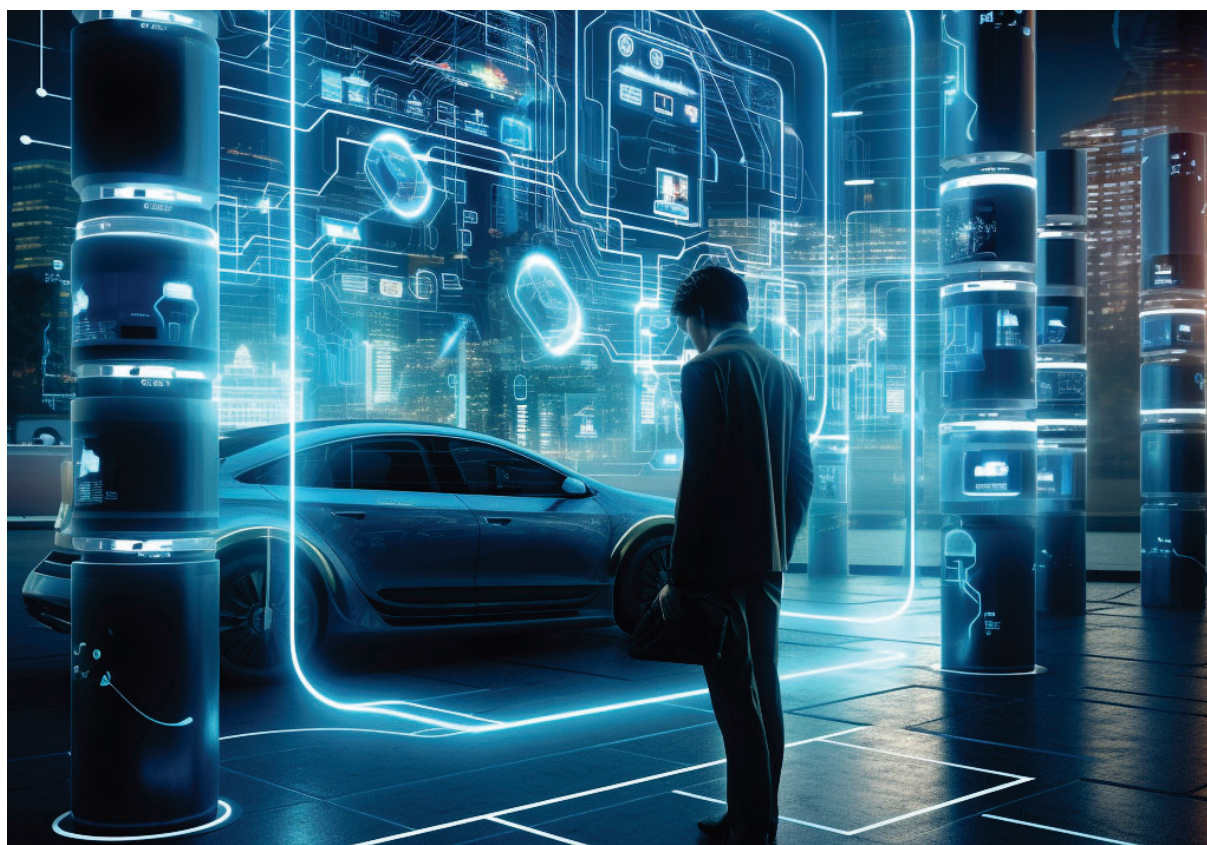


# FREEDOM

## From Connected to Sustainable Mobility



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A project within FFI: Effective and connected transport system

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# 1 Executive summary

Today, the transport sector stands for 25% of global carbon dioxide emissions, a number that has to go down drastically to reach the Paris Agreement. To this end, many initiatives are ongoing: to rethink the need, to adapt behaviour, to change fuel, etc. Connected car data is a surprisingly untapped resource, and machine learning based on it is a crucial tool for making many of these mobility initiatives sustainable. Using vehicle data in the right way has a huge potential, which we aim to explore, to decouple pollution and CO<sub>2</sub> emissions from the mission of providing the necessary mobility for all. Innovative transport solutions require accurate insights as input to decision-makers. However, car manufacturers lack detailed knowledge of real-world usage for the vehicles they produce; owners and drivers are confused about the consequences the decisions they make will have in their particular context, both for sustainability and economy; fleet operators provide inadequate arrangements and inefficient management due to lack of understanding of their distinct needs. All these actors can benefit from the data of millions of connected vehicles once it is analysed. A pipeline from a large-scale car usage data lake maintained at WirelessCar into novel machine learning algorithms developed at Halmstad University was used to help develop services that can lead to sustainable and efficient resource utilisation, while at the same time being realistic in terms of convenience and cost.

Mobility data is characterised by two crucially essential dimensions, namely spatial and temporal aspects. From a technical perspective, obtaining a complete picture requires a framework capable of modelling them simultaneously to take advantage of the insights embedded in the interrelations between the two. Graph Neural Networks (GNNs) are an emerging and promising field of machine learning, in the intersection of deep neural networks and graph theory, that is uniquely suitable to address both aspects. Spatial information is captured by the graph structure, while temporal information is modelled by recurrent neural networks in parallel with the neighbourhood aggregation message passing stage.

Besides the technical aspects of data analysis, service design focuses on design thinking to create and improve services to meet user needs, enhance experiences, and optimise service delivery. It encompasses a holistic approach, considering touchpoints, processes, and interactions throughout the service lifecycle. Integrating service design with data analysis shows high potential for identifying how value can be captured in the mobility context for users and to assess the business value of the service.

The FREEDOM project was a two-year collaboration between Halmstad University (the coordinator), WirelessCar and Laholm Municipality.

## 2 Background

Within a period of just a few decades, the term “sustainability” has become one of the defining features of the 21st century’s reality. Sustainability is, however, not a property of a thing. Things in isolation cannot be sustainable. It is, instead, an emergent feature of complete systems. It is not so much about the parts, as to how the parts work together to enable effective overall outcomes. An electric car is not really sustainable if the power system it uses imports coal from the other side of the planet to provide it with electricity. Neither is a person driving a hybrid car when their travelling patterns do not take advantage of this technology.

The transportation of people and goods today accounts for nearly 25% of the global CO<sub>2</sub> emissions, making it one of the most significant challenges facing cities today; but it also presents an excellent opportunity for low-carbon urban development. Cities around the world have begun to recognise these opportunities and are busy transitioning from the current fossil-fuel dependency to a future built on efficiency and renewable energy. People are also engaged and conscious that they can make a difference by changing their behaviour and demanding environment-friendly alternatives. We are witnessing a shift in attitude towards solutions that protect the planet while improving people’s lives. However, such disruption is not easy. The cities and their transportation systems have become so complex that most people lack the knowledge of what, in their specific situation, can and should be done.

Awareness of travel patterns of vehicles and people makes it possible to evaluate the actual effectiveness of various initiatives and interventions, to provide performance improvement advice, and to propose new strategies to improve transport sustainability. An example is digital services for assisting the end-user in changing their habits to become more efficient travellers, taking into consideration their particular context, i.e., anything from the engine type of their car to the reason for their trips. Another example would be support for company fleet operators to plan just the right composition of the fleet for their specific needs, and the incentives perfectly tailored towards their drivers. The benefit of these findings will affect not only the end-user (individual and fleet) but also vehicle OEMs who can better adapt their designs to actual usage, and city centres in terms of, e.g., congestion and pollution. It is well known that “what gets measured gets managed”. By focusing on the data-driven approach, it is our goal to identify common patterns of mobility and quantify the crucial factors affecting the efficiency of the whole system.

Today’s transportation in our cities is so complex that these factors are generally only understood in a very broad sense, and applying this knowledge in individual contexts is challenging. Generally, adding more roads reduces congestion; however, sometimes, it can increase congestion as people make optimal but only self-interested decisions. There is no hope, realistically, for our cities to reduce in complexity – but we can use the data to build tools for managing this complexity in better, more effective ways, making it possible to consider various perspectives. The outcomes from the FREEDOM project contribute to making the mobility energy efficient and sustainable, by providing all the actors with a more complete view of the consequences of their (both real and potential) actions. The algorithms, insights and digital services resulting from the project assist people in making better holistic decisions on many different levels in order to reduce CO<sub>2</sub> from their transportation, considering multiple criteria; anything from choosing the optimal route, the best time to travel, all the way to selecting the most effective vehicle engine – all based on the analysis of past driving patterns, and comparing them to driving patterns of other people in similar situations.

### 3 Purpose, research questions, and method

With Sustainability as a driver, Data as fuel and ML as an open road, the FREEDOM project was a very exciting journey! Starting with data mining and data pre-processing, moving on to model implementation, training and evaluation, taking a break for parameter tuning and finally peaking at delivering a digital service based on a refined ML model – all to demonstrate how connectivity data leads to more sustainable transportation. We also addressed how to improve the ML model using input from studies of users to identify other types of data that could enhance the value creation of the service. From cutting-edge research to deploying the final trained model in an industrial setting, as well as creating and delivering new services and tools with clear business objectives – the FREEDOM project led to new knowledge and secured a pole position on the front edge of technology and sustainable thinking for both partners.

WirelessCar is a Swedish company, based in Gothenburg and with subsidiaries in the USA, China, and soon Germany. WirelessCar operates the global backend services and telematics for millions of connected vehicles on the roads, with millions of kilometres driven every day. The company is a service provider for the vehicle industry and has in its portfolio some of the most prominent OEMs from around the world: Volvo Cars, Volkswagen, Jaguar, Land Rover, Daimler/Mercedes-Benz, Nissan, and Subaru, to name just a few.

The Centre for Applied Intelligent Systems Research (CAISR) at Halmstad University has been working with Artificial Intelligence (AI), Machine Learning (ML) and Data Mining (DM) related to the automotive industry for many years, collaborating with prominent companies, including Volvo Group, and driving cutting edge research in data-driven solutions for mobility and transport. In addition, Halmstad University has built up a specialisation in Digital Service Design, with a focus on user experience (UX), that we develop together with OEMs in the automotive industry.

Laholm Municipality, a unique landmark of Sweden's longest sandy beach, aims to be a developing professional service and authority organisation within both the town and the countryside.

This combination of the massive amount of relevant but under-utilised data and the AI/ML expertise is what gave birth to the idea of the FREEDOM project, with the Laholm Municipality to give direction. Given that electromobility has gained significant attention in the automotive industry, it is natural that electric vehicles (EVs) have been the primary focus of our analysis. While we covered many different aspects, from reasons to switch to an EV, and the challenges associated with them, to the most important lessons learnt, one particularly promising direction has been the charging process. The charging remains one of the most discussed aspects of EV ownership, and car manufacturers are continuously striving to improve the charging experience for their users.

We have set up a DataOps pipeline as a “single point of truth” to ensure that data was imported, prepared, organised and cleaned in such a way that new data can be consumed with its lineage preserved and with data pre-processing automated wherever possible. For data requiring manual classification work, we have structured it to complement existing data feeds and ensure the process is as fair and bias-free as possible. Model definitions and parameter settings are version-controlled, and jobs are triggered by changes and/or periodically invoked. We have also set up an ML-Ops pipeline that can automate tests to standardise data science development environments, lower the costs of data science experiments and add value to improve the overall quality of Machine Learning, validating data distribution, validating model quality metrics and validating model bias and fairness.



## 4 Goal

The project was designed from the beginning with several layers of goals in mind.

The first level is pure factual statements, answers to concrete questions. As of today, our society's understanding of the immensely complex relations within the mobility domain is a somewhat dangerous mix of facts and opinions. Getting to uncover the true picture, measured in a definite and objective way, was going to be immensely useful both inside and outside of the FREEDOM consortium. Analysis of data in the project provided answers to many important questions. Without such knowledge, almost all services and initiatives to improve sustainability end up being based on guesswork rather than facts, and in the end, turn out to be impossible to evaluate rigorously.

The second level of results concerns the service design part of the project will explore the potential for sustainability improvements using Customer Journey Maps, Business Model Canvas, Personas and Scenarios, Ecosystem Maps, and other techniques. In particular, if driver behaviour would improve within realistic limits, what would be the magnitude of the environmental benefits? Are these benefits substantial in themselves, or is our focus better directed towards technological advances? How big is the potential of low-inconvenience carpooling in different Swedish cities? Does it depend on local conditions, and does it vary across different areas or seasons? Looking at technology advancements, what is the difference, in terms of environmental benefits, between hybrid vehicle adoption and electric vehicle adoption? Are hybrids worthwhile as an interim solution, or not? Would people whose driving patterns today make hybrid vehicles not a suitable alternative, be realistically able to change their behaviour to still benefit from hybrids, assuming their overall transport needs remain constant?

The third level of results comprises developing novel cutting-edge AI and ML algorithms, both general approaches towards handling highly structured input data, and specifically in understanding travel information and patterns. Historically, analysing data of such spatial and temporal complexity using ML has been challenging – results depended heavily on the time-consuming and error-prone process of hand-crafting informative features. Moreover, such solutions are historically only developed for small-scale problems, for example, estimating anomalous traffic situations on a single road segment. Our FREEDOM results, however, are partially built on a relatively recent idea of using Graph Neural Networks (GNNs) to model various transport-related factors. It is a field that combines the success of deep learning, most prominent in analysing images, with the flexibility of graph theory. It extends the classical deep neural network paradigm to allow encoding of the inherent structure in the input space – in this context, there is a clear application to map data, with key infrastructure nodes and their spatial relations. This rich structure can then be augmented with another critical aspect of travel data, namely the temporal dimension, which one typically models within each node of the graph using recurrent neural networks. Particularly from the mobility point of view, the concept of message passing between nodes of GNNs is well-suited to model the flow of vehicles between nodes, along with all relevant information, including energy consumption, CO<sub>2</sub> emissions, and so on.

Finally, the fourth level of results concerns the collaboration findings and knowledge dissemination, in particular, how to integrate academic work into industrial product and service development. The recent focus on data and AI is proving challenging for companies to act upon and integrate into day-to-day operations. At the same time, though, it promises a revolutionary change in how research and academic collaboration are being approached – no longer are research projects limited to early phases of product development, years or decades from customer deployment. We now have opportunities for

cutting-edge research to end up on the market within months. Doing so, however, requires addressing several important challenges, including the right level of integration between technical aspects of AI, and the service design part; and reliability, scalability and reproducibility aspects of academic ML.

## 5 Results and Goal Achievement

### 5.1 Data, Infrastructure and Processing

Ensuring production-level quality of the data, and the reproducibility of machine learning models is a crucial requirement for complex collaborative work, especially a project like FREEDOM that involves multiple people and organisations. The starting point for the practical analytics work was a data lake with cleaned, validated and catalogued data, enabling insights from direct data analysis, such as answers to factual statements and charts illustrating the source data. Also, information not required for the analysis was either eliminated, pseudonymised or reduced in precision to limit the amount of personal data processed, in accordance with GDPR regulations.

### 5.2 Artificial Intelligence and Service Design

One important goal was to merge Service Design and Machine Learning/Data Analytics to create tools and methodologies that encourage users to reduce their carbon footprint. This effort focused on iterative development using available and potential data sources to identify how ML models can integrate service design outcomes effectively.

**Deliverables:** The main deliverable was an established data-driven methodology. A methodology combining service design, ML, and analytics was established to support carbon footprint reduction. Activities included workshops and studies on car sharing with connected car data, the electric vehicle (EV) ecosystem, stakeholder management, and the creation of a value model for the EV ecosystem.

**Web Article Publication:** "How can EV driver insights improve connected car service design?" This article summarised a study on EV drivers' experiences and concerns, identifying diverse driver groups to enhance connected car services through a better understanding of driver needs.

**Service Innovations in the EV Sector:** An empirical study of EV users' everyday charging and driving behaviour was conducted to identify value processes. This qualitative data was then analysed against the outcome of ML models (see 5.3).

**Drivers:** Little is previously known in service design research about the connection between EV drivers' driving and charging behaviour. The study provided novel results on actual behaviour and how drivers adapt charging and driving when switching from ICE to EV. Our study shows that range anxiety, which has been identified in previous mobility research as a major threat against transformation towards EVs, had little bearing on actual behaviour. Drivers change driving behaviour towards more planning using apps and actual experience of using an EV in everyday activities. A common pattern was that drivers divided their activities into short, medium, and long-range drives using different charging and driving approaches for each type of journey, such as planning stops during long-range travel. The latter was especially prominent among families going on holiday trips. We identified the need for predicting price fluctuation as a possible new value source for EV drivers, which led to the development of the service *Plug & Save* based on price prediction using ML. The other most important result was that, while previous research has identified range anxiety as a

hindrance to the transformation of mobility towards EVs, personal experience of switching from ICE to EV radically reduced range anxiety. Based on these insights, we identified the need to provide ICE drivers with a service that recommends a suitable EV based on users' current driving behaviour. This was implemented in the service *BEV4ME*, which uses data of actual driving to map current driving behaviour to EV battery capacity, to reduce range anxiety and support actual swap from ICE to EV.

Our research focused on understanding the adoption and usage patterns of electric vehicles (EVs) among 21 urban residents. We explored their demographic backgrounds, ownership and leasing behaviours, motivations for choosing EVs, and the challenges they encountered. This approach provided insights into the factors that influence urban dwellers to transition from internal combustion engine (ICE) vehicles to EVs.

**General Findings:** The study predominantly involved female participants, primarily aged between 46 and 55 years, living in urban areas. This demographic trend underscores a significant inclination towards EV adoption among city dwellers. A notable finding was the preference for company lease options over personal ownership and private leasing, highlighting the impact of corporate policies and incentives on facilitating EV adoption. Most participants were in the early stages of their EV journey, with a direct shift from ICE vehicles to EVs, indicating a readiness to embrace fully electric technology.



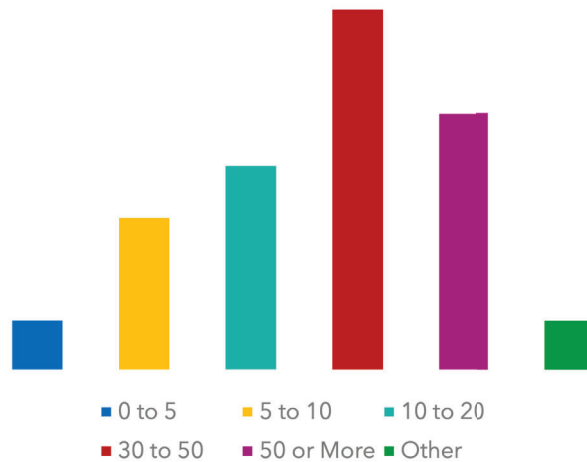
*Demographics of study participants*

The study further revealed that the majority of EV users have a daily commute ranging between 30 to 50 kilometres. This finding is particularly relevant as it falls well within the range of capabilities of most current EV models, assuaging concerns about battery life and the feasibility of using an EV for daily transportation needs.

The convenience of charging an EV at home means that for these daily commutes, the vehicle is more than capable of meeting the day's travel requirements on a single charge. This ease of use, combined with the knowledge that their commute is environmentally friendly, contributes significantly to the satisfaction levels of EV users.



Avg. Daily Distance (km)



Furthermore, for those with longer daily commutes of over 50 kilometres, the increasing availability of public charging infrastructure has made EV ownership more practical. This group's commuting behaviour supports the expansion of charging networks and the need for strategic placement of charging stations to accommodate longer-distance EV commuters.

In contrast, individuals with shorter commutes, particularly those travelling less than 20 kilometres per day, find EVs exceptionally convenient, as their vehicles often require less frequent charging. This flexibility in charging, coupled with the reduced operational costs of EVs compared to ICE vehicles, underscores the economic benefits of EV ownership across various commuting distances.

### Driving Personas

In applying Rogers' (1995) Innovation Diffusion Theory, we categorised the study participants into distinct personas—Innovators, Early Adopters, Early Majority, and Late Majority—based on factors like their duration of EV usage, driving experiences, encountered challenges, and underlying motivations.

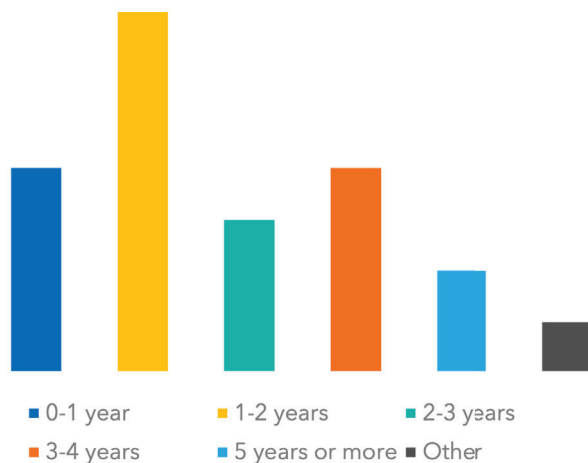
Innovators, with over five years of experience using EVs, demonstrated a deep commitment to embracing new technologies, fueled by a desire to address environmental issues and a passion for innovation.

Early Adopters, who have been using EVs for 3 to 4 years, struck a balance between a fascination with new technologies and practicality, often maintaining an ICE or hybrid vehicle as a contingency.

The Early Majority, with 2 to 3 years of EV usage, are steadily becoming more comfortable with EV technology, marking a critical segment in achieving wider EV acceptance.

The Late Majority, characterised by their environmental awareness, cost sensitivity, technological curiosity, and appreciation for convenience, still exhibit caution towards range and charging anxiety. However, they are increasingly willing to share their EV experiences and participate in social platforms dedicated to EV discussions.

## EV ownership duration



Despite the enthusiasm for EVs, participants reported several challenges, highlighting concerns over the availability and functionality of charging infrastructure, the costs of EV ownership, and the vehicle's performance. Issues such as the scarcity of charging stations, especially in rural areas, the unpredictability of charging costs, and the perceived inadequacies in EV performance under harsh conditions were noted. Additionally, the complexity of navigating multiple applications for charging access and concerns about the resale value of EVs were seen as barriers to adoption.

### Motivations for adopting EVs

On the motivations behind EV ownership, our study unearthed several key drivers influencing urban residents' decision to adopt EV technology. These motivations span environmental, economic, and social dimensions, reflecting a complex web of considerations that guide individuals toward making the transition from ICE vehicles to EVs.

### Environmental Concerns

A primary motivation among participants was the desire to reduce their carbon footprint and contribute to environmental sustainability. The transition to EVs is seen as a crucial step in mitigating the impact of personal transportation on climate change. Participants expressed a keen awareness of the environmental benefits associated with EVs, such as zero tailpipe emissions, which align with broader goals of reducing air pollution and conserving natural resources.

### Economic Factors

Economic considerations also played a significant role in the decision to own an EV. Many participants were drawn to the potential cost savings over the life of the vehicle, including lower fuel costs, reduced maintenance expenses, and various government incentives and subsidies for EV purchase and ownership. The perception of EVs as being more cost-effective in the long term, despite higher upfront costs compared to ICE vehicles, emerged as a compelling factor for adoption.

## Technological Attraction and Social Influences

The allure of advanced technology and the opportunity to engage with innovative automotive features were also cited as motivations. Participants valued the cutting-edge technology inherent in EVs, including regenerative braking, electric drivetrains, and smart connectivity features, which enhance the driving experience and vehicle efficiency.

Social influences, including the impact of friends, family, and societal trends, further motivated individuals to consider EVs. The growing visibility of EVs on the road and in media, combined with positive word-of-mouth from existing EV owners, contributed to a social momentum towards electric mobility. Additionally, owning an EV was seen as a statement of commitment to sustainability and technological progress, reinforcing the owner's identity as a forward-thinking individual.

**Value creation in charging ecosystems:** In addition, qualitative interviews with different stakeholders in the charging ecosystem identified how value creation is related to stakeholder roles in the value creation process for charging. Our research identified how these stakeholders contribute to shaping the value-creation process within charging ecosystems. We identified eight value sources and their role in value creation and value realisation and identified four types of resource combinations in the orchestration of value creation in charging mobility ecosystems. The eight key value sources identified within charging mobility ecosystems are the distribution of charging facilities, travel planning, cost predictions, payment handling, availability of digital services, facilitation of electromobility, city planning, and EV residual value. The eight value sources constitute four value creation dimensions (infrastructure, payments, deployment, and planning), which play a crucial role in driving the value creation process and influencing interactions among stakeholders. The table below illustrates the value creation framework in charging mobility ecosystems. This identified framework consists of three main parts: value sources, value creation and value realisation. It also gives a comprehensive overview of the identified value creation and value realisation patterns.

#	Value Sources	Value Creation		Value Realization		
		Resource Combination	Resource Exchange	Opportunities	Parties	Perception
1	Distribution of charging facilities	Charging Mobility Infrastructure	Intrinsic Value	Institutional Infrastructure	- Drivers. - Municipalities. - Charging facility providers.	Distributing charging stations to drivers.
2	Travel planning		Economic Value	Social	- Drivers. - OEMs. - Third-party developers. - Data Service providers	Helping drivers by providing detailed travel planning solutions.
3	Cost predictions	Charging Mobility Payments	Economic Value	Environmental, Economical	- Drivers. - Third-party developers. - Data Service providers	Providing detailed cost energy and charging costs for drivers.
4	Payment Handling			Settlement	- Charging facility providers. - Third-party developers.	Processing payments for charging stations to drivers.
5	Availability of Digital Services	Charging Mobility Deployment	Intrinsic Value	Logistics	- Third-party developers. - Data Service providers	Deployment of digital services for drivers.
6	Facilitation of electromobility			Environmental	- Drivers. - Municipalities. - Charging facility providers. - Third-party developers. - Data Service providers - OEMs.	Enabling electromobility services and solutions.
7	City planning	Charging Mobility Planning	Intrinsic Value	Planning	- Drivers. - Municipalities. - Data Service providers	Planning of cities based on electromobility services and drivers' routes.
8	Residual value			Environmental	- Drivers. / Fleet Operator - Municipalities	Providing residual values to drivers.

*Value Creation in Charging Mobility Ecosystems*

**Plug & Save:** A service offering daily recommendations on optimal charging times to reduce costs and environmental impact for EV owners. Using service design methods, the functions, interface, and UX were designed and tested.

**BEV4ME:** A service recommending the most suitable EV based on a user's driving behaviour, aimed at those transitioning from ICE vehicles to EVs.

### 5.3 Machine Learning for Mobility Data

Several different AI/ML tools, methods and algorithms have been developed as part of the project, some of them – but not all – based on the original ideas of GNNs. Most of them are described in detail in the scientific publications resulting from the project. We describe the five most relevant ones here.

#### 5.3.1 Evaluating Charging Strategies for Electric Vehicles

A significant difference between electric vehicles and fossil-fuel-powered vehicles is the widely different prices for energy across time. Although the prices of oil, gasoline and diesel fuel do vary over longer periods of time, the fact that such commodities can be stored results in a natural cushioning of the price variations as experienced by consumers. Additionally, there are several levels of price hedging in the industry, which again protects consumers from price spikes. In contrast, electrical energy cannot easily be stored in large quantities and over long periods of time, which in combination with a greater reliance on non-dispatchable electricity sources, results in a more volatile price. This volatility is, to an increasing degree, passed on to the consumer, through either voluntary or mandatory time-variable prices. As a result, the cost of electricity itself can vary by an order of magnitude during the hours of the day – from a combination of recurring daily, weekly and yearly patterns as well as events such as unexpected power plant closures or unusually cold, windy or sunny days.

Due to these significant price variations, there is a much greater opportunity for optimising the charging of an electric vehicle than there is for fuelling up a fossil fuel vehicle. We have focused on optimising for *price*, primarily because there is historical ground truth data available for prices. An alternative would have been to optimise for CO<sub>2</sub> emissions (or equivalents), which would also have been interesting but has less accessible – and less objective – ground truth data available. For the purposes of this paper, we therefore focused on prices and left other evaluations for future work.

In evaluating the charging strategies, there are several possible methods and benchmarks available. For example, one possibility is to model the electricity system and simulate many different possible outcomes. This has the benefit of providing large amounts of data, and also the ability to simulate situations which have never occurred in practice. However, it has the drawback of requiring a very accurate model to capture every detail of the electricity system. Therefore, we opted for one of the other possible methods: backtesting strategies on actual historical data. This means a more limited data set, with 24x365 data points per year and electricity region, but ensures an anchoring to real-world performance – at least historically.

Another factor in evaluating strategies is choosing the comparison benchmarks. It is not unreasonable to assume a variation in user patterns, with some enthusiasts and early adopters paying especially close attention to charging costs, while other users simply plug in the car when they return home from work, or whenever they feel that it has a too low state of charge. We compare our results to several of these benchmarks in order to paint a fair and realistic picture of what savings can be achieved.

Finally, the potential savings are affected by the size of the battery of the vehicle. A larger battery can soak up more excess energy from the grid, and therefore achieve greater savings over time. However, a larger battery also comes with a higher cost of materials, as well as a greater environmental impact, meaning there is a sweet spot where incremental savings in electricity consumption are no longer justified purely from an economical perspective.

### *5.3.2 Semantics-aware Dynamic Graph Convolutional Network for Traffic Flow Forecasting*

Traffic flow forecasting is a challenging task due to its spatio-temporal nature and the stochastic features underlying complex traffic situations. Currently, Graph Convolutional Network (GCN) methods are among the most successful and promising approaches. However, most GCN methods rely on a static graph structure, which is generally unable to extract the dynamic spatio-temporal relationships of traffic data and interpret trip patterns or motivations behind traffic flows. In this paper, we propose a novel Semantics-aware Dynamic Graph Convolutional Network (SDGCN) for traffic flow forecasting. A sparse, state-sharing, hidden Markov model is applied to capture the patterns of traffic flows from sparse trajectory data; this way, latent states, as well as transition matrices that govern the observed trajectory, can be learned. Consequently, we can build dynamic Laplacian matrices adaptively by jointly considering the trip pattern and motivation of traffic flows. Moreover, high-order Laplacian matrices can be obtained by a newly designed forward algorithm of low time complexity. GCN is then employed to exploit spatial features, and Gated Recurrent Unit (GRU) is applied to exploit temporal features. We conduct extensive experiments on three real-world traffic datasets. Experimental results demonstrate that the prediction accuracy of SDGCN outperforms existing traffic flow forecasting methods. In addition, it provides better explanations of the generative Laplace matrices, making it suitable for traffic flow forecasting in large cities and providing insight into the causes of various phenomena such as traffic congestion. The

### *5.3.3 Dynamic Causal Explanation-Based Diffusion-Variational Graph Neural Network for Spatio-temporal Forecasting*

Graph neural networks (GNNs), especially dynamic GNNs, have become a research hotspot in spatio-temporal forecasting problems. While many dynamic graph construction methods have been developed, relatively few of them explore the causal relationship between neighbour nodes. Thus, the resulting models lack strong explainability for the causal relationship between the neighbour nodes of the dynamically generated graphs, which can easily lead to a risk in subsequent decisions. Moreover, few of them consider the uncertainty and noise of dynamic graphs based on the time series datasets, which are ubiquitous in real-world graph structure networks. In this paper, we propose a novel Dynamic Diffusion-Variational Graph Neural Network (DVGNN) for spatio-temporal forecasting. For dynamic graph construction, an unsupervised generative model is devised. Two layers of graph convolutional network (GCN) are applied to calculate the posterior distribution of the latent node embeddings in the encoder stage. Then, a diffusion model is used to infer the dynamic link probability and reconstruct causal graphs in the decoder stage adaptively. The new loss function is derived theoretically, and the reparameterisation trick is adopted in estimating the probability distribution of the dynamic graphs by Evidence Lower Bound (ELBO) during the backpropagation period. After obtaining the generated graphs, dynamic GCN and temporal attention are applied to predict future states. Experiments are conducted on four real-world datasets of different graph structures in different domains. The results demonstrate that the proposed DVGNN model outperforms state-of-the-art approaches and achieves outstanding Root Mean Squared Error (RMSE) results while exhibiting



higher robustness. Also, by F1-score and probability distribution analysis, we demonstrate that DVGNN better reflects the causal relationship and uncertainty of dynamic graphs

### *5.3.4 Enhancing Energy Efficiency in Connected Vehicles for Traffic Flow Optimization*

In urban settings, the prevalence of traffic lights often leads to fluctuations in traffic patterns and increased energy utilisation among vehicles. Recognising this challenge, this research addresses the adverse effects of traffic lights on the energy efficiency of electric vehicles (EVs) through the introduction of a Multi-Intersections-Based Eco-Approach and Departure strategy (M-EAD). This innovative strategy is designed to enhance various aspects of urban mobility, including vehicle energy efficiency, traffic flow optimisation, and battery longevity, all while ensuring a satisfactory driving experience. The M-EAD strategy unfolds in two distinct stages: First, it optimises eco-friendly green signal windows at traffic lights, with a primary focus on minimising travel delays by solving the shortest path problem. Subsequently, it employs a receding horizon framework and leverages an iterative dynamic programming algorithm to refine speed trajectories. The overarching objective is to curtail energy consumption and reduce battery wear by identifying the optimal speed trajectory for EVs in urban environments. Furthermore, the research substantiates the real-world efficacy of this approach through on-road vehicle tests, attesting to its viability and practicality in actual road scenarios. In the proposed case, the simulation results showcase notable achievements, with energy consumption reduced by 0.92% and battery wear minimised to a mere 0.0017%. This research, driven by the pressing issue of urban traffic energy efficiency, not only presents a solution in the form of the M-EAD strategy but also contributes to the fields of sustainable urban mobility and EV performance optimisation. By tackling the challenges posed by traffic lights, this work offers valuable insights and practical implications for improving the sustainability and efficiency of urban transportation systems.

### *5.3.5 Deep Learning for Generating Synthetic Traffic Data*

In this study, we demonstrated the feasibility of combining traffic simulator technology with Machine Learning methods to create realistic and comprehensive synthetic traffic data. Synthetic data alleviates many ethical and privacy concerns, significantly reduces the costs associated with data collection, and enables researchers to study scenarios and conditions that are difficult or impossible to replicate in real-world environments. Access to large amounts of diverse and controlled data is essential for developing and testing Artificial Intelligence models and leads to more reliable and robust results. Traffic simulators like SUMO have been successfully used for that purpose in the past, creating realistic vehicular traces. One drawback is that, without coupling them with complex physics emulators, they are not capable of generating internal vehicle parameters. Such parameters, on the other hand, are crucial for many purposes, from understanding energy efficiency and optimising driver behaviour to predictive maintenance and monitoring the degradation of key components, such as driveline batteries. In this paper, we propose a Synthetic Traffic Data Generator (STDG) and demonstrate that an ML model that is trained on the internal parameters of a vehicle in one set of conditions (Sweden) can be used to generate synthetic data corresponding to another setting (Monaco). The proposed method promises to eliminate the need for an expensive collection of the original vehicle parameters across many different settings. Moreover, sharing the synthetic data with additional stakeholders is easier due to the reduced security and integrity risk of exposing the vehicle's privacy-sensitive original parameters. This study compares several ML techniques, including Deep Learning (DL), for generating internal parameters of vehicles, such as fuel rate, engine speed, and wet tank air pressure. Using the actual bus data from a small city to train our ML models, we attempt to

forecast the internal parameters of the buses in various scenarios. The proposed method first utilises SUMO to generate synthetic waypoints for the bus and then predicts the other parameters using the trained model, thereby producing synthetic data with internal parameters for buses operating in a new urban environment. Our preliminary results indicated that our model is performing well within a 90% confidence interval.

## 5.4 Sustainability

Our work in the project aimed to enhance the sustainability and efficiency of the transportation system, with a particular focus on accelerating the transition to electric vehicles (EVs). The two directions that were particularly in focus during the FREEDOM project: accelerating the EV transition and strategies to reduce EV GHG emissions during the use phase. Through comprehensive research and development efforts, we sought to generate objective knowledge about the current state of transportation sustainability and identify improvement potentials across various areas. The deliverables included educational materials disseminated via talks and publications, the development of Graph Neural Network (GNN) models for predicting travel parameters, and a counterfactual model for optimising travel decisions.

The project's insights were synthesised in publications, both scientific and for a wide audience, focusing on how digital services leveraging connected car data can drive sustainable mobility. These publications aim to capture attention by simplifying complex findings into key learnings, emphasising the role of data analytics and digital solutions in promoting EV adoption and sustainability in transportation.

**Data-Driven Insights for Sustainable Transportation:** Developed and shared factual knowledge on the efficiency and potential enhancements within the transportation sector. This was achieved through various channels, including presentations, applied scientific publications, and talks, focusing on the optimisation of electrification and the promotion of green electricity.

**Replacement of ICE Vehicles with EVs:** Supported initiatives to enable a smooth transition from Internal Combustion Engine (ICE) vehicles to EVs, including the development of digital services based on connected car data.

**Seamless Charging with Renewable Energy:** Assisted Original Equipment Manufacturers (OEMs) in providing solutions for fleet owners and end-users to charge EVs with renewable energy sources, thus supporting a greener energy system.

**Maximising Vehicle Lifetime Value:** Worked on increasing utilisation rates and creating alternative revenue streams for EVs, aiming to reduce operating costs and emissions while enhancing vehicle durability and residual value.

**Increasing Vehicle Efficiency:** Suggested improvements in vehicle design, such as powertrain efficiency, weight reduction, and aerodynamics, to lower emissions.

**Promoting Sustainable Driving:** Encouraged the adoption of efficient driving practices through training and digital nudges, potentially integrated into vehicle interfaces.

**Data-Driven Emissions Understanding:** Advocated for the use of real usage data to accurately calculate GHG emissions, enabling targeted reduction strategies.

**Supporting Renewable Energy and Efficient Charging:** Proposed partnerships with renewable energy providers and the integration of green charging station data into car interfaces, encouraging charging at times that align with lower emissions and energy costs.

## 5.5 Business Opportunity

An important objective of the FREEDOM project was to define the business value and establish a business case for services designed to support the principal project partner, WirelessCar, in its strategic business objectives. The research was aimed at providing actionable insights that could serve as inputs for investment decisions, aid in shaping the scope and value propositions for customer engagement, and help position WirelessCar as a leader in environmental sustainability within the automotive industry.

In terms of contributions to WirelessCar's business strategy, the FREEDOM project achieved several key objectives:

- **To better understand the EV users' behaviours and preferences:** This understanding is key to developing services that resonate with the target market and meet the evolving needs of EV owners.
- **To develop services that address specific challenges faced by EV owners:** By focusing on the real-world issues that EV owners encounter, the services aim to enhance the overall EV ownership experience.
- **To assist WirelessCar in reducing the environmental impact of EVs:** The services were designed not only with the end-user in mind but also to support WirelessCar's commitment to sustainability.

### 5.5.1 Plug & Save

This service was developed to establish WirelessCar as a vital contributor to the electrification of the automotive industry, assisting OEMs in mitigating buyer concerns and improving the EV ownership experience. By advising EV owners on the optimal time to charge their vehicles based on electricity price predictions, Plug & Save facilitates cost savings and environmental benefits.

#### Outcomes:

- The launch of the Plug & Save pilot garnered significant attention with over 1000 website visitors.
- Publication of a detailed blog article on WirelessCar's website to educate and engage users.
  - [AI-research project started for sustainable mobility](#)
  - [How can EV driver insights improve connected car service design?](#)
  - [How does machine learning contribute to WirelessCar's development of connected car services?](#)
  - [How do digital services based on connected car data contribute to sustainable mobility?](#)
  - [Mobility Insights: How connected car data optimizes mobility and incentivizes greater sustainability](#)
  - [How can electric vehicle \(EV\) drivers save money and reduce their environmental footprint at the same time?](#)
- Presentation of the concept to potential customers, furthering business development efforts.

### 5.5.2 Best EV For Me

This service positions WirelessCar as a supportive entity in the automotive industry's shift toward electrification, particularly in helping OEMs minimise their environmental footprint. By using actual driving data to recommend the most suitable battery size, "Best EV for Me" enables a more informed purchase decision, contributing to environmental sustainability.

#### Outcomes:

- The application of driver patterns based on journey data has provided valuable insights into the vehicle battery design for a WirelessCar customer.

By fulfilling these objectives, the research has contributed significantly to supporting WirelessCar's positioning as an environmentally conscious and customer-centric company in the competitive automotive market.

## 6 Dissemination and publication

### 6.1 Dissemination of knowledge and results

How have/are the project results used and disseminated?	Mark	Comments
Increase knowledge in the area	X	The project increased our knowledge due to many interviews with EV owners, leading to a better understanding of EV barriers.  It also increased technical knowledge of applying AI in real business settings, and the infrastructure that is needed to make that happen.
Carried forward to other advanced technology development projects	X	WirelessCar is continuing with creating an MVP for the ML pipeline to hopefully have a solid foundation for internal and customer-trained ML models in the future.
Forwarded to product development projects	X	Product management within WirelessCar is considering moving forward with Plug & Save as a WirelessCar offering to its customers.
Introduced to the market	X	A first POC of the Plug & Save service is available on the WirelessCar page at: <a href="https://www.wirelesscar.com/plugandsave/">https://www.wirelesscar.com/plugandsave/</a>
Used in regulations and political decisions		No, outside of the project scope

## Events:

- Organised the workshop and tutorial “IoT Streams for Predictive Maintenance Third Edition”, ECML/PKDD 2022.
- Presentation on Synthetic Data at Polestar Knowledge Session.
- Presentation at WirelessCar internal Town Hall meeting.
- “Bridging Two Worlds - Navigating Research Frontier and Real-World Relevance” keynote at the 12th International Conference on Prestigious Applications of Intelligent Systems, 2023.
- Organised “XAI<sup>3</sup> Joint workshops on XAI methods, challenges, and applications” at ECAI 2023, Krakow, Poland.
- Organised tutorial “XAI for Predictive Maintenance” at KDD 2023, Long Beach, CA, USA.
- Presented FREEDOM and Plug&Save during WirelessCar Customer Summit day, June 2023.
- (upcoming) Presentation at the FFI conference in Stockholm, on 28 May 2024.

## 6.2 Publications

The FREEDOM project resulted in a number of publications summarising the newly developed algorithms and reporting performed experiments.

- Zeinab Shahbazi, Siddhant Som, Sławomir Nowaczyk, Jens Andersson, Sami Fatmi. *Evaluating Charging Strategies for Electric Vehicles*. Preprints 2024, 2024020337.
- G Liang, U Kintak, X Ning, P Tiwari, S Nowaczyk, N Kumar. *Semantics-aware Dynamic Graph Convolutional Network for Traffic Flow Forecasting*. IEEE Transactions on Vehicular Technology, 2023.
- G Liang, P Tiwari, S Nowaczyk, S Byttner, F Alonso-Fernandez. *Dynamic Causal Explanation Based Diffusion-Variational Graph Neural Network for Spatio-temporal Forecasting*. arXiv preprint arXiv:2305.09703, 2023.
- Zeinab Shahbazi, Sławomir Nowaczyk. *Enhancing Energy Efficiency in Connected Vehicles for Traffic Flow Optimization*. Smart Cities 2023, 6(5), 2574-2592.
- Summrina Kanwal, Sławomir Nowaczyk, Mahmoud Rahat, Jens Lundström, Faiza Khan. *Deep Learning for Generating Synthetic Traffic Data*. 9th International Congress on Information and Communication Technology, London, 2024.
- Sławomir Nowaczyk, Andrea Resmini, Vicky Long, Vaïke Fors, Martin Cooney, Eduardo K. Duarte, Sarah Pink, Eren Erdal Aksoy, Alexey Vinel, Mark Dougherty. *Smaller is smarter: A case for small to medium-sized smart cities*. Journal of Smart Cities and Society, vol. 1, no. 2, pp. 95-117, 2022.
- Ågerfalk, P. J., Axelsson, K., & Bergquist, M. (2022). Addressing climate change through stakeholder-centric Information Systems research: A Scandinavian approach for the masses. *International Journal of Information Management*, 63, 102447.
- Ghazawneh, A., Bergquist, M., Senyemi, C. *Unpacking The Complexity Of Value Creation In Charging Mobility Ecosystems: A Multi-stakeholder User Perspective* paper was submitted to the European Conference on Information Systems (ECIS) 2024.



## 7 Conclusions and Continued Research

We believe there is low-hanging fruit available when it comes to time-shifting the charging patterns of electric vehicles, even before solutions such as V2G become widely available. Changing from one charging strategy to another does not need to affect the behaviour of the user if implemented appropriately, and in regions where hourly pricing is available, the gains can be realised by unilateral action from individual car owners. Ideally, this action would only mean opting in to optimised charging – or that the car manufacturers provide optimised charging by default, similar to how both iOS and Android phones nowadays automatically apply battery-conserving charging patterns unless the user explicitly opts out of it.

## 8 Participating parties and contact persons

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