

Data-Driven Decision Support for Planning and Operating Electric Vehicle Workplace Charging Infrastructure

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Abstract

The rapid adoption of electric vehicles (EVs) intensifies the need for workplace charging infrastructure. 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) designed to support executives in evaluating trade-offs between peak demand, costs, and emissions. Using firm-specific data and data-driven modelling, it simulates the medium- to long-term impacts (5–15 years) of different workplace charging strategies. Following Design Science Research, we developed, demonstrated, and evaluated the DSS with real-world data from eight German companies. Interviews with 14 practitioners showed that executives particularly value the tool

for making trade-offs explicit and fostering cross-departmental dialogue. Usability evaluation with the System Usability Scale yielded a score of 81.8, indicating high usability. Our research extends DSS design for sustainability transitions by integrating 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 scholarly calls in green information systems and energy informatics, our study demonstrates an applicable, user-oriented DSS that supports organisational transitions towards low-carbon mobility.

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

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 [38]. 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 [36, 46].

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 tCO₂ [20]. With the number of workplace charge points expected to increase fivefold in the UK and more than double in Germany by 2030 [16, 53], 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 [22]. 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 [14]. 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*” [36, 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*” [36, p. 7] at the macroeconomic level [76]. 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) [66].

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 [40]. Scholars in energy modelling, green information systems (IS), and energy informatics have studied the benefits of grid service provision from EV batteries [8, 44, 59, 72], partly also in the context of EV workplace

139 charging [78]. However, most of these studies adopt the perspective of network opera-
140 tors or electricity market agents, i.e., a system-level perspective. As Ketter et al. [42]
141 and Schroer et al. [64] highlight, academic research has yet to provide practitioners
142 with adequate methods, data, and systems in the context of the sustainable mobility
143 transition, such as those needed to evaluate the trade-offs that arise when planning
144 and operating workplace charging infrastructure. Addressing this gap motivates our
145 work. More broadly, Power et al. [57] call for research on novel decision scenarios where
146 emerging technologies support organisational decision-making, encouraging “*design sci-*
147 *ence, case studies, [...] and empirical studies [that] help resolve the dilemmas of man*
148 *versus machine and create a beneficial partnership*” [57, p. 15]. Our study responds
149 directly to this call by developing, demonstrating, and evaluating a model-driven DSS
150 that augments executive judgement in the context of EV workplace charging.
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152 We address this organisational problem by posing the following research question:
153 *How can a decision support system (DSS) tailored to firm-specific electricity data help*
154 *executives evaluate trade-offs between peak load, costs, and emissions in the context of*
155 *EV workplace charging?* To answer this, we developed, demonstrated, and evaluated
156 an applicable, i.e., user-friendly, and context-specific, open-source web application.
157 The tool allows workplace practitioners to model the impact of EV charging on their
158 firm-specific electricity profile.

159 With our study, we further aim to quantify the decision tensions firms face when
160 applying the DSS to real-world data. Moreover, we aim to assess the perceived value
161 of our DSS for practitioners and to identify ways to improve it. We follow the Design
162 Science Research (DSR) paradigm [54]. Accordingly, we use rich real-world electricity
163 data and several in-depth qualitative interviews with eight medium- to large-sized
164 German companies for the development and demonstration of our DSS. In addition,
165 we apply quantitative usability testing using the System Usability Scale (SUS) to
166 rigorously evaluate the applicability of our artefact. Based on an overall SUS score of
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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 [42]. 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 [43]. 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 [33], (digital) carbon accounting systems [62], energy-aware business process management [67], and organisational digital decarbonisation approaches [50] 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,

231 and consumption, often referred to as energy informatics [74]. Studies address smart
232 grid management [41], decentralised energy systems [60], and demand-side energy
233 management [26], all aiming to facilitate renewable integration and create smart,
234 adaptive energy markets and systems.
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236
237 In the context of mobility, both green IS and energy informatics have contributed
238 to EV charging infrastructure development. Examples include optimised load balancing
239 and renewable integration into charging networks [8], as well as Vehicle-to-Grid (V2G)
240 approaches that mitigate peaks through predictive algorithms and dynamic pricing [51].
241 Since the majority of these studies focus on network operators or electricity market
242 agents, their perspective tends to remain at the systemic level, with an emphasis on
243 market and grid implications. User-oriented approaches have improved the EV charging
244 experience, with tools for intelligent navigation to available charging stations, real-
245 time availability updates, and dynamic pricing to promote energy-efficient charging
246 behaviours [9, 58]. More broadly, recent research has highlighted the importance
247 of active stakeholder engagement in sustainable energy transitions, emphasising co-
248 creation and participatory approaches to foster adoption [61]. Despite these advances,
249 little user-oriented guidance exists on how to plan and operate EV workplace charging
250 infrastructure using firm-specific data - a key enabler for scaling EV adoption and
251 reducing emissions in the mobility sector [36, 55].
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264 2.2 Smart EV charging

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266 Smart charging is central to sustainable mobility systems. It involves managing EV
267 charging loads according to predefined objectives, such as minimising peak demand,
268 reducing costs, or lowering carbon emissions [37]. To this end, Zheng et al. [77] provide
269 a review on common objective functions and modelling approaches in this field. In
270 workplace contexts, algorithms have been developed to jointly optimise infrastructure
271 sizing and the assignment of vehicles to charging spots, see e.g., [46]. When combined
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with on-site solar generation, real-time energy management systems can produce optimal charging schedules, thereby increasing self-sufficiency and lowering operational costs [48]. Bidirectional charging (V2G) provides an additional benefit by drawing energy from EV batteries during electricity demand peaks at industrial sites [39]. 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 [4]. Less attention is given to the organisational decision-making processes that guide infrastructure deployment and management [66]. 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 [42, 57]. They frequently use advanced analytical methods such as Artificial Intelligence (AI)-driven forecasting, simulation, and optimisation to support operational decisions about electricity demand [8, 64]. Examples include Gust et al. [30], who combine predictive analytics and optimisation for grid planning, or Schuller et al. [65], 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. Similarly, Ludwig et al. [47] demonstrate how Big Data analytics, specifically LASSO regression and random forests, can substantially improve electricity price forecasting through automated feature selection, underscoring the importance of selecting relevant variables from

large datasets for data-driven decision support. Bregar [11] proposes a DSS for self-sustainable smart grids that integrates machine learning, multi-criteria negotiation protocols, and blockchain technology to support decision-making in decentralised energy communities. Closer to our application domain, Abdelwahed et al. [1] develop a real-time DSS for electric bus networks that combines optimisation with predictions to update charging schedules under operational uncertainty, illustrating the practical value of data-driven DSSs for managing EV charging at the operational level. Hart et al. [32] evaluate an open-access, web-based DSS for multi-energy planning matched to the needs and capabilities of stakeholders in developing countries, while Caballero et al. [15] show that widely used microgrid design tools remain difficult for non-expert users to operate. Despite these advances, most DSSs either address technical optimisation alone or rely on generic datasets. Few integrate detailed, data-driven load simulation with firm-specific decision contexts. As Power [56] argues, the value of data science for decision support lies not in analytical sophistication per se, but in its ability to deliver actionable insights to targeted users. This need for targeted, user-oriented decision support is further underscored by research on EV adoption, where Shareeda et al. [68] show that stakeholder-specific factors, such as consumer awareness, purchasing power, and infrastructure availability, are critical determinants, highlighting the multi-dimensional nature of decisions in the sustainable mobility transition. Recent work in green IS has explicitly called for such integration [42, 64].

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” [34, p. 77]. DSR has been applied successfully in *Energy Informatics* to study, e.g., financial decision support for repowering onshore wind farms [73]. 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. [54], we report on steps 4 and 5 together, as previous studies have done [63].

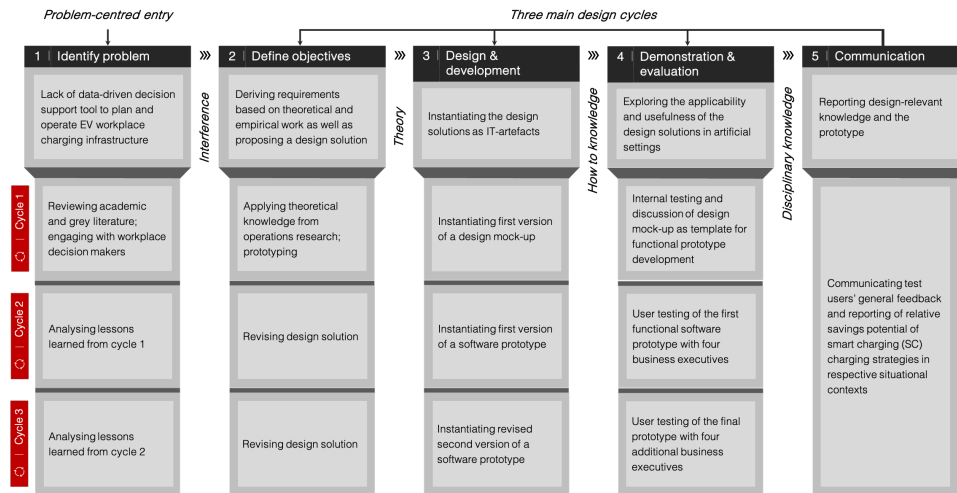


Figure 1 Overview of our DSR process; adapted from Peffers et al. [54] and Schoormann et al. [63]

As outlined above, we identified a central organisational problem in line with previous literature [66]: 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

[66], particularly regarding the quantification of their impacts. While uncontrolled charging typically 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 [37]. 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) [77]. A mathematical formulation of the optimisation model can be found in Tables A1–A2 in Appendix A 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.

In addition to the artefact itself, we contribute transferable design knowledge in the form of design principles (DPs). Following Gregor et al. [28], we derived six DPs from two complementary sources: (i) the design rationale underlying the artefact, i.e., the key design decisions made during development (cf. §4), and (ii) the empirical evaluation evidence gathered through qualitative interviews and quantitative usability testing (cf. §5). We grouped the DPs under three overarching meta-requirements that emerged from the decision problem and its evaluation, and structured each DP according to the anatomy proposed by Gregor et al. [28]: aim, context, mechanism, and rationale. The resulting design principles are presented and discussed in §6.

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.

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 [14] (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 [66], we evenly distributed the firms between design cycles 2 and 3. Companies 1–4 (IDs) evaluated the initial version of our artefact (cf. Figure S1 in Additional file 1) in design cycle 2, while companies 5–8 (IDs) assessed the enhanced version (cf. Figure S2 in Additional file 1) 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.

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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

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 [7] using Microsoft Teams. The interview guides are listed in Tables S1–S2 in Additional file 1. 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 [45] to measure perceived usability.

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.

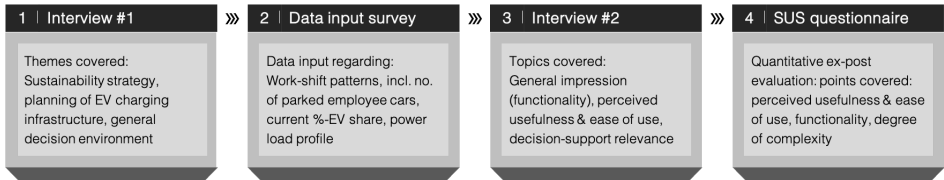


Figure 2 Summary of data collection points for each participating firm.

For qualitative analysis, we applied a primarily deductive coding approach [10], i.e., three of our four coding categories were defined in advance, based on established DSS and IS evaluation dimensions. 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. The first three categories were deductively derived from

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	Interview 2
			Duration (mm:ss)	Duration (mm:ss)
2	1	a: Corporate sustainability	26.11.2024	04.12.2024
		b: Finance/energy procurement	(45:39)	(49:54)
2	2	a: Head of facility management	10.12.2024 (28:29)	14.01.2025 (42:33)
2	3	a: Strategic purchasing	28.11.2024	17.01.2025
		b: Fleet management	(31:01)	(39:06)
2	4	a: Energy provisioning (engineering)	22.01.2025	21.02.2025
		b: Head of corporate responsibility	(36:22)	(46:39)
3	5	a: Executive assistant CEO	05.03.2025	30.04.2025
		b: Energy portfolio manager	(36:41)	(49:07)
3	6	a: Sustainability manager	05.03.2025	06.05.2025
		b: Project manager (engineering)	(38:17)	(40:39)
		c: Team lead maintenance		
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.

prior frameworks, while the fourth served as an inductively populated open category [24]. This hybrid strategy ensured theoretical grounding while remaining responsive to context-specific insights. Specifically, perceived usefulness corresponds to Davis' [17] 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 [18] IS Success Model and often assessed through usability instruments such as the SUS [13] or user satisfaction surveys [5]. Organisational value reflects the dimension of net benefits in the DeLone & McLean [18] model, capturing how systems contribute

to broader organisational performance and decision-making. Finally, suggestions for improvement captured user-driven recommendations not covered by the deductive categories.

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 linear programming (LP) model for smart charging, drawing on the formulations of Ioakimidis et al. [39] and Zheng et al. [77]. 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. Notably, the number of charge points is not optimised by the model but treated as an exogenous input parameter. This reflects the decision structure in practice, where infrastructure sizing is a strategic capital investment decision made upstream of operational charging optimisation. The model assumes a one-to-one assignment between EVs and charge points, i.e., each arriving EV occupies a dedicated charger. While this simplifies the real-world problem of shared charger allocation, it allows users to explore different infrastructure scales by varying the EV adoption rate, which proportionally determines the number of charge points required. The model operates at a temporal resolution of 15-minute intervals and permits the optimiser to pause and resume charging across non-contiguous time slots within a vehicle's parking window. This does not require driver intervention: employees plug in their vehicle once upon arrival and unplug upon departure, while the smart charging controller autonomously modulates the charging current according to the optimised schedule. To model heterogeneity in charging demand, initial state-of-charge levels (E_m^{ini}) upon arrival are randomly sampled between 10% and 80% of battery capacity

676 for each EV, and minimum departure charge requirements (E_m^{fin}) between 80% and
677 100%, reflecting variation in individual driving patterns and charging needs.
678

679 Our modelling framework follows the approach introduced by the authors of [66],
680 to which we refer for details on the full optimisation problem and solution method. In
681 our implementation, we coded the optimisation algorithms in Python and connected
682 them to the DSS interface through a modular back-end (cf. design cycles 2-3). This
683 allows users to run firm-specific simulations based on their own data. The full model
684 formulation, including objective functions and constraint sets, is provided in Tables
685 A1–A2 in Appendix A for transparency and reproducibility. By concluding design cycle
686 1, we had established a technically validated optimisation module that served as the
687 engine of the DSS, forming the basis for subsequent cycles of real-world application
688 and user evaluation (design cycles 2-3).
689

690 To support early design decisions, we created a high-fidelity mock-up of the user
691 interface in Figma. This is a widely used approach to save valuable resources (time,
692 development costs etc.) within Design Science and user-centred design [31]. The mock-
693 up defined the layout and components of the dashboard, including a three-column
694 structure with a collapsible sidebar for data input, a central panel for line graphs, and
695 a right-hand panel for key metrics. This static prototype (cf. Figure S1 in Additional
696 file 1) served as the basis for subsequent development.
697

698 4.2 Design cycle 2

699 In the second cycle, we translated the static Figma prototype into a functional web
700 application (cf. Figure S2 in Additional file 1). We used the open-source toolkit Streamlit,
701 which offers Python packages for building interactive applications without resource-
702 intensive front-end programming. The application interface consists of three main parts.
703 First, a sidebar collects firm-specific input such as (a) number and timing of work shifts,
704 (b) number of employee cars per shift, (c) EV battery size distributions, (d) electricity
705

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 S2 in Additional file 1). 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 ($\% \Delta$) 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) [35] and grid-carbon intensity data from *electricity maps* [19]; 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 Section D of Additional file 1. 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.

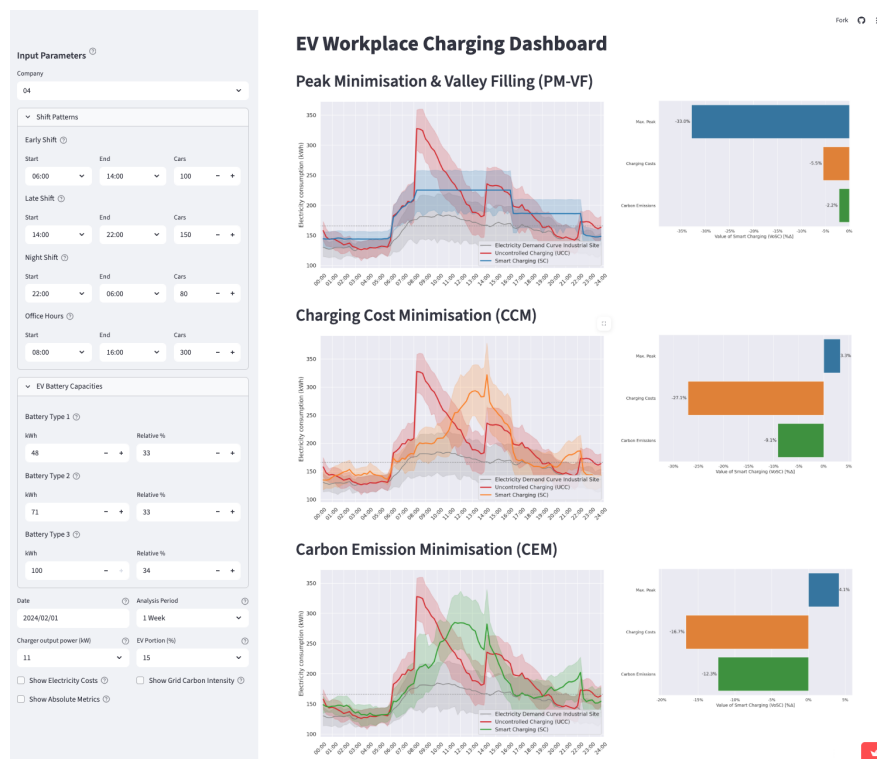


Figure 3 Updated web application post implementation of interviewees' feedback (design cycle 3)

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 Section D of Additional file 1.

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 S8 in Additional file 1 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 publicly available standard load profile. This case serves as a robustness check, demonstrating that the DSS can operate even when firm-specific data are unavailable, albeit with less contextualised outputs. It also illustrates the added value of firm-specific data: results for ID 7 are less tailored than those for firms where actual load profiles were available, underscoring the importance of contextual data embedding (cf. DP1). 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

860 response to varying EV adoption rates [%]. For each scenario, the DSS also calculated
861 the VoSC, expressed as the relative change [% Δ] in peak demand, charging costs, or
862 carbon emissions compared to uncontrolled charging.
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865 Figure 4 presents the savings potential ('VoSC' [% Δ]) from smart charging strategies,
866 exemplarily for firms 5 and 6 (ID). It includes results for all three charging strategies
867 (PM-VF, CCM, CEM). The boxplots, which entail 28 single-day model results from
868 February 2024/25, show how the savings potential changes as the rate of EV adoption
869 [%] increases.
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873 VoSC [% Δ] model results of all firms (IDs 1–8) are provided in Figure S3 in
874 Additional file 1. In general, we find three key insights: First, if firms opt for peak
875 minimal charging (PM-VF), the graphs show that this charging strategy yields the
876 lowest overall peaks across the sample (IDs), with higher savings potential as the EV
877 rate increases. Second, contrary to peak minimal charging, if optimising for charging
878 costs (CCM) or carbon emissions (CEM), the achieved savings potential remains
879 relatively constant, independent of the EV adoption rate. Third, and lastly, when
880 comparing results across firms (IDs 1–8), we observe substantial differences in variability,
881 measured by the boxplots' whisker lengths, for certain key metrics (e.g. cf. Figure 4:
882 PM-VF (top row): charging costs, ID 5 vs. ID 6). This suggests that the model results
883 for each firm are highly context-dependent. Several firm characteristics appear to
884 drive this variability (cf. Table 1). First, baseline energy intensity plays a key role: for
885 firms with low annual electricity consumption (e.g., ID 2: 232 MWh), even modest EV
886 charging loads represent a substantial relative perturbation to the existing load profile,
887 amplifying the VoSC. In contrast, for energy-intensive firms (e.g., ID 5: 197,290 MWh),
888 EV charging constitutes a marginal addition to an already large base load, yielding
889 smaller relative effects. Second, work shift patterns influence the temporal distribution
890 of EV arrivals and thus the degree of peak coincidence: firms operating multiple shifts
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(e.g., IDs 1, 4, 5) naturally distribute charging demand across the day, whereas single-shift office operations (e.g., IDs 2, 7) concentrate arrivals and create sharper peaks. Third, fleet size determines the absolute magnitude of charging demand, with larger fleets (e.g., ID 7: 500 cars) amplifying both the potential benefits and risks of different charging strategies. These observations underscore the importance of firm-specific analysis and further support DP1 (Contextual Data Embedding): generic benchmarks are insufficient for guiding infrastructure decisions when contextual factors vary so substantially across firms.

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 supports executives in explicitly weighing 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 CO₂?’ 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*

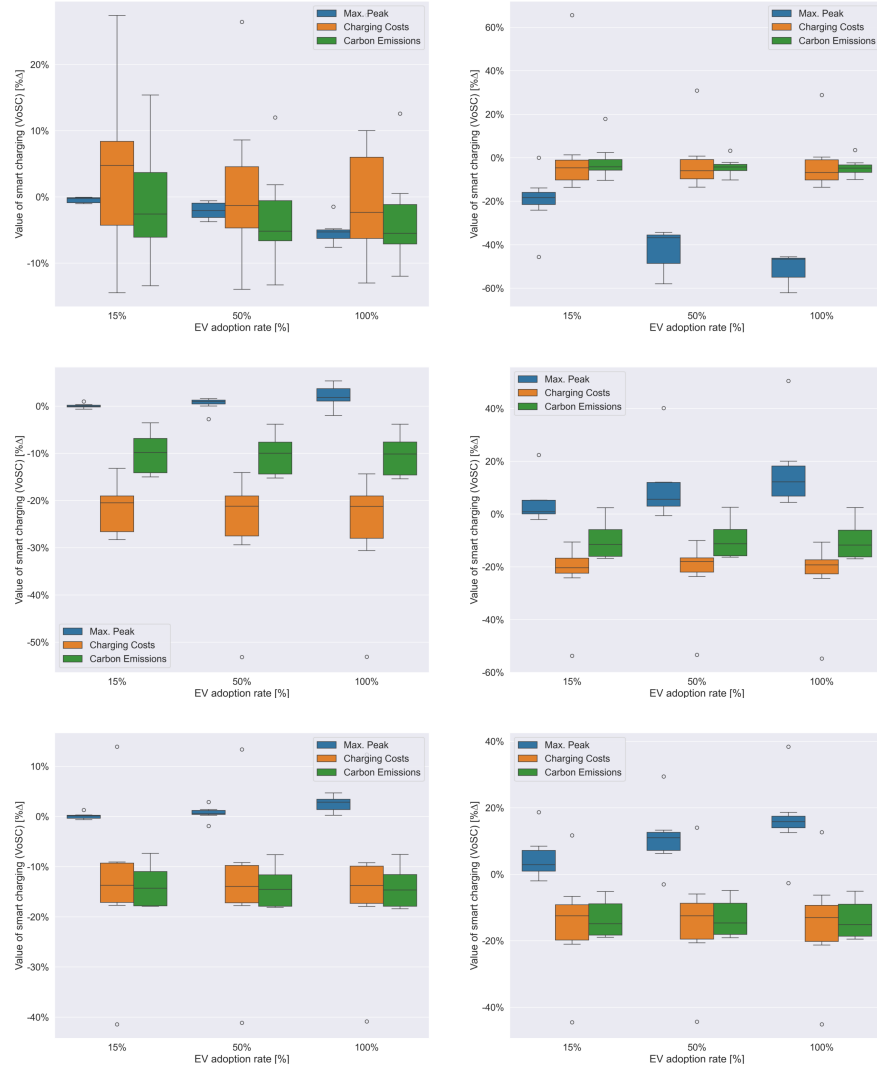


Figure 4 Visual summary of VoSC [%Δ] (y-axis) model results for increasing EV adoption rates of 15%, 50%, 100% (x-axis) w.r.t. each key metric *max. peak demand* (blue), *charging costs* (orange), and *carbon emissions* (green), differentiated by charging strategies *PM-VF* (top row), *CCM* (middle row),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

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 supports non-specialists in contributing 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 Section D of Additional file 1.

1136 5.3 Quantitative findings: System Usability Scale (SUS)

1137 questionnaire 1138

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1140 We assessed the DSS’s usability with the SUS questionnaire [13]. SUS consists of ten
1141 standardised statements, alternating between positive and negative wording, each rated
1142 on a five-point Likert scale from ‘*strongly disagree*’ (1) to ‘*strongly agree*’ (5) [71]. Scores
1143 are calculated on a 0–100 scale, where values above 71 indicate good usability and values
1144 above 81 are considered ‘*excellent*’. The formal mathematical derivation to obtain the
1145 SUS score is included in Section A of Additional file 1. Moreover, an overview of the
1146 ten SUS items, together with the individual ratings from each respondent differentiated
1147 by design cycles 2 and 3, is provided in Table S9 in Additional file 1. We received 11
1148 completed questionnaires: six from design cycle 2 and five from design cycle 3. The
1149 average SUS score across all responses was 81.8, which falls into the ‘*excellent*’ category.
1150 By comparison, the average SUS score for web-based user interfaces is 68 [6]. This
1151 suggests that our DSS performs well above typical benchmarks. Looking at the design
1152 cycles separately, cycle 2 achieved an average SUS of 87.1 (‘*best imaginable*’). Cycle 3
1153 averaged 75.5, which is considered ‘*good*’. However, because the two cycles involved
1154 different respondent groups from different firms ($n = 6$ and $n = 5$, respectively), direct
1155 cross-cycle comparison is confounded by differences in respondents’ digital literacy,
1156 organisational context, and prior expectations.

1157 Figure 5 illustrates the distribution of responses for each of the ten SUS items
1158 across both cycles. The combined results indicate strong usability ratings, reflecting
1159 positive user perceptions regarding ease of use (Q3), simplicity (Q2), integration of
1160 system functions (Q5), consistency (Q6), and overall willingness to frequently use the
1161 system (Q1). Respondents also clearly indicated that the system does not require
1162 extensive initial learning (Q10) or technical support (Q4), nor did they perceive it
1163 as cumbersome (Q8). Furthermore, participants generally felt confident using the
1164 system (Q9) and believed most people would learn the system quickly (Q7), although
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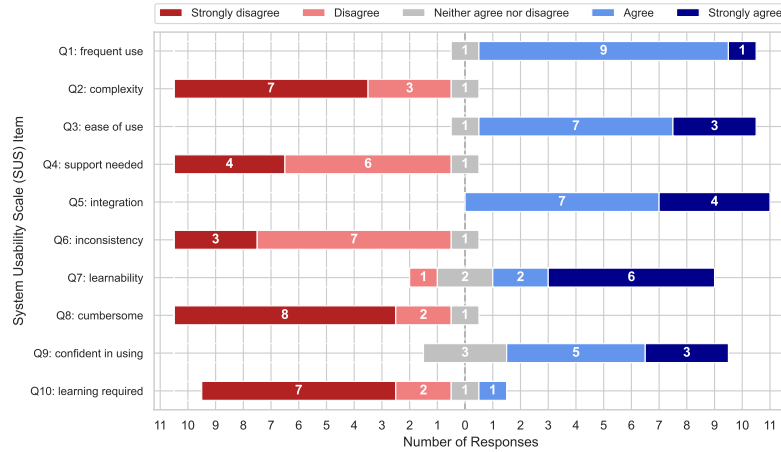


Figure 5 Distribution of participants' responses in each Likert category, from '*strongly disagree*' (dark red) to '*strongly agree*' (dark blue). Results combine responses from design cycle 2 ($n = 6$) and 3 ($n = 5$).

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. It is important to note that SUS measures perceived usability, not whether the DSS improves the quality of decisions made. While the interviews (§5.2) do not measure decision quality directly, they provide indicative evidence that practitioners perceived the DSS as supporting their reasoning, helping them surface trade-offs, reframe strategic decisions, and facilitate cross-departmental dialogue. Together, the triangulation of quantitative usability assessment (SUS) and these qualitative findings provides a comprehensive early-stage evaluation. This mixed-method approach resonates with Mora et al.'s [49] call for evaluating decision-making support systems along multiple dimensions. Measuring actual decision quality improvement would require controlled experiments comparing outcomes with and without the DSS, which represents a direction for future research. The overall SUS score of 81.8 suggests strong usability and indicates potential for adoption in organisational settings.

1228 6 Discussion and contribution

1229
1230 Investing in EV workplace charging and electrifying company fleets can deliver sub-
1231 stantial benefits. Prior studies estimate annual savings, per firm, of up to 100k€ and
1232 emission reductions of around 250 tCO₂ [20]. Our findings build on this evidence
1233 by showing how such benefits can be contextualised, quantified, and operationalised
1234 through a DSS.

1235
1236 Beyond the situated artefact, our study contributes transferable design knowledge
1237 in the form of six design principles (DPs) for DSSs that support organisational sus-
1238 tainability transitions. Following Gregor et al. [28], we structure each DP along four
1239 components: aim, context, mechanism, and rationale. The DPs are grounded in both
1240 the design rationale of our artefact and the empirical evaluation evidence from in-
1241 terviews with 14 practitioners across eight firms. We group the six DPs under three
1242 overarching meta-requirements (MRs), each reflecting a distinct class of demands that
1243 emerged from the decision problem and its evaluation (cf. Table 3).

1244
1245 **MR1: Context-specific decision support.** The DSS should generate insights
1246 grounded in the user’s organisational context to produce actionable, trusted outputs.
1247 Two design principles address this requirement. *DP1 : Contextual data embedding*
1248 stipulates that the DSS should integrate organisation-specific operational data (load
1249 profiles, shift patterns, fleet composition) to generate tailored insights. Our cross-firm
1250 comparison revealed substantial differences in model results (cf. Figure 4), confirming
1251 that generic datasets fail to capture the contextual variability that drives firm-level
1252 outcomes. As one interviewee noted: “a tool like this would definitely be a huge support,
1253 especially if it provides real values based on company-specific data” [8a]. *DP5 : Output*
1254 *credibility through data mirroring* requires that the DSS produce outputs which users
1255 can validate against their existing monitoring systems. This principle reflects the finding
1256 that credibility is a prerequisite for adoption: “the red curve reflects reality – that’s a
1257 good start, because I checked in my own program in parallel, and it looks similar” [4a].

MR2: Multi-objective decision transparency. The DSS should make trade-offs between competing objectives explicit and enable users to explore how outcomes change across future scenarios. *DP2 : Explicit trade-off visualisation* requires presenting competing objectives side-by-side to support multi-criteria reasoning. Prior energy-related DSSs typically focus on single-objective optimisation [3]; our approach quantifies the Value of Smart Charging (VoSC) for all three key metrics simultaneously, enabling informed prioritisation: “*Just being able to say: ‘OK, what alternatives do I have? Do I want to reduce costs or do I want to reduce CO₂?’ And that really does make a difference*” [2a]. *DP6 : Scenario-based foresight* enables users to anticipate medium- to long-term impacts by freely adjusting EV adoption rates and observing how outcomes evolve. This addresses the foresight gap identified in prior literature [36]: “*What definitely helps is getting guidance on: How large should I dimension my charging infrastructure?*” [5b].

MR3: Organisational adoption and collaborative use. The DSS should be accessible to non-technical decision makers across departments and support collaborative, cross-functional dialogue. *DP3 : Cross-functional accessibility* stipulates that the DSS should function as a boundary object [69], a shared artefact that stakeholders from sustainability, energy, facilities, fleet, and finance can interpret from their own perspective: “*I would now immediately feel able to join a larger meeting, make suggestions*” [2a]; “*It’s just an excellent basis for discussion*” [6a]. *DP4 : Cognitive simplicity* requires balancing analytic depth with interface simplicity to prevent information overload. This principle is supported by the tension we observed between added functionality and usability: “*the more overloaded it is, the less people will use it*” [7a]. The SUS score decline between design cycles 2 (87.1) and 3 (75.5) further suggests that feature additions can introduce complexity that hinders adoption, although this comparison is confounded by different respondent groups across cycles (cf. §5.3).

Concerning the nature of our DSR contribution, our solution classifies as a model-driven decision support system within the taxonomy proposed by Power et al. [57],

1320 where humans (business executives) and machines (optimisation algorithms) “interact
1321 in mutually supportive patterns of iterative sequential or parallel activities”, thereby
1322 augmenting human cognitive abilities [70, p. 2]. Following Power et al.’s [57] frame-
1323 work of organisational decision systems (cf. their Figure 4), our DSS operates in the
1324 ‘Alternative Generation and Evaluation’ phase: it uses simulation and optimisation to
1325 help executives evaluate competing charging strategies, supporting the transition from
1326 problem identification to informed choice. While our web application constitutes a situ-
1327 ated implementation at ‘Level 1’ [27], the six design principles elevate the contribution
1328 to ‘Level 2’: a nascent design theory that offers prescriptive knowledge transferable
1329 to other sustainability transition DSSs beyond the specific context of EV workplace
1330 charging [28]. The DPs were derived from both the artefact’s design rationale and its
1331 empirical evaluation; they are structured following the anatomy of a design principle
1332 proposed by Gregor et al. [28] and summarised in Table 3.

1341 Responding to recent scholarly calls [42, 64], the novelty of our work lies in its user-
1342 centred approach to solving a real-world organisational problem within the broader
1343 challenge of the sustainable mobility transition. Our DSS is designed to support business
1344 executives in making informed decisions about planning and operating EV workplace
1345 charging infrastructure. We demonstrated and evaluated the system using real-world
1346 electricity consumption data from our sample firms, combining qualitative interviews
1347 to assess perceived usefulness and organisational value with the SUS questionnaire to
1348 assess usability. We selected DSR as the guiding paradigm because of its iterative and
1349 practice-oriented nature. This approach enabled us to continuously refine the prototype
1350 based on participant feedback across three design cycles.

1351 The resulting open-source web application, accessible online [23], provides detailed
1352 insights into how different charging strategies (PM-VF, CCM, CEM) affect peak
1353 demand, charging costs, and carbon emissions. These simulations explicitly account for
1354 varying employee EV adoption rates (15–100%) and are tailored to each site’s unique
1355

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 4). Previous systems often rely on generic or grid-level datasets, focus on a single optimisation objective, and are primarily designed for technical experts [3, 75, 78]. 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. This tension has also been documented in adjacent operations contexts, such as mixed hydrogen/diesel truck fleets [29]. 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.

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Table 3 Design principles for decision support systems supporting organisational sustainability transitions, structured following the anatomy of a design principle [28].

DP	Design Principle	Aim	Context	Mechanism	Rationale
MR1: Context-specific decision support					
DP1	Contextual data embedding	Enable firm-specific decision support by integrating organisational data into the analysis	Planning and operation of EV workplace charging, where firms differ in load profiles, shift patterns, fleet size, and energy intensity	Parametrise the DSS with firm-specific inputs (load profiles, shift schedules, fleet composition, EV adoption rates) uploaded by the user	Generic datasets fail to capture the contextual variability that drives firm-level outcomes; cross-firm comparison confirmed substantial differences in results
DP5	Output credibility through data mirroring	Build user trust in DSS outputs by enabling validation against existing monitoring systems	Settings where executives rely on familiar data systems and need to verify output credibility before strategic use	Display the firm’s actual (historical) load profile alongside simulated scenarios, enabling visual comparison with existing energy management data	Credibility is a prerequisite for adoption; when users verify that the DSS reproduces known patterns, trust extends to simulated scenarios
MR2: Multi-objective decision transparency					
DP2	Explicit trade-off visualisation	Support multi-criteria reasoning by presenting competing objectives side-by-side	Charging decisions where optimising for one objective can adversely affect another, creating implicit decision tensions	Visualise outcomes of three charging strategies (PM-VF, CCM, CEM) simultaneously, quantifying the VoSC for each metric relative to uncontrolled charging	Prior DSSs focus on single-objective optimisation; presenting all three objectives enables informed prioritisation
DP6	Scenario-based foresight	Enable users to anticipate medium-to long-term impacts under varying future conditions	Infrastructure planning horizons of 5–15 years, where EV adoption rates are uncertain and today’s decisions have compounding consequences	Allow users to adjust EV electrification rates (0–100%) and observe how outcomes evolve; support multi-period analysis with confidence intervals	Most firms underestimate long-term implications of EV charging; the DSS addresses this foresight gap through what-if exploration
MR3: Organisational adoption and collaborative use					
DP3	Cross-functional accessibility	Enable stakeholders from diverse functions to engage with the DSS as a shared basis for decision-making	Charging decisions spanning sustainability, energy, facilities, fleet, and finance, requiring multi-functional input and buy-in	Design an interactive web application with self-explanatory visualisations, contextual tooltips, and a streamlined layout accessible without technical expertise	The DSS functions as a boundary object that stakeholders interpret from their own perspective, fostering cross-departmental dialogue
DP4	Cognitive simplicity	Ensure sustained adoption by balancing analytic depth with interface simplicity	Settings where decision makers have limited time, varying technical literacy, and information overload reduces engagement	Maintain a streamlined interface with selective display options, progressive disclosure of complexity, and clear visual hierarchy	Analytic richness and cognitive simplicity exist in tension; the SUS decline between cycles (87.1 → 75.5) suggests added features can hinder usability

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 S3 in Additional file 1: 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)* [21], which has been transposed into German law through *GEIG* [14], 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, we concluded the DSR process after three design cycles based on the convergence of qualitative feedback themes and available resources. While the overall SUS score of 81.8 indicates high usability, the cycle-level scores differed: cycle 2 averaged 87.1, whereas cycle 3 averaged 75.5. This decline should be interpreted with caution, as different firms evaluated different prototype versions (IDs 1–4 in cycle 2; IDs 5–8 in cycle 3), meaning that observed differences may partly reflect firm-specific characteristics and respondent profiles rather than design changes alone. Additionally, the feature enhancements implemented in

cycle 3 may have introduced additional complexity, consistent with the tension between analytic richness and cognitive simplicity noted in DP4.

Table 4 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 [47, 78]	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) [3]	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) [2, 75]	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 [11, 25]	Open-source, interactive web application, validated with eight firms; achieves high usability (SUS 81.8)
Contribution to DSS field	Extend modelling capabilities in energy informatics [12, 65]	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. The underlying LP model is entirely deterministic and does not explicitly account for uncertainty in EV usage patterns or electricity demand fluctuations. Although the EV adoption rate is treated as a user-adjustable scenario parameter, the model does not capture stochastic variation within a given scenario (e.g., day-to-day deviations in employee driving behaviour or charging needs). While the day-level variability captured in our boxplot results (cf. Figure 4) provides some indication of outcome dispersion, a formal treatment of uncertainty through stochastic optimisation or sensitivity analysis is not yet incorporated. Second, the current version of our DSS does not yet accommodate complex, firm-specific tariff structures. Third, although the model introduces heterogeneity in charging demand through random sampling of initial and departure state-of-charge levels (cf. §4.1), it does not yet allow users to specify these distributions based on observed vehicle- or user-specific data. Fourth, the optimisation focuses on peak electricity demand, charging costs, and carbon emissions, and does not incorporate practical deployment factors that real-world decision makers typically also consider, such as employee convenience and willingness to participate in managed charging programmes, capital expenditure budgets for charger procurement and installation, or physical space constraints at the workplace site. These represent important complementary considerations for real-world infrastructure deployment. Fifth, our evaluation was based on a sample of eight firms, all located in Germany, which limits the generalisability of the findings. Several elements

1591 of the DSS are context-specific: the regulatory framing draws on the German *GEIG*
1592 legislation, electricity price data are sourced from the *entso-e* transparency platform
1593 (bidding zone DE-LU), and grid carbon intensity data are retrieved from *electricity*
1594 *maps* for Germany. Transferring the DSS to other national or regulatory contexts would
1595 require adapting these data sources, as well as accommodating different tariff structures,
1596 emissions factor methodologies, and regulatory incentives for workplace charging.
1597 That said, the underlying optimisation model and the web application architecture
1598 are context-agnostic, and the open-source nature of the tool is designed to facilitate
1599 such adaptation. We therefore scope our empirical claims to German firms operating
1600 under comparable regulatory and market conditions, while the design principles (cf.
1601 Table 3) are intended to be transferable to DSSs for organisational sustainability
1602 transitions more broadly. These limitations also point to directions for future research
1603 and development. Subsequent iterations of the DSS could integrate stochastic time-
1604 series forecasting methods to enhance predictive power. Emerging AI models, such as
1605 TimeGPT [52], could provide off-the-shelf solutions for this task. Future studies could
1606 also extend the functionality of the DSS to incorporate more complex tariff structures
1607 and the integration of on-site renewable generation. Moreover, replication of the study
1608 in different geographical and industrial contexts would be valuable in assessing the
1609 system’s robustness and transferability. Looking further ahead, the DSS framework
1610 could be adapted to manage other forms of distributed energy resources, such as depot
1611 charging for delivery fleets or heavy-duty vehicles, as well as the operation of stationary
1612 battery energy storage systems.

1627 In conclusion, our DSS contributes a practical, user-centred solution to a pressing
1628 organisational and societal challenge. It is designed to help firms better plan and
1629 operate EV workplace charging infrastructure while explicitly surfacing the trade-
1630 offs between peak demand, costs, and emissions. By doing so, it not only advances
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DSS research but also offers policymakers and practitioners an actionable pathway to support the sustainable mobility transition.

Supplementary information. Additional file 1: Supplementary information (PDF). Supplementary Information for: Data-Driven Decision Support for Planning and Operating Electric Vehicle Workplace Charging Infrastructure. Contains the SUS scoring method (Section A), the semi-structured interview guides (Section B), screenshots of the web application from design cycles 1–2 (Section C), in-depth qualitative data (Section D), and in-depth quantitative data (Section E).

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Declarations

Ethics approval and consent to participate. This study was approved by the Central University Research Ethics Committee, University of Oxford (Approval Ref.: SOGE C1A 24 124).

Consent for publication. Not applicable.

Availability of data and materials. The source code of the open-source web application is publicly available at <https://github.com/segermarcel/EVWorkplaceChargingPublic>. Supplementary material, including anonymised interview quotes and full SUS calculations, is deposited at <https://zenodo.org/records/17151001>. Firm-specific electricity data cannot be shared due to confidentiality agreements with participating companies.

Competing interests. The authors report there are no competing interests to declare.

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Authors’ contributions. M.S.: Conceptualisation, methodology, software development, data collection, formal analysis, writing (original draft). C.B.: Supervision, writing (review and editing). C.C.: Software development, writing (review and editing). M.-F.K.: Conceptualisation, methodology, writing (review and editing). C.W.: Supervision, funding acquisition, writing (review and editing). All authors approved the final version of the manuscript and agree to be accountable for all aspects of the work.

Declaration of generative AI and AI-assisted technologies in the writing process. In preparing this manuscript, the authors used ChatGPT (GPT-5.2, Edu license, OpenAI) and Claude Code (Opus 4.6, Anthropic) to assist with idea generation and exploration, improving readability and language, conducting interactive online searches via LLM-enhanced search engines, and classifying relevant literature. After using these tools, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

Appendix A Mathematical formulation of optimisation model

Table A1 Complete model formulation including objective functions and constraints

Model type		PM-VF	CCM	CEM	eq.
Obj. function	$min.$	$z = \sum_{t \in T} (P_t + y_t - C)^2$	$z = \sum_{t \in T} y_t \lambda_t$	$z = \sum_{t \in T} y_t \gamma_t$	(A1)
Constraints	$s.t.$	$y_t = \sum_{m \in M} x_{mt} f_{mt}$		$\forall t \in T$	(A2)
		$0 \leq E_m^{ini} + \sum_{k \in T: k \leq t} \tau x_{mk} f_{mk} \leq E_m^{cap}$		$\forall t \in T; m \in M$	(A3)
		$E_m^{fin} = E_m^{ini} + \sum_{k \in T: k \leq t} \tau x_{mk} f_{mk} \geq E_{T+1}$		$\forall t \in T; m \in M$	(A4)
		$0 = x_{mt} (1 - f_{mt})$		$\forall t \in T; m \in M$	(A5)
		$0 \leq x_{mt} \leq p_{max}$		$\forall t \in T; m \in M$	(A6)
where,		$C = \frac{\max(P_t) + \min(P_t)}{2}$			(A7)
and		$f_{mt} = \begin{cases} 1, & \text{if EV } m \in M \text{ is parked at the workplace at time } t \in T, \\ 0, & \text{otherwise.} \end{cases}$			(A8)

Source: Adapted from Zheng et al. [77] and Ioakimidis et al. [39].

Table A2 Nomenclature

<i>Sets</i>	
$M = \{m\}$	Set of EVs, where m represents a single EV
$T = \{t\}$	Set of time slots, with fixed duration for each t
<i>Parameters</i>	
P_t	Electricity demand curve of industrial site at time step t [kWh]
λ_t	Time-of-Use (ToU) electricity price tariff at time step t [p/kWh]
γ_t	Grid carbon intensity at time step t [gCO ₂ /kWh]
E_m^{cap}	Total battery capacity of EV m [kWh]
E_m^{ini}	Initial battery charge level of EV m upon arrival at workplace [kWh]
E_{T+1}	Minimum battery charge requirement after work shift (specified by EV user) [kWh]
p_{max}	Maximum charging power capacity of charge point [kW]
f_{mt}	Parking availability matrix (binary parameter) of EV m indicating arrival and departure times
C	Average of daily max. and min. P_t [kWh]
τ	Length of each time interval t [15 min]
<i>Auxiliary variables (AVs)</i>	
y_t	Total electricity demand from EV charging at time step t [kWh]
E_m^{fin}	Final battery charge level of EV m upon departure from workplace [kWh]
<i>Decision variable (DV)</i>	
x_{mt}	Charging electricity demand for EV m at time step t [kWh]

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