive (request-driven)	3.2	3.0–3.3	39	0.48	0.08	
0	Concession – Proactive (data-driven)	3.2	3.1–3.3	92	0.41	0.04	
0	Concession – Proactive (strategic)	3.3	3.2–3.4	31	0.29	0.05	
0	Open market – Reactive (request-driven)	3.1	2.8–3.3	14	0.52	0.14	
0	Open market – Proactive (data-driven)	3.2	2.7–3.6	2	0.3	0.21	△
0	Open market – Proactive (strategic)	3.3	2.6–3.9	4	0.69	0.35	△
1	Concession – Reactive (request-driven)	3.2	3.0–3.5	18	0.56	0.13	
1	Concession – Proactive (data-driven)	3.1	3.0–3.2	45	0.44	0.06	
1	Concession – Proactive (strategic)	3.2	3.0–3.4	25	0.49	0.10	
1	Open market – Reactive (request-driven)	3.2	3.0–3.3	4	0.16	0.8	△
1	Open market – Proactive (strategic)	2.7	–8.6–13.9	2	0.9	0.64	△
2	Concession – Reactive (request-driven)	3.0	2.6–3.4	6	0.51	0.21	
2	Concession – Proactive (data-driven)	3.2	3.0–3.5	14	0.51	0.14	
2	Concession – Proactive (strategic)	3.0	2.8–3.2	17	0.39	0.09	
2	Open market – Proactive (strategic)	2.7	n/a	1	–	–	△

Across all clusters, the distribution of unique users is highly consistent, with mean values clustering between 3.0 and 3.3 users per charging point per day. Confidence intervals are narrow for concession-based configurations, indicating stable, reliable estimates, whereas open-market strategies—particularly those with small sample sizes—display broader intervals and thus greater uncertainty.
In **Cluster 0 (Urban)**, all strategies show similar user engagement, with means between 3.1 and 3.3 users/day/charging point. In **Cluster 1 (Suburban)**, results follow the same pattern, although data scarcity in open-market strategies introduces wider uncertainty bands. Finally, in **Cluster 2 (Rural)**, concession-based strategies maintain stable user counts around 3.0–3.2, while only a single open-market observation was recorded, precluding meaningful comparison.

The Tukey HSD post-hoc test did not reveal any statistically significant pairwise differences in mean unique user counts across strategy types or clusters ($p > 0.05$). The full results are summarised in Table 6.12, showing mean values, confidence intervals, and sample sizes for each configuration.

Table 6.12: Tukey HSD results for unique users across clusters and strategies (95% CI)

Cluster	Strategy	Users (users/day/ charging point)	95% CI	N	Sig. ($p < 0.05$)
0	Concession – Proactive (strategic)	3.3	3.2–3.4	31	
0	Open market – Proactive (strategic)	3.3	2.2–4.4	4	
0	Concession – Proactive (data-driven)	3.2	3.1–3.3	92	
0	Concession – Reactive (request-driven)	3.2	3.0–3.3	39	
0	Open market – Proactive (data-driven)	3.2	0.5–5.8	2	
0	Open market – Reactive (request-driven)	3.1	2.8–3.3	14	
1	Concession – Reactive (request-driven)	3.2	2.9–3.5	18	
1	Concession – Proactive (strategic)	3.2	3.0–3.4	25	
1	Open market – Reactive (request-driven)	3.2	2.9–3.4	4	
1	Concession – Proactive (data-driven)	3.1	3.0–3.2	45	
1	Open market – Proactive (strategic)	2.7	–8.6–13.9	2	
2	Concession – Proactive (data-driven)	3.2	2.9–3.5	14	
2	Concession – Proactive (strategic)	3.0	2.8–3.2	17	
2	Concession – Reactive (request-driven)	3.0	2.5–3.5	6	
2	Open market – Proactive (strategic)	2.7	n/a	1	

7
Discussion

This chapter discusses the results presented in Chapter 5 and situates them within the broader context of PCSI planning and policy. It interprets the empirical findings in light of the theoretical framework, examines how performance patterns vary across spatial contexts, and reflects on their methodological and policy relevance. The discussion starts with synthesising the findings and is then structured into four main parts: (i) interpretation of KPI outcomes, (ii) contextual differences across clusters, (iii) methodological and data-related limitations, and (iv) implications for planning practice and policy.

7.1. Synthesis and Outlook

This section brings together the findings and reflections presented throughout the study, summarising how roll-out strategies and spatial context jointly shape the performance of PCSI networks. It also considers the broader implications of these findings for the understanding of strategy–performance relationships in sustainable mobility systems and outlines avenues for future research.

Across all analyses, a consistent pattern emerges: concession-based governance models, particularly those adopting proactive, data-driven planning styles, achieve higher and more stable performance across utilisation and energy delivery indicators. These results highlight the value of coordinated institutional frameworks that integrate local policy objectives with operational accountability. At the same time, the findings point to the contextual dependence of such advantages — their strength diminishes in more dispersed suburban and rural areas, where charging demand is lower and infrastructure conditions are more heterogeneous. This underlines the need for adaptive governance approaches that can accommodate diverse local scenarios rather than applying uniform regulatory solutions.

The study also demonstrates the analytical potential of integrating operational data, spatial clustering, and statistical testing to assess the effectiveness of roll-out strategies in infrastructure systems. By combining descriptive performance metrics with contextual analysis, this work contributes to a more evidence-based understanding of how public–private coordination influences network efficiency and accessibility. However, the limitations discussed — particularly those related to data coverage and sample balance — emphasise that current insights remain preliminary and should be validated with more comprehensive longitudinal datasets.

Future research could build on this framework in several directions. First, expanding data representation for open-market networks and incorporating socio-economic variables such as EV ownership or income distribution would improve the robustness of comparative analysis. Second, future studies could use a more causal-based analysis rather than a descriptive and comparative one to better understand how roll-out strategies directly affect network performance. Third, extending the analysis to include grid impact, pricing policies, or user satisfaction could more clearly link roll-out strategy choices to overall sustainability goals.

Overall, this study contributes to a growing body of research highlighting that effective PCSI governance depends on both strategic coordination and adaptive flexibility. Its findings underscore the importance of data-driven planning, balanced governance models, and transparent data sharing in achieving reliable, equitable, and future-ready charging networks. The next chapter draws these insights together into final conclusions.

7.2. Interpretation of KPI Results Across Roll-out Strategies

This section interprets the results for the three KPIs — occupancy, delivered energy, and unique users — across different roll-out strategies. Together, these indicators capture complementary aspects of PCSI performance: utilisation intensity, operational throughput, and user engagement.

Across all three metrics, the results show that *concession-based* roll-out strategies generally achieve higher and more stable performance than *open-market* configurations. This difference is most evident in occupancy and delivered energy, where concession-based approaches consistently record higher mean values and narrower confidence intervals across clusters. Open-market models, in contrast, show greater variability and several statistically lower outcomes, particularly in urban contexts.

These trends indicate that governance structure influences operational consistency within PCSI. The higher and steadier results under concession frameworks likely stem from the coordinated planning and contractual arrangements that enable local authorities to align infrastructure deployment with demand and policy objectives. Open-market models, being more dependent on private initiative and market risk, may lead to uneven spatial coverage and fluctuating utilisation in emerging or low-demand areas.

The following subsections discuss each KPI in turn, examining how these overall patterns manifest in occupancy, energy throughput, and user engagement, and what they imply for the relationship between roll-out strategies and network performance.

7.2.1. Occupancy

The results in Chapter 5 showed that occupancy rates were generally higher for concession-based strategies across all clusters, particularly for proactive and data-driven approaches. In urban contexts, the *concession – proactive data-driven* and *concession – reactive request-based* models achieved the highest mean occupancies, while open-market strategies consistently recorded lower values. Suburban and rural clusters displayed similar patterns, though differences were less pronounced, and smaller sample sizes in open-market categories limited statistical significance.

These findings suggest that governance centralisation and structured planning play an important role in supporting stable utilisation levels. Concession-based frameworks, by design, enable coordination between local authorities and CPOs, allowing infrastructure to be deployed in line with local demand projections and policy goals. This systematic allocation likely contributes to higher and more consistent occupancy rates. In contrast, open-market systems depend more heavily on private investment decisions, which can lead to uneven station distribution and underutilisation in areas with uncertain profitability. Such dynamics align with existing research that associates public–private coordination with more balanced network performance and better resource allocation in early infrastructure phases.

The observed variation between proactive and reactive planning styles further supports this interpretation. Proactive approaches — particularly data-driven ones — appear to yield steadier, more predictable utilisation patterns, suggesting that analytical site selection can help align infrastructure capacity with real demand. The relatively strong performance of reactive concession models in urban areas may reflect their responsiveness to concentrated user demand and shorter feedback loops between local authorities and operators.

However, these results should be interpreted cautiously. The sample of open-market local authorities was small, especially in suburban and rural clusters, resulting in wide confidence intervals and limited statistical power. Therefore, while the data indicate a performance advantage for concession-based systems, it remains unclear whether this pattern would persist in a more balanced dataset. Future research using broader or longitudinal data could help determine whether the observed differences stem from governance effects or reflect uneven data coverage in the LINDA dataset.

7.2.2. Delivered Energy

The delivered energy results presented in Chapter 5 largely mirror the occupancy trends, with concession-based strategies outperforming open-market models across all clusters. In urban areas, *concession – proactive strategic* and *concession – proactive data-driven* configurations recorded the highest average energy throughput, while open-market strategies showed lower mean values and wider confidence intervals. In suburban and rural contexts, the same general pattern was observed, although differences between strategies were smaller and often statistically insignificant due to limited sample sizes.

These outcomes suggest that coordinated and strategically managed charging networks not only attract higher usage but also support greater operational throughput. The higher delivered energy levels under concession frameworks likely reflect both stronger utilisation and a more balanced distribution of charging demand across stations. This may be a result of integrated planning and public oversight, which allow charging capacity to be aligned with local mobility needs and grid capabilities. In contrast, the lower and more variable energy delivery observed in open-market systems may stem from fragmented investment decisions, where profitability considerations can delay network expansion or result in under-provisioned capacity in less lucrative areas.

From an operational standpoint, delivered energy provides a complementary measure to occupancy, as it captures both session frequency and session length. The alignment between high occupancy and high energy throughput among proactive concession models suggests that these strategies succeed not only in attracting users but also in facilitating longer or more efficient charging sessions — possibly linked to more reliable station availability or a higher proportion of long-stay locations. This relationship supports previous findings in the literature that associate coordinated infrastructure deployment with more consistent load management and improved utilisation efficiency.

Nonetheless, these interpretations should be viewed with caution. The small number of open-market observations, particularly in suburban and rural clusters, limits the statistical robustness of the comparisons. It therefore remains uncertain whether the observed performance gap reflects a structural governance effect or is partly correlated with uneven data representation. Further work using time-series data or more detailed session-level information could help untangle these effects and clarify how roll-out strategies influence energy delivery performance over time.

7.2.3. Unique Users

As shown in Chapter 5, the number of unique users per charging point remained remarkably stable across all roll-out strategies and spatial clusters. Mean values consistently ranged between 3.0 and 3.3 users/day/charging point, and no statistically significant differences were detected by the Tukey post-hoc tests. This uniformity contrasts with the clearer performance gaps observed in occupancy and energy throughput.

The stability in user counts suggests that the diversity and frequency of user access to the public charging network are largely independent of roll-out strategy. In other words, while concession-based systems may yield higher utilisation intensity, they do not necessarily attract a broader or narrower user base than open-market configurations. This pattern implies a degree of accessibility consistency across the national network, likely supported by the open interoperability standards and roaming agreements that characterise the Dutch charging ecosystem.

These findings indicate that user engagement — at least as measured by unique user counts — is less sensitive to strategic or institutional variation and may instead reflect broader factors such as national EV adoption rates, travel behaviour, and the spatial distribution of residential versus destination charging. From a policy perspective, this stability can be interpreted positively: despite roll-out strategy differences, access to PCSI appears relatively equitable across contexts. However, it also highlights that improvements in operational efficiency (e.g., higher occupancy or energy delivery) may not directly translate into greater user inclusivity, underscoring the need to address accessibility and affordability through complementary policy measures rather than relying solely on network management.

7.3. Cross-Cluster Patterns and Contextual Explanations

This section compares KPI results across the three urban–infrastructural clusters (urban, suburban, rural). It explores how local context shapes charging infrastructure performance and how roll-out strategies interact with spatial characteristics to influence utilisation and network outcomes.

7.3.1. Urban Contexts

Across the urban cluster, results from Chapter 5 showed the highest overall KPI levels, with concession-based strategies — particularly the *proactive data-driven* and *proactive strategic* variants — achieving superior occupancy and delivered energy performance. Open-market configurations recorded lower and more variable outcomes, though user counts remained stable across all roll-out strategies.

These findings are consistent with expectations for dense urban areas, where concentrated charging demand, short travel distances, and high public charging dependence create favourable conditions for systematically planned networks. Concession-based governance allows stakeholders to coordinate site selection, grid connections, and demand forecasts across multiple operators, leading to denser, well-balanced station coverage and smoother utilisation patterns. The performance edge of proactive and data-driven strategies in this context likely reflects their ability to anticipate demand growth, optimise placement, and avoid surplus in high-use areas.

The relatively weaker and more volatile results of open-market systems in urban settings can be understood through market fragmentation and competition dynamics. Without a central coordinating authority, CPOs may prioritise commercially attractive sites or delay expansion in saturated zones, leading to local overcapacity and under-use elsewhere. These outcomes align with findings in the literature on infrastructure governance, which highlight that decentralised market allocation often struggles to match service supply to mobility demand in rapidly evolving urban environments (Rajon and Hall 2021).

Importantly, the strong urban performance of concession-based systems also underscores the role of integrated policy frameworks. Cities often link public charging concessions to sustainability objectives, parking regulation, and data-sharing policies, creating interactions between local energy management and mobility planning. Such policy integration may partly explain the higher and more consistent KPI outcomes observed.

In summary, the urban results reflect how structural coordination, policy alignment, and proactive planning interact to sustain efficient network operation in high-demand contexts. The observed patterns align with theoretical expectations, underlining the view that in mature or densely populated areas, structured governance and data-informed planning provide measurable operational advantages.

7.3.2. Suburban Contexts

Results for the suburban cluster in Chapter 5 showed more heterogeneous KPI outcomes compared to urban areas. While concession-based strategies again displayed slightly higher mean occupancy and delivered energy levels, the performance gap with open-market systems was narrower, and statistical significance was limited. Among the concession-based models, the *proactive data-driven* approach maintained the most consistent performance, whereas reactive and strategic variants varied more widely.

These mixed results can be interpreted as a reflection of the transitional character of suburban areas. Suburban local authorities often combine features of both dense urban and dispersed rural contexts: residential land use predominates, trip patterns are more car-dependent, and public charging demand is less concentrated in specific areas. Under such conditions, network utilisation depends less on central coordination and more on local behavioural factors such as home charging availability and commuting routines. This may explain why the advantages of concession-based frameworks, which are more pronounced in dense urban settings, become less distinct in suburban contexts.

At the same time, suburban areas are frequently sites of overlapping governance influences. Some local authorities operate under concession contracts, while others permit partial market entry, leading to hybrid deployment environments. This diversity may contribute to the wider confidence intervals observed in the results. In these settings, the effectiveness of planning style likely depends on how flexibly the governing body can adapt concession rules or data-sharing mechanisms to evolving demand, rather than on the governance form itself.

The relatively steady performance of proactive, data-driven concession strategies in suburban contexts suggests that analytical siting remains advantageous even in moderate-demand areas. By contrast, purely reactive or market-driven approaches may face longer feedback cycles due to slower demand signals, which can delay adjustments and lead to underutilised capacity. This finding aligns with research emphasising the importance of anticipatory planning in emerging suburban EV markets, where adoption rates are uneven and land-use density offers limited economies of scale (Rajon and Hall 2021).

Overall, the suburban results illustrate that performance differences between roll-out strategies become less clear-cut where charging demand is spread out and governance structures are mixed. In these transitional zones, data-driven coordination appears to provide a stabilising influence, helping maintain consistent utilisation despite moderate charging intensity and more fragmented local demand structures.

7.3.3. Rural Contexts

Results for the rural cluster in Chapter 5 revealed the lowest overall KPI levels and the greatest variability between strategies. While concession-based approaches maintained moderate occupancy and energy throughput values, open-market configurations were either underrepresented or based on isolated observations, limiting the reliability of statistical comparisons. Within the concession framework, proactive and data-driven models performed slightly better than reactive ones, though the differences were small and confidence intervals wide.

The Composite Performance Index results further illustrated this variability. Concession-based strategies achieved CPI_{LA} scores between 0.29 and 0.64, indicating modest but relatively balanced performance from a policy perspective, while operator-oriented indices (CPI_{CPO}) remained lower overall. This suggests that although public planning objectives — such as coverage and accessibility — are partially met, operational efficiency and utilisation rates remain challenging in these contexts.

These patterns reflect the structural and demographic realities of rural environments, where lower population densities, longer trip distances, and a higher prevalence of home charging reduce demand for public infrastructure. In such settings, coordinated concession governance can help ensure minimum service coverage, but its advantages in utilisation efficiency are constrained by lower demand. Open-market participation is rare, as private operators face limited profitability and longer payback horizons. The single open-market case with a high CPI_{CPO} value highlights that individual high-use stations may exist, yet these are exceptions rather than indicators of systemic performance.

From a planning perspective, rural results underscore the tension between efficiency and equity in PCSI roll-out. Ensuring spatial equity requires maintaining infrastructure even where utilisation is low, implying that concession-based frameworks must balance commercial viability with accessibility commitments. This balance is more difficult to achieve without direct policy support, which explains why open-market systems are under-represented in rural clusters. The observed stability among concession models, despite modest performance levels, therefore points to their role as instruments of infrastructural inclusion rather than pure efficiency optimisation.

In summary, the rural findings indicate that while governance coordination preserves network continuity and access, both utilisation and throughput remain limited, likely due to structural demand factors. These results are consistent with expectations for low-density areas, reaffirming that the benefits of concession-based governance lie primarily in ensuring equitable service provision rather than achieving high operational intensity.

7.4. Methodological Reflections and Limitations

This section reflects on the methodological choices, data characteristics, and analytical constraints that may have influenced the interpretation of the study's results. It evaluates both the reliability and representativeness of the empirical data and the assumptions underlying the analytical approach. Particular attention is given to the design of the clustering and normalisation procedures, the statistical testing framework, and the potential effects of uneven data coverage across roll-out strategies.

The discussion is structured into two subsections. The first examines analytical simplifications related to clustering design, KPI normalisation, and statistical testing, outlining how these methodological decisions affect comparability and interpretability. The second focuses on data and sampling constraints within the LINDA dataset, addressing issues of coverage, completeness, and potential sample bias that may influence the generalisability of the findings.

7.4.1. Data and Sampling Constraints

The LINDA dataset serves as the empirical foundation of this study, yet its coverage and composition introduce limitations that should be considered when interpreting the results. Data availability is uneven across governance types: concession-based networks are comprehensively represented due to structured data-sharing agreements between local authorities and CPOs, whereas open-market configurations are less well represented and inconsistent. Several open-market cases include incomplete KPI records or small observation counts, particularly in suburban and rural clusters.

This asymmetry may introduce a sampling bias toward concession-based systems, which could partly explain their higher stability and narrower confidence intervals across indicators. In contrast, the limited sample size and greater variability within open-market data reduce the statistical power of comparisons, making it difficult to distinguish whether observed differences reflect actual roll-out strategy effects or

incomplete reporting.
Moreover, the LINDA dataset aggregates operational data from multiple sources with varying temporal and spatial resolutions. While the dataset provides a robust overview of national PCSI performance, inconsistencies in data completeness and reporting frequency may affect the precision of some indicators, particularly where $N < 4$ or coverage is intermittent. These limitations restrict the generalisability of the results beyond the sample represented and underline the importance of improving standardised data collection across all roll-out strategies.
Thus, while the dataset offers valuable insights into PCSI operation at scale, its coverage leans toward concession-based systems. Future work should aim to expand open-market data representation and enhance longitudinal consistency, enabling more balanced and statistically robust assessments of roll-out strategy performance across contexts.
Taken together, these data-related choices imply that the conclusions about concession-based roll-out strategies are comparatively robust within the Dutch context. In contrast, insights on open-market performance should be interpreted as indicative rather than definitive. The discussion and policy implications in this chapter should therefore be read primarily as well-founded tendencies for concession-based systems and as hypotheses or early signals for open-market configurations, not as firm evidence that can be generalised to all current or future open-market settings.

7.4.2. Analytical Simplifications

The analytical design of this study involved simplifications to enable systematic comparison across roll-out strategies. The clustering procedure, based on k-means classification, grouped local authorities into three categories — urban, suburban, and rural — using infrastructure and contextual variables. While this approach effectively captures broad spatial trends, it also imposes fixed boundaries on what is in practice a transition between different spatial contexts. Consequently, within-cluster heterogeneity may persist, particularly in transitional local authority territory that combines characteristics of multiple contexts.
The choice and weighting of clustering variables further influence how spatial categories were defined. Although the selected variables align with mobility and infrastructure literature, they cannot fully account for socio-economic or behavioural dimensions, such as income distribution, EV ownership rates, or local policy maturity, which may also shape charging demand. Future studies could refine the clustering process through multi-dimensional or hierarchical approaches that integrate more infrastructural and socio-demographic indicators.
The statistical testing framework also introduces methodological limitations. The Tukey HSD post-hoc test was used to identify significant pairwise differences among strategies. However, several groups — especially open-market categories in suburban and rural clusters — contained small sample sizes, which limits the reliability and sensitivity of the test. This constraint may lead to non-detection of meaningful effects or wide confidence intervals that obscure true differences.
Finally, the analytical procedures adopted in this study are descriptive rather than causal. While the tests reveal patterns of association between roll-out strategy and performance, they do not establish direct causation. Factors such as operator portfolio intentions or charging behaviour could also contribute to observed differences. The results should therefore be interpreted as indicative of structural tendencies rather than definitive causal relationships.
Overall, these simplifications represent necessary trade-offs to ensure methodological clarity and comparability. They provide a transparent framework for evaluating PCSI performance, while acknowledging that finer-grained data and more sophisticated modelling would be required to capture the full causal complexity of interactions between roll-out strategy and performance.
These methodological choices imply that the findings and recommendations derived in this chapter are most appropriate at an aggregate, comparative level. They indicate which roll-out strategies tend to perform better in which types of context, but they should not be read as detailed design rules for individual local authorities or as proof that a given governance model mechanically causes specific KPI outcomes. Similarly, because the KPIs and composite indices reflect a particular weighting of utilisation, throughput and accessibility, the identification of "better-performing" strategies is tied to these normative choices; alternative indicator sets or weightings (for example, emphasising equity or grid impact) could lead to different rankings and would therefore entail different strategic implications.

7.5. Strategic and Policy Implications

This section synthesises the empirical and contextual findings to identify implications for future PCSI roll-out strategies. It connects the observed performance patterns across governance models and planning styles to broader questions of institutional design, data utilisation, and policy alignment. The discussion emphasises how structural coordination, proactive planning, and transparent data exchange can enhance both operational efficiency and spatial equity.

Building on the comparative results, the section is divided into two parts. The first (*Strategic Insights for Strategies*) outlines broader strategic lessons derived from the performance differences between the strategies, and considers how they can evolve toward more adaptive and balanced models. The second (*Practical and Policy Implications*) translates these strategic insights into concrete recommendations for local authorities and CPOs — focusing on planning processes, data standardisation, and long-term network sustainability.

7.5.1. Insights for Strategies

The comparative results across roll-out strategies highlight operational and strategic dynamics within the PCSI landscape. Concession-based frameworks consistently demonstrated higher and more stable KPI performance, suggesting that coordinated planning, contractual accountability, and policy alignment contribute to efficient utilisation and reliable service delivery. These outcomes reinforce the strategic value of structured governance in steering infrastructure deployment toward public objectives while maintaining operational consistency across spatial contexts.

However, the findings also indicate that rigidly centralised models may not be optimal in all situations. Open-market systems, despite showing lower average performance, can encourage innovation, flexibility, and faster response to emerging user needs. In mature markets, where charging demand is already well distributed, introducing competitive or partially liberalised mechanisms may complement concession frameworks by improving cost efficiency and supporting a wider variety of operators.

The observed differences between roll-out strategies suggest that a balanced or hybrid approach could combine the strengths of both systems. Under such arrangements, local authorities could retain strategic oversight — defining spatial priorities, equity goals, and data-sharing requirements — while allowing private operators greater flexibility in siting and pricing decisions within defined zones. Adaptive concession models, featuring performance-based extensions or variable contractual terms, could further enhance responsiveness to evolving market and technological conditions.

From a strategic perspective, the results emphasise the importance of maintaining coordination mechanisms even as the market matures. Without structured guidance, differences in utilisation and service coverage could widen between high- and low-demand areas. Conversely, over-regulation may constrain private initiative and slow deployment. Policymakers should therefore consider roll-out strategies that combine public steering capacity with market-driven adaptability, ensuring that efficiency, innovation, and accessibility remain balanced as PCSI networks expand.

7.5.2. Practical and Policy Implications

The findings of this study have several practical and policy implications for local authorities and CPOs. First, the consistently higher and more stable performance of concession-based and data-driven strategies highlights the value of proactive, evidence-based planning. Local authorities can strengthen network resilience by integrating local mobility data, grid information, and user behaviour patterns into their siting and procurement processes. This approach enables demand-responsive roll-outs and reduces the risk of underutilised or over-concentrated charging capacity.

For CPOs, the results underline the importance of collaboration with local authorities and the benefits of operating within clear governance frameworks. Concession contracts that include transparent performance metrics and shared data requirements can improve operational efficiency while aligning commercial objectives with public accessibility goals. Such agreements also provide the stability needed to attract private investment in infrastructure while maintaining policy oversight.

From a policy perspective, the results emphasise the need to strengthen data transparency and standardisation across governance models. The LINDA dataset demonstrates the analytical potential of shared operational data, yet uneven reporting among open-market systems limits comparability. Establishing national data standards for public charging — covering utilisation, throughput, and accessibility — would enhance the ability of both researchers and policymakers to monitor network performance

and identify spatial gaps.
Finally, the findings suggest that long-term network sustainability depends on adaptive governance. As charging demand evolves, concession frameworks could incorporate periodic performance reviews, flexible renewal conditions, and incentives for data sharing and innovation. By combining structured oversight with flexibility for market participation, policymakers can ensure that PCSI remains reliable, inclusive, and responsive to changing mobility needs.

8 Conclusions

8.1. Summary of Findings

This research aimed to examine how different PCSI roll-out strategies influence network performance across varying spatial and institutional contexts. By combining operational data from the LINDA dataset with a classification of governance and planning styles, the study sought to uncover how institutional arrangements and spatial characteristics jointly shape utilisation, efficiency, and accessibility outcomes.

Overall, the results show differences between roll-out strategies. Concession-based approaches, particularly those following proactive, data-driven planning methods, demonstrated higher and more stable performance across the most KPIs — occupancy, delivered energy, and composite performance index (CPI). Open-market systems, by contrast, exhibited greater variability and generally lower mean values, especially in urban contexts. These findings suggest that structured coordination and data-informed planning contribute to more efficient and balanced network operation.

At the same time, the analysis revealed that these advantages are context-dependent. The performance gap between governance models narrows in suburban areas and becomes least pronounced in rural contexts, where charging demand is more diffuse and profitability lower. Across all settings, user engagement, as measured by unique users per charging point, remained remarkably stable, indicating equitable access across governance types. Together, these results highlight that the effectiveness of PCSI strategies depends on aligning governance design with spatial demand conditions and maintaining a balance between coordination, flexibility, and inclusivity.

8.2. Answers to Research Questions

Sub-question 1: How can local authorities be meaningfully classified based on spatial and infrastructural characteristics to reflect differences in charging demand and network context?

Local authorities were classified into three distinct clusters — urban, suburban, and rural — using k-means clustering based on infrastructural and contextual indicators, i.e. address density, land area and income. This approach effectively captured structural variation in charging contexts across the Netherlands. This approach was chosen because local authorities base their public charging station prognoses on neighbourhood level, but their jurisdiction covers multiple neighbourhoods. Urban areas are characterised by high charger density and concentrated demand, suburban areas represent transitional conditions with mixed residential and commuting patterns, and rural areas show dispersed infrastructure and lower utilisation intensity. These clusters provided a meaningful framework for contextualising performance differences among roll-out strategies.

Sub-question 2: What types of roll-out strategies can be applied by local authorities?

The analysis identified six roll-out strategies that combine two governance models — *concession-based* and *open-market* — with three planning styles: *reactive request-based*, *proactive strategic*, and *proac-*

tive data-driven. Concession-based models involve contractual coordination between local authorities and CPOs, emphasising policy alignment and equitable coverage. Open-market models rely on market initiative and competitive siting by private operators. Within both governance types, planning style captures the degree of anticipatory or data-supported decision-making, allowing for comparison of strategic depth and responsiveness across contexts.

Sub-question 3: Which performance differences emerge across roll-out strategies and urban-infrastructural pro- files based on station-level operational data?

The performance comparison revealed clear and consistent patterns across KPIs. Concession-based strategies achieved higher and more stable outcomes in occupancy and delivered energy across all clusters, particularly for proactive, data-driven variants. These strategies also recorded the highest CPI values, with both local authority and CPO perspectives showing alignment in high-performing cases. Open-market models, by contrast, displayed greater variability and lower averages, particularly in urban areas, reflecting less coordination and more fragmented deployment patterns.
In suburban and rural contexts, performance differences were smaller and less statistically significant. While concession-based frameworks maintained stability, open-market systems were underrepresented in the dataset, limiting comparability. User engagement, measured by unique users per charging point, remained largely consistent across all strategies, suggesting that access to public charging is relatively equitable regardless of roll-out strategy. These findings demonstrate that roll-out strategies affect operational efficiency more than accessibility.

Sub-question 4: How can these differences be interpreted to better understand the alignment between strategy type and urban context?

The results show that spatial context strongly moderates the influence of roll-out strategies on network performance. In dense urban areas, where demand is high and predictable, concession-based and data-driven approaches leverage coordination and data use to achieve high utilisation and throughput. In suburban areas, mixed governance arrangements and a more spread demand reduce the performance gap between strategies, while in rural areas, low demand limits efficiency regardless of roll-out strategy.
These outcomes suggest that no single roll-out strategy is universally optimal. Instead, effectiveness depends on aligning the roll-out strategy with the spatial and behavioural characteristics of each area. Structured coordination yields benefits in complex, high-demand environments, whereas flexibility and adaptive mechanisms may be more suitable in emerging or low-demand regions.

Main Research Question: How do different roll-out strategies for public EV charging station infrastructure perform across various urban-infrastructural profiles, as measured by key performance indicators?

Overall, the study finds that roll-out strategies have a measurable impact on PCSI performance, particularly in utilisation and energy throughput. Concession-based frameworks, especially those that adopt proactive, data-driven planning, demonstrate clear advantages in stability, efficiency, and strategic alignment. However, these benefits are context-dependent and diminish when charging demand is more spread-out. Open-market models offer flexibility and innovation potential but face challenges in ensuring consistent utilisation and coverage.

8.3. Reflection on the Research Objective

The objective of this research was to analyse how different PCSI roll-out strategies perform across distinct spatial and institutional contexts. This goal was achieved by integrating operational performance data with a governance–planning typology and a spatial clustering framework, enabling a structured comparison of utilisation, efficiency, and accessibility outcomes.
The study successfully demonstrated that both governance model and planning style influence network performance, and that their effectiveness varies by urban context. By developing and applying the Composite Performance Index (CPI), the analysis provided an integrated measure of operational and policy outcomes from both local authority and CPO perspectives. The findings contribute to a

clearer understanding of how coordinated, data-driven governance frameworks can enhance infrastructure efficiency while maintaining equitable access.
Beyond its empirical results, the research advances methodological approaches for evaluating PCSI strategies through a combination of spatial classification, normalised performance metrics, and comparative analysis. While limitations in data coverage restrict the generalisability of some findings, the study achieves its overarching aim: to generate evidence-based insights that inform more adaptive, transparent, and context-sensitive planning of public charging networks.

8.4. Recommendations for Future Research

This section outlines recommendations for future research that follow from the findings and limitations of this study. Building on the analytical framework developed here — combining spatial clustering, a governance–planning typology, and KPI-based performance evaluation — several extensions could deepen understanding of how PCSI roll-out strategies perform across contexts.
First, future work should expand data representation for open-market networks and strengthen longitudinal coverage across all governance types. Incorporating additional socio-economic variables at neighbourhood or local-authority level — such as EV ownership rates, income distribution, or car dependence — would improve the robustness of comparative analysis and allow more nuanced interpretation of contextual effects.
Second, subsequent studies could adopt more explicitly causal analytical designs rather than the predominantly descriptive and comparative approach adopted here. Examples include panel-data models, quasi-experimental designs, and before–and–after evaluations of strategy changes. Such methods would help to better identify the direct impact of specific roll-out strategies on network performance, beyond the associations observed in this thesis.
Third, extending the evaluation framework to include additional system dimensions would further connect roll-out strategies to broader sustainability goals. Integrating indicators on grid impact, pricing policies, or user satisfaction would enable assessment of how governance and planning choices influence not only utilisation and throughput but also energy-system performance, affordability, and perceived service quality.
Finally, future research could test the transferability of the proposed framework to other national or regional contexts and to different types of charging infrastructure, such as semi-public or fast-charging networks. Applying the methodology in comparative settings would help to assess its generalisability and provide richer insights into how institutional arrangements and spatial structures jointly shape the development of public charging infrastructure.
Taken together, these directions would strengthen the empirical basis for evaluating PCSI roll-out strategies and support the development of more adaptive, evidence-based, and context-sensitive planning approaches.

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A

Cluster Analysis

01-standardisation

```python
import pandas as pd
from sklearn.preprocessing import RobustScaler

# Step 1: Load the original KWB dataset
df = pd.read_excel("/Users/pierrepalazzi/Documents/TU/Scriptie/Cluster␣Analysis/01_Standardisation/kwb-2022.xlsx")
# Step 2: Keep only neighbourhood-level records
df_buurt = df[df['recs'] == 'Buurt'].copy()

# Step 3: Select relevant columns
columns_needed = ['gwb_code', 'gm_naam', 'g_hh_sti', 'ste_oad', 'a_lan_ha']
df_buurt = df_buurt[columns_needed]

# Step 4: Convert comma-decimal strings to numeric
for col in ['g_hh_sti', 'ste_oad', 'a_lan_ha']:
    df_buurt[col] = df_buurt[col].astype(str).str.replace(',', '.')
    df_buurt[col] = pd.to_numeric(df_buurt[col], errors='coerce')

# Step 5: Drop rows with missing values
df_buurt.dropna(subset=['g_hh_sti', 'ste_oad', 'a_lan_ha'], inplace=True)

# Step 6: Apply RobustScaler for standardisation
scaler = RobustScaler()
scaled_values = scaler.fit_transform(df_buurt[['g_hh_sti', 'ste_oad', 'a_lan_ha']])
df_buurt[['std_g_ink_pi', 'std_ste_oad', 'std_a_lan_ha']] = scaled_values

# Step 7: Keep only standardised and ID columns
df_output = df_buurt[['gwb_code', 'gm_naam', 'std_g_ink_pi', 'std_ste_oad', 'std_a_lan_ha']]

# Step 8: Export to Excel file
df_output.to_excel("/Users/pierrepalazzi/Documents/TU/Scriptie/Cluster␣Analysis/01_Standardisation/KWB_neighbourhood_standardised.xlsx", index=False)
```

02-Neighbourhood Clustering

```
import pandas as pd
from sklearn.cluster import KMeans
from sklearn.metrics import silhouette_score
import matplotlib.pyplot as plt
from mpl_toolkits.mplot3d import Axes3D

# Step 1: Load the standardised neighbourhood data
df = pd.read_excel("/Users/pierrepalazzi/Documents/TU/Scriptie/Cluster Analysis/01
    _Standardisation/KWB_neighbourhood_standardised.xlsx")

# Step 2: Define input features for clustering
X = df[['std_g_ink_pi', 'std_ste_oad', 'std_a_lan_ha']]

# Step 3: Compute silhouette scores for k = 2 to 10
silhouette_scores = {}
for k in range(2, 11):
    kmeans = KMeans(n_clusters=k, random_state=42, n_init=10)
    labels = kmeans.fit_predict(X)
    score = silhouette_score(X, labels)
    silhouette_scores[k] = score

# Step 4: Print silhouette scores
print("Silhouette scores per k:")
for k, score in silhouette_scores.items():
    print(f"k = {k}: silhouette score = {score:.4f}")

# Step 5: Plot silhouette scores
plt.figure(figsize=(8, 5))
plt.plot(list(silhouette_scores.keys()), list(silhouette_scores.values()), marker='o')
plt.title("Silhouette Scores for Neighbourhood Clustering")
plt.xlabel("Number of clusters (k)")
plt.ylabel("Average silhouette score")
plt.grid(True)
plt.tight_layout()
plt.show()
```

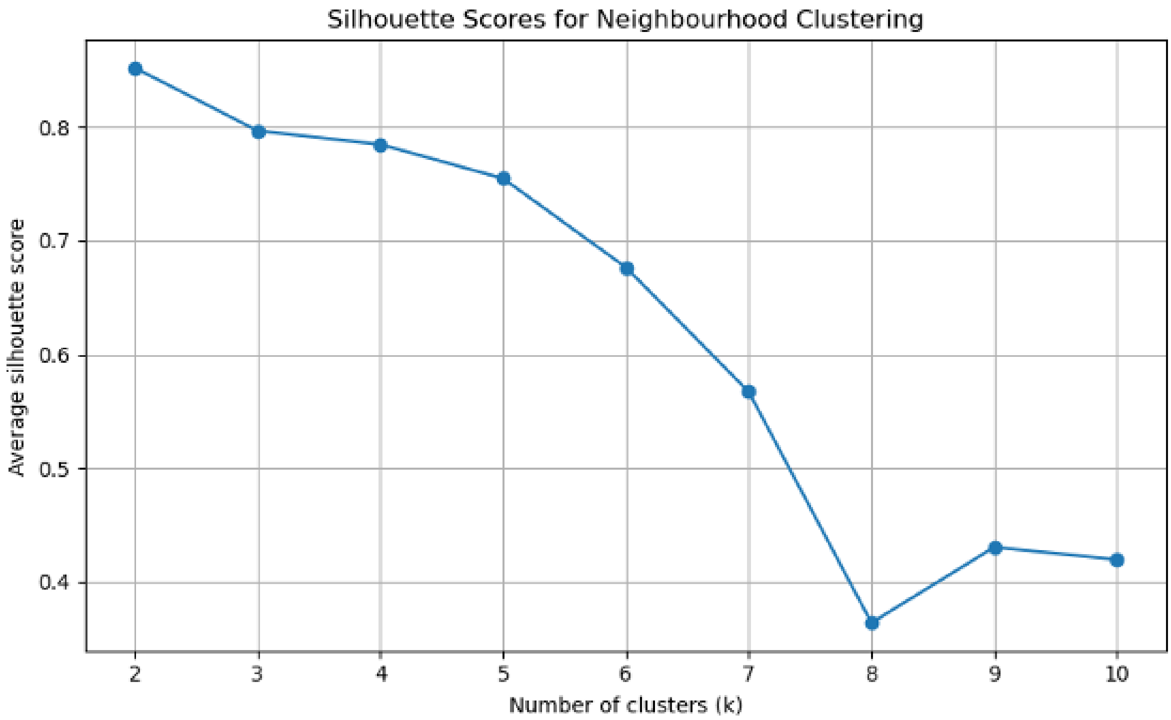

Figure A.1: Silhouette scores for neighbourhood-level clustering.

Silhouette scores per k:

$k = 2$: 0.8522 $k = 3$: 0.7969 $k = 4$: 0.7848
$k = 5$: 0.7549 $k = 6$: 0.6767 $k = 7$: 0.5672
$k = 8$: 0.3639 $k = 9$: 0.4305 $k = 10$: 0.4195

```python
# Step 5: Choose the optimal number of clusters based on the silhouette plot
best_k = 3  # Based on a combination of score, distinctiveness, and policy relevance

# Step 6: Apply KMeans clustering for k = 3
kmeans = KMeans(n_clusters=best_k, random_state=42, n_init=10)
df['neighbourhood_cluster'] = kmeans.fit_predict(X)

# Step 7: Display number of neighbourhoods per cluster
print("Number of neighbourhoods per cluster:")
print(df['neighbourhood_cluster'].value_counts().sort_index())

# Step 8: 3D visualisation of neighbourhood clusters
fig = plt.figure(figsize=(10, 8))
ax = fig.add_subplot(111, projection='3d')

sc = ax.scatter(
    df['std_g_ink_pi'],         # X-axis: Income
    df['std_ste_oad'],          # Y-axis: Address density
    df['std_a_lan_ha'],         # Z-axis: Land area
    c=df['neighbourhood_cluster'],  # Colour by cluster
    cmap='viridis',
    s=40,
    alpha=0.8
)

# Axis labels
ax.set_xlabel('Standardised income')
ax.set_ylabel('Standardised address density')
ax.set_zlabel('Standardised land area')

# Colour bar for cluster IDs
plt.colorbar(sc, label='Neighbourhood cluster')
```

```python

# Plot title
plt.title(f'3D␣Clustering␣of␣Neighbourhoods␣(k␣=␣3)')
plt.tight_layout()
plt.show()

# Step 9: Save the clustering results to an Excel file
df.to_excel("/Users/pierrepalazzi/Documents/TU/Scriptie/Cluster␣Analysis/02_neighb_clustering
    /KWB_neighbourhood_clustered.xlsx", index=False)
```

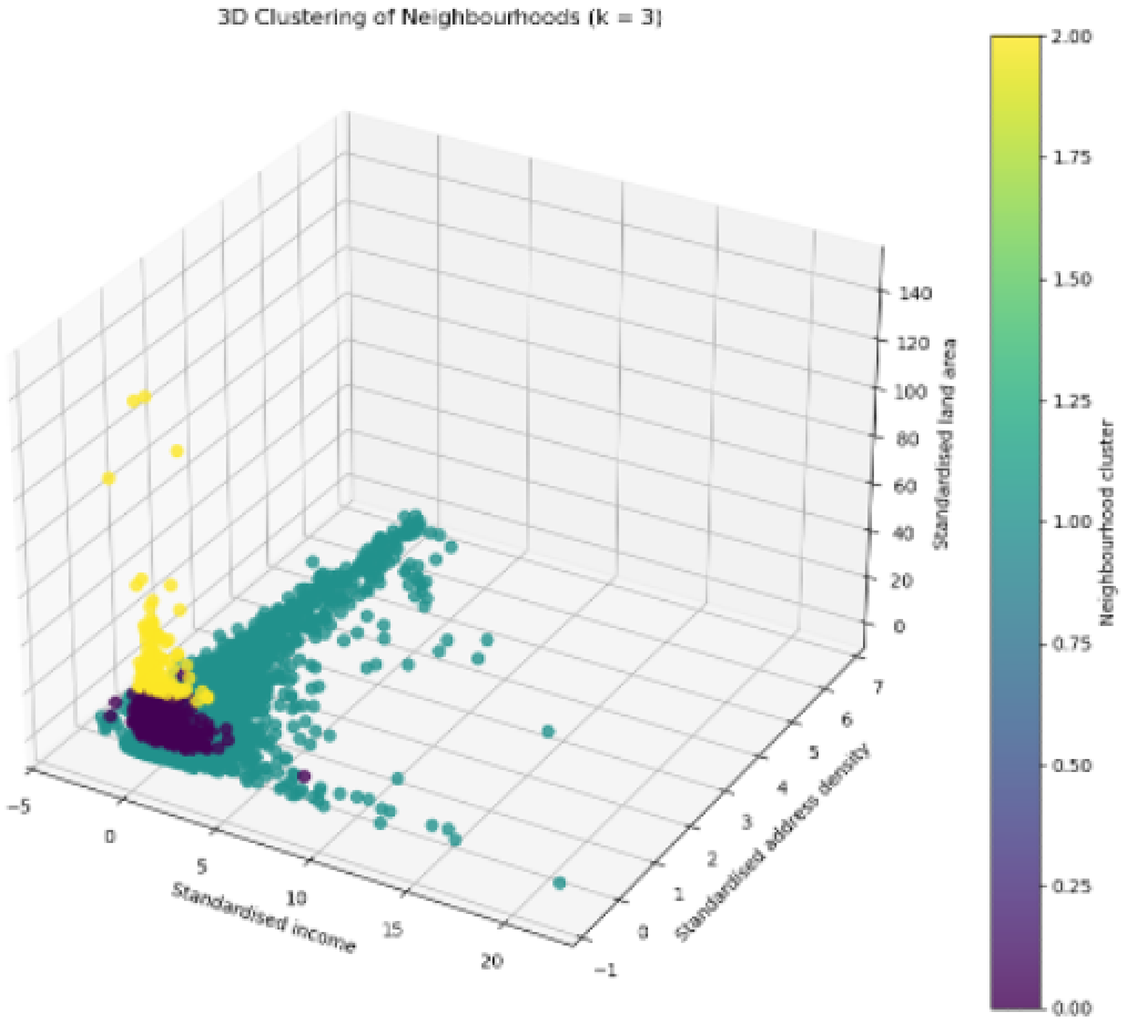

Figure A.2: 3D visualisation of neighbourhood clusters ($k = 3$).

Number of neighbourhoods per cluster:

Cluster 0: 798 Cluster 1: 9,076 Cluster 2: 129

03-Local Authority Clustering

```
import pandas as pd
from sklearn.cluster import KMeans
from sklearn.metrics import silhouette_score
import matplotlib.pyplot as plt
from sklearn.decomposition import PCA

# Step 1: Load the file with clustered neighbourhoods (output from 02_neighb_clustering)
df_neighbourhood = pd.read_excel("/Users/pierrepalazzi/Documents/TU/Scriptie/Cluster Analysis
    /02_neighb_clustering/KWB_neighbourhood_clustered.xlsx")  # Adjust path if necessary

# Step 2: Calculate the distribution of neighbourhoods over clusters per local authority
cluster_counts = df_neighbourhood.groupby(['gm_naam', 'neighbourhood_cluster']).size().
    unstack(fill_value=0)
cluster_distribution = cluster_counts.div(cluster_counts.sum(axis=1), axis=0)  # Proportions

# Step 3: Calculate silhouette scores for local authority clustering (k = 2 to 10)
X_local authority = cluster_distribution.copy()
silhouette_scores = {}

for k in range(2, 11):
    kmeans = KMeans(n_clusters=k, random_state=42, n_init=10)
    labels = kmeans.fit_predict(X_local authority)
    score = silhouette_score(X_local authority, labels)
    silhouette_scores[k] = score

# Step 4: Display silhouette scores in text
print("Silhouette scores per k (municipalities):")
for k, score in silhouette_scores.items():
    print(f"k = {k}: silhouette score = {score:.4f}")

# Step 5: Plot the silhouette scores for local authorities
plt.figure(figsize=(8, 5))
plt.plot(list(silhouette_scores.keys()), list(silhouette_scores.values()), marker='o')
plt.title("Silhouette Scores for local authority Clustering")
plt.xlabel("Number of clusters (k)")
plt.ylabel("Average silhouette score")
plt.grid(True)
plt.tight_layout()
plt.show()
```

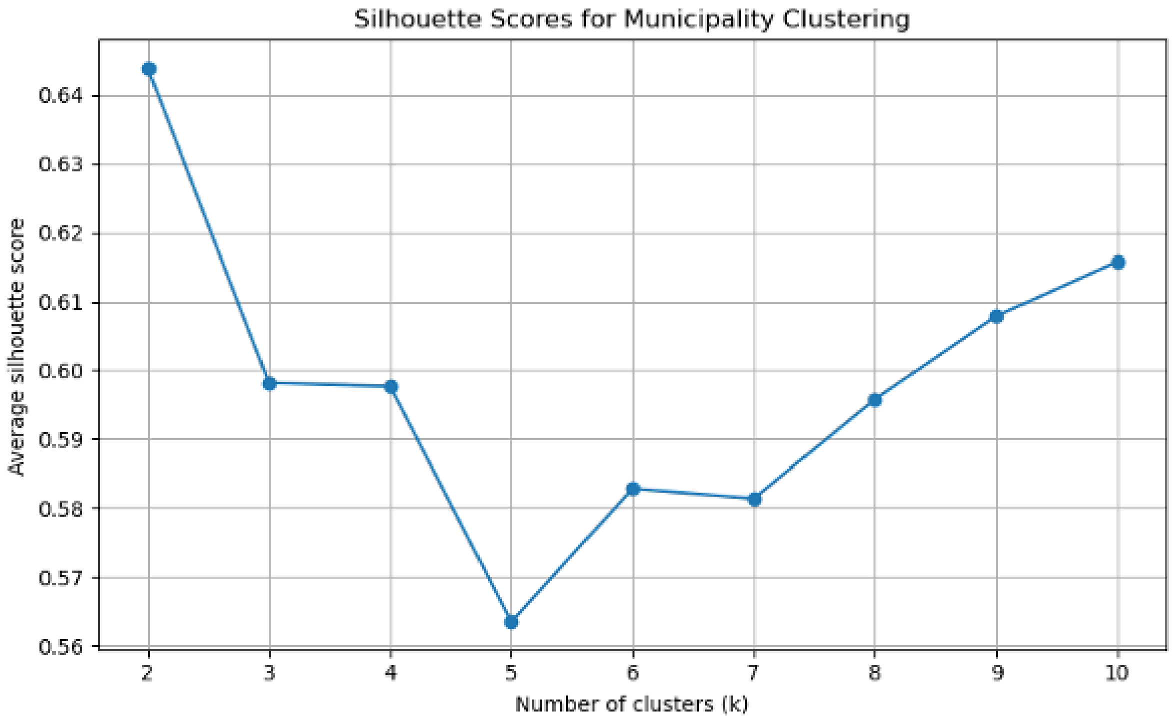

Figure A.3: Silhouette scores for local authority-level clustering.

Silhouette scores per k (Local Authorities):

$k = 2$: 0.6439	$k = 3$: 0.5982	$k = 4$: 0.5976
$k = 5$: 0.5634	$k = 6$: 0.5828	$k = 7$: 0.5813
$k = 8$: 0.5958	$k = 9$: 0.6079	$k = 10$: 0.6158

```python
# Step 6: Choose the optimal number of clusters (based on silhouette results)
best_k = 3 # ← Adjustable based on your silhouette plot results

# Step 7: Run KMeans clustering on local authority-level profiles
# Ensure column names are strings
cluster_distribution.columns = cluster_distribution.columns.astype(str)

kmeans = KMeans(n_clusters=best_k, random_state=42, n_init=10)
cluster_distribution['local authority_cluster'] = kmeans.fit_predict(cluster_distribution)

# Step 8: Show number of municipalities per cluster
print("Number of municipalities per cluster:")
print(cluster_distribution['local authority_cluster'].value_counts().sort_index())

# Step 9: Save the result to Excel
cluster_distribution.to_excel(
    "/Users/pierrepalazzi/Documents/TU/Scriptie/Cluster Analysis/03_municip_clustering/
        KWB_local authority_clustered.xlsx",
    index=True
)

# Step 10: Perform PCA to reduce dimensions for 2D visualisation
pca = PCA(n_components=2)
pca_result = pca.fit_transform(cluster_distribution.drop(columns='local authority_cluster'))

# Step 11: Plot 2D PCA visualisation of local authority clusters
plt.figure(figsize=(8, 6))
plt.scatter(pca_result[:, 0], pca_result[:, 1], c=cluster_distribution['local
    authority_cluster'], cmap='viridis', s=50, alpha=0.8)
plt.colorbar(label='local authority Cluster')
plt.title(f'2D PCA Visualisation of Municipal Clusters (k = {best_k})')
plt.xlabel('PCA Component 1')
plt.ylabel('PCA Component 2')
```

```
plt.tight_layout()
plt.show()

# Step 12: Generate cluster summary table
cluster_summary = cluster_distribution.groupby('local authority_cluster').mean()
cluster_summary = cluster_summary.sort_values(by='local authority_cluster')
print("Cluster Summary Table:")
print(cluster_summary)
```

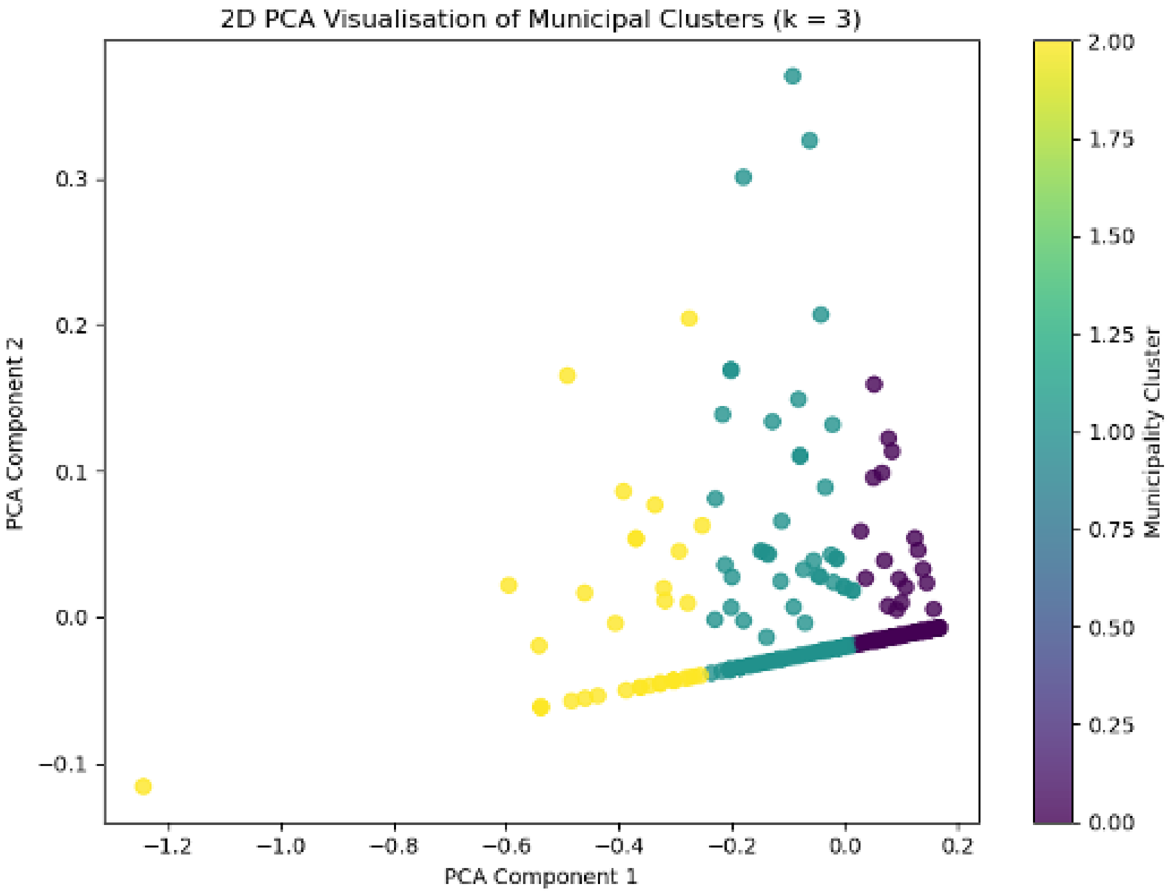

Figure A.4: 2D visualisation of local authority clustering.

Number of local authorities per cluster:

Cluster 0: 199
Cluster 1: 106
Cluster 2: 40

Table A.1: Distribution of neighbourhood clusters within municipality clusters

Local Authority Cluster	Neighbourhood Cluster 0	Neighbourhood Cluster 1	Neighbourhood Cluster 2
0	0.0230	0.9722	0.0048
1	0.1681	0.7991	0.0328
2	0.3763	0.5923	0.0314

B

Final Dataset Sample

Local Authority	Cluster	Governance Model	Approach	Strategy	Occupancy Rate (%)	kWh/Day	Unique Users/Day	Notes
Aalsmeer	URBAN	Concession (MRA-e)	Proactive	Data-Driven	18,40	20,09	3,27	Strategic and request driven exist, but data-driven is leading.
Aalten	RURAL	Concession (GO-RAL)	Proactive	Strategic	11,80	23,83	3,04	This strategy is categorised as strategic because it is based on predefined locations, with a clear long-term focus and limited dynamic adaptation.
Aa en Hunze	URBAN	Concession (Groningen-Drenthe)	Reactive	Request-Driven	12,68	27,25	4,00	Hybrid approach. The main driver is reactive on request, with additional proactive strategic elements for a basic network and specific locations like OV Hubs.
Alphen aan den Rijn	URBAN	Open Market (Zuid-Holland)	Proactive	Data-Driven	14,36	20,51	3,37	Annual forecasts and usage data guided placement, but requests were also accepted; thus, placement is proactive and data-driven rather than purely reactive.
Culemborg	URBAN	Open-Market (Gelderland)	Reactive	Request-Driven	18,05	20,90	3,11	Placement was solely request-based through market parties using fixed criteria; no strategic grid or data-driven planning existed
Waalre	SUBURBAN	Open Market (Noord-Brabant)	Proactive	Strategic	6,68	17,20	1,80	Based on a location plan and pre-analysis

Table B.1: Sample of the final dataset illustrating the structure of the collected data. The complete dataset was used in the analysis but is not included here due to its size. Available on request

C

Statistical Validation

```python
import numpy as np, pandas as pd

# Step 1: Data cleaning - Trim spaces from column names
df.columns = [c.strip() for c in df.columns]
print("Columns␣before␣renaming:", df.columns.tolist())

# Step 2: Rename columns to make them more understandable
rename_map = {
    "GEM_Code": "municipality_id",  # GEM_Code -> municipality_id for better clarity
    "Cluster": "cluster",  # Rename 'Cluster' for consistency
    "Strategy6": "strategy6",  # Full strategy name
    "Strategy": "strategy_short",  # Short label for the strategy
    "occupancyRate(%)": "occupancy_pct",  # Occupancy rate as percentage
    "averageKwhPerDay": "avg_kwh",  # Rename average kWh per day
    "averageNumberOfUniqueRfidPerDay": "unique_users",  # Unique users per day
}

# Apply the renaming
df = df.rename(columns=rename_map)
print("Columns␣after␣renaming:", df.columns.tolist())

# Display first 3 rows to verify
df.head(3)


# Step 3: Statistical calculations for occupancy, kWh, and unique users
# The mean, standard deviation (std), count (N), and standard error (se) for each variable
    are calculateed.
# The results will be grouped by 'strategy_short' and 'cluster' to explore different
    strategies and clusters.

summary_stats = df.groupby(['strategy_short', 'cluster']).agg(
    mean_occupancy=('occupancy_pct', 'mean'),
    std_occupancy=('occupancy_pct', 'std'),
    N_occupancy=('occupancy_pct', 'count'),
    se_occupancy=('occupancy_pct', lambda x: x.std() / np.sqrt(x.count())),

    mean_kwh=('avg_kwh', 'mean'),
    std_kwh=('avg_kwh', 'std'),
    N_kwh=('avg_kwh', 'count'),
    se_kwh=('avg_kwh', lambda x: x.std() / np.sqrt(x.count())),

    mean_users=('unique_users', 'mean'),
    std_users=('unique_users', 'std'),
    N_users=('unique_users', 'count'),
    se_users=('unique_users', lambda x: x.std() / np.sqrt(x.count()))
)

# Flag rows where N is low (less than 4 data points)
```

```
summary_stats['flag_lowN'] = summary_stats['N_occupancy'] < 4

w# Display first few rows of summary statistics
summary_stats.head(3)

# Horizontal Confidence Interval (CI) Calculation for occupancy, kWh, and users
# CI will be calculated as: mean +/- (1.96 * standard error) for 95% confidence

# For occupancy (horizontal CI calculation)
summary_stats['ci_lower_occupancy'] = summary_stats['mean_occupancy'] - (1.96 * summary_stats
    ['se_occupancy'])
summary_stats['ci_upper_occupancy'] = summary_stats['mean_occupancy'] + (1.96 * summary_stats
    ['se_occupancy'])

# For kWh (horizontal CI calculation)
summary_stats['ci_lower_kwh'] = summary_stats['mean_kwh'] - (1.96 * summary_stats['se_kwh'])
summary_stats['ci_upper_kwh'] = summary_stats['mean_kwh'] + (1.96 * summary_stats['se_kwh'])

# For unique users (horizontal CI calculation)
summary_stats['ci_lower_users'] = summary_stats['mean_users'] - (1.96 * summary_stats['
    se_users'])
summary_stats['ci_upper_users'] = summary_stats['mean_users'] + (1.96 * summary_stats['
    se_users'])

# Display CI columns to confirm the calculations
summary_stats[['ci_lower_occupancy', 'ci_upper_occupancy',
               'ci_lower_kwh', 'ci_upper_kwh',
               'ci_lower_users', 'ci_upper_users']].head(3)


# Step 5: Tukey Test for Statistical Comparison
# The Tukey HSD test helps to compare the means across multiple groups and determine if there
     are statistically significant differences.
# We apply this test to occupancy, kWh, and unique users for different strategies.

from statsmodels.stats.multicomp import pairwise_tukeyhsd

# Tukey test for occupancy
tukey_occupancy = pairwise_tukeyhsd(df['occupancy_pct'], df['strategy_short'], alpha=0.05)

# Tukey test for kWh
tukey_kwh = pairwise_tukeyhsd(df['avg_kwh'], df['strategy_short'], alpha=0.05)

# Tukey test for unique users
tukey_users = pairwise_tukeyhsd(df['unique_users'], df['strategy_short'], alpha=0.05)

# Display Tukey test results for all three variables
tukey_occupancy.summary(), tukey_kwh.summary(), tukey_users.summary()
```