Navigating the Sustainable Mobility Transition: Designing a Data-Driven Decision Support System for Planning and Operating Electric Vehicle Workplace Charging Infrastructure

Marcel Seger[a,*], Christian Brand[a,b], Christoph Clement[c], Marc-Fabian Körner[d], Charlie Wilson[a,e]

[a] Environmental Change Institute, University of Oxford, 3 S Parks Rd, Oxford, OX1 3QY, UK
[b] Transport Studies Unit, University of Oxford, 3 S Parks Rd, Oxford, OX1 3QY, UK
[c] Center for Artificial Intelligence in Medicine, University of Bern, Murtenstrasse 50, Bern, 3008, CH
[d] FIM Research Center, University of Bayreuth, Wittelsbacherring 10, Bayreuth, 95444, DE
[e] International Institute for Applied Systems Analysis, Schlossplatz 1, Laxenburg, 2361, AT

Abstract

The rapid adoption of electric vehicles (EVs) intensifies the need for workplace charging infrastructure, which can shift demand from peak evening hours to daytime and better align with renewable generation. Yet many firms underestimate the long-term implications of workplace charging for electricity demand, costs, and carbon emissions. To address this foresight gap, we developed an open-source decision support system (DSS) that uses firm-specific data and data-driven modelling to simulate the medium- to long-term impacts (5-15 years) of different workplace charging strategies. Our DSS enables executives to evaluate trade-offs between peak load management, cost minimisation, and emissions reduction when planning and operating EV charging infrastructure. Following the Design Science Research approach, we developed, demonstrated, and evaluated our DSS with rich real-world data from eight German companies. Additional interviews showed that executives particularly value the tool for making trade-offs explicit and for fostering cross-departmental dialogue. Usability evaluation with the System Usability Scale resulted in a score of 81.8, confirming

*Corresponding author

Email addresses: marcel.seger@eci.ox.ac.uk (Marcel Seger), christian.brand@ouce.ox.ac.uk (Christian Brand), clement.christoph@icloud.com (Christoph Clement), marc.koerner@fim-rc.de (Marc-Fabian Körner), charlie.wilson@eci.ox.ac.uk (Charlie Wilson)

high usability. Our research advances the DSS literature by extending prevailing DSS design for sustainability transitions through the integration of firm-specific data, explicit trade-off representation, and collaborative decision support. In doing so, it strengthens the user-oriented perspective within the sustainable mobility transition discourse, which has so far been dominated by system-level analyses. Responding to several scholarly calls, our study contributes to green information systems, data-driven operations research, and energy modelling by demonstrating an applicable, user-oriented DSS. Ultimately, our artefact supports organisational transitions towards low-carbon mobility by revealing decision tensions that are otherwise obscured.

Keywords: Green Information Systems, Design Science Research, Sustainable Mobility, Charging Infrastructure, Open-Source Web Application, Decision Support.

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1. Introduction

By 2030, the International Energy Agency projects annual sales of eight million passenger electric vehicles (EVs) in Europe. This is almost four times the 2024 level. It will increase electricity demand for EV charging more than threefold, reaching 82 GWh [1]. Public charging stations, including those at workplaces, will therefore play an increasingly important role. This is particularly relevant for people without access to home charging, who are more likely to come from less affluent backgrounds [2, 3].

For firms, the stakes are considerable: Recent analyses suggest that investing in workplace charging infrastructure and electrifying company fleets with renewable-powered EVs can yield annual savings, per firm, of up to €$100k$ and cut emissions by 250 tCO_2 [4]. With the number of workplace charge points expected to increase fivefold in the UK and more than double in Germany by 2030 [5, 6], the need for evidence-based and firm-specific decision support to guide these investments is becoming increasingly urgent. In response, business executives now face the task of strategically planning the build-out of EV charging infrastructure.

This is partly driven by stricter environmental regulations, such as the obligation to report commuting practices as part of Scope 3 emissions [7]. In Germany, firms are further required by the *'Gebäude-Elektromobilitätsinfrastruktur-Gesetz (GEIG)'* to provide at least one EV charge point in parking lots with more than 20 spaces, effective January 1, 2025 [8]. Yet many decision makers still adopt a short-term view. As a McKinsey & Company report notes, *"many building owners do not think or plan for EV charging needs five to eight years out"* [2, p. 6]. Such short-term orientation can have substantial financial consequences: *"Decisions made today (...) could cause EV infrastructure costs to compound to hundreds of billions of dollars"* [2, p. 7] at the macroeconomic level [9]. Business executives in particular lack firm-specific decision support for the complex task of planning and operating EV workplace charging infrastructure, including modelling how different charging strategies affect peak demand, charging costs, and emissions in the medium to long term (5–15 years) [10].

The groundbreaking advancements in data-driven computing and reasoning capabilities now enable organisations to access such highly contextual insights, empowering them to navigate these complex, decision-critical environments through advanced analytical insights: To plan effectively for low-carbon mobility, workplace operators need tools that can anticipate the long-term benefits of installing and operating EV charging infrastructure. This requires analysing trade-offs between charging strategies and their impacts on both environmental and economic sustainability. As we will outline, executives face a threefold, interdependent decision problem: First, sizing infrastructure by deciding how many charge points to install based on anticipated employee EV uptake; second, managing demand by choosing whether to leave charging unmanaged or coordinate it through smart charging algorithms; and third, choosing objectives, which, if smart charging is used, involves deciding whether to minimise peak demand, costs, or emissions. These choices determine the firm's aggregate load profile and influence key metrics such as maximum peak demand, total charging cost, and carbon emissions, from which trade-off decision tensions arise [11]. Scholars in energy modelling, green information systems (IS), and energy informatics have studied the benefits of grid service provision from EV batteries [12, 13, 14, 15], partly also in the context of EV workplace charging [16]. However, most of these studies adopt the perspective of network operators or electricity market agents, i.e., a system-level perspective. As Ketter et al. [17] and Schroer et al. [18] highlight, academic research has yet to provide practitioners with adequate methods, data, and systems in the context of the sustainable mobility transition, such as those needed to evaluate the trade-offs that arise when planning and operating workplace charging infrastructure. Addressing this gap motivates our work.

We address this organisational problem by posing the following research question: *How can a decision support system (DSS) tailored to firm-specific electricity data help executives evaluate trade-offs between peak load, costs, and emissions in the context of EV workplace charging?* To answer this, we developed, demonstrated, and evaluated an applicable, i.e., user-friendly and context-specific, open-source web application. The tool enables workplace practitioners to model the impact of EV charging on their firm-specific electricity profile.

With our study, we further aim to quantify the decision tensions firms face when applying the DSS to real-world data. Moreover, we aim to assess the perceived value of our DSS for practitioners and to identify ways to improve it. We follow the Design Science Research (DSR) paradigm [19]. Accordingly, we use rich real-world electricity data and several in-depth qualitative interviews with eight medium- to large-sized German companies for the development and demonstration of our DSS. In addition, we apply quantitative usability testing using the System Usability Scale (SUS) to rigorously evaluate the applicability of our artefact. Based on an overall SUS score of 81.8, interviewees have reported to find the web application of high practical use, while providing actionable advice for further improvements.

The remainder of this paper is structured as follows. §2 reviews related literature in three areas: (green) IS for low-carbon energy and mobility, smart EV charging, and DSSs for data-driven power load modelling. §3 introduces our methodological approach. §4 presents the design and development of the artefact. §5 reports the demonstration and evaluation, including findings from interviews and usability testing. §6 discusses broader implications and contributions of our study, while §7 concludes with key results and an outlook.

2. Background and related literature

2.1. Information systems for low-carbon energy and mobility systems

For decades, green IS has emerged as pivotal research community in addressing the challenges of sustainability and efficiency in energy and mobility systems by analysing and designing digital and applicable solutions with real-world impact [17]. In particular, we situate our work within the broader discourse in IS research advocating for more applicable knowledge and impactful solutions to address the challenges of the energy transition and climate change [20]. Corresponding research focuses, among others, on the design, implementation, and use of IS to improve environmental performance across various domains and areas, e.g. with respect to sustainable supply chain management [21], (digital) carbon accounting systems [22], energy-aware business process management [23], and organisational digital decarbonisation approaches [24] for environmental sustainability. While, on the one hand, such systems aim to enable organisations to monitor, measure, and optimise their resource consumption and reduce their ecological footprint, there is, on the other hand, also research that emphasises the role of digital technology systems in optimising energy generation, distribution, and consumption, often referred to as energy informatics [25]. Studies address smart grid management [26], decentralised energy systems [27], and demand-side energy management [28], all aiming to facilitate renewable integration and create smart, adaptive energy markets and systems.

In the context of mobility, both green IS and energy informatics have contributed to EV charging infrastructure development. Examples include optimised load balancing and renewable integration into charging networks [12], as well as Vehicle-to-Grid (V2G) approaches that mitigate peaks through predictive algorithms and dynamic pricing [29]. Since the majority of these studies focus on network operators or electricity market agents, their perspective tends to remain at the systemic level, with an emphasis on market and grid implications. User-oriented approaches have improved the EV charging experience, with tools for intelligent navigation to available charging stations, real-time availability updates, and dynamic pricing to promote energy-efficient charging behaviours [30, 31]. Despite these advances, little user-oriented guidance exists on how to plan and operate EV workplace charging infrastructure using firm-specific data - a key enabler for scaling EV adoption and reducing emissions in the mobility sector [2, 32].

2.2. Smart EV charging

Smart charging is central to sustainable mobility systems. It involves managing EV charging loads according to predefined objectives, such as minimising peak demand, reducing costs, or lowering carbon emissions [33]. To this end, Zheng et al. [34] provide a review on common objective functions and modelling approaches in this field. In workplace contexts, algorithms have been developed to jointly optimise infrastructure sizing and the assignment of vehicles to charging spots, see e.g., [3]. When combined with on-site solar generation, real-time energy management systems can produce optimal charging schedules, thereby increasing self-sufficiency and lowering operational costs [35]. Bidirectional charging (V2G) provides an additional benefit by drawing energy from EV batteries during electricity demand peaks at industrial sites [36]. While these studies provide valuable insights, they are not easily transferable across workplace settings. Much of the literature frames workplace charging primarily as an engineering problem, focusing on energy or cost optimisation [37]. Less attention is given to the organisational decision-making processes that guide infrastructure deployment and management [10]. This gap highlights a practical challenge for operators: evaluating the strategic trade-offs among different charging strategies. Addressing this requires integrated DSSs that combine robust optimisation models with support for organisational decision-making.

2.3. Decision support systems for data-driven modelling of power loads

DSSs have a long history in sustainability and energy management research, especially within the green IS and energy informatics communities [17]. They frequently use advanced analytical methods such as Artificial Intelligence (AI)-driven forecasting, simulation, and optimisation to support operational decisions about electricity demand [18, 12]. Examples include Gust et al. [38], who combine predictive analytics and optimisation for grid planning, or Schuller et al. [39], who benchmark smart charging and V2G strategies while accounting for driving patterns, battery degradation, and energy price variability, thus emphasising the complexity and practical relevance of detailed economic modelling within DSS frameworks. Despite these advances, most DSSs either focus on technical optimisation alone or rely on generic datasets. Few integrate detailed, data-driven load simulation with firm-specific decision contexts. Recent work in green IS has explicitly called for such integration [17, 18].

Our study responds to this gap by contributing a DSS that combines technical modelling with managerial decision processes. By embedding firm-specific data and making trade-offs explicit, we extend DSS design beyond optimisation and toward broader organisational sustainability transitions.

3. Methodology

3.1. Research design

We applied a Design Science Research (DSR) approach, which *"creates and evaluates IT artefacts intended to solve identified organisational problems"* [40, p. 77]. Our process followed five steps: (i) problem identification, (ii) definition of objectives, (iii) design and development of the artefact, (iv) demonstration and rigorous evaluation, and (v) communication of design knowledge. Three design cycles (cf. Figure 1) allowed us to iteratively refine the artefact. Unlike the six-step process by Peffers et al. [19], we report on steps 4 and 5 together, as previous studies have done [41].

As outlined above, we identified a central organisational problem in line with previous literature [10]: executives often lack analytical foresight about the grid impacts of EV workplace charging. In particular, they have limited awareness of the benefits of managing charging points through smart charging versus leaving charging uncontrolled [10], particularly regarding the quantification of their impacts. While uncontrolled charging typically

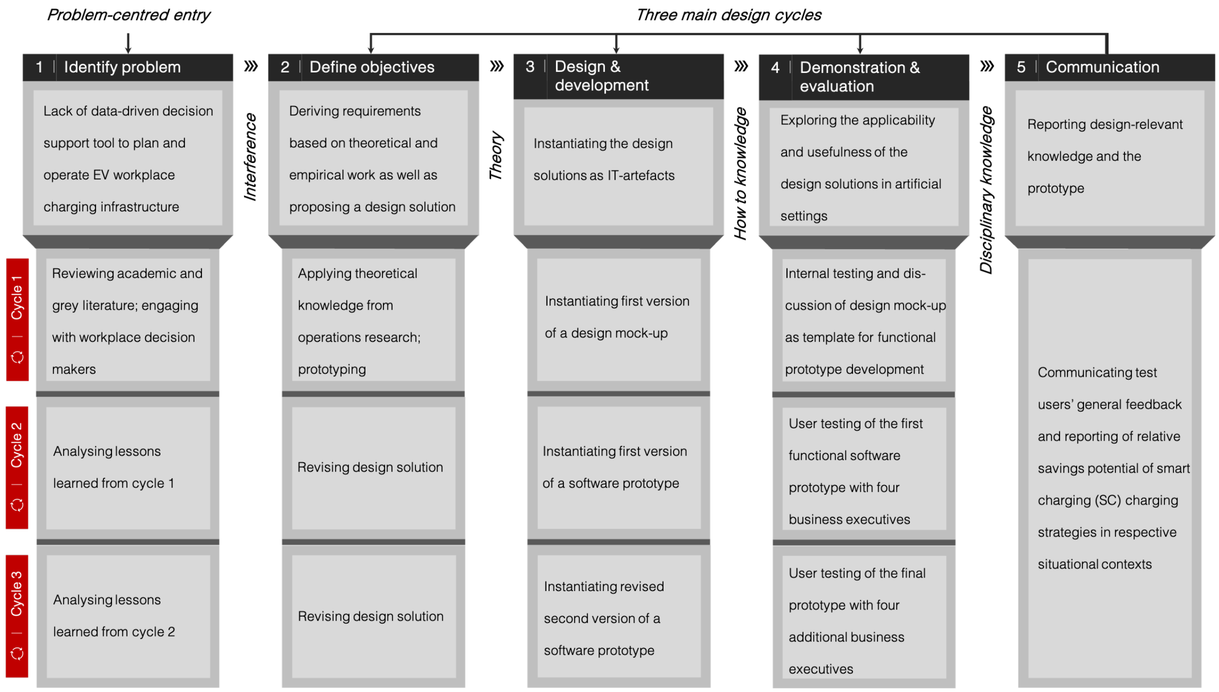

Figure 1: Overview of our DSR process; adapted from Peffers et al. [19] and Schoormann et al. [41]

begins immediately upon plug-in as employees arrive at the workplace, potentially leading to significant peak demand spikes at the aggregate level when large numbers of EVs require simultaneous charging, smart charging allows for distributed load management aligned with pre-defined objectives, such as minimising peak demand, reducing charging costs, or lowering emissions [33]. The choice among these smart charging strategies depends upon the local decision context, for instance, reducing peak demand to accommodate limited on-site grid capacity, or addressing financial considerations (charging costs) and environmental or regulatory compliance requirements (carbon emissions minimisation) [34]. A mathematical formulation of the optimisation model can be found in Tables 4–5 of [42] and is explained in §4.1 in more detail. To address this real-world challenge, we designed a generic, open-source DSS prototype that enables firms to model charging strategies with their own data. After identifying the problem (step 1), we defined objectives (step 2), designed a prototype (step 3), and demonstrated and evaluated it with firms in our sample (steps 4–5). Note that we use the data collected during steps 2-5 comprehensively across design cycles 1-3.

3.2. Sampling approach

We recruited eight firms for the demonstration and evaluation of our DSS. These firms, introduced in Table 1 in full detail based on decision-critical data, form our sample. We do not treat them as *'case studies'* in the conventional sense. Instead, we used their contextual and load profile data to develop and parametrise the DSS and to demonstrate its usability.

Table 1: Sample overview, including firm-specific modelling inputs. IDs are used as anonymous identifiers.

DC [1]	ID	Sector	Electricity consumption (p.a.)	Main demand source	Work shifts	# Cars	EV rate (status quo)	Type of analysis
2	1	Media & publishing	20,000 MWh	Printing machinery	AM (06:00–14:00)	90	5%	Firm-specific data
					PM (14:00–22:00)	80		
					Night (22:00–06:00)	60		
2	2	Office supplies	232 MWh	Office buildings	Office staff (08:00–16:00)	50	25%	Firm-specific data
2	3	Healthcare	6,137 MWh	Hospital operations	Fleet (16:00–07:30)	50	10%	Firm-specific data
2	4	Pharma	6,000 MWh	Drug manufacturing	AM (06:00–14:00)	100	10%	Firm-specific data
					PM (14:00–22:00)	150		
					Night (22:00–06:00)	80		
					Office staff (08:00–16:00)	300		
3	5	Paper production	197,290 MWh	Production machinery	AM (06:00–14:00)	250	5%	Firm-specific data
					PM (14:00–22:00)	175		
					Night (22:00–06:00)	80		
					Office staff (08:00–16:00)	60		
3	6	Manufacturing	4,000 MWh	Compressed air generation	AM (06:00–14:00)	100	30%	Firm-specific data
					PM (14:00–22:00)	70		
					Office staff (08:00–16:00)	100		
3	7	Building materials	2,000 MWh	Office buildings, HVAC	Office staff (07:30–17:00)	500	12%	Standard load profile
3	8	Energy infrastructure	1,724 MWh	Production machinery	AM (06:00–14:00)	170	3%	Firm-specific data
					PM (14:00–22:00)	30		
					Office staff (07:00–16:00)	140		

[1] DC = Design cycle

We selected firms according to three criteria. First, they were medium- to large-sized organisations with extensive parking spaces (>40) and concrete plans to install EV charging. The sector each firm operates in and the respective energy intensity of its underlying business processes can vary from small-scale, energy-efficient office operations to large-scale, manufacturing-heavy and energy-intensive environments operating on multiple work shift schedules daily (cf. Table 1). Second, we targeted firms with limited in-house energy management capabilities, indicated by the absence of dedicated procurement departments. Third, we restricted the sample to Germany, where the EU's Directive 2018/844 on the energy performance of buildings (GEIG) has applied since January 2025 [8] (cf. §1).

Table 1 summarises the eight sample firms, including their sectors, annual electricity consumption, and main sources of demand. While we developed a first version of the tool, i.e., design cycle 1, based on prior literature, such as [10], we evenly distributed the firms between design cycles 2 and 3. Companies 1–4 (IDs) evaluated the initial version of our artefact (cf. Figure 6 of [42]) in design cycle 2, while companies 5–8 (IDs) assessed the enhanced version (cf. Figure 7 of [42]) in design cycle 3. We sourced participating firms through three channels: (i) digital flyer advertisements on LinkedIn, (ii) targeted outreach via cold emailing, and (iii) the authors' professional networks.

3.3. Data collection and analysis

We used a mixed-methods interview design with both qualitative and quantitative components. For each firm, we conducted two semi-structured interviews using Microsoft Teams. The interview guides are listed in Tables 6–7 of [42]. The first interview explored the firm's current practices and plans for EV workplace charging, energy management, and procurement, and included a short demonstration of the DSS. Between interviews, firms were asked to provide contextual data (Table 1) which parametrised the DSS. The second interview demonstrated the DSS using the firm's own data, presented analytical insights, and collected feedback on functionality, usability, and perceived usefulness. At the end, participants completed the SUS questionnaire [43] to measure perceived usability.

Table 2: Data collection timeline and interviewees' role descriptions, grouped by design cycles

DC [1]	ID	Role of interview partner(s) [2]	Date of interviews: Interview 1 Duration (mm:ss)	Date of interviews: Interview 2 Duration (mm:ss)
2	1	a: Corporate sustainability b: Finance/energy procurement	26.11.2024 (45:39)	04.12.2024 (49:54)
2	2	a: Head of facility management	10.12.2024 (28:29)	14.01.2025 (42:33)
2	3	a: Strategic purchasing b: Fleet management	28.11.2024 (31:01)	17.01.2025 (39:06)
2	4	a: Energy provisioning (engineering) b: Head of corporate responsibility	22.01.2025 (36:22)	21.02.2025 (46:39)
3	5	a: Executive assistant CEO b: Energy portfolio manager	05.03.2025 (36:41)	30.04.2025 (49:07)
3	6	a: Sustainability manager b: Project manager (engineering) c: Team lead maintenance	05.03.2025 (38:17)	06.05.2025 (40:39)
3	7	a: Sustainability manager	11.04.2025 (47:05)	28.04.2025 (29:11)
3	8	a: Engineer sustainability manager	30.04.2025 (18:55)	07.05.2025 (36:13)

[1] DC = Design cycle;

[2] Note that interviews were attended by either one, two, or three company representatives, where letters (a), (b), and (c) specify each individual's role.

In total, we conducted interviews with 14 practitioners from the eight firms. Participants represented roles across sustainability, energy, facilities, fleet, and finance. This variety ensured that our evaluation reflected diverse organisational perspectives. Table 2 provides more contextual information pertaining interviewees' roles within the firm, and the date and duration of each interview. Moreover, Figure 2 depicts the entire data collection process for each participating firm.

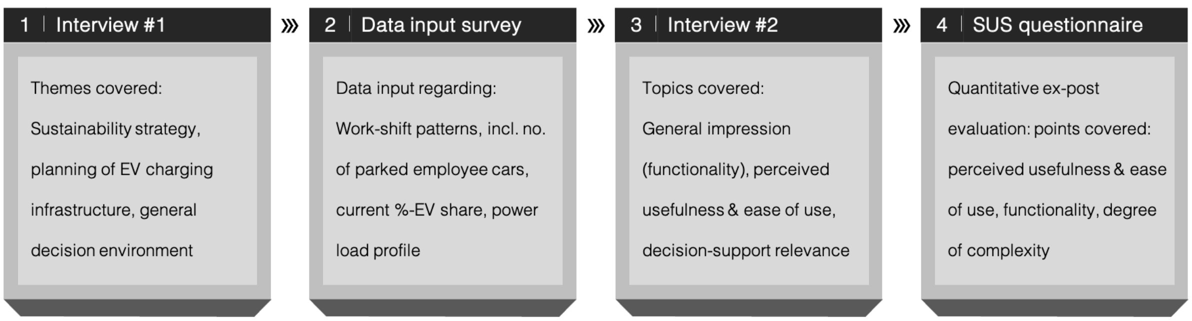

Figure 2: Summary of data collection points for each participating firm.

For qualitative analysis, we applied a deductive coding approach, i.e., our coding categories were defined in advance, based on established DSSs and IS evaluation dimensions. In our study, we structured the coding scheme around four categories: (i) Perceived usefulness, (ii) usability and ease of use, (iii) organisational value, and (iv) suggestions for improvement. These categories align closely with prior frameworks. Perceived usefulness corresponds to Davis' [44] construct of usefulness in the Technology Acceptance Model. Usability and ease of use map onto system quality and user satisfaction, as outlined in the DeLone & McLean [45] IS Success Model and often assessed through usability instruments such as the SUS [46] or user satisfaction surveys [47]. Organisational value reflects the dimension of net benefits in the DeLone & McLean [45] model, capturing how systems contribute to broader organisational performance and decision-making. Finally, suggestions for improvement serve as an open category to capture user-driven recommendations not covered by existing frameworks, ensuring that our analysis remained responsive to context-specific insights.

4. Design and development of the artefact

4.1. Design cycle 1

In the first design cycle, we focused on building the optimisation core of the DSS. We implemented a mixed-integer linear programming model for smart charging, drawing on the formulations of Ioakimidis et al. [36] and Zheng et al. [34]. The model determines optimal charging schedules by minimising one of three objectives - peak demand, electricity costs, or carbon emissions - subject to physical and operational constraints such as battery capacities, charging power limits, arrival and departure times, and exogenous load profiles.

Our modelling framework follows the approach introduced by Seger et al. [10], to which we refer for details on the full optimisation problem and solution method. In our implementation, we coded the optimisation algorithms in Python and connected them to the DSS interface through a modular back-end (cf. design cycles 2-3). This allows users to run firm-specific simulations based on their own data. The full model formulation, including objective functions and constraint sets, is provided in Tables 6–7 of [42] for transparency and reproducibility. By concluding design cycle 1, we had established a technically validated optimisation module that served as the engine of the DSS, forming the basis for subsequent cycles of real-world application and user evaluation (design cycles 2-3).

To support early design decisions, we created a high-fidelity mock-up of the user interface in Figma. This is a widely used approach to save valuable resources (time, development costs etc.) within Design Science and user-centred design [48]. The mock-up defined the layout and components of the dashboard, including a three-column structure with a collapsible sidebar for data input, a central panel for line graphs, and a right-hand panel for key metrics. This static prototype (cf. Figure 6 of [42]) served as the basis for subsequent development.

4.2. Design cycle 2

In the second cycle, we translated the static Figma prototype into a functional web application (cf. Figure 7 of [42]). We used the open-source toolkit Streamlit, which offers

Python packages for building interactive applications without resource-intensive front-end programming. The application interface consists of three main parts. First, a sidebar collects firm-specific input such as (a) number and timing of work shifts, (b) number of employee cars per shift, (c) EV battery size distributions, (d) electricity load profiles (uploaded as .xls or .csv files), and (e) analysis preferences (date, solver, charger power). While these exogenous input parameters are held constant, the decision maker gets to choose the EV electrification rate freely between 0% (no EV present) to 100% (fully electrified car fleet), in alignment with different future electrification scenarios. Second, the main panel visualises electricity demand profiles under three charging strategies: peak minimisation & valley filling (PM-VF) (top row), charging cost minimisation (CCM) (middle row), and carbon emission minimisation (CEM) (bottom row; cut off in the screenshot in Figure 7 of [42]). Each plot compares uncontrolled charging with the corresponding smart charging strategy. Third, bar charts display the Value of Smart Charging (VoSC), defined as the relative change (%Δ) between smart- and uncontrolled charging for each key metric (i) maximum peak, (ii) total charging costs, or (iii) carbon emissions. The system updates results in real time when input parameters are changed.

4.3. Design cycle 3

After demonstrating the first functional prototype with firms in our sample (design cycle 2, cf. §3.3), we obtained valuable user feedback with actionable advice on what should be improved within design cycle 3. We identified 16 feature requests which we subsequently clustered into three priority levels (*high, medium, low*). We categorised feature requests as 'high' based on (i) relevance (certain features have been requested several times throughout interviews), (ii) technical feasibility, and (iii) resource availability (e.g. time) to develop the request. In the third design cycle, we implemented the following high-priority improvements: a multi-period analysis allowing users to view results daily, weekly, or monthly, with shaded confidence intervals indicating variability; external data integration enabling automated retrieval of German electricity price data from *entso-e*'s transparency platform (bidding zone

DE-LU) [49] and grid-carbon intensity data from *electricity maps* [50]; in-app explanations providing contextual tooltips to improve self-efficacy and understanding; graph enlargement and export functions for reporting purposes; an option to display the VoSC in absolute rather than relative terms; and improved visual clarity through tick boxes allowing selective display of external electricity price and carbon intensity curves.

Remaining medium- and low-priority features are documented in §A.5 of [42]. These relate to (a) tariff-specific grid carbon intensity measures, (b) tariff-specific electricity price data (fixed/dynamic), (c) data-driven forecasting of firm's electricity load profile, (d) firm-specific peak pricing, (e) analytical specifications (CO_2 emissions: accounted vs. actually emitted), and (f) advanced analytics for tracking of seasonal effects. The updated and final DSS is shown in Figure 3.

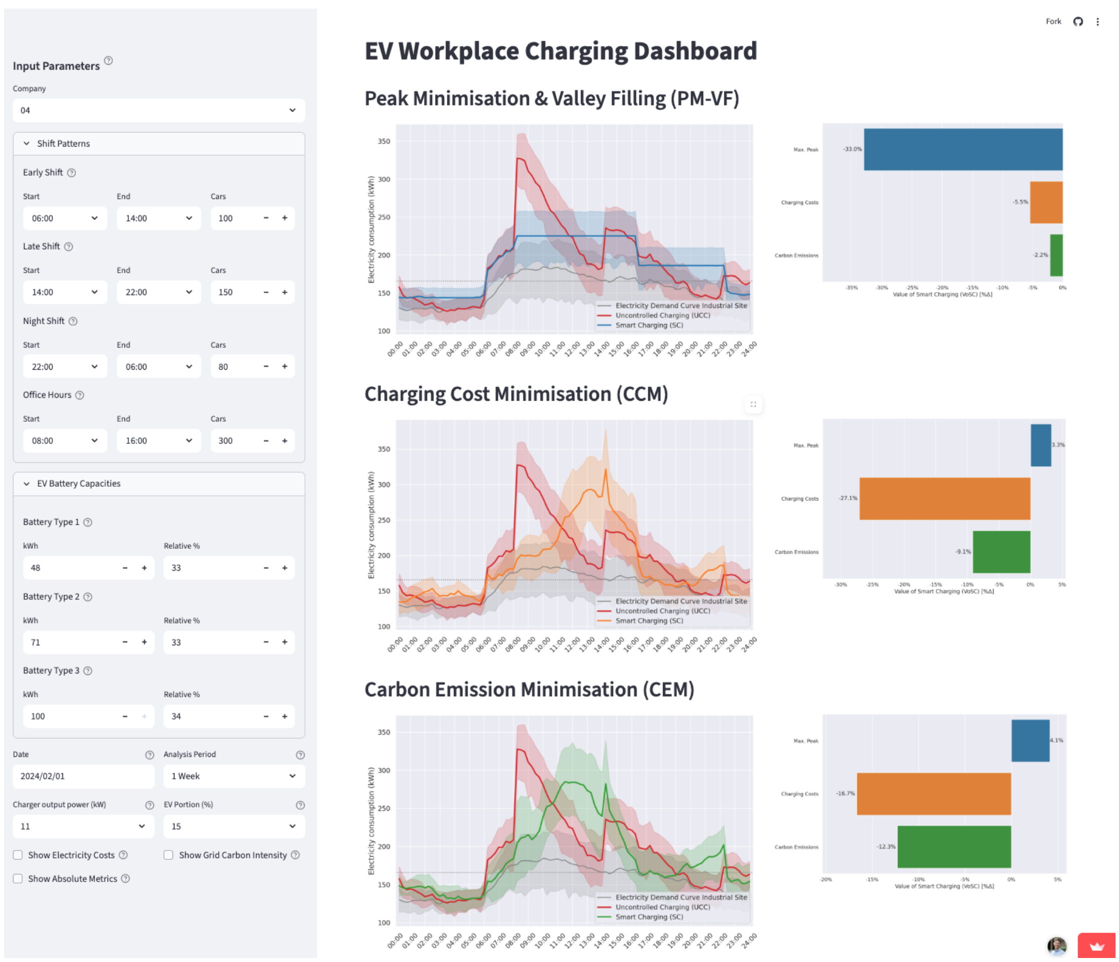

Figure 3: Updated web application post implementation of interviewees' feedback (design cycle 3)

We evaluated the impact of these feature changes on users' perceived usefulness of the system by repeating qualitative- (semi-structured interviews) and quantitative (SUS questionnaire) data collection with four additional firms (cf. §3.3) as part of design cycle 3. These findings are reported in more detail in §5.3 and §A.5 of [42].

5. Demonstration, evaluation, and findings

5.1. Application of our artefact

We demonstrated the DSS using firm-specific empirical data rather than generic or synthetic inputs. This approach increased the external validity of our results and gave interviewees a strong incentive to participate. Using their own data also made the simulation outputs more meaningful and easier to relate to.

Each firm in our sample provided information on its annual electricity consumption, main demand sources, work shift schedules, number of employee cars, and current EV adoption rates. We used these data, summarised in Table 1, to parametrise the DSS. Further contextual information is provided in Table 13 of [42] regarding (i) high-level characteristics of the firm's electricity load profile, (ii) procurement strategy, (iii) expected future electricity consumption, and (iv) anticipated challenges in managing electricity demand. One firm (ID 7) was unable to share detailed load profiles; in this case, we relied on a standard load profile. For the remaining firms, we simulated electricity load profiles under three charging strategies - peak minimisation & valley filling (PM-VF), charging cost minimisation (CCM), and carbon emission minimisation (CEM), in response to varying EV adoption rates [%]. For each scenario, the DSS also calculated the VoSC, expressed as the relative change [%Δ] in peak demand, charging costs, or carbon emissions compared to uncontrolled charging.

Figure 4 presents the savings potential ('VoSC' [%Δ]) from smart charging strategies, exemplarily for firms 5 and 6 (ID). It includes results for all three charging strategies (PM-VF, CCM, CEM). The boxplots, which entail 28 single-day model results from February 2024/25, show how the savings potential changes as the rate of EV adoption [%] increases.

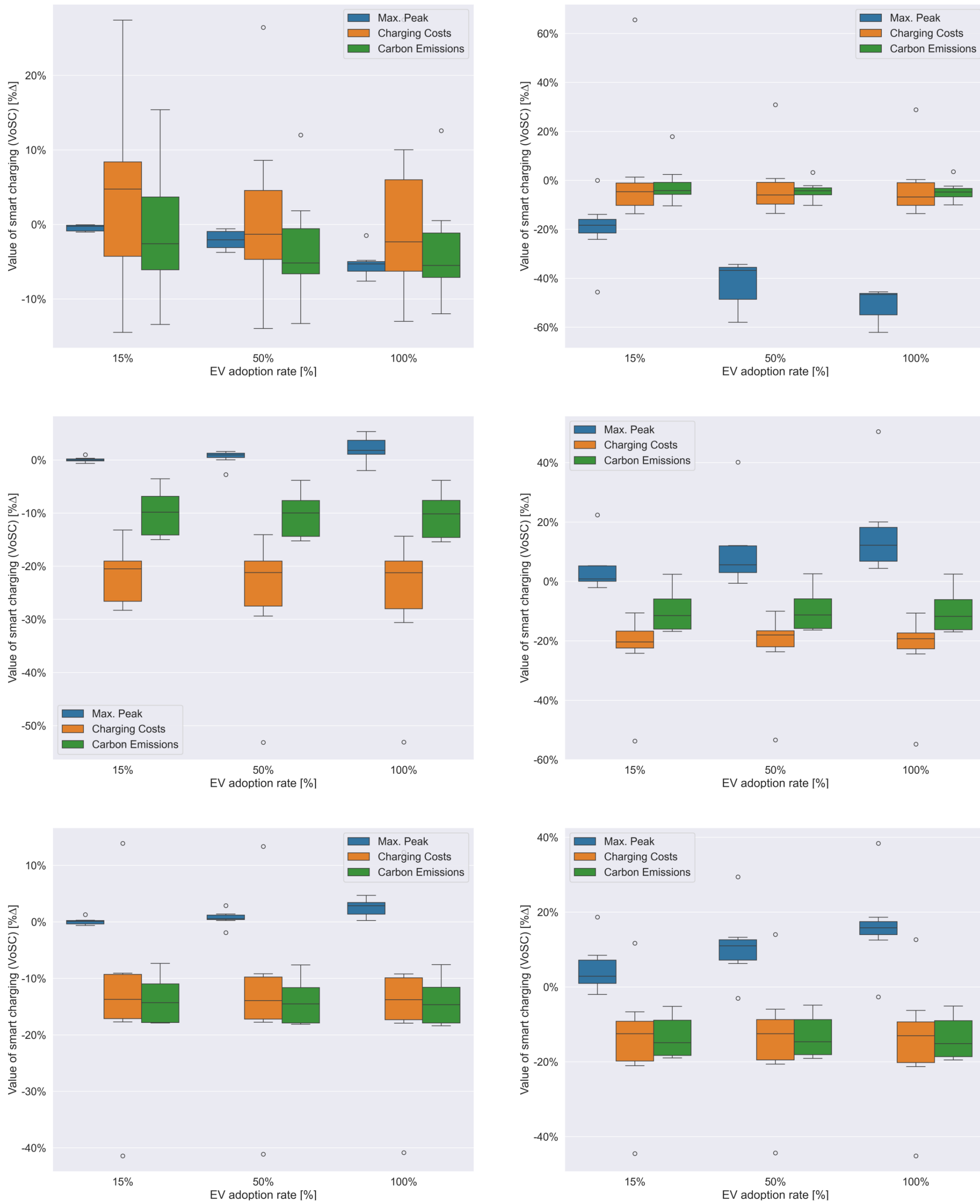

Figure 4: Visual summary of VoSC [%Δ] (y-axis) model results for increasing EV adoption rates of 15%, 50%, 100% (x-axis) w.r.t. each key metric *max. peak demand (blue)*, *charging costs (orange)*, and *carbon emissions (green)*, differentiated by charging strategies *PM-VF (top row)*, *CCM (middle row)*, *CEM (bottom row)*, exemplarily for participating firm 5+6 (ID) (column view). Note that lower %Δ numbers (y-axis) refer to higher saving potentials.

VoSC [%Δ] model results of all firms (IDs 1–8) are provided in Figure 8 of [42]. In general, we find three key insights: First, if firms opt for peak minimal charging (PM-VF), the graphs show that this charging strategy yields the lowest overall peaks across the sample (IDs), with higher savings potential as the EV rate increases. Second, contrary to peak minimal charging, if optimising for charging costs (CCM) or carbon emissions (CEM), the achieved savings potential remains relatively constant, independent of the EV adoption rate. Third, and lastly, when comparing results across firms (IDs 1–8), we observe substantial differences in variability, measured by the boxplots' whisker lengths, for certain key metrics (e.g. cf. Figure 4: PM-VF (top row): charging costs, ID 5 vs. ID 6). This suggests that the model results for each firm are highly context-dependent.

5.2. Qualitative findings: Managerial insights from interviews

The purpose of this study is not only to evaluate the usability of the developed artefact (cf. §5.3), but also to examine how the DSS influences executives' understanding, dialogue, and capacity for long-term planning regarding EV workplace infrastructure. To this end, we conducted interviews with 14 practitioners from 8 firms, each holding managerial responsibilities across sustainability, energy, facilities, fleet, and finance departments. In the following, we present our findings as six themes that illustrate how the DSS shapes decision-making.

Surfacing and managing trade-offs: Our findings indicate that the DSS enables executives to explicitly weigh costs, peak load, and emissions, thereby moving beyond intuition toward structured comparisons. This is illustrated by interviewee 2a, who noted feeling empowered to compare quantitative trade-offs across alternatives: *"Just being able to say: 'OK, what alternatives do I have? Do I want to reduce costs or do I want to reduce* CO_2*?' And that really does make a difference."* [ID: 2a]. He further emphasised the value of prioritisation and data-driven decision-making: *"To set priorities and (...) start working with data in the company instead of relying on gut feelings"* [ID: 2a], and highlighted the efficiency gains: *"It's just nice to be able to argue using valid data, (...) something I'd otherwise have to gather myself with a lot of effort."* [ID: 2a]. Likewise, respondent 6a stressed the practical usefulness of the web application *"because it shows how you can weigh different factors"* [ID: 6a], which, in turn, *"help[s] to make a more informed decision than one might otherwise have made"* [ID: 6a]. The role of data-driven guidance is also evident in interviewee 5b's reflections on determining the appropriate scale of charging infrastructure: *"What definitely helps is getting guidance on: How large should I dimension my charging infrastructure? What do I need to consider, what kind of costs and savings are actually involved if I incorporate different automation features?"* [ID: 5b]. He also stressed the importance of integrating cost considerations with smart charging strategies: *"What I find especially interesting is the combination of charging cost optimisation with smart charging, because (...) you can really see the impact of trying to control your demand based on cost, rather than just managing everything purely based on demand."* [ID: 5b]. Collectively, these insights highlight the DSS's role in revealing decision tensions and supporting multi-objective reasoning.

Changing mental models and strategic framing: The analysis also reveals that the DSS encourages a shift in perspective from operational concerns toward strategic planning and investment. Interviewee 4a underscored the future relevance of data-driven tools, stating: *"I think a tool like this is incredibly important for the future, especially because it helps you see what's going on and how things can be optimised."* [ID: 4a]. Adding to this, interviewee 5b perceived the tool to *"be helpful as one element in discussing an investment decision"* [ID: 5b]. Respondent 8a expressed strong interest in integrating such a decision-enhancing tool into strategic planning, viewing it as a way to strengthen the currently rather limited planning practices: *"At the moment, we really don't have anything in our discussions - except maybe what we calculate ourselves somehow. But a tool like this would definitely be a huge support, especially if it provides real values based on company-specific data."* [ID: 8a]. In summary, our DSS fosters foresight planning and strategic framing, situating EV charging within broader organisational transitions.

Facilitating cross-departmental dialogue: Feedback from the interviews suggests that the DSS empowers non-specialists to contribute to discussions while fostering a shared understanding across departments. This is exemplified by participant 2a, who expressed increased confidence in engaging with broader decision-making forums: *"I would now immediately feel able to join a larger meeting, make suggestions, (...) being able to say: Okay, what happens in scenario X or Y? How does it behave there?"* [ID: 2a]. Interviewee 6a, a Sustainability Manager, reinforced this point by highlighting the value of visualisation for making complex issues more accessible: *"A lot of what you usually try to explain just in words is shown visually here - and that makes it memorable. (...) It's just an excellent basis for discussion, and everyone would approach it from their own perspective - and I believe that would really help with making a decision."* [ID: 6a]. She further noted its potential in executive-level discussions: *"I could definitely imagine that if we were to discuss this with our commercial director, it would be an exciting foundation to build on."* [ID: 6a]. Taken together, these accounts highlight how the DSS functions as a boundary object, supporting collaboration across sustainability, energy, facilities, fleet, and finance functions.

Perceived usability and adoption potential: Usability, which is further examined in the following section (§5.3) through quantitative results from the SUS questionnaire, also emerged as a central theme in the qualitative interviews. Simplicity, clarity, and visual design were consistently noted as factors that build user confidence and reduce barriers to adoption. For example, interviewees described the DSS as *"kept pretty simple"* [ID: 1b], making it *"definitely user-friendly and dynamic"* [ID: 1b], with *"three clear goals and graphics that are self-explanatory"* [ID: 2a]. Interviewee 7a emphasised the appeal of a streamlined interface, noting that the web application *"is clearly laid out, attractive to use, and not overloaded"* [ID: 7a]. Visual aspects were further underlined by interviewee 8a, who remarked: *"I'm (...) a very visual person, and I like that there are lots of charts."* [ID: 8a]. Overall, the interviews point to a strong perception of usability, reinforced by the SUS score of 81.8 (§5.3), which indicates high adoption potential at the organisational level.

External validation and credibility: Executives particularly valued instances where the DSS outputs aligned with their own systems and data, as this alignment reinforced trust in the tool. Interviewee 4a illustrated this point, noting: *"I already like that the red curve reflects reality - that's a good start, because I checked in my own program in parallel, and it looks similar."* [ID: 4a]. He further added: *"It's great that the theory already reflects the reality, I really like that."* [ID: 4a]. These reflections underscore that credibility of model outputs is a prerequisite for adoption in strategic decision-making contexts.

Overwhelm and complexity concerns: Although most respondents described the DSS as simple and easy to use, several interviewees raised concerns about potential information overload, highlighting the importance of maintaining simplicity. Interviewee 7a noted that *"the more overloaded it [the DSS] is, the less people will use it."* [ID: 7a]. Similarly, respondent 5b cautioned against excessive complexity, stating: *"I can't use something that suddenly overwhelms me with so much information that I can't see the forest for the trees. I actually need to see the specific information that's supposed to come through - clearly and deliberately."* [ID: 5b]. These perspectives show that adoption hinges on striking a balance between analytic richness and cognitive simplicity, a well-known challenge in DSS design.

Together, the themes demonstrate how the DSS not only optimises EV workplace charging technically, but also reveals trade-offs between competing metrics, reframes decision problems strategically, facilitates cross-departmental dialogue, and builds trust through usability and validation, while balancing analytic richness against risks of overload. These are core DSS contributions that extend beyond the energy domain into the broader challenge of supporting organisational sustainability transitions. The full list of interview quotes can be accessed in §A.5 of [42].

5.3. Quantitative findings: System Usability Scale (SUS) questionnaire

We assessed the DSS's usability with the SUS questionnaire [46]. SUS consists of ten standardised statements, alternating between positive and negative wording, each rated on a five-point Likert scale from '*strongly disagree*' (1) to '*strongly agree*' (5) [51]. Scores are calculated on a 0–100 scale, where values above 71 indicate good usability and values above 81 are considered '*excellent*'. The formal mathematical derivation to obtain the SUS score is included in §A.2 of [42]. Moreover, an overview of the ten SUS items can be found in Table 14 of [42], in line with the individual rating from each respondent, differentiated by design cycles 2 and 3. We received 11 completed questionnaires: six from design cycle 2 and five from design cycle 3. The average SUS score across all responses was 81.8, which falls into the '*excellent*' category. By comparison, the average SUS score for web-based user interfaces is 68 [52]. This suggests that our DSS performs well above typical benchmarks. Looking at the design cycles separately, cycle 2 achieved an average SUS of 87.1 (*'best imaginable'*). Cycle 3 averaged 75.5, which is considered *'good'*.

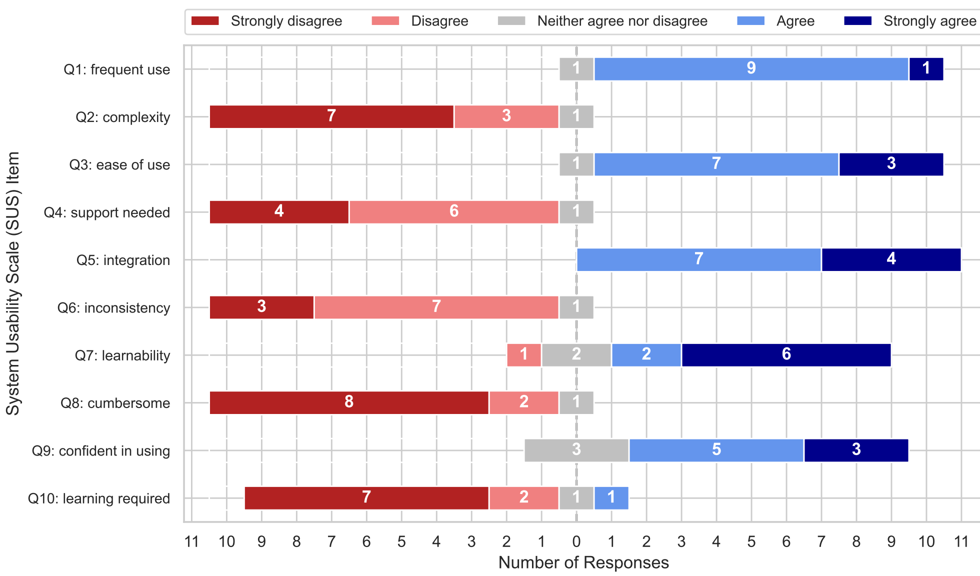

Figure 5: Distribution of participants' responses in each Likert category, from '*strongly disagree*' (dark red) to '*strongly agree*' (dark blue). Results combine responses from design cycle 2 ($n = 6$) and 3 ($n = 5$).

Figure 5 illustrates the distribution of responses for each of the ten SUS items across both cycles. The combined results indicate strong usability ratings, reflecting positive user perceptions regarding ease of use (Q3), simplicity (Q2), integration of system functions (Q5), consistency (Q6), and overall willingness to frequently use the system (Q1). Respondents also clearly indicated that the system does not require extensive initial learning (Q10) or technical support (Q4), nor did they perceive it as cumbersome (Q8). Furthermore, participants generally felt confident using the system (Q9) and believed most people would learn the system quickly (Q7), although minor neutral responses suggest potential for further enhancing user guidance. In sum, the quantitative results align with our qualitative findings: users perceived the DSS as clear, practical, and highly usable. The SUS score of 81.8 confirms its strong adoption potential in organisational settings. Overall, the evaluation of our artefact illustrates the high real-world applicability and strong usability of our web application, which serves as a DSS for business executives.

6. Discussion and contribution

Investing in EV workplace charging and electrifying company fleets can deliver substantial benefits. Prior studies estimate annual savings, per firm, of up to €$100k$ and emission reductions of around 250 tCO_2 [4]. Our findings build on this evidence by showing how such benefits can be contextualised, quantified, and operationalised through a DSS.

From a theoretical perspective, our work follows an *'exaptation'* strategy within the *Knowledge Innovation Matrix* [53]. We repurpose existing optimisation algorithms for the dedicated application of workplace charging. In doing so, we instantiate a DSS artefact tailored to a specific organisational context. Our solution also classifies as *'Decision-support system'*, where humans (business executives) and machines (optimisation algorithms) *"interact in mutually supportive patterns of iterative sequential or parallel activities"*, thus augmenting human cognitive abilities [54, p. 2]. Concerning DSR contributions, our web application is a situated implementation of an artefact, tailored to the decision context of EV workplace charging. Hence, we argue that our software instantiation contributes to DSR through practical, highly specific knowledge at *'Level 1'*, as classified by Gregor and Hevner [55].

Responding to recent scholarly calls [17, 18], the novelty of our work lies in its user-centred approach to solving a real-world organisational problem within the broader challenge of the sustainable mobility transition. Our DSS empowers business executives to make informed decisions about planning and operating EV workplace charging infrastructure. We demonstrated and rigorously evaluated the system using real-world electricity consumption data from our sample firms and assessing usability with the SUS questionnaire. We selected DSR as the guiding paradigm because of its iterative and practice-oriented nature. This approach enabled us to continuously update and improve the prototype based on participant feedback across three design cycles.

The resulting open-source web application, accessible at `https://ev-workplace-charging.streamlit.app/`, provides detailed insights into how different charging strategies (PM-VF, CCM, CEM) affect peak demand, charging costs, and carbon emissions. These simulations explicitly account for varying employee EV adoption rates (15–100%) and are tailored to each site's unique load profile and workplace context. The outputs deliver decision-critical information, enabling executives from sustainability, energy, facilities, fleet, and finance to understand and navigate trade-offs that were previously implicit. Consequently, we argue that the DSS facilitates informed consensus-building around optimal charge point operations.

We compared our artefact to prior energy-related DSSs (cf. Table 3). Previous systems often rely on generic or grid-level datasets, focus on a single optimisation objective, and are primarily designed for technical experts [56, 57, 58]. By contrast, our DSS integrates firm-specific data by embedding contextual load profiles into the analysis, represents trade-offs explicitly by quantifying costs, peak demand, and emissions side by side, and targets organisational decision makers, thereby fostering dialogue across sustainability, facilities, finance, and fleet management. This combination extends DSS design beyond technical optimisation. It shows how firm-specific modelling and trade-off representation can support sustainability transitions at the organisational level.

Firms can derive several practical implications from our study. First, when evaluating the results of each charging strategy in isolation, we find that, on average, each strategy achieves its intended outcome. For example, PM-VF consistently produces the lowest peaks, while CCM leads to the lowest charging costs (cf. Figure 4). This finding demonstrates the external validity of our model, as each optimisation strategy delivers what it was designed to achieve. Second, however, our results also show that optimising for the overall lowest charging costs (CCM) or the lowest carbon emissions (CEM) comes at a trade-off. Specifically, these strategies incur substantially higher peak loads, an effect that becomes more pronounced as EV adoption increases (cf. Figure 4: second and third row). Third, when comparing results across firms (cf. Figure 4), we observe substantial contextual variability. This is evident in the different lengths of the whiskers in the boxplots, which capture the variability of the results across individual model runs. These differences underline the importance of firm-specific data and analysis, and they demonstrate the added value of our web application as a tool tailored to each organisational context. In addition, from a DSS evaluation perspective, the combined qualitative and quantitative results of our study provide tangible evidence of the system's usability and practical value for corporate decision makers. Simplicity and clarity emerge as key success factors for adoption, as they lower barriers for non-technical users and increase confidence in applying the system to strategic decision-making.

For policymakers, our study highlights the importance of managing EV workplace charging loads in a comprehensive manner by using highly granular DSSs that incorporate firm-specific parameters. Across most firms in our sample, the DSS simulations indicate an average carbon emissions savings potential of approximately 20% (cf. Figure 8 of [42]: second row). This demonstrates that firm-level optimisation measures are both feasible and actionable, and that they can significantly enhance demand-side flexibility in the electricity system. Such flexibility is widely recognised as a critical element in achieving the EU's net-zero emissions target by 2050. While the EU-wide *Energy Performance of Buildings Directive (EPBD)* [59], which has been transposed into German law through *GEIG* [8], represents an important first step towards scaling workplace charging infrastructure, we argue that additional regulatory frameworks are needed to incentivise the uptake of smart charging algorithms.

Lastly, in terms of methodological procedure, it is worthwhile noting that we ended the DSR process after three design cycles due to SUS score saturation (final score: 81.8).

Table 3: Comparison of existing energy-related DSSs and our DSS contribution.

Dimension	Prior energy-related DSSs	Our DSS contribution
Data scope	Rely on generic scenarios, grid-level datasets, or engineering assumptions [56]	Integrates firm-specific electricity load data and workplace context to deliver tailored insights
Decision framing	Emphasise single-objective optimisation (e.g., cost, peak demand, or emissions separately) [57]	Makes multi-objective trade-offs explicit by quantifying costs, peak demand, and carbon emissions simultaneously
User orientation	Designed primarily for technical experts (e.g., grid operators, energy engineers) [58]	Designed for organisational decision makers (sustainability, energy, facilities, fleet, finance) to enable cross-departmental dialogue
System design	Often research prototypes with limited validation in practice [60]	Open-source, interactive web application, validated with eight firms; achieves high usability (SUS 81.8 = 'excellent')
Contribution to DSS field	Extend modelling capabilities in energy informatics [39]	Extend DSS design for sustainability transitions by embedding firm-specific data, trade-off representation, and collaborative decision support

7. Conclusion and outlook

Data-driven DSSs are becoming increasingly important tools for facilitating the electrification of mobility and broader organisational sustainability transitions (cf. §2.3). Although many business executives recognise the complexity of this transition, particularly in relation to workplace charging (cf. §5.2), our findings show that most firms lack the granular insights needed to anticipate how this shift will unfold in practice. The web application we developed, demonstrated, and evaluated with real-world data is designed to address this gap by providing a dedicated environment in which firms can simulate EV charging strategies based on their own data and parameters. By making trade-offs explicit and easy to understand, the system supports decision makers in navigating a challenging and highly dynamic landscape.

At the same time, we acknowledge several limitations of our study. First, the DSS currently produces static, non-probabilistic forecasts based on historical load profiles, which restricts its predictive capacity. Second, the current version of our DSS does not yet accommodate complex, firm-specific tariff structures. Third, our evaluation was based on a sample of eight firms, all located in Germany. This limits the generalisability of the findings to other countries or sectors. These limitations also point to directions for future research and development. Subsequent iterations of the DSS could integrate stochastic time-series forecasting methods to enhance predictive power. Emerging AI models, such as TimeGPT, could provide off-the-shelf solutions for this task. Future studies could also extend the functionality of the DSS to incorporate more complex tariff structures and the integration of on-site renewable generation. Moreover, replication of the study in different geographical and industrial contexts would be valuable in assessing the system's robustness and transferability. Looking further ahead, the DSS framework could be adapted to manage other forms of distributed energy resources, such as depot charging for delivery fleets or heavy-duty vehicles, as well as the operation of stationary battery energy storage systems.

In conclusion, our DSS contributes a practical, user-centred solution to a pressing organisational and societal challenge. It enables firms to better plan and operate EV workplace charging infrastructure while explicitly surfacing the trade-offs between peak demand, costs, and emissions. By doing so, it not only advances DSS research but also offers policymakers and practitioners an actionable pathway to support the sustainable mobility transition.

Declaration of generative AI and AI-assisted technologies in the writing process

In preparing this manuscript, the authors used ChatGPT (Edu license) to assist, e.g., with improving readability and refining language. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

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