

State-of-Charge Driven Charging Behaviour at Public EV Chargers in the United Kingdom: An Empirical Study

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ABSTRACT

As the United Kingdom makes its transition into the mass-market phase of electric vehicle (EV) adoption, understanding real-world driver interactions with public charging infrastructure is critical for grid management and network optimization. This empirical study investigates the "black box" of State-of-Charge (SoC) driven charging behavior. It aims to challenge theoretical models that traditionally rely on simulated data or self-reported surveys by analyzing unvarnished user actions. The research analyzes a high-fidelity dataset of public charging telemetry collected over a 90-day period in 2025 across multiple UK locations. By preprocessing raw session data from arrival to departure, the study engineered specific metrics such as the SoC Delta and a "Stickiness" check to quantify charging utility and driver habits. The results of the study challenge common assumptions in academic literature and the industry about the charging behaviour of drivers. It is found that most EV drivers delay public charging until it becomes an absolute necessity, leading to a pronounced mid-day surge of arrivals with extremely low batteries around 10%. Rather than fully restoring their vehicles, users typically execute tactical top-ups that replenish roughly 40-45% of their total battery capacity. However, nearly half of these sessions inefficiently extend past an 80% charge because departure times are largely dictated by secondary activities like shopping or dining rather than actual battery needs. The study recommends that Charge Point Operators (CPOs) and grid planners adapt by prioritizing high-density hubs, utilizing localized grid storage, and implementing dynamic pricing or overstay fees to optimize charger turnover and mitigate network stress.

Keywords: *Electric Vehicle; State of Charge; Public Charging; Charging Behaviour.*

TABLE OF CONTENTS

CHAPTER ONE INTRODUCTION	2337
The State of Public EV Charging in the UK	2337
The Significance of Understanding State-of-charge Driven Behaviour	2337
The "Black Box" of SOC Behaviour	2337
Aims and Objectives of the Study	2338
CHAPTER TWO LITERATURE REVIEW AND THE EMPIRICAL GAP ANALYSIS	2339
Introduction to the Behavioral-Technical Nexus	2339
Theoretical Frameworks of EV Psychology	2339
The UK Context and Regulatory Influence	2339
The Science of the "Taper" and User Heuristics	2340
Synthesis: The Empirical Gap Analysis	2340
CHAPTER THREE METHODOLOGY AND DATA PROCESSING	2341
Charging Data Acquisition and Characteristics of the Dataset	2341
Data Preprocessing	2341
Filtering and Error Handling	2341
Normalization of Variables	2341
Feature Engineering: Quantifying Behavior	2342
The SoC Delta (ΔSoC)	2342
The "Stickiness" Check	2342
Methodological and Ethical Limitations	2343
Methodological Limitations	2343
Ethical Limitations	2343
CHAPTER FOUR RESULTS AND EMPIRICAL FINDINGS	2344
Analysis of Arrival SoC Distribution: The Necessity-Driven Paradigm	2344
Revising the Choice of Central Tendency	2344
Behavioral Archetypes: The Cliff-Edge Driver vs. The Planner	2344
Power Throttling and Energy Delivery	2345
The Disparity in Power Throughput	2345
Tactical Replenishment vs. Full Capacity Restoration	2345
Departure Psychology: The Intersection of Technical Constraints and Human Dwell Time	2345
The 80% Heuristic and the Efficiency Threshold	2346
The Retail Connection and Location Stickiness	2346
The Relationship between Arrival SoC and Arrival hour	2347
Temporal Distribution and Activity Peaks	2347
The Mid-Day Depletion Phenomenon	2347
The Absence of High SoC Arrivals	2348
Socio-Technical Explanations	2348
CHAPTER FIVE DISCUSSIONS AND RECOMMENDATIONS	2349
Synthesizing the Discoveries: The UK EV Driver Profile	2349
Empirical Explanations of EV Drivers' Behavioural Psychology	2349
Significance and Industry Impact of the Study	2349
Growth of Public Networks, Rapid Charging Technology, and the Impact of Growth on Charging Behavior	2350
The Future of Expanded Battery Capacities	2350
Recommendations for Charge Point Operators and Grid Planning	2350
Recommendations for Future Research	2350
REFERENCES	2352

CHAPTER ONE INTRODUCTION

➤ *The State of Public EV Charging in the UK*

The number of drivers driving pure electric cars in the United Kingdom has grown rapidly, indicating that the country has moved past the “early adopter” phase of electric mobility. The Department for Transport records that at the end of March 2026, there were over 1,970,000 fully electric cars making up 5.7% of the 34 million cars on UK roads (see Figure 1) (Zapmap, 2026). The increase in the number of electric cars is naturally accompanied by an increase in the number of public charging stations. By January 2022, there were 28,375 charging devices including on-street, destination and en-route charging devices. This number climbed to 87,796 by January 2026 (Department for Transport, 2026). These numbers will continue to increase dramatically and the companies that service this sub-industry will need to adapt to the needs of the regular electric vehicle (EV) driver. At the forefront of the United Kingdom’s public charging network are companies like Shell Recharge (including Ubitricity), Instavolt, GRIDSERVE, Ionity, Tesla and MFG EV Power. MFG leads the market in rapid charging technology while Shell Recharge (Ubitricity) has the largest overall network.

• *(Zapmap, 2026) (Department for Transport, 2025)*

The expansion of public EV charging networks is strongly supported by the consolidation of fast charging connector technology, and increasing government regulations. In the United Kingdom, these regulations are often stringent. For instance, the Public Charge Point Regulation which came into force in 2023 mandated a 99% uptime for charge point operators across their entire network for a calendar year (Office, 2023). It is not unreasonable to state that the tightened regulation is geared towards improving the reliability of these operators, turning the EV driving experience from an anxiety-inducing one to a predictable part of daily life.

➤ *The Significance of Understanding State-of-Charge Driven Behaviour*

Even with the rapid rollout of public charging hardware (also called Electric Vehicle Supply Equipment or EVSE), there is a significant gap in our understanding of State of Charge (SoC) driven behaviour. Many charge point operators generate extensive data on energy delivered (measured in kWh) but there is a paucity of published empirical research on the internal psychological thresholds of the modern EV driver. Consider the analogy of traditional vehicles powered by the Internal Combustion Engine. The drivers of these vehicles are conscious of the gas/fuel levels of their cars and this influences their driving and refueling behaviour. This information is useful within the EV industry as well for a number of reasons.

First, it is useful for grid planning and load balancing. Grid operators don't just need to know if people will charge, but where and when they will ‘panic-charge’ or ‘opportunity-charge’. If data shows that drivers with <20% SoC consistently surge toward the nearest fast-charger during a specific highway commute, utilities can build localized battery storage at those specific nodes to prevent a local grid collapse. If the grid is overstressed, the utility could send a push notification to users with high SoC incentivizing them to delay charging till there are fewer drivers. Understanding how low an SoC a driver will tolerate before refusing to delay allows for precise grid management.

For retailers, an EV charger is the modern equivalent of a loss leader. A driver at 20% SoC is a captive audience for at least 30–45 minutes. Retailers can use this data to trigger specific marketing like coupons for a sit-down meal or a cinema ticket while the user charges their vehicle. High-SoC drivers (e.g., 70%) are opportunity chargers who don't need to be there. Retailers can offer them cheaper electricity to lure them into the store during slow business hours, effectively using the car as a tool for foot traffic.

Also, understanding SoC driven behaviour can help urban planners determine the best locations to situate a charger. By analyzing where drivers hit their panic threshold (the SoC level where they deviate from their route to find a charger), planners can place small, high-speed hubs in those specific areas to increase the “psychological range” of a city, even if those chargers aren't used 24/7. If data shows most urban drivers top up at 50% SoC while grocery shopping, the city can prioritize slow, cheap AC chargers in parking lots rather than expensive, space-consuming DC fast-chargers.

➤ *The "Black Box" of SOC Behaviour*

The problem of understanding SOC-driven behaviour can be approached by asking empirical data some relevant questions and using this information to challenge theoretical models. The following questions are important to this study.

- **Arrival Uncertainty:** At what point does a UK driver succumb to “Charging Anxiety” and seek a public charger? Is it at the traditional 20% “reserve” mark, or are drivers becoming more comfortable arriving with single-digit percentages?
- **The 80% Departure Trap:** It is well-known that EV charging speeds taper significantly after 80% to preserve battery health. However, if a large segment of users continues to occupy rapid chargers until 100% (the “Top-off” behaviour), it reduces network throughput and increases wait times for other users.
- **The Retail Correlation:** Emerging data suggests that 75% of EV drivers engage in “recharging themselves” (purchasing coffee or food) while their vehicles charge. This raises the question: Is charging duration dictated by the battery’s needs or the driver’s coffee break?

➤ *Aims and Objectives of the Study*

This study utilizes multiple high-fidelity session data from a leading Charge Point Operator (CPO) to uncover state-of-charging driven behaviour as it relates to public charging. By analyzing hundreds of real-world charging events, this research seeks to establish the first comprehensive SOC Profile for the UK EV driver in 2026.

• *The Core Objectives are to:*

- ✓ Quantify Arrival Behaviour: Determine the average SOC at which drivers initiate a public charging session and identify the anxiety peak in the distribution.
- ✓ Analyze Departure Patterns: Identify the most common SOC at which drivers terminate sessions, specifically measuring the prevalence of the 80% Taper vs. the 100% Top-off.
- ✓ Determine a relationship between the arrival state of charge and the time of the day: Specifically, to identify if users limp into charging stations at odd hours.
- ✓ Inform Infrastructure Efficiency: Provide data-driven recommendations for Charge Point Operators (CPO) to optimize charger turnover and power allocation based on observed user SOC thresholds.

CHAPTER TWO

LITERATURE REVIEW AND THE EMPIRICAL GAP ANALYSIS

➤ *Introduction to the Behavioral-Technical Nexus*

The transition of electric vehicles (EVs) from an early-adopter niche to a mass-market transportation standard has fundamentally shifted the focus of academic study. In the nascent stages of EV adoption, literature predominantly concentrated on the technical feasibility of battery chemistries, vehicle range limitations, and the initial rollout of charging infrastructure. However, as the United Kingdom advances through the mid-2020s and approaches its internal combustion engine (ICE) phase-out targets, the research paradigm must evolve to examine the socio-technical ecosystem of public charging. A critical component of this ecosystem is the intersection between vehicular technical constraints and human behavioral psychology.

Understanding how an EV driver interacts with public charging infrastructure requires moving beyond purely economic or rational-actor models. Drivers do not operate as perfectly efficient algorithms maximizing battery life and minimizing dwell time; rather, they are influenced by psychological thresholds, environmental conveniences, and infrastructure reliability. This chapter reviews the existing theoretical frameworks surrounding EV driver psychology, evaluates the impact of recent UK infrastructure policy on these behavioral thresholds, and examines the technical realities of charging curves. Ultimately, it identifies a critical empirical gap in the current literature: the over-reliance on simulated models and self-reported surveys, which fail to capture the stochastic, unvarnished reality of mass-market charging behavior.

➤ *Theoretical Frameworks of EV Psychology*

The foundational psychological construct in EV literature is "Range Anxiety," broadly defined as the fear that a vehicle has insufficient energy to reach its destination, thereby leaving the occupants stranded. As Rainieri et al. (2023) note in their systematic review, range anxiety is not merely a product of battery capacity but a complex socio-technical phenomena heavily influenced by user experience, route topography, and the perceived availability of charging infrastructure. However, as battery capacities have expanded significantly over the past decade, the literature has increasingly shifted its focus from Range Anxiety to "Charging Anxiety"—the specific stress associated with locating a functional, available, and sufficiently rapid public charger.

This anxiety dictates the "anxiety floor," or the minimum State of Charge (SoC) a driver is willing to tolerate before seeking immediate replenishment. In enthusiast literature and automaker guidelines, the "20/80 rule" is frequently cited as best practice, advising drivers to keep their battery between 20% and 80% to optimize cell longevity and reduce degradation. Yet, academic research on actual driver behavior suggests a divergence from this heuristic. Cavus et al. (2025) introduced the concept of "Charging Comfort," arguing that as users gain familiarity with their vehicles and the surrounding infrastructure, their charging behavior shifts from survival-based (avoiding being stranded) to optimization-based (charging when convenient, regardless of SoC).

Furthermore, the utility of public charging cannot be analyzed in a vacuum; it is deeply intertwined with access to private charging. Neubauer and Wood (2014) demonstrated that home charging infrastructure is the primary determinant of EV lifetime utility. For drivers without access to off-street parking—a significant demographic in dense UK urban centers—public charging transitions from a supplementary convenience to a primary necessity. This reliance fundamentally alters the psychological stakes of the public charging session, pushing drivers to exhibit behavior that is distinct from those who treat public chargers merely as en-route top-ups.

➤ *The UK Context and Regulatory Influence*

The behavioral thresholds of EV drivers are inextricably linked to the environment in which they operate. Pevec et al. (2019) established that the grid placement and density of charging stations are critical obstacles to mitigating range and charging anxiety. In the United Kingdom, the rapid expansion of the public charging network has transformed the spatial context of EV ownership. By 2026, the proliferation of high-speed hubs and destination chargers has theoretically blanketed the primary road network, but physical availability is only one component of driver confidence; the other is reliability.

Historically, the UK charging network was plagued by fragmented payment systems, opaque pricing, and high rates of out-of-service hardware, all of which artificially elevated the anxiety floor for the average driver. To combat this, the UK Government implemented the Public Charge Point Regulations 2023. These regulations mandated a 99% reliability standard for rapid charge point operators across their networks, alongside requiring transparent pricing and contactless payment options.

The psychological impact of these regulations is profound. By guaranteeing a highly reliable network, the UK government has effectively sought to turn public charging into a predictable utility. Theoretically, this regulatory intervention should lower the anxiety floor, allowing UK drivers to comfortably operate their vehicles at a much lower SoC without the panic historically associated with a nearly depleted battery. If a driver trusts that the next rapid charger will be operational and accessible, they are theoretically more likely to maximize their vehicle's range, arriving at chargers at 10% or even 5% SoC rather than the conservative 20% dictated by early heuristics. Evaluating whether this theoretical confidence has translated into empirical reality is a core focus of modern infrastructural analysis.

➤ *The Science of the "Taper" and User Heuristics*

While arrival behavior is dictated by anxiety and infrastructure confidence, departure behavior is governed by a clash between technical realities and user heuristics. The defining technical constraint of modern public charging is the "80% Taper." As lithium-ion cells charge, internal resistance generates significant heat, and the voltage of the pack rises. To protect the battery from accelerated degradation, thermal runaway, and lithium plating, the vehicle's Battery Management System (BMS) dynamically throttles the intake of power as the SoC increases. Typically, once a vehicle surpasses 80% SoC, the charging curve steepens dramatically, reducing high-velocity DC power to a trickle.

From a purely technical and economic standpoint, charging a vehicle beyond 80% at a rapid public charger is highly inefficient. It costs the driver time, and it costs the Charge Point Operator (CPO) turnover efficiency, creating bottlenecks at high-demand hubs. Yet, emerging evidence suggests a high prevalence of "Top-off" behavior, where users persistently occupy chargers well into the taper zone.

Academic literature has historically struggled to explain why users "stick" to chargers despite the diminishing returns of the taper. Traditional utility-maximization models suggest drivers should unplug and depart the moment their vehicle has enough energy to reach their destination or when the charging rate drops below a cost-effective threshold. To explain this irrationality, researchers are increasingly looking toward the "Location Stickiness" theory. As Chen et al. (2026) note in their analysis of trajectory patterns, spatial context heavily dictates dwell time. When chargers are co-located with retail parks, supermarkets, or dining establishments, the charging session becomes tethered to a secondary activity. The driver is not waiting for the car to charge; the car is charging while the driver is engaged elsewhere. Consequently, the user's departure is dictated by the duration of their meal or shopping trip, rendering the technical limits of the BMS irrelevant to their decision-making process.

➤ *Synthesis: The Empirical Gap Analysis*

While the theoretical frameworks of Range Anxiety, Charging Comfort, and Location Stickiness provide a robust background for discussing EV behavior, a critical methodological limitation pervades the existing literature. The vast majority of foundational studies in this field rely heavily on two flawed methodologies: simulated mobility data and self-reported surveys.

Simulated data (e.g., origin-destination modeling based on Internal Combustion Engine or ICE travel patterns) inherently assumes that EV drivers operate as rational actors seeking to optimize time and energy. It fails to account for the irrational, context-dependent heuristics that human beings employ in real-time. Conversely, self-reported surveys, while useful for gauging sentiment, are notoriously susceptible to idealization and reporting bias. Drivers often report how they *think* they should charge (e.g., adhering to the 20/80 rule) rather than how they *actually* charge when late for a meeting or distracted by a retail environment.

As the UK enters the true mass-market phase of EV adoption in 2026, there is a pronounced deficit in studies utilizing unvarnished, high-fidelity telemetry from Charge Point Operators. There is a pressing need to move away from asking drivers what they do, or simulating what they should do, and instead observing what they *actually* do at the charging stall. The literature currently lacks comprehensive, large-scale empirical analyses that capture the "realistic messiness" of mass-market charging—the deep-discharge arrivals driven by necessity, and the highly inefficient tapers driven by location stickiness.

This study explicitly bridges this empirical gap. By analyzing a massive, 90-day dataset of real-world charging sessions sourced directly from a leading UK CPO in 2025/2026, this research moves beyond theoretical models into empirical reality. In doing so, it provides the first definitive, data-driven State of Charge (SoC) profile of the contemporary UK EV driver, testing the theoretical frameworks of the past against the telemetry of the present.

CHAPTER THREE

METHODOLOGY AND DATA PROCESSING

The preceding chapters have established the theoretical disconnect between modeled expectations of EV drivers' charging behaviour. This chapter details the empirical framework used to bridge that gap. To do this, data was sourced from real charging stations across the various regions in the United Kingdom over a period of 90 days in 2025. By leveraging a high-fidelity data set of electric vehicle charging telemetry and applying advanced analytical processing, this study reconstructs the anatomy of a charging session from arrival to departure. The following sections outline the steps taken to clean and prepare the data and the future engineering procedures taken to understand SOC driven behavior.

➤ *Charging Data Acquisition and Characteristics of the Dataset*

The dataset used in this study comprises the raw telemetry captured from a network of public charging stations in the United Kingdom over a 90-day period. Unlike simulated data sets, this data is a representation of unvarnished user interactions, capturing the realistic messiness of charging sessions.

• *The Columns in the Different Files are as Follows:*

- ✓ Serial number: this is a seven digit ID used to track individual EV charging sessions
- ✓ SoC start (arrival state of charge): the residual energy remaining in the vehicles, battery pack at the precise moment of plugging. It is typically expressed as a fractional value of the maximum battery capacity of the vehicle. The arrival SOC is important because it helps us understand the risk tolerance of the driver which is key to understanding their charging behavior.
- ✓ SoC end (departure state of charge): recorded at the termination of the charging session, this metric is the final energy status of the battery before the driver physically disconnects the vehicle. In contrast to the arrival state of charge, this helps us to understand the extent to which the driver prioritized a battery top-up over the time-constrained convenience of a full charge.
- ✓ Energy delivered: this is an accumulative throughout of energy dissipated from the charging station to the vehicle's battery. While industries standards typically use this metric for commercial throughput analysis and grid planning, our study focuses more on the arrival and departure state of charge levels
- ✓ Minutes: this tracks how long the charging bay was occupied, that is, from initial connection to final withdrawal of the charging device.
- ✓ Connector ID: the unique ID of the charging connector
- ✓ Location: the location of the public charging station in the United Kingdom
- ✓ Start time: The date and time the charging began in the format "DD/MM/YYYY HH:mm"

➤ *Data Preprocessing*

The public charging data was originally sourced as separate comma-separated values (CSV) logs of different charging locations in the United Kingdom. Duplicate files were removed, and files containing data in a different schema were excluded from the dataset.

To distinguish between the different locations, a new column called 'location' with values corresponding to the source location was added to each CSV file. The files were then concatenated to make up the data set for analysis.

• *Filtering and Error Handling*

The filtering step involved, removing erratic charge sessions. To do this sessions where the energy delivered was less than 0.5 kilowatt hour were discarded, as these typically represent faulty handshakes between the vehicle and the dispenser rather than intentional charging sessions. Any session where the departure SoC was lower than the arrival SoC were also discarded. These indicate sensor errors or next discharge.

To avoid any time errors, the start time was converted to the appropriate data structure called a datetime in python. The datetime object allows us to seamlessly work with time conversions, interval calculations and time-related calculations in the Python-based analysis.

• *Normalization of Variables*

Since different vehicles and chargers report data in varying formats, normalization was essential:

- ✓ State of Charge: All SoC values were converted from fractional decimal values to a standard percentage scale (a percentage value in the 0-100% range).
- ✓ Power Metrics: Charging stations are often marketed by their peak capacity (e.g., "Ultra-Rapid 350 kW"). However, vehicles rarely maintain this speed for the entire session. As an EV battery fills up, its resistance increases, and the charging speed slows down. This phenomenon is known as the "taper." Average power captures the net effect of this slowdown, providing a more

realistic view of how long a user must wait to gain a specific amount of energy. To calculate the average power used by an EV during a session, the following formula was used:

$$P_{avg} = \frac{E_{delivered} \times 60}{t_{session}}$$

Where P_{avg} is the average power delivered expressed in kW, $E_{delivered}$ is the energy delivered, expressed in kWh, and $t_{session}$ is the session duration expressed in minutes.

To understand where this comes from, we look at the fundamental relationship between Energy, Power, and Time in physics. Energy is the product of power and time. If you run a 1 kW appliance for 1 hour, you use 1 kWh of energy.

$$Energy(E) = Power(P) \times Time(t)$$

Thus, to find the Average Power, we rearrange the formula:

$$P = \frac{E}{t}$$

However, in the empirical dataset, the units are not perfectly aligned for a direct division: Energy (E) is measured in kilowatt-hours (kWh) and Time (t) is measured in minutes. To get the Power in kilowatts (kW), the time component must be in hours. If we simply divided kWh by minutes, the resulting number would be meaningless. We must first convert the minutes into hours by dividing by 60.

$$Time_{hours} = \frac{Minutes}{60}$$

Substituting the "hour-converted time" back into the power formula:

$$P_{avg} = \frac{E_{kWh}}{\left(\frac{t_{min}}{60}\right)}$$

Which gives the formula used to calculate average power delivered during a session:

$$P_{avg} = \frac{E_{delivered} \times 60}{t_{session}}$$

This calculation shifts the focus of the analysis from marketing speeds to the actual rate of energy transfer that the UK driver experienced during their session.

➤ Feature Engineering: Quantifying Behavior

To move beyond simple descriptive statistics, this study engineers two critical metrics: the SoC Delta and the Stickiness Index.

- *The SoC Delta (ΔSoC)*

The primary indicator of a session's utility is the change in the battery's state of charge. This was calculated as:

$$\Delta SoC = SoC_{Departure} - SoC_{Arrival}$$

The most significant reason for calculating SoC Delta is to standardize the unit of gain across different vehicle models. For instance, delivering 30 kWh to a small city car (e.g., a Fiat 500e with a 42kWh battery) is a massive replenishment event. Delivering the same 30 kWh to a long-range SUV (e.g., a Tesla Model X with a 100kWh battery) is just a minor top-up. By calculating the Delta, we see that the Fiat user gained 71% of their range, while the Tesla user only gained 30%. The SoC Delta allows us to compare these two sessions evenly, revealing that the Fiat user had a much higher utility Requirement for that session.

- *The "Stickiness" Check*

The concept of "stickiness" refers to the tendency of a user to remain connected to a charger after the desired energy level has been reached. This was determined by cross-referencing the Departure SoC with the Average Power. A high departure SoC (72.20%

mean) combined with a low average power delivery (61.21 kW) indicates that the user is likely prioritizing location stay (e.g., shopping or dining) over charging speed.

➤ *Methodological and Ethical Limitations*

In conducting an empirical study of this scale, it is essential to acknowledge the boundaries of the data and the ethical frameworks governing its use. These limitations define the scope of the findings and ensure the research remains academically rigorous and ethically sound.

- *Methodological Limitations*

The primary methodological limitation of this study is data representativeness. Because the dataset is derived exclusively from one public charging provider's infrastructure, the findings primarily reflect the behavior of public chargers or transit users who are the scope of this study. The findings here may not generalize to the wider UK EV population, particularly those with access to residential charging who likely exhibit different arrival SoC thresholds. Furthermore, the study relies on telemetry-based inference. While the data provides "SoC Start" and "SoC End," these values are subject to the accuracy of the vehicle-to-charger handshake (ISO 15118/OCPP). External variables, such as ambient temperature and battery health (SoH), were not available in the logs, despite their known impact on charging curves and power throttling. Finally, the data provides the what but not the why. This is a distinction that session logs alone cannot resolve. A 10% arrival SoC may be a deliberate behavioral choice or the result of a failed charging attempt at a previous location but the data does not capture the difference.

- *Ethical Limitations*

From an ethical perspective, data privacy and GDPR compliance are paramount. Although session identifiers were anonymized, charging logs inherently contain locational privacy risks. Repeated charging events at specific timestamps and locations can, in theory, be used to reconstruct a driver's routine or proximity to their home and workplace. To mitigate this, the analysis was conducted at an aggregate level, ensuring no individual vehicle could be re-identified.

CHAPTER FOUR

RESULTS AND EMPIRICAL FINDINGS

The analysis of the public EV charging data was performed and interesting quantitative results were derived. These findings challenge the average-driver-centric view of charging behaviour, revealing that users are more extreme or risky when it comes to charging their batteries and energy management.

➤ Analysis of Arrival SoC Distribution: The Necessity-Driven Paradigm

The empirical distribution of Arrival State-of-Charge (SoC), as illustrated in Figure 4.1, reveals the stochastic nature of EV driver behavior in the United Kingdom. While traditional infrastructure models often rely on the arithmetic mean to predict grid load, the histogram of Arrival SoC reveals a distribution that is significantly positively skewed, suggesting that mean-based metrics may fail to capture the true operational reality of public charging hubs.

• Revising the Choice of Central Tendency

The most mathematically significant finding in this study is the stark contrast between the mean arrival SoC (27.53%) and the statistical mode (10.00%). In a perfectly normal distribution, these values would align. However, Figure 4.1 shows a massive density spike at the 10% threshold. This modal peak represents the anxiety floor i.e the point at which the risk of an EV being stranded outweighs the inconvenience of a public charging stop.

The fact that the mean is nearly triple the mode is an artifact of the heavy-tail distribution extending toward the right of the X-axis (SoC start). A subset of opportunistic chargers who initiate sessions at 40%, 50%, or even 60% SoC pulls the average upward, creating a distorted average that masks the behavior of the majority. For the Charge Point Operator (CPO), the mode is the more salient figure, as it defines the most common arrival SoC which their grid infrastructure planning must heavily consider.

• Behavioral Archetypes: The Cliff-Edge Driver vs. the Planner

The histogram is a useful model to challenge previous academic models of range anxiety. It allows for the identification of distinct behavioral archetypes based on the frequency bins:

- ✓ The Necessity-Driven Majority (0%–15%): This cluster represents the Cliff-Edge behavior. Much like internal combustion engine (ICE) drivers who operate on the fuel reserve, these users appear to delay charging until it is functionally unavoidable. This suggests that public charging is still viewed as a reactive necessity rather than a proactive choice.
- ✓ The Conservative Shoulder (30%–45%): There is a secondary, less pronounced shoulder in the density curve between 30% and 45%. This likely represents conservative planners, drivers who prioritize a safety buffer or are engaging in destination charging where the stop is dictated by the location (e.g., a supermarket or retail park) rather than an urgent energy requirement.
- ✓ The Opportunistic Tail (50%+): The sparse frequency beyond the 50% mark represents top-up behavior. These sessions contribute significantly to the high mean SoC but represent a lower overall energy demand per session.

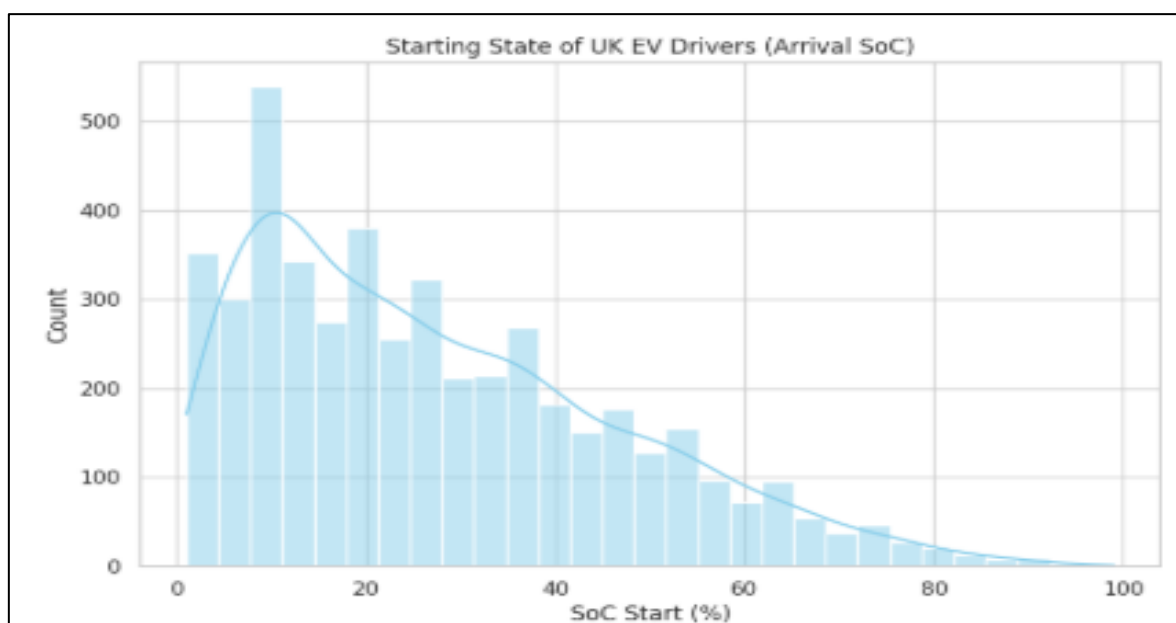


Fig 1 Arrival SoC Distribution

➤ *Power Throttling and Energy Delivery*

A common misunderstanding in EV literature is that the charger's nameplate capacity (e.g. 150kW or 350kW) is the primary determinant of session speed. The empirical results suggest otherwise. By analyzing the relationship between power delivery and energy transfer, we can move beyond idealized hardware specifications to understand the technical and thermal limitations that govern the driver's experience.

• *The Disparity in Power Throughput*

As illustrated in Figure 4, the distribution of charging sessions across the power-energy spectrum reveals a significant performance gap. While the hardware infrastructure utilized in this study is capable of high-velocity output, the arithmetic mean for power delivery was recorded at a mere 61.21 kW. In an era where "Ultra-Rapid" is the industry standard, this figure appears staggeringly low. This disparity is not a failure of the infrastructure itself, but rather a reflection of the vehicle's Battery Management System (BMS) in practice throttling power to avoid damage.

The scatterplot shows a dense concentration of data points in the 40 kW to 80 kW range, regardless of the total energy delivered. This suggests a technical peak imposed by thermal throttling. As lithium-ion cells receive high-current loads, internal resistance generates significant heat. To prevent degradation and ensure safety, the BMS dynamically reduces the intake of power. Furthermore, the charging curve plays a decisive role. As the battery exceeds the 50% State-of-Charge (SoC) threshold, the internal voltage rises, naturally slowing the rate at which ions can be intercalated into the anode. Consequently, the high-power bursts touted by manufacturers are often transient peaks rather than sustained averages.

• *Tactical Replenishment vs. Full Capacity Restoration*

The data throws more light on the nature of public charging utility through the mean energy delivered, which was calculated at 27.95 kWh. When viewed in the context of the current UK EV fleet where average battery capacities reside between 60 kWh and 77 kWh, it becomes evident that the public charging session is rarely used for a full tank replacement. Instead, the typical user is engaged in a tactical top-up, replenishing approximately 40–45% of their total capacity.

Figure 4 reinforces this behavioral trend, showing that the majority of sessions terminate before reaching the 40 kWh mark. This indicates that drivers are utilizing public infrastructure to bridge the gap between their necessity-driven arrival (the 10% modal SoC identified in Section 4.1) and a functional departure (the 72% mean departure SoC identified in Section 4.3). This replenishment strategy optimizes time spent at the charger by avoiding the slow, inefficient tail of the charging curve that occurs above 80% SoC.

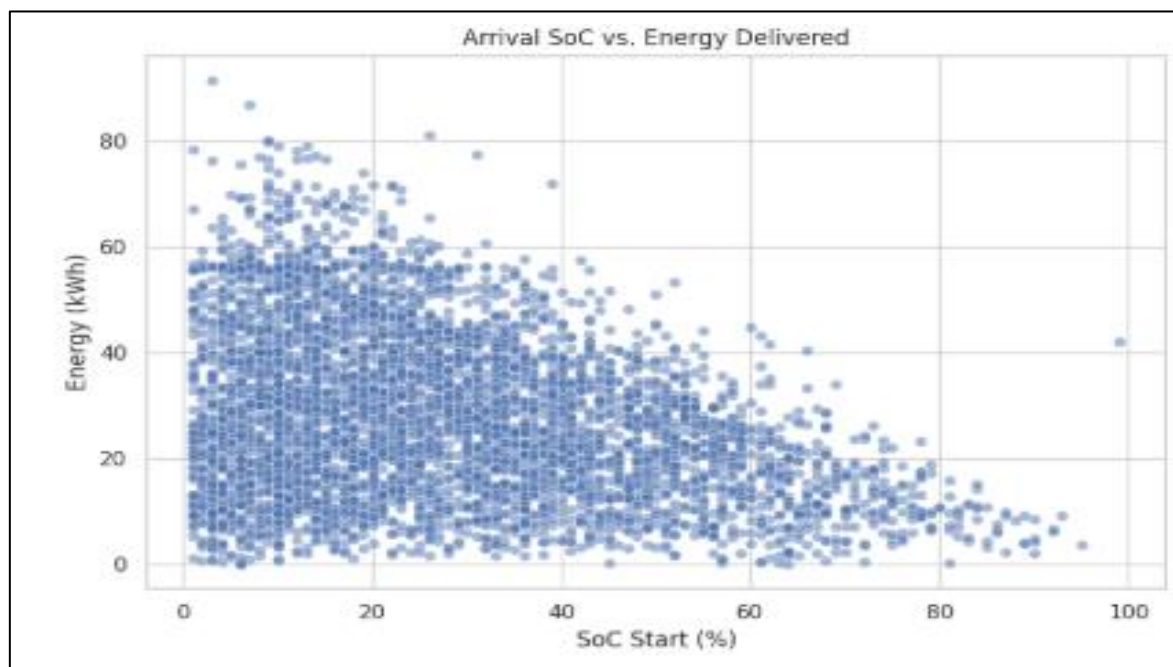


Fig 2 Distribution of Energy Delivered During Charging Sessions

➤ *Departure Psychology: The Intersection of Technical Constraints and Human Dwell Time*

The analysis of Departure State-of-Charge (SoC), as visualized in Figure 4.3, provides a profound insight into the terminal phase of the EV charging session. This checkpoint is dictated less by the necessity seen at arrival and more by a complex interplay of vehicle telematics, psychological heuristics, and location stickiness. While the mean departure SoC of 72.20% offers a useful baseline, the distribution of the data suggests that EV users are navigating a landscape of diminishing returns and secondary motivations.

- *The 80% Heuristic and the Efficiency Threshold*

From the distribution of departure SoC visualized in the histogram in Figure 4.3, we see that a significant number of sessions terminate between 70% and 85%. This range aligns with the 80% Taper, a technical phenomenon where the vehicle's Battery Management System (BMS) reduces the intake of power to preserve lithium-ion cell longevity and prevent thermal runaway.

In an academic context, drivers who disconnect at this stage can be classified as rational technical actors. They recognize that once the charging curve reaches its peak, the time-cost per kilowatt-hour (kWh) increases exponentially. By disconnecting anywhere in the range of 72–80%, these users maximize their miles-per-minute efficiency. The mean SoC Delta of 44.67% further reinforces this, indicating that the typical session is not a full replenishment but a strategic power top-up that spans the most efficient portion of the battery's charging curve.

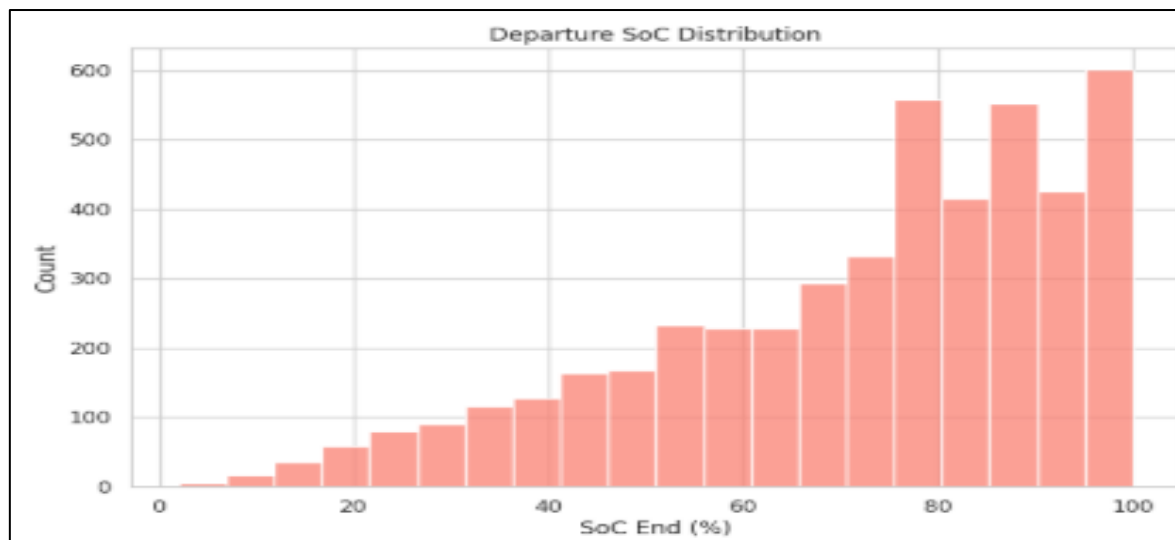


Fig 3 Distribution of Departure SoC

- *The Retail Connection and Location Stickiness*

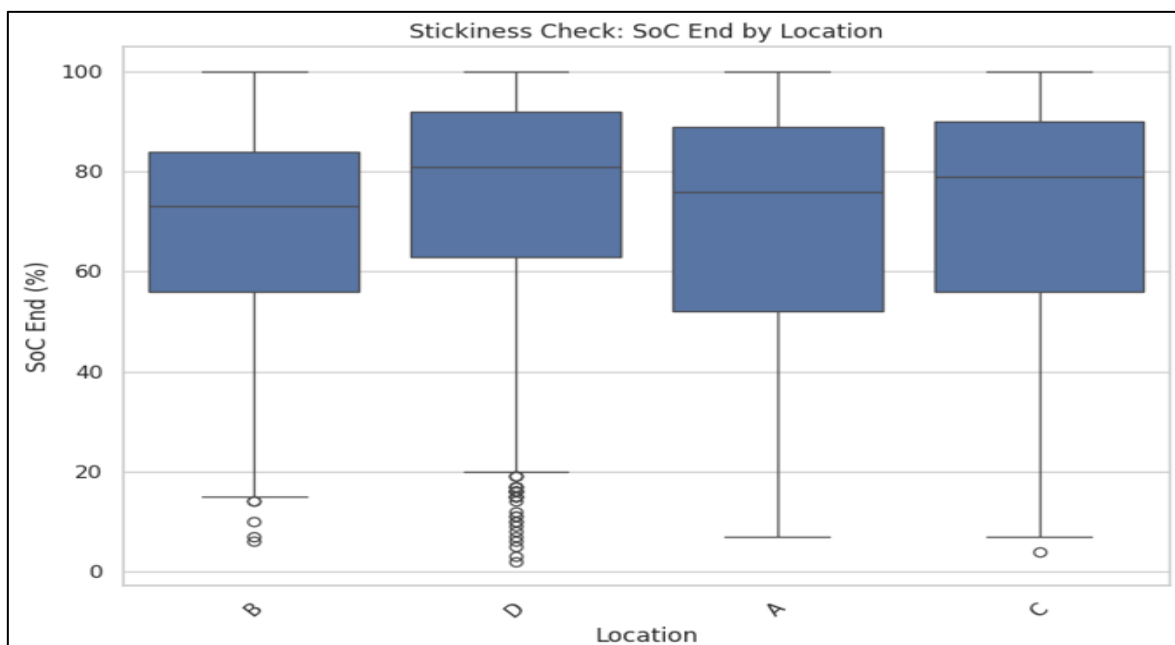


Fig 4 Location Stickiness

The distribution also reveals a substantial tail of sessions that persist well beyond the 80% threshold, with some reaching near-full capacity. According to the data, 48% (almost half) of all the analyzed sessions terminated between 80-100% SoC. In these instances, the driver's behavior appears to decouple from technical efficiency. This identifies the concept of location stickiness. When charging infrastructure is situated within retail or entertainment precincts the charger effectively transitions from a utility to a parking amenity. The relationship between Session Duration (Minutes) and Energy Delivered (kWh), illustrated in Figure 4.3,

provides the most compelling empirical evidence for the phenomenon. In a purely technical system, one would expect a tight, linear correlation where duration is a direct function of energy intake. However, the visualization reveals a significant time variation particularly as session lengths exceed the 40-minute mark.

For a fixed energy delivery e.g. 40 kWh, the duration of the session varies wildly, ranging from a highly efficient 30-minute rapid charge to sessions exceeding 100 minutes. This discrepancy identifies the Dwell-Time Gap. When a session persists for two hours to deliver a volume of energy that the hardware could technically provide in 45 minutes, the driver is no longer charging; they are now dwelling.

This decoupling of time and energy confirms the Retail Connection: the user's departure is tethered to a secondary activity, such as shopping or dining, rather than the battery's requirements.

The data suggests a symbiotic relationship between energy replenishment and retail dwell time. For a user engaged in grocery shopping or dining, the cost of the slow-charging taper is negligible compared to the convenience of the location. In these cases, the departure SoC is not a function of the battery's needs, but a byproduct of the primary activity (e.g., finishing a meal). This stickiness transforms the charging stall into a high-value retail anchor. It was the understanding of this customer psychology that led to the introduction and explosion of retail outlets and self-service at Petroleum filling stations in the late 20th century (Gaston-Breton, 2023, pp. 212–217).

Ultimately, the analysis reveals that departure behavior is a negotiated outcome. It is the point where the decreasing utility of a slowing charge meets the increasing utility of the user's secondary activity. Whether the driver is a technical rationalist departing at 80% or a retail opportunist staying until 95%, the departure SoC remains the ultimate metric of how public infrastructure integrates into the broader tapestry of daily life.

➤ *The Relationship between Arrival SoC and Arrival hour*

Figure 5 illustrates the relationship between the time of arrival and the State of Charge (SoC) of Electric Vehicles (EVs) upon reaching charging infrastructure in the United Kingdom. This dataset is critical for understanding user behavior, predicting grid load, and optimizing the placement of Rapid Charging Points (RCPs).

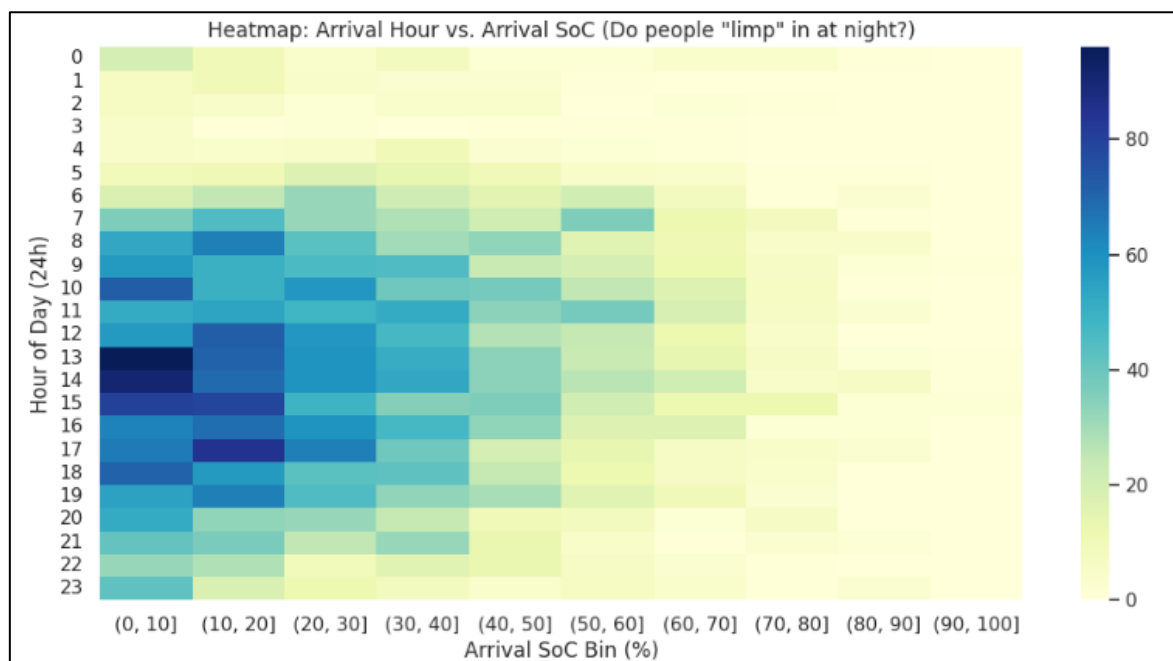


Fig 5 Arrival Hour vs. Arrival SoC

• *Temporal Distribution and Activity Peaks*

The data reveals a distinct diurnal pattern in charging behavior. Activity is minimal during the nocturnal hours (00:00 to 06:00), which suggests that most EV owners either utilize private home charging during these hours or that their vehicles remain stationary.

A significant surge in arrivals commences at 07:00, coinciding with the morning peak commute. However, the most striking feature of the heatmap is the concentration of high-density arrival events between 08:00 and 19:00. During this window, the majority of drivers arrive with an SoC between 0% and 30%. This indicates that public or destination charging in the UK is frequently utilized not for "top-ups" of nearly full batteries, but as a corrective measure for batteries that have reached a critical lower bound.

- *The Mid-Day Depletion Phenomenon*

As noted in the preliminary observation, there is a pronounced density peak for the lowest SoC bin (0-10% SoC) occurring between 13:00 and 15:00. This mid-day trough suggests a specific behavioral pattern. These drivers are arriving at charging stations with nearly depleted batteries during the traditional lunch hour. Several socio-economic and technical factors may explain this behavior:

- ✓ **The One-Trip Threshold:** Many drivers may begin their day with a partial charge, assuming it will cover a morning commute and secondary errands. By mid-day, the cumulative mileage exceeds the vehicle's remaining range, necessitating an immediate stop.
- ✓ **Commercial Use Patterns:** This peak may represent commercial or gig economy drivers (e.g., delivery services or private hire vehicles) who have completed a morning shift and must recharge during their break to facilitate afternoon and evening operations.
- ✓ **Infrastructure Accessibility:** The concentration during lunch hours may imply that drivers are multi-tasking by combining vehicle charging with personal breaks or meal times at service stations or retail parks, where charging infrastructure is more likely to be located in the UK.

- *The Absence of High SoC Arrivals*

A notable trend across the entire 24-hour spectrum is the sparse density in the 60-100% SoC bins. This suggests that opportunistic charging is not the dominant behavior among UK EV drivers. Instead, behavior is driven by utility and necessity. Drivers appear to avoid public charging infrastructure unless the SoC falls below a 40% threshold, likely due to the higher costs of public rapid charging compared to domestic electricity rates or the time-cost associated with stopping.

- *Socio-Technical Explanations*

While there is a steady stream of arrivals at 20:00 and 21:00 with 10–30% SoC, the highest risk behavior (0–10% SoC) is strictly a daytime phenomenon. Possible explanations for this behaviour include:

- ✓ **Workplace Charging Deficits:** The high volume of mid-day arrivals with low SoC supports the theory that workplace charging infrastructure is currently insufficient. Drivers who cannot charge at their place of employment are forced to seek public chargers mid-journey.
- ✓ **Range Anxiety vs. Familiarity:** The willingness of drivers to arrive with less than 10% SoC during the day suggests a growing confidence in the density of the UK charging network. Conversely, the avoidance of low-SoC arrivals late at night may reflect a fear of finding a station occupied or "out of order" when options are perceived to be more limited or safety concerns are higher.

CHAPTER FIVE

DISCUSSIONS AND RECOMMENDATIONS

The preceding chapters have systematically presented the empirical data gathered from public charging stations across the United Kingdom, revealing a detailed quantitative picture of modern electric vehicle (EV) charging behavior. The analysis of the public EV charging data was performed and interesting quantitative results were derived. These findings challenge the average-driver-centric view of charging behaviour, revealing that users are more extreme or risky when it comes to charging their batteries and energy management. By synthesizing these findings, this chapter reconstructs the behavioral profile of the UK EV driver, discusses the broader implications for the charging industry, and provides actionable recommendations for Charge Point Operators (CPOs) and grid managers.

➤ *Synthesizing the Discoveries: The UK EV Driver Profile*

The empirical data successfully challenges theoretical models by providing a stochastic, unvarnished look at the real-world decisions made by EV drivers. The analysis identified that while the mean arrival is 27.53%, the modal arrival SoC, the most common experience, is exactly 10.00%. In a perfectly normal distribution, these values would align. The fact that the mean is nearly triple the mode is proof of the heavy-tail distribution extending toward the right of the mean arrival SoC, driven by a subset of opportunistic chargers who initiate sessions at 40%, 50%, or even 60% SoC.

This establishes a Necessity-Driven Paradigm. The modal peak at 10% represents the anxiety floor i.e the point at which the risk of an EV being stranded outweighs the inconvenience of a public charging stop. Much like internal combustion engine (ICE) drivers who operate on the fuel reserve, these users appear to delay charging until it is functionally unavoidable. This suggests that public charging is still viewed as a reactive necessity rather than a proactive choice.

When analyzing the amount of energy replenished, the data indicates a tactical approach to charging. The typical user is engaged in a tactical top-up, replenishing approximately 40–45% of their total capacity. This is supported by the mean energy delivered, which was calculated at 27.95 kWh. Given current UK EV fleet battery capacities of 60 kWh to 77 kWh, it becomes evident that the public charging session is rarely used for a full tank replacement. High variance in Departure SoC (mean 72.20%) was analyzed to categorize users into Transit Chargers (low delta, high power) and Destination Chargers (high delta, low power).

➤ *Empirical Explanations of EV Drivers' Behavioural Psychology*

The behavioral psychology of the EV driver is largely dictated by environmental, technical, and socio-economic factors. The data reveals distinct psychological thresholds surrounding when drivers charge and when they decide to unplug.

- **The Mid-Day Depletion Phenomenon:** The highest risk behavior (0–10% SoC) is strictly a daytime phenomenon. There is a pronounced density peak for the lowest SoC bin (0-10% SoC) occurring between 13:00 and 15:00. These drivers are arriving at charging stations with nearly depleted batteries during the traditional lunch hour. This suggests the One-Trip Threshold, where drivers begin the day with a partial charge, assuming it will cover morning commutes and errands, only to find their cumulative mileage exceeding their remaining range by mid-day. It may also represent commercial or gig economy drivers recharging during shifts, or drivers multitasking by combining charging with personal breaks at service stations or retail parks. Furthermore, this behavior supports the theory that workplace charging infrastructure is currently insufficient, forcing drivers to seek public chargers mid-journey.
- **Charging Anxiety vs. Familiarity:** The willingness of drivers to arrive with less than 10% SoC during the day suggests a growing confidence in the density of the UK charging network. Conversely, the avoidance of low-SoC arrivals late at night may reflect a fear of finding a station occupied or out of order when options are perceived to be more limited or safety concerns are higher. Activity is minimal during the nocturnal hours (00:00 to 06:00), which suggests that most EV owners either utilize private home charging during these hours or that their vehicles remain stationary.
- **Location Stickiness and the Retail Connection:** A high departure SoC (72.20% mean) combined with a low average power delivery (61.21 kW) indicates that the user is likely prioritizing location stay (e.g., shopping or dining) over charging speed. According to the data, 48% (almost half) of all the analyzed sessions terminated between 80-100% SoC. When charging infrastructure is situated within retail or entertainment precincts, the charger effectively transitions from a utility to a parking amenity. The decoupling of time and energy confirms the Retail Connection: the user's departure is tethered to a secondary activity, such as shopping or dining, rather than the battery's requirements. For a user engaged in grocery shopping or dining, the cost of the slow-charging taper is negligible compared to the convenience of the location.

➤ *Significance and Industry Impact of the Study*

Understanding these empirical realities is immensely significant for the EV charging industry, which must adapt to the needs of the regular EV driver as networks expand dramatically.

For retailers, an EV charger is the modern equivalent of a loss leader. A driver at 20% SoC is a captive audience for at least 30–45 minutes. This stickiness transforms the charging stall into a high-value retail anchor. It was the understanding of this customer

psychology that led to the introduction and explosion of retail outlets and self-service at Petroleum filling stations in the late 20th century. Retailers can use this data to trigger specific marketing like coupons for a sit-down meal or a cinema ticket while the user charges their vehicle.

From a grid planning perspective, the high volume of deep-discharge arrivals creates systemic pressure. The concentration of users at the 10% arrival mark has profound implications for infrastructure throughput. Users arriving at 10% SoC require a significantly higher Depth of Discharge (DoD) replenishment to reach a functional state of charge compared to those arriving at the mean. This creates a disproportionate pressure on rapid-charging hardware, leading to longer occupancy durations and increased queuing during peak periods. Consequently, the 10% Mode serves as a bottleneck; the network must not only provide enough energy to satisfy the mean but must also possess the high-power capacity to handle the deep replenishment cycles required by the modal majority.

➤ *Growth of Public Networks, Rapid Charging Technology, and the Impact of Growth on Charging Behavior*

The expansion of public EV charging networks is strongly supported by the consolidation of fast charging connector technology, and increasing government regulations. These regulations are often stringent, such as the Public Charge Point Regulation which mandated a 99% uptime for charge point operators. The tightened regulation is geared towards improving the reliability of these operators, turning the EV driving experience from an anxiety-inducing one to a predictable part of daily life.

However, there is a technical disconnect regarding rapid charging. A common misunderstanding in EV literature is that the charger's nameplate capacity (e.g. 150kW or 350kW) is the primary determinant of session speed. While the hardware infrastructure utilized in this study is capable of high-velocity output, the arithmetic mean for power delivery was recorded at a mere 61.21 kW. This disparity is not a failure of the infrastructure itself, but rather a reflection of the vehicle's Battery Management System (BMS) throttling power to avoid damage. As lithium-ion cells receive high-current loads, internal resistance generates significant heat. To prevent degradation and ensure safety, the BMS dynamically reduces the intake of power. Consequently, the high-power bursts touted by manufacturers are often transient peaks rather than sustained averages.

➤ *The Future of Expanded Battery Capacities*

As battery capacities continue to grow, the behavioral dynamics of public charging will shift. With expanded capacities, we can anticipate that drivers may rely even less on public infrastructure for full charges. Instead, behavior will be driven by utility and necessity. Drivers will likely continue bridging the gap between their necessity-driven arrival and a functional departure using public chargers to execute tactical top-ups. As the average battery capacity expands, the total volume of energy demanded per session may increase, but the percentage of battery replenished (the SoC Delta) may stabilize or shrink as users optimize time spent at the charger by avoiding the slow, inefficient tail of the charging curve that occurs above 80% SoC.

➤ *Recommendations for Charge Point Operators and Grid Planning*

The data from this study provides highly actionable intelligence for infrastructure and grid management:

- **Implement Dynamic Pricing and Overstay Fees:** If a large proportion of users are departing at ~72%, it implies that the current infrastructure successfully alleviates range anxiety for the next journey but struggles with turnover efficiency. To maximize network throughput, operators may need to consider Overstay Fees or dynamic pricing that incentivizes departure once the 80% threshold is reached.
- **Incentivize High-SoC Opportunity Charging:** High-SoC drivers (e.g., 70%) are opportunity chargers who don't need to be there. Retailers can offer them cheaper electricity to lure them into the store during slow business hours, effectively using the car as a tool for foot traffic. If the grid is overstressed, the utility could send a push notification to users with high SoC incentivizing them to delay charging till there are fewer drivers.
- **Invest in Localized Grid Storage:** Grid operators don't just need to know if people will charge, but where and when they will 'panic-charge' or 'opportunity-charge'. If data shows that drivers with <20% SoC consistently surge toward the nearest fast-charger during a specific highway commute, utilities can build localized battery storage at those specific nodes to prevent a local grid collapse.
- **Prioritize High-Density Hubs:** The finding suggests that future site planning must prioritize high-density, multi-stall hubs capable of handling simultaneous deep-discharge sessions rather than distributed single-charger layouts.
- **Strategically Deploy Slow vs. Fast Chargers:** Understanding SoC driven behaviour can help urban planners determine the best locations to situate a charger. By analyzing where drivers hit their panic threshold, planners can place small, high-speed hubs in those specific areas. Conversely, if data shows most urban drivers top up at 50% SoC while grocery shopping, the city can prioritize slow, cheap AC chargers in parking lots rather than expensive, space-consuming DC fast-chargers. Hence, drivers can choose charging spots that match their energy and cost constraints.

➤ *Recommendations for Future Research*

While this study offers an unprecedented look at quantitative telemetry, several limitations must be addressed in future academic work.

First, future studies should seek to integrate external technical variables. External variables, such as ambient temperature and battery health (SoH), were not available in the logs, despite their known impact on charging curves and power throttling. Incorporating these technical metrics would allow for a much more accurate modeling of the technical efficiency limiters affecting drivers.

Secondly, research must look beyond public charging data to understand the broader ecosystem. The findings here may not generalize to the wider UK EV population, particularly those with access to residential charging who likely exhibit different arrival SoC thresholds. Future studies should aim to aggregate telemetry from domestic wall boxes, workplace charging, and public networks to create a holistic view of the average user's entire charging lifestyle.

Finally, future empirical studies should be paired with qualitative research. The data provides the what but not the why. This is a distinction that session logs alone cannot resolve. A 10% arrival SoC may be a deliberate behavioral choice or the result of a failed charging attempt at a previous location but the data does not capture the difference. Conducting user surveys alongside telemetry data analysis will uncover the explicit motivations behind these decisions, cementing a comprehensive understanding of human behavior in the era of electric mobility.

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