

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

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## Keywords

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

## 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.

# 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<sub>2</sub> [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 [12–15], 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. More broadly, Power et al. [19] call for research on novel decision scenarios where emerging technologies support organisational decision-making, encouraging “*design science, case studies, [...] and*

empirical studies [that] help resolve the dilemmas of man versus machine and create a beneficial partnership” [19, p. 15]. Our study responds directly to this call by developing, demonstrating, and evaluating a model-driven DSS that augments executive judgement in the context of EV workplace charging.

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 allows 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 [20]. 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 [21]. 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 [22], (digital) carbon accounting systems [23], energy-aware business process management [24], and organisational digital decarbonisation approaches [25] 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 [26]. Studies address smart grid management [27], decentralised energy systems [28], and demand-side energy management [29], 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

89 algorithms and dynamic pricing [30]. Since the majority of these studies focus on network operators  
90 or electricity market agents, their perspective tends to remain at the systemic level, with an emphasis  
91 on market and grid implications. User-oriented approaches have improved the EV charging experience,  
92 with tools for intelligent navigation to available charging stations, real-time availability updates, and  
93 dynamic pricing to promote energy-efficient charging behaviours [31, 32]. More broadly, recent research has  
94 highlighted the importance of active stakeholder engagement in sustainable energy transitions, emphasising  
95 co-creation and participatory approaches to foster adoption [33]. Despite these advances, little user-oriented  
96 guidance exists on how to plan and operate EV workplace charging infrastructure using firm-specific data  
97 - a key enabler for scaling EV adoption and reducing emissions in the mobility sector [2, 34].

## 98 2.2. Smart EV charging

99 Smart charging is central to sustainable mobility systems. It involves managing EV charging loads  
100 according to predefined objectives, such as minimising peak demand, reducing costs, or lowering carbon  
101 emissions [35]. To this end, Zheng et al. [36] provide a review on common objective functions and  
102 modelling approaches in this field. In workplace contexts, algorithms have been developed to jointly  
103 optimise infrastructure sizing and the assignment of vehicles to charging spots, see e.g., [3]. When  
104 combined with on-site solar generation, real-time energy management systems can produce optimal  
105 charging schedules, thereby increasing self-sufficiency and lowering operational costs [37]. Bidirectional  
106 charging (V2G) provides an additional benefit by drawing energy from EV batteries during electricity  
107 demand peaks at industrial sites [38]. While these studies provide valuable insights, they are not easily  
108 transferable across workplace settings. Much of the literature frames workplace charging primarily as  
109 an engineering problem, focusing on energy or cost optimisation [39]. Less attention is given to the  
110 organisational decision-making processes that guide infrastructure deployment and management [10]. This  
111 gap highlights a practical challenge for operators: evaluating the strategic trade-offs among different  
112 charging strategies. Addressing this requires integrated DSSs that combine robust optimisation models  
113 with support for organisational decision-making.

## 114 2.3. Decision support systems for data-driven modelling of power loads

115 DSSs have a long history in sustainability and energy management research, especially within the green  
116 IS and energy informatics communities [17, 19]. They frequently use advanced analytical methods such as  
117 Artificial Intelligence (AI)-driven forecasting, simulation, and optimisation to support operational decisions  
118 about electricity demand [12, 18]. Examples include Gust et al. [40], who combine predictive analytics and  
119 optimisation for grid planning, or Schuller et al. [41], who benchmark smart charging and V2G strategies  
120 while accounting for driving patterns, battery degradation, and energy price variability, thus emphasising  
121 the complexity and practical relevance of detailed economic modelling within DSS frameworks. Similarly,  
122 Ludwig et al. [42] demonstrate how Big Data analytics, specifically LASSO regression and random forests,  
123 can substantially improve electricity price forecasting through automated feature selection, underscoring  
124 the importance of selecting relevant variables from large datasets for data-driven decision support. Bregar  
125 [43] proposes a DSS for self-sustainable smart grids that integrates machine learning, multi-criteria  
126 negotiation protocols, and blockchain technology to support decision-making in decentralised energy  
127 communities. Despite these advances, most DSSs either focus on technical optimisation alone or rely on  
128 generic datasets. Few integrate detailed, data-driven load simulation with firm-specific decision contexts.  
129 As Power [44] argues, the value of data science for decision support lies not in analytical sophistication per  
130 se, but in its ability to deliver actionable insights to targeted users. This need for targeted, user-oriented

131 decision support is further underscored by research on EV adoption, where Shareeda et al. [45] show that  
 132 stakeholder-specific factors, such as consumer awareness, purchasing power, and infrastructure availability,  
 133 are critical determinants, highlighting the multi-dimensional nature of decisions in the sustainable mobility  
 134 transition. Recent work in green IS has explicitly called for such integration [17, 18].

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

### 138 3. Methodology

#### 139 3.1. Research design

140 We applied a Design Science Research (DSR) approach, which “creates and evaluates IT artefacts  
 141 intended to solve identified organisational problems” [46, p. 77]. Our process followed five steps: (i) problem  
 142 identification, (ii) definition of objectives, (iii) design and development of the artefact, (iv) demonstration  
 143 and rigorous evaluation, and (v) communication of design knowledge. Three design cycles (cf. Figure 1)  
 144 allowed us to iteratively refine the artefact. Unlike the six-step process by Peffers et al. [20], we report on  
 145 steps 4 and 5 together, as previous studies have done [47].

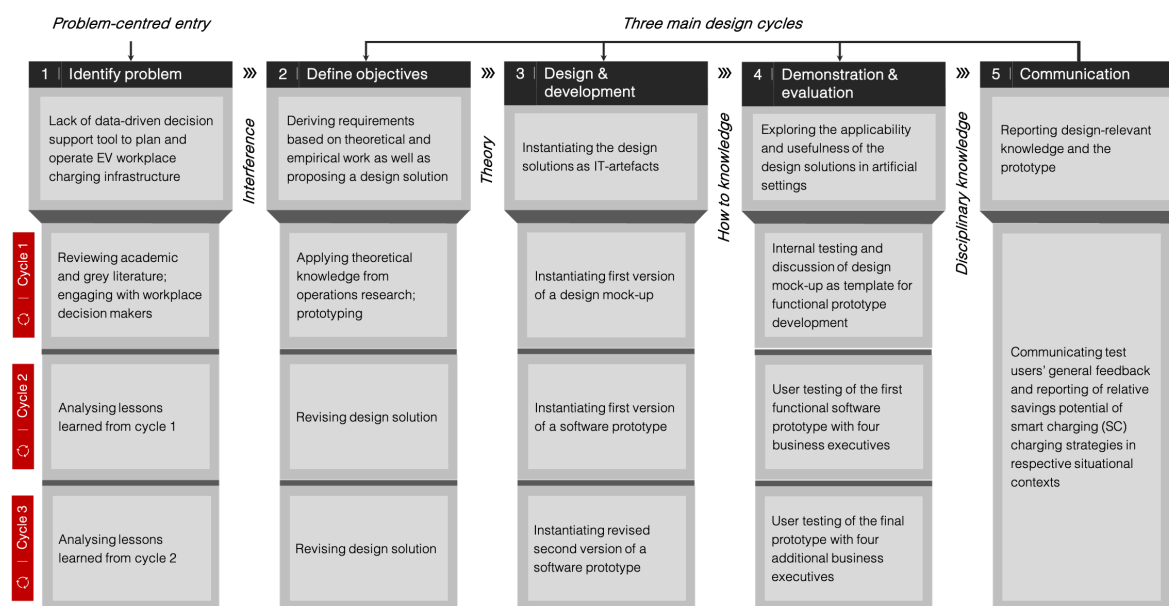


Figure 1: Overview of our DSR process; adapted from Peffers et al. [20] and Schoormann et al. [47]

146 As outlined above, we identified a central organisational problem in line with previous literature [10]:  
 147 executives often lack analytical foresight about the grid impacts of EV workplace charging. In particular,  
 148 they have limited awareness of the benefits of managing charging points through smart charging versus  
 149 leaving charging uncontrolled [10], particularly regarding the quantification of their impacts. While  
 150 uncontrolled charging typically begins immediately upon plug-in as employees arrive at the workplace,  
 151 potentially leading to significant peak demand spikes at the aggregate level when large numbers of EVs  
 152 require simultaneous charging, smart charging allows for distributed load management aligned with  
 153 pre-defined objectives, such as minimising peak demand, reducing charging costs, or lowering emissions  
 154 [35]. The choice among these smart charging strategies depends upon the local decision context, for  
 155 instance, reducing peak demand to accommodate limited on-site grid capacity, or addressing financial

156 considerations (charging costs) and environmental or regulatory compliance requirements (carbon emissions  
157 minimisation) [36]. A mathematical formulation of the optimisation model can be found in Tables 5–6 in  
158 Appendix A and is explained in §4.1 in more detail. To address this real-world challenge, we designed a  
159 generic, open-source DSS prototype that enables firms to model charging strategies with their own data.  
160 After identifying the problem (step 1), we defined objectives (step 2), designed a prototype (step 3), and  
161 demonstrated and evaluated it with firms in our sample (steps 4–5). Note that we use the data collected  
162 during steps 2–5 comprehensively across design cycles 1–3.

163 In addition to the artefact itself, we contribute transferable design knowledge in the form of design  
164 principles (DPs). Following Gregor et al. [48], we derived six DPs from two complementary sources: (i)  
165 the design rationale underlying the artefact, i.e., the key design decisions made during development (cf.  
166 §4), and (ii) the empirical evaluation evidence gathered through qualitative interviews and quantitative  
167 usability testing (cf. §5). We grouped the DPs under three overarching meta-requirements that emerged  
168 from the decision problem and its evaluation, and structured each DP according to the anatomy proposed  
169 by Gregor et al. [48]: aim, context, mechanism, and rationale. The resulting design principles are presented  
170 and discussed in §6.

### 171 3.2. Sampling approach

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

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

184 Table 1 summarises the eight sample firms, including their sectors, annual electricity consumption,  
185 and main sources of demand. While we developed a first version of the tool, i.e., design cycle 1, based on  
186 prior literature, such as [10], we evenly distributed the firms between design cycles 2 and 3. Companies  
187 1–4 (IDs) evaluated the initial version of our artefact (cf. Figure 6 in Appendix D) in design cycle 2,  
188 while companies 5–8 (IDs) assessed the enhanced version (cf. Figure 7 in Appendix D) in design cycle 3.  
189 We sourced participating firms through three channels: (i) digital flyer advertisements on LinkedIn, (ii)  
190 targeted outreach via cold emailing, and (iii) the authors’ professional networks.

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

DC <sup>1</sup> 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	90	5%	Firm-specific data
2	2	Office supplies	232 MWh	Office staff (08:00–16:00)	50	25%	Firm-specific data
2	3	Healthcare	6,137 MWh	Hospital operations	50	10%	Firm-specific data
2	4	Pharma	6,000 MWh	Drug manufacturing	100	10%	Firm-specific data
3	5	Paper production	197,290 MWh	Production machinery	175	5%	Firm-specific data
3	6	Manufacturing	4,000 MWh	Compressed air generation	70	30%	Firm-specific data
3	7	Building materials	2,000 MWh	Office buildings, HVAC	500	12%	Standard load profile
3	8	Energy infrastructure	1,724 MWh	Production machinery	30	3%	Firm-specific data

<sup>1</sup> 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 [49] using Microsoft Teams. The interview guides are listed in Tables 7–8 in Appendix C. 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 [50] to measure perceived usability.

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

DC <sup>1</sup>	ID	Role of interview partner(s) <sup>2</sup>	Date of interviews	
			Interview 1 Duration (mm:ss)	Interview 2 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	14.01.2025
			(28:29)	(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)
3	7	a: Sustainability manager	11.04.2025	28.04.2025
			(47:05)	(29:11)
3	8	a: Engineer sustainability manager	30.04.2025	07.05.2025
			(18:55)	(36:13)

<sup>1</sup> DC = Design cycle;

<sup>2</sup> 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.

For qualitative analysis, we applied a primarily deductive coding approach [51], 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 prior frameworks, while the fourth served as an inductively populated open category [52]. This hybrid strategy ensured theoretical grounding while remaining responsive to context-specific insights.

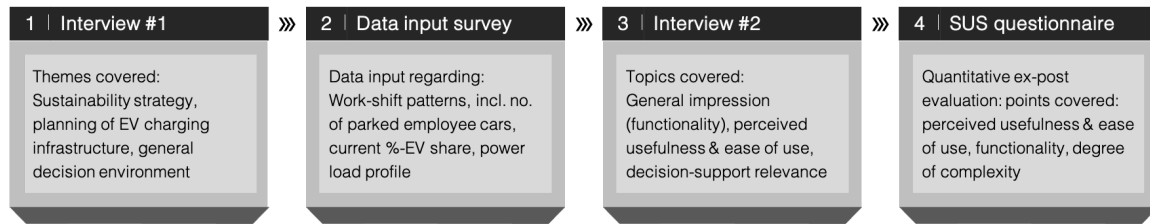


Figure 2: Summary of data collection points for each participating firm.

Specifically, perceived usefulness corresponds to Davis' [53] 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 [54] IS Success Model and often assessed through usability instruments such as the SUS [55] or user satisfaction surveys [56]. Organisational value reflects the dimension of net benefits in the DeLone & McLean [54] 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. [38] and Zheng et al. [36]. 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 for each EV, and minimum departure charge requirements ( $E_m^{fin}$ ) between 80% and 100%, reflecting variation in individual driving patterns and charging needs.

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 5-6 in Appendix A for transparency and reproducibility. By concluding design cycle 1, we had established a

245 technically validated optimisation module that served as the engine of the DSS, forming the basis for  
246 subsequent cycles of real-world application and user evaluation (design cycles 2-3).

247 To support early design decisions, we created a high-fidelity mock-up of the user interface in Figma.  
248 This is a widely used approach to save valuable resources (time, development costs etc.) within Design  
249 Science and user-centred design [57]. The mock-up defined the layout and components of the dashboard,  
250 including a three-column structure with a collapsible sidebar for data input, a central panel for line graphs,  
251 and a right-hand panel for key metrics. This static prototype (cf. Figure 6 in Appendix D) served as the  
252 basis for subsequent development.

## 253 4.2. Design cycle 2

254 In the second cycle, we translated the static Figma prototype into a functional web application (cf.  
255 Figure 7 in Appendix D). We used the open-source toolkit Streamlit, which offers Python packages for  
256 building interactive applications without resource-intensive front-end programming. The application  
257 interface consists of three main parts. First, a sidebar collects firm-specific input such as (a) number  
258 and timing of work shifts, (b) number of employee cars per shift, (c) EV battery size distributions, (d)  
259 electricity load profiles (uploaded as .xls or .csv files), and (e) analysis preferences (date, solver, charger  
260 power). While these exogenous input parameters are held constant, the decision maker gets to choose the  
261 EV electrification rate freely between 0% (no EV present) to 100% (fully electrified car fleet), in alignment  
262 with different future electrification scenarios. Second, the main panel visualises electricity demand profiles  
263 under three charging strategies: peak minimisation & valley filling (PM-VF) (top row), charging cost  
264 minimisation (CCM) (middle row), and carbon emission minimisation (CEM) (bottom row; cut off in the  
265 screenshot in Figure 7 in Appendix D). Each plot compares uncontrolled charging with the corresponding  
266 smart charging strategy. Third, bar charts display the Value of Smart Charging (VoSC), defined as the  
267 relative change ( $\% \Delta$ ) between smart- and uncontrolled charging for each key metric (i) maximum peak,  
268 (ii) total charging costs, or (iii) carbon emissions. The system updates results in real time when input  
269 parameters are changed.

## 270 4.3. Design cycle 3

271 After demonstrating the first functional prototype with firms in our sample (design cycle 2, cf. §3.3),  
272 we obtained valuable user feedback with actionable advice on what should be improved within design  
273 cycle 3. We identified 16 feature requests which we subsequently clustered into three priority levels (*high*,  
274 *medium*, *low*). We categorised feature requests as ‘high’ based on (i) relevance (certain features have  
275 been requested several times throughout interviews), (ii) technical feasibility, and (iii) resource availability  
276 (e.g. time) to develop the request. In the third design cycle, we implemented the following high-priority  
277 improvements: a multi-period analysis allowing users to view results daily, weekly, or monthly, with  
278 shaded confidence intervals indicating variability; external data integration enabling automated retrieval  
279 of German electricity price data from *entso-e*’s transparency platform (bidding zone DE-LU) [58] and  
280 grid-carbon intensity data from *electricity maps* [59]; in-app explanations providing contextual tooltips to  
281 improve self-efficacy and understanding; graph enlargement and export functions for reporting purposes;  
282 an option to display the VoSC in absolute rather than relative terms; and improved visual clarity through  
283 tick boxes allowing selective display of external electricity price and carbon intensity curves.

284 Remaining medium- and low-priority features are documented in Appendix E. These relate to (a)  
285 tariff-specific grid carbon intensity measures, (b) tariff-specific electricity price data (fixed/dynamic),  
286 (c) data-driven forecasting of firm’s electricity load profile, (d) firm-specific peak pricing, (e) analytical

287 specifications ( $CO_2$  emissions: accounted vs. actually emitted), and (f) advanced analytics for tracking of  
 288 seasonal effects. The updated and final DSS is shown in Figure 3.

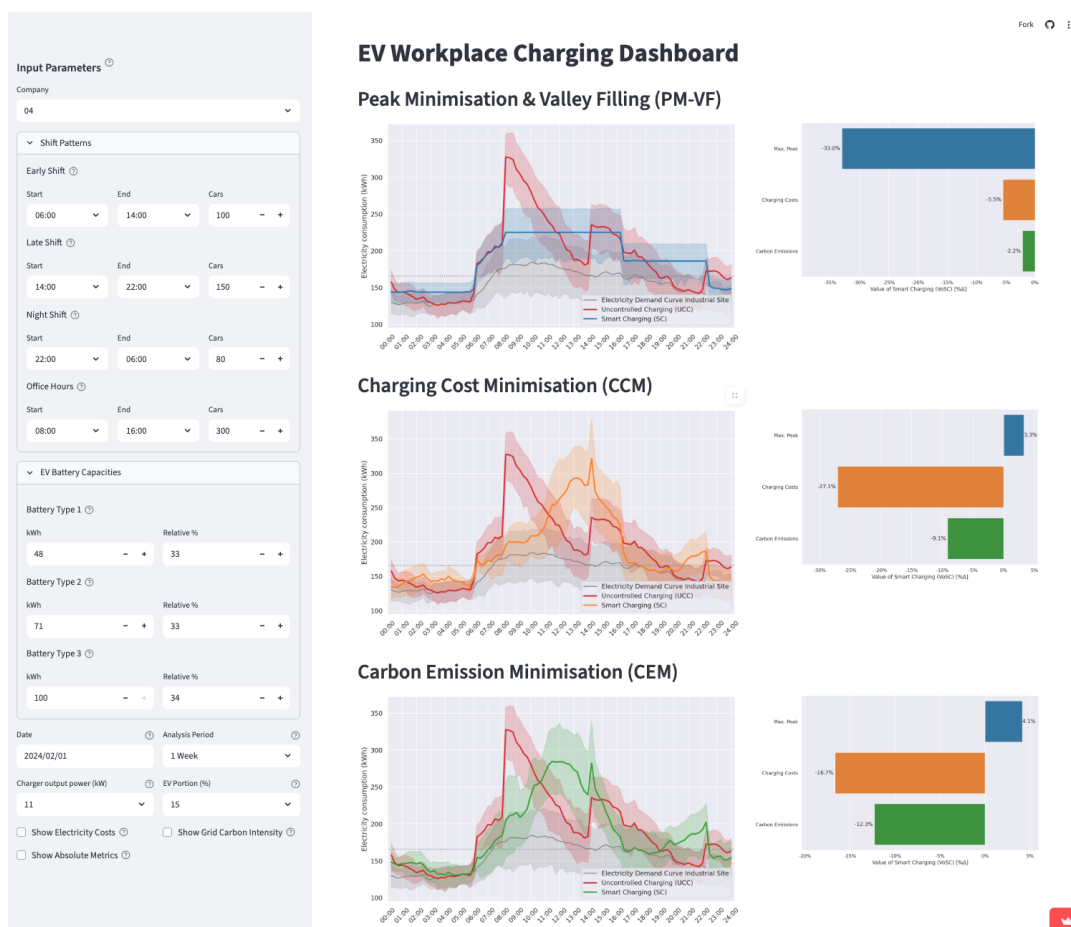


Figure 3: Updated web application post implementation of interviewees' feedback (design cycle 3)

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

## 293 5. Demonstration, evaluation, and findings

### 294 5.1. Application of our artefact

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

299 Each firm in our sample provided information on its annual electricity consumption, main demand  
 300 sources, work shift schedules, number of employee cars, and current EV adoption rates. We used these  
 301 data, summarised in Table 1, to parametrise the DSS. Further contextual information is provided in  
 302 Table 14 in Appendix E regarding (i) high-level characteristics of the firm's electricity load profile, (ii)  
 303 procurement strategy, (iii) expected future electricity consumption, and (iv) anticipated challenges in

304 managing electricity demand. One firm (ID 7) was unable to share detailed load profiles; in this case, we  
305 relied on a publicly available standard load profile. This case serves as a robustness check, demonstrating  
306 that the DSS can operate even when firm-specific data are unavailable, albeit with less contextualised  
307 outputs. It also illustrates the added value of firm-specific data: results for ID 7 are less tailored than  
308 those for firms where actual load profiles were available, underscoring the importance of contextual data  
309 embedding (cf. DP1). For the remaining firms, we simulated electricity load profiles under three charging  
310 strategies - peak minimisation & valley filling (PM-VF), charging cost minimisation (CCM), and carbon  
311 emission minimisation (CEM), in response to varying EV adoption rates [%]. For each scenario, the DSS  
312 also calculated the VoSC, expressed as the relative change [% $\Delta$ ] in peak demand, charging costs, or carbon  
313 emissions compared to uncontrolled charging.

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

318 VoSC [% $\Delta$ ] model results of all firms (IDs 1–8) are provided in Figure 8 in Appendix E. In general,  
319 we find three key insights: First, if firms opt for peak minimal charging (PM-VF), the graphs show  
320 that this charging strategy yields the lowest overall peaks across the sample (IDs), with higher savings  
321 potential as the EV rate increases. Second, contrary to peak minimal charging, if optimising for charging  
322 costs (CCM) or carbon emissions (CEM), the achieved savings potential remains relatively constant,  
323 independent of the EV adoption rate. Third, and lastly, when comparing results across firms (IDs 1–8),  
324 we observe substantial differences in variability, measured by the boxplots' whisker lengths, for certain  
325 key metrics (e.g. cf. Figure 4: PM-VF (top row): charging costs, ID 5 vs. ID 6). This suggests that the  
326 model results for each firm are highly context-dependent. Several firm characteristics appear to drive  
327 this variability (cf. Table 1). First, baseline energy intensity plays a key role: for firms with low annual  
328 electricity consumption (e.g., ID 2: 232 MWh), even modest EV charging loads represent a substantial  
329 relative perturbation to the existing load profile, amplifying the VoSC. In contrast, for energy-intensive  
330 firms (e.g., ID 5: 197,290 MWh), EV charging constitutes a marginal addition to an already large base  
331 load, yielding smaller relative effects. Second, work shift patterns influence the temporal distribution of  
332 EV arrivals and thus the degree of peak coincidence: firms operating multiple shifts (e.g., IDs 1, 4, 5)  
333 naturally distribute charging demand across the day, whereas single-shift office operations (e.g., IDs 2,  
334 7) concentrate arrivals and create sharper peaks. Third, fleet size determines the absolute magnitude of  
335 charging demand, with larger fleets (e.g., ID 7: 500 cars) amplifying both the potential benefits and risks  
336 of different charging strategies. These observations underscore the importance of firm-specific analysis  
337 and further support DP1 (Contextual Data Embedding): generic benchmarks are insufficient for guiding  
338 infrastructure decisions when contextual factors vary so substantially across firms.

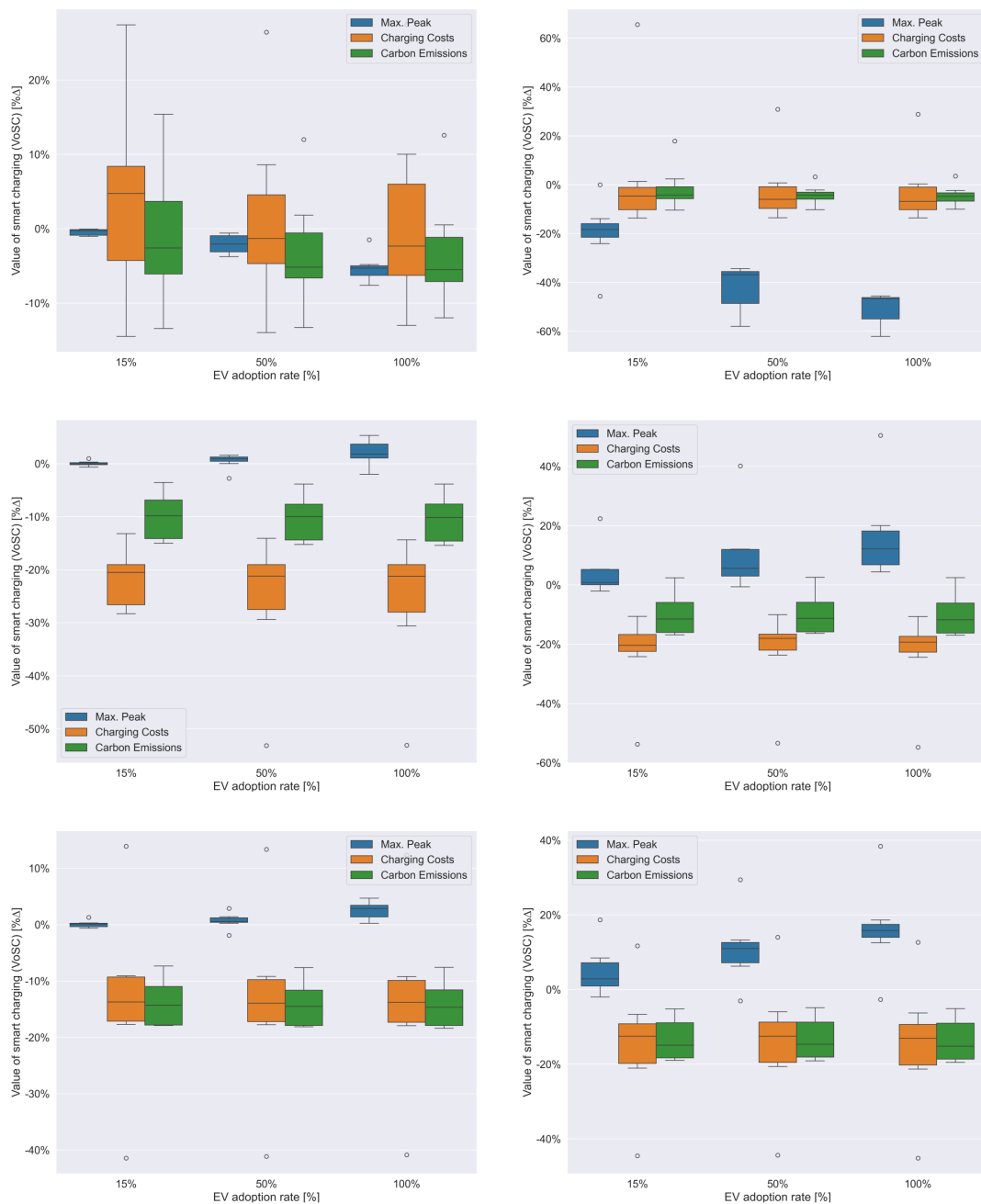


Figure 4: Visual summary of VoSC [% $\Delta$ ] (y-axis) model results for increasing EV adoption rates of 15%, 50%, 100% (x-axis) w.r.t. each key metric *max. peak demand* (blue), *charging costs* (orange), and *carbon emissions* (green), differentiated by charging strategies *PM-VF* (top row), *CCM*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

## 339 5.2. Qualitative findings: Managerial insights from interviews

340 The purpose of this study is not only to evaluate the usability of the developed artefact (cf. §5.3), but  
 341 also to examine how the DSS influences executives' understanding, dialogue, and capacity for long-term  
 342 planning regarding EV workplace infrastructure. To this end, we conducted interviews with 14 practitioners  
 343 from 8 firms, each holding managerial responsibilities across sustainability, energy, facilities, fleet, and

344 finance departments. In the following, we present our findings as six themes that illustrate how the DSS  
345 shapes decision-making.

346 **Surfacing and managing trade-offs:** Our findings indicate that the DSS supports executives in  
347 explicitly weighing costs, peak load, and emissions, thereby moving beyond intuition toward structured  
348 comparisons. This is illustrated by interviewee 2a, who noted feeling empowered to compare quantitative  
349 trade-offs across alternatives: *“Just being able to say: ‘OK, what alternatives do I have? Do I want to  
350 reduce costs or do I want to reduce CO<sub>2</sub>?’ And that really does make a difference.”* [ID: 2a]. He further  
351 emphasised the value of prioritisation and data-driven decision-making: *“To set priorities and (...) start  
352 working with data in the company instead of relying on gut feelings”* [ID: 2a], and highlighted the efficiency  
353 gains: *“It’s just nice to be able to argue using valid data, (...) something I’d otherwise have to gather  
354 myself with a lot of effort.”* [ID: 2a]. Likewise, respondent 6a stressed the practical usefulness of the web  
355 application *“because it shows how you can weigh different factors”* [ID: 6a], which, in turn, *“help[s] to  
356 make a more informed decision than one might otherwise have made”* [ID: 6a]. The role of data-driven  
357 guidance is also evident in interviewee 5b’s reflections on determining the appropriate scale of charging  
358 infrastructure: *“What definitely helps is getting guidance on: How large should I dimension my charging  
359 infrastructure? What do I need to consider, what kind of costs and savings are actually involved if I  
360 incorporate different automation features?”* [ID: 5b]. He also stressed the importance of integrating cost  
361 considerations with smart charging strategies: *“What I find especially interesting is the combination of  
362 charging cost optimisation with smart charging, because (...) you can really see the impact of trying to  
363 control your demand based on cost, rather than just managing everything purely based on demand.”* [ID:  
364 5b]. Collectively, these insights highlight the DSS’s role in revealing decision tensions and supporting  
365 multi-objective reasoning.

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

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

389 a boundary object, supporting collaboration across sustainability, energy, facilities, fleet, and finance  
390 functions.

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

402 **External validation and credibility:** Executives particularly valued instances where the DSS  
403 outputs aligned with their own systems and data, as this alignment reinforced trust in the tool. Interviewee  
404 4a illustrated this point, noting: *“I already like that the red curve reflects reality - that’s a good start,*  
405 *because I checked in my own program in parallel, and it looks similar.”* [ID: 4a]. He further added: *“It’s*  
406 *great that the theory already reflects the reality, I really like that.”* [ID: 4a]. These reflections underscore  
407 that credibility of model outputs is a prerequisite for adoption in strategic decision-making contexts.

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

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

### 422 5.3. Quantitative findings: System Usability Scale (SUS) questionnaire

423 We assessed the DSS’s usability with the SUS questionnaire [55]. SUS consists of ten standardised  
424 statements, alternating between positive and negative wording, each rated on a five-point Likert scale  
425 from ‘strongly disagree’ (1) to ‘strongly agree’ (5) [60]. Scores are calculated on a 0–100 scale, where values  
426 above 71 indicate good usability and values above 81 are considered ‘excellent’. The formal mathematical  
427 derivation to obtain the SUS score is included in Appendix B. Moreover, an overview of the ten SUS  
428 items, together with the individual ratings from each respondent differentiated by design cycles 2 and 3, is  
429 provided in Table 15 in Appendix F. We received 11 completed questionnaires: six from design cycle 2  
430 and five from design cycle 3. The average SUS score across all responses was 81.8, which falls into the  
431 ‘excellent’ category. By comparison, the average SUS score for web-based user interfaces is 68 [61]. This  
432 suggests that our DSS performs well above typical benchmarks. Looking at the design cycles separately,

433 cycle 2 achieved an average SUS of 87.1 (*'best imaginable'*). Cycle 3 averaged 75.5, which is considered  
 434 *'good'*. However, because the two cycles involved different respondent groups from different firms ( $n = 6$   
 435 and  $n = 5$ , respectively), direct cross-cycle comparison is confounded by differences in respondents' digital  
 436 literacy, organisational context, and prior expectations.

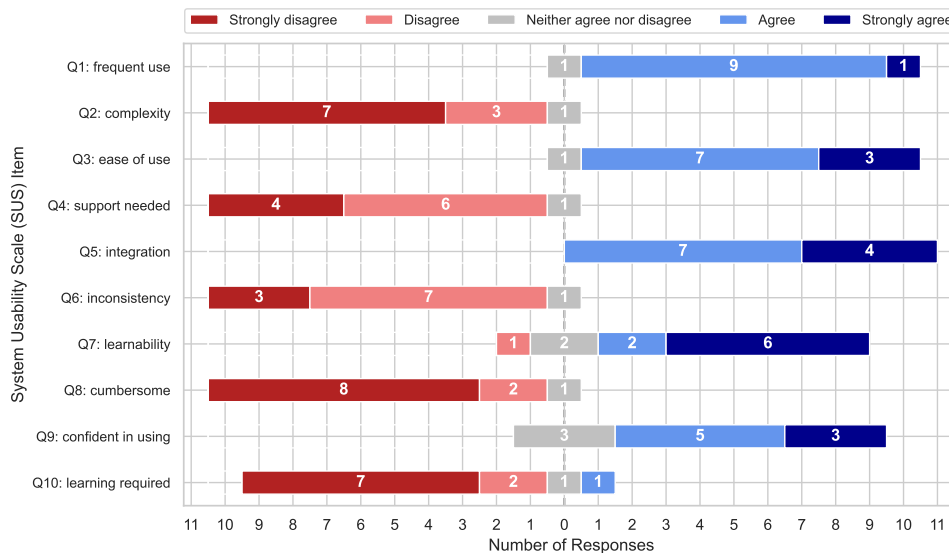


Figure 5: Distribution of participants' responses in each Likert category, from *'strongly disagree'* (dark red) to *'strongly agree'* (dark blue). Results combine responses from design cycle 2 ( $n = 6$ ) and 3 ( $n = 5$ ).

437 Figure 5 illustrates the distribution of responses for each of the ten SUS items across both cycles. The  
 438 combined results indicate strong usability ratings, reflecting positive user perceptions regarding ease of  
 439 use (Q3), simplicity (Q2), integration of system functions (Q5), consistency (Q6), and overall willingness  
 440 to frequently use the system (Q1). Respondents also clearly indicated that the system does not require  
 441 extensive initial learning (Q10) or technical support (Q4), nor did they perceive it as cumbersome (Q8).  
 442 Furthermore, participants generally felt confident using the system (Q9) and believed most people would  
 443 learn the system quickly (Q7), although minor neutral responses suggest potential for further enhancing  
 444 user guidance. In sum, the quantitative results align with our qualitative findings: users perceived  
 445 the DSS as clear, practical, and highly usable. It is important to note that SUS measures perceived  
 446 usability, not whether the DSS improves the quality of decisions made. While the interviews (§5.2)  
 447 do not measure decision quality directly, they provide indicative evidence that practitioners perceived  
 448 the DSS as supporting their reasoning, helping them surface trade-offs, reframe strategic decisions, and  
 449 facilitate cross-departmental dialogue. Together, the triangulation of quantitative usability assessment  
 450 (SUS) and these qualitative findings provides a comprehensive early-stage evaluation. This mixed-method  
 451 approach resonates with Mora et al.'s [62] call for evaluating decision-making support systems along  
 452 multiple dimensions. Measuring actual decision quality improvement would require controlled experiments  
 453 comparing outcomes with and without the DSS, which represents a direction for future research. The  
 454 overall SUS score of 81.8 suggests strong usability and indicates potential for adoption in organisational  
 455 settings.

## 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<sub>2</sub> [4]. Our findings build on this evidence by showing how such benefits can be contextualised, quantified, and operationalised through a DSS.

Beyond the situated artefact, our study contributes transferable design knowledge in the form of six design principles (DPs) for DSSs that support organisational sustainability transitions. Following Gregor et al. [48], we structure each DP along four components: aim, context, mechanism, and rationale. The DPs are grounded in both the design rationale of our artefact and the empirical evaluation evidence from interviews with 14 practitioners across eight firms. We group the six DPs under three overarching meta-requirements (MRs), each reflecting a distinct class of demands that emerged from the decision problem and its evaluation (cf. Table 3).

**MR1: Context-specific decision support.** The DSS should generate insights grounded in the user’s organisational context to produce actionable, trusted outputs. Two design principles address this requirement. *DP1 : Contextual data embedding* stipulates that the DSS should integrate organisation-specific operational data (load profiles, shift patterns, fleet composition) to generate tailored insights. Our cross-firm comparison revealed substantial differences in model results (cf. Figure 4), confirming that generic datasets fail to capture the contextual variability that drives firm-level outcomes. As one interviewee noted: “a tool like this would definitely be a huge support, especially if it provides real values based on company-specific data” [8a]. *DP5 : Output credibility through data mirroring* requires that the DSS produce outputs which users can validate against their existing monitoring systems. This principle reflects the finding that credibility is a prerequisite for adoption: “the red curve reflects reality – that’s a 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 [63]; 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 CO<sub>2</sub>?’ 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 [2]: “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 [64], 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

501 support system within the taxonomy proposed by Power et al. [19], where humans (business executives)  
502 and machines (optimisation algorithms) “interact in mutually supportive patterns of iterative sequential  
503 or parallel activities”, thereby augmenting human cognitive abilities [65, p. 2]. Following Power et  
504 al.’s [19] framework of organisational decision systems (cf. their Figure 4), our DSS operates in the  
505 ‘Alternative Generation and Evaluation’ phase: it uses simulation and optimisation to help executives  
506 evaluate competing charging strategies, supporting the transition from problem identification to informed  
507 choice. While our web application constitutes a situated implementation at ‘Level 1’ [66], the six design  
508 principles elevate the contribution to ‘Level 2’: a nascent design theory that offers prescriptive knowledge  
509 transferable to other sustainability transition DSSs beyond the specific context of EV workplace charging  
510 [48]. The DPs were derived from both the artefact’s design rationale and its empirical evaluation; they  
511 are structured following the anatomy of a design principle proposed by Gregor et al. [48] and summarised  
512 in Table 3.

513 Responding to recent scholarly calls [17, 18], the novelty of our work lies in its user-centred approach  
514 to solving a real-world organisational problem within the broader challenge of the sustainable mobility  
515 transition. Our DSS is designed to support business executives in making informed decisions about  
516 planning and operating EV workplace charging infrastructure. We demonstrated and evaluated the system  
517 using real-world electricity consumption data from our sample firms, combining qualitative interviews to  
518 assess perceived usefulness and organisational value with the SUS questionnaire to assess usability. We  
519 selected DSR as the guiding paradigm because of its iterative and practice-oriented nature. This approach  
520 enabled us to continuously refine the prototype based on participant feedback across three design cycles.

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

528 We compared our artefact to prior energy-related DSSs (cf. Table 4). Previous systems often rely on  
529 generic or grid-level datasets, focus on a single optimisation objective, and are primarily designed for  
530 technical experts [16, 63, 67]. By contrast, our DSS integrates firm-specific data by embedding contextual  
531 load profiles into the analysis, represents trade-offs explicitly by quantifying costs, peak demand, and  
532 emissions side by side, and targets organisational decision makers, thereby fostering dialogue across  
533 sustainability, facilities, finance, and fleet management. This combination extends DSS design beyond  
534 technical optimisation. It shows how firm-specific modelling and trade-off representation can support  
535 sustainability transitions at the organisational level.

536 Firms can derive several practical implications from our study. First, when evaluating the results of  
537 each charging strategy in isolation, we find that, on average, each strategy achieves its intended outcome.  
538 For example, PM-VF consistently produces the lowest peaks, while CCM leads to the lowest charging  
539 costs (cf. Figure 4). This finding demonstrates the external validity of our model, as each optimisation  
540 strategy delivers what it was designed to achieve. Second, however, our results also show that optimising  
541 for the overall lowest charging costs (CCM) or the lowest carbon emissions (CEM) comes at a trade-off.  
542 Specifically, these strategies incur substantially higher peak loads, an effect that becomes more pronounced  
543 as EV adoption increases (cf. Figure 4: second and third row). Third, when comparing results across  
544 firms (cf. Figure 4), we observe substantial contextual variability. This is evident in the different lengths  
545 of the whiskers in the boxplots, which capture the variability of the results across individual model runs.

Table 3: Design principles for decision support systems supporting organisational sustainability transitions, structured following the anatomy of a design principle [48].

DP	Design Principle	Aim	Context	Mechanism	Rationale
<b>MR1: Context-specific decision support</b>					
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
<b>MR2: Multi-objective decision transparency</b>					
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
<b>MR3: Organisational adoption and collaborative use</b>					
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

546 These differences underline the importance of firm-specific data and analysis, and they demonstrate  
 547 the added value of our web application as a tool tailored to each organisational context. In addition, from  
 548 a DSS evaluation perspective, the combined qualitative and quantitative results of our study provide  
 549 tangible evidence of the system’s usability and practical value for corporate decision makers. Simplicity  
 550 and clarity emerge as key success factors for adoption, as they lower barriers for non-technical users and  
 551 increase confidence in applying the system to strategic decision-making.

552 For policymakers, our study highlights the importance of managing EV workplace charging loads  
 553 in a comprehensive manner by using highly granular DSSs that incorporate firm-specific parameters.  
 554 Across most firms in our sample, the DSS simulations indicate an average carbon emissions savings  
 555 potential of approximately 20% (cf. Figure 8 in Appendix E: second row). This demonstrates that  
 556 firm-level optimisation measures are both feasible and actionable, and that they can significantly enhance  
 557 demand-side flexibility in the electricity system. Such flexibility is widely recognised as a critical element in  
 558 achieving the EU’s net-zero emissions target by 2050. While the EU-wide *Energy Performance of Buildings*  
 559 *Directive (EPBD)* [68], which has been transposed into German law through *GEIG* [8], represents an  
 560 important first step towards scaling workplace charging infrastructure, we argue that additional regulatory  
 561 frameworks are needed to incentivise the uptake of smart charging algorithms.

562 Lastly, in terms of methodological procedure, we concluded the DSR process after three design cycles  
 563 based on the convergence of qualitative feedback themes and available resources. While the overall SUS  
 564 score of 81.8 indicates high usability, the cycle-level scores differed: cycle 2 averaged 87.1, whereas cycle 3  
 565 averaged 75.5. This decline should be interpreted with caution, as different firms evaluated different  
 566 prototype versions (IDs 1–4 in cycle 2; IDs 5–8 in cycle 3), meaning that observed differences may partly  
 567 reflect firm-specific characteristics and respondent profiles rather than design changes alone. Additionally,  
 568 the feature enhancements implemented in cycle 3 may have introduced additional complexity, consistent  
 569 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
<b>Data scope</b>	Rely on generic scenarios, grid-level datasets, or engineering assumptions [16, 42]	Integrates firm-specific electricity load data and workplace context to deliver tailored insights
<b>Decision framing</b>	Emphasise single-objective optimisation (e.g., cost, peak demand, or emissions separately) [63]	Makes multi-objective trade-offs explicit by quantifying costs, peak demand, and carbon emissions simultaneously
<b>User orientation</b>	Designed primarily for technical experts (e.g., grid operators, energy engineers) [67, 69]	Designed for organisational decision makers (sustainability, energy, facilities, fleet, finance) to enable cross-departmental dialogue
<b>System design</b>	Often research prototypes with limited validation in practice [43, 70]	Open-source, interactive web application, validated with eight firms; achieves high usability (SUS 81.8)
<b>Contribution to DSS field</b>	Extend modelling capabilities in energy informatics [41, 71]	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 of the DSS are context-specific: the regulatory framing draws on the German *GEIG* legislation, electricity price data are sourced from the *entso-e* transparency platform (bidding zone DE-LU), and grid carbon intensity data are retrieved from *electricity maps* for Germany. Transferring the DSS to other national or regulatory contexts would require adapting these data sources, as well as accommodating different tariff structures, emissions factor methodologies, and regulatory incentives for workplace charging. That said, the underlying optimisation model and the web application architecture are context-agnostic, and the open-source nature of the tool is designed to facilitate such adaptation. We therefore scope our empirical claims to German firms operating under comparable regulatory and market conditions, while the design principles (cf. Table 3) are intended to be transferable to DSSs for organisational sustainability transitions more broadly. 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

615 the operation of stationary battery energy storage systems.

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

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

627 **Ethics approval** This study was approved by the Central University Research Ethics Committee,  
628 University of Oxford (Approval Ref.: SOGE C1A 24 124).

629 **Disclosure of interest** The authors report there are no competing interests to declare.

630 **Funding** This work was supported by the European Research Council (ERC) under Grant [#101003083](#)  
631 ([iDODDLE](#) project, M.S. and C.W.); and the UK Energy Research Centre under Grant [EP/S029575/1](#)  
632 (C.B.).

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

638 **Data availability statement** The source code of the open-source web application is publicly available at  
639 <https://github.com/segermarcel/EVWorkplaceChargingPublic>. Supplementary material, including  
640 anonymised interview quotes and full SUS calculations, is deposited at [https://zenodo.org/records/](https://zenodo.org/records/17151001)  
641 [17151001](https://zenodo.org/records/17151001). Firm-specific electricity data cannot be shared due to confidentiality agreements with partici-  
642 pating companies.

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643

## A. Mathematical formulation of optimisation model

Table 5: Complete model formulation including objective functions and constraints

Model type		PM-VF	CCM	CEM	eq.
Obj. function	<i>min.</i>	$z = \sum_{t \in T} (P_t + y_t - C)^2$	$z = \sum_{t \in T} y_t \lambda_t$	$z = \sum_{t \in T} y_t \gamma_t$	(1)
Constraints	<i>s.t.</i>	$y_t = \sum_{m \in M} x_{mt} f_{mt}$		$\forall t \in T$	(2)
		$0 \leq E_m^{ini} + \sum_{k \in T: k \leq t} \tau x_{mk} f_{mk} \leq E_m^{cap}$		$\forall t \in T; m \in M$	(3)
		$E_m^{fin} = E_m^{ini} + \sum_{k \in T: k \leq t} \tau x_{mk} f_{mk} \geq E_{T+1}$		$\forall t \in T; m \in M$	(4)
		$0 = x_{mt} (1 - f_{mt})$		$\forall t \in T; m \in M$	(5)
		$0 \leq x_{mt} \leq p_{max}$		$\forall t \in T; m \in M$	(6)
where,		$C = \frac{\max(P_t) + \min(P_t)}{2}$			(7)
and		$f_{mt} = \begin{cases} 1, & \text{if EV } m \in M \text{ is parked at the workplace at time } t \in T, \\ 0, & \text{otherwise.} \end{cases}$			(8)

Source: Adapted from Zheng et al. [36] and Ioakimidis et al. [38].

Table 6: Nomenclature

Sets	
$M = \{m\}$	Set of EVs, where $m$ represents a single EV
$T = \{t\}$	Set of time slots, with fixed duration for each $t$
Parameters	
$P_t$	Electricity demand curve of industrial site at time step $t$ [kWh]
$\lambda_t$	Time-of-Use (ToU) electricity price tariff at time step $t$ [p/kWh]
$\gamma_t$	Grid carbon intensity at time step $t$ [gCO <sub>2</sub> /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]
$\tau$	Length of each time interval $t$ [15 min]
Auxiliary variables (AVs)	
$y_t$	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]
Decision variable (DV)	
$x_{mt}$	Charging electricity demand for EV $m$ at time step $t$ [kWh]

## 644 B. SUS scoring method

645 Let the responses to the ten statements of the SUS questionnaire be denoted as  $R_i$ , where  $R_i \in$   
 646  $\{1, 2, 3, 4, 5\}$  for all  $i = 1, \dots, 10$ . The adjusted scores ( $A_i$ ) for each response are computed as follows:

$$A_i = \begin{cases} R_i - 1, & \text{for odd-numbered items (positively worded) } (i = 1, 3, 5, 7, 9), \\ 5 - R_i, & \text{for even-numbered items (negatively worded) } (i = 2, 4, 6, 8, 10). \end{cases} \quad (9)$$

647 The sum of all adjusted scores is given by:

$$\text{SUS}_{\text{total}} = \sum_{i=1}^{10} A_i \quad (10)$$

648 The final SUS score, normalised to 0–100, is obtained by multiplying the total by 2.5:

$$\text{SUS Score} = 2.5 \times \text{SUS}_{\text{total}} = 2.5 \times \sum_{i=1}^{10} A_i \quad (11)$$

649 This yields a SUS score ranging from 0 to 100, with an average usability benchmark typically considered  
 650 around 68.

## C. Semi-structured interview guides

Table 7: Semi-structured interview guide (round 1/2): Exploring the decision context

#	German	#	English
0	<p><b>Einführende Fragen</b></p> <ul style="list-style-type: none"> <li>- Können Sie mir bitte einen kurzen Überblick über <i>[Unternehmen]</i>'s Nachhaltigkeitsstrategie geben? Inwiefern spielt der Ausbau der E-Ladeinfrastruktur hierbei eine Rolle?</li> <li>- Wo steht <i>[Unternehmen]</i> zum jetzigen Zeitpunkt? Sind bereits E-Ladesäulen in Betrieb und falls ja, wie viele, an welchen Standorten? Ladegeschwindigkeit?</li> <li>- Können Sie mir bitte mehr über den lokalen Kontext erzählen: (i) Wie viele Mitarbeitende pendeln täglich mit dem Auto zum Arbeitsplatz? (ii) Wie hoch ist der aktuelle Anteil von Elektrofahrzeugen am Gesamtfahrzeugbestand? (iii) Wie viele Parkplätze stehen vor Ort zur Verfügung?</li> </ul>	0	<p><b>Introductory questions</b></p> <ul style="list-style-type: none"> <li>- Could you please give me a brief overview of <i>[Company]</i>'s sustainability strategy? To what extent does the expansion of EV charging infrastructure play a role in this strategy?</li> <li>- Where does <i>[Company]</i> currently stand? Are there already EV charging stations in operation? If so, how many, at which locations, at what charging speed?</li> <li>- Could you please tell me more about the local context: (i) How many employees commute to work by car on a daily basis? (ii) What is the current proportion of EVs within the total vehicle fleet? (iii) How many parking spaces are available on-site?</li> </ul>
1	<p><b>Entscheidungskontext und Umfang</b></p> <ul style="list-style-type: none"> <li>- Können Sie den generellen Prozess beschreiben, den <i>[Unternehmen]</i> bei der Entscheidung über E-Ladeinfrastruktur verfolgt? Was waren die Haupttreiber hinter dieser Entscheidung?</li> </ul>	1	<p><b>Decision context and scope</b></p> <ul style="list-style-type: none"> <li>- Could you describe the general process that <i>[Company]</i> follows when deciding on EV charging infrastructure? What were the main drivers behind this decision?</li> </ul>
2	<p><b>Identifizierung der Entscheidungskriterien</b></p> <ul style="list-style-type: none"> <li>- Welche int. und ext. Kriterien berücksichtigen Sie typischerweise bei der Bewertung der Notwendigkeit und der Realisierbarkeit für E-Ladeinfrastruktur am Arbeitsplatz? (z.B. finanziell, ökologisch, regulatorisch, Mitarbeiterbedarf etc.)</li> <li>- Wie priorisieren oder gewichten Sie diese Kriterien?</li> </ul>	2	<p><b>Identification of decision criteria</b></p> <ul style="list-style-type: none"> <li>- Which internal and external criteria do you typically consider when evaluating the necessity and feasibility of EV charging infrastructure at the workplace? (e.g., financial, environmental, regulatory factors, employee demand, etc.)</li> <li>- How do you prioritise or weight these criteria?</li> </ul>
3	<p><b>Stakeholder-Einbindung</b></p> <ul style="list-style-type: none"> <li>- Wer sind die wichtigsten internen Stakeholder, die an diesem Entscheidungsprozess beteiligt sind? Welche Rollen spielen sie?</li> </ul>	3	<p><b>Stakeholder involvement</b></p> <ul style="list-style-type: none"> <li>- Who are the most important internal stakeholders involved in this decision-making process, and what roles do they play?</li> </ul>
4	<p><b>Informationsbeschaffung und -bewertung</b></p> <ul style="list-style-type: none"> <li>- Welche Art von Daten oder Informationen ziehen Sie bei der Entscheidungsfindung zum weiteren E-Ladeinfrastrukturausbau heran? (z.B. Kostenvorschläge, Energiebedarfsprognosen, MA-Befragungen)</li> <li>- Bezogen auf die Energiebedarfsplanung: Inwiefern machen Sie hierbei bereits Bedarf von datengestützten Tools / von bestimmter Simulations-Software?</li> </ul>	4	<p><b>Information acquisition and evaluation</b></p> <ul style="list-style-type: none"> <li>- What type of data or information do you use when making decisions about the further expansion of EV charging infrastructure? (e.g., cost estimates, energy demand forecasts, employee surveys)</li> <li>- Regarding energy demand planning: To what extent do you already utilise data-driven tools or specific simulation software?</li> </ul>
5	<p><b>Herausforderungen bei Entscheidungsfindung</b></p> <ul style="list-style-type: none"> <li>- Hintergrundinformationen: (i) Wodurch kennzeichnet sich das bisherige Stromlastprofil? Zyklisch? Abhängig von welchen Faktoren? (ii) Welchen Einfluss haben die Ladevorgänge auf ihr Lastprofil zum jetzigen Zeitpunkt? (iii) Wie gestaltet sich ihr bisheriger Stromtarif (grob)?</li> <li>- Wie erfolgt die Steuerung der Ladesäulen zum jetzigen Stand? Wird nach gewissen Zielen optimiert?</li> <li>- Wie gehen Sie mit Zielkonflikten zwischen konkurrierenden Kriterien um?</li> </ul>	5	<p><b>Challenges in decision-making</b></p> <ul style="list-style-type: none"> <li>- Background information: (i) How would you characterise your current electricity load profile? Is it cyclical? Which factors influence it? (ii) What impact do charging processes currently have on your load profile? (iii) Could you briefly describe your current electricity tariff?</li> <li>- How are the charging stations currently controlled? Is the operation optimised acc. to specific objectives?</li> <li>- How do you address conflicts between competing criteria or objectives?</li> </ul>
6	<p><b>Abschließende Frage(n)</b></p> <ul style="list-style-type: none"> <li>- Glauben Sie, dass zusätzliche Werkzeuge, wie eine dedizierte entscheidungsunterstützende Software, Ihren Prozess verbessern könnten? Welche Kernfunktionen stellen Sie sich für eine Software vor?</li> </ul>	6	<p><b>Concluding question(s)</b></p> <ul style="list-style-type: none"> <li>- Do you think that additional tools, such as dedicated decision-support software, could improve your decision-making process? What key features would you envision for such software?</li> </ul>

Table 8: Semi-structured interview guide (**round 2/2**): Demonstrating and evaluating our DSS

#	German	#	English
0	<b>Live Demonstration der Web Applikation</b> - Detaillierte Einführung und Erklärung der Software-Lösung basierend auf unternehmensspezifischen Daten der Interview Partner	0	<b>Live demonstration of web application</b> - Detailed introduction and explanation of the software solution based on firm-specific data from the interview partners
1	<b>Erste Eindrücke</b> - Was sind Ihre ersten Gedanken zur Benutzeroberfläche und zur Funktionalität der Webanwendung? Ist das nützlich? (Wenn nicht, warum nicht?)	1	<b>First impressions</b> - What are your first impressions of the user interface and the functionality of the web application? Do you find it useful? If not, why not?
2	<b>Entscheidungsunterstützung</b> - Hilft die Anwendung, verschiedene Faktoren auf eine sinnvolle Weise zu priorisieren/zu gewichten?	2	<b>Decision support</b> - Does the application help you prioritise or weigh different factors in a meaningful way?
3	<b>Benutzerfreundlichkeit</b> - Wie benutzerfreundlich ist die Anwendung? Gibt es Bereiche, die verwirrend/schwierig zu navigieren sind? - Wie einfach oder schwierig ist es, relevante Daten einzugeben und nützliche Auswertungen für Ihren Entscheidungsprozess zu erhalten?	3	<b>Ease of use</b> - How easy is the application to use? Are there any areas that you find confusing or difficult to navigate? - How easy or difficult is it to enter relevant data and get useful analyses to support your decision-making process?
4	<b>'Cognitive Fit': Problemdarstellung</b> - Entspricht die Art, wie Informationen in der Web Applikation präsentiert werden (z.B. Diagramme, Auswahl der Kriterien etc), Ihren Vorstellungen?)	4	<b>'Cognitive Fit': Visualising the problem</b> - Does the way the information is presented in the web application (e.g., charts, selection of criteria, etc.) meet your expectations?
5	<b>Praxisrelevanz</b> - Wie schätzen Sie die Praxistauglichkeit der Web Applikation ein? - Würde das Tool Ihnen helfen, tatsächliche Investitionsentscheidungen in Bezug auf den Ausbau von E-Ladeinfrastruktur in Ihrem Unternehmen zu treffen?	5	<b>Practical relevance</b> - How would you assess the practical usefulness of the web application? - Would this application help you make actual investment decisions regarding the expansion of EV workplace charging infrastructure in your company?
6	<b>Verbesserungsvorschläge und Feedback</b> - Gibt es Funktionen, die Sie gerne hinzugefügt oder verbessert sehen würden?	6	<b>Suggestions for improvement and feedback</b> - Are there any features you would like to see added or improved?

## D. Screenshots of web application (design cycles 1–2)

This appendix displays screenshots from design cycles 1 and 2 only. The final artefact resulting from design cycle 3 is presented in the main manuscript (Figure 3).

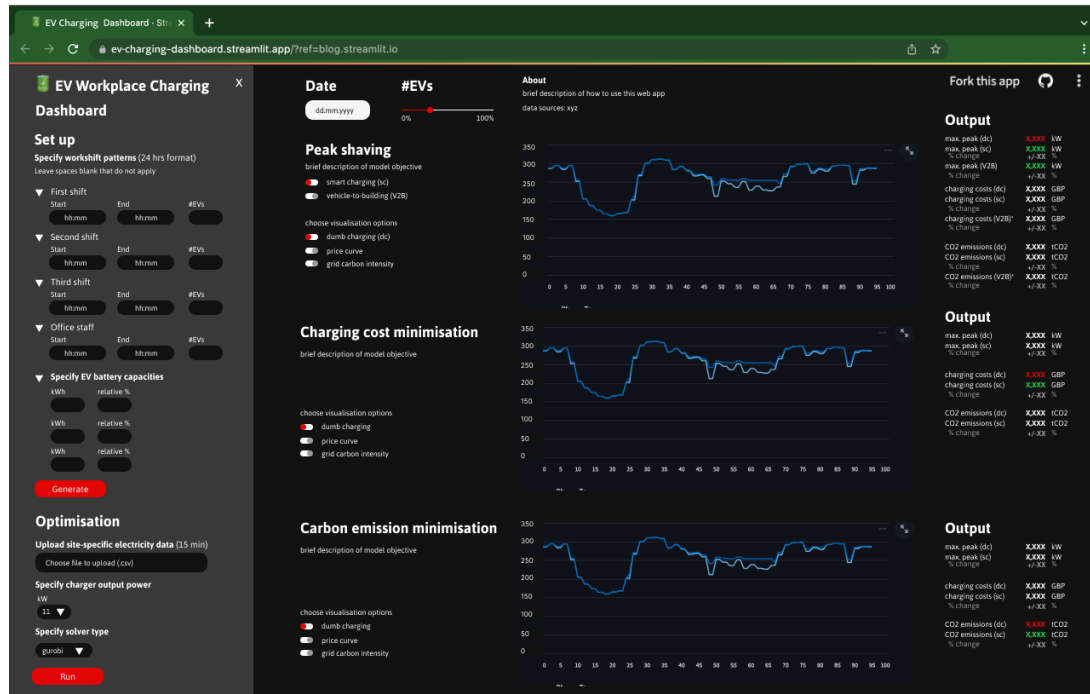


Figure 6: Static high-fidelity mock-up of our IT artefact using Figma's design suite (design cycle 1)

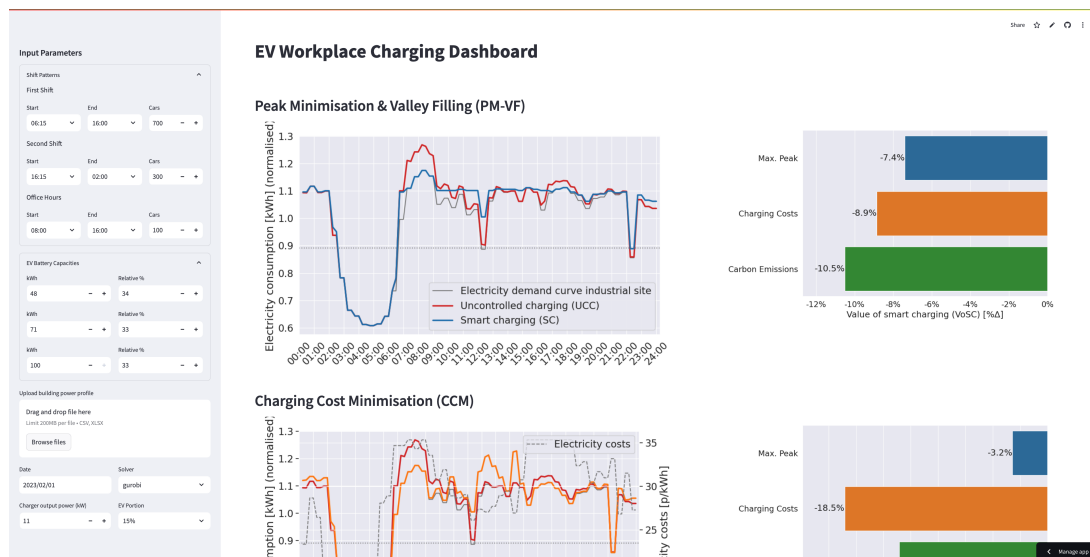


Figure 7: First functional version of our web application using Streamlit (design cycle 2)

## E. In-depth qualitative data

Tables 9–13 list the complete direct interview quotes from design cycles 2 and 3, categorised by priority levels for feature development, which have been translated from German to English as accurately as possible without losing contextual information.

Table 9: Qualitative codes, categorised as ‘high priority’ for feature development (design cycle 2)

DC <sup>1</sup>	ID	Quote from interviews (round 2)	Timing (mm:ss)	Qualitative code(s)	Prio.
2	1b	“Something I might even wish for more is this: You’ve now (...) taken the load profile of a single day at our site and analysed it. As a complement or extension, one could perhaps create some kind of average.”	16:07	Aggregated analytics	High
2	1b	“In Germany, we also have (...) a dynamic tariff. (...) You can basically take the numbers themselves and, in the end, go back to all time periods, even into the past. (...) [Then], of course, you can also retrieve the German prices from the website.”	18:10	Germany-specific market price data integration (entso-e)	High
2	1b	“And regarding CO <sub>2</sub> – specifically grid carbon intensity – I’m not sure if there are actually data available for download to display them properly here. But there is something called the Electricity Map. Do you happen to know it? (...) And there, of course, you can also specifically check for Germany what the electricity mix is on a given day.”	21:01	Germany-specific grid carbon intensity data integration (electricity maps)	High
2	2a	“What would actually be interesting for me personally as a user would be to have a document to understand what the system is doing with the value I’m changing – just to have a sense of security. I don’t like blindly trusting technical systems 100%, and even if they’ve proven themselves many times, I just like to know: what exactly is changing here? Maybe also what assumptions are being made when I change something – and does that also affect the validity of my result?”	26:43	User guide	High
2	2a	“What I always find quite practical is having an export function for the respective charts. (...) Maybe a CSV file, and possibly also an export version in high resolution that I can use in presentations or similar [outputs]. I also always like to look at the numbers in a CSV – just to get a feel for it myself.”	34:11	Export function of data/graphs	High
2	3a/b	“As a next step, it might have been interesting, for example with the costs or other metrics, if the unit were simultaneously scaled up – what does that mean? For instance, with CO <sub>2</sub> emissions, if you want to use that for sustainability reports. What also would have been interesting is the absolute amount and what the reduction actually is.” [3a] “To say: this is a fact, this is what we actually achieved.” [3b]	24:54	Quantification of absolute savings	High

<sup>1</sup> DC = Design cycle

Table 10: Qualitative codes, categorised as ‘low- & medium prio.’ for feature development (**design cycle 2**)

DC <sup>1</sup>	ID	Quote from interviews (round 2)	Timing (mm:ss)	Qualitative code(s)	Prio.
2	1a/b	“And maybe as an addition: Regarding CO <sub>2</sub> emissions, as a user, I would find it quite appealing if I could enter the CO <sub>2</sub> emissions caused by my specific electricity tariff myself, so that I can calculate it specifically for my company. (...) From a user perspective, I think that would be quite attractive to see exactly what savings I have actually achieved, specifically for my office building.” [1a] “I think that’s a very good point [referring to the previous comment], by the way. Because this CO <sub>2</sub> mix is not dynamic – it is provided to us once a year by our energy supplier. (...) It’s simply fixed, not dynamic.” [1b]	22:13	Data input of tariff-specific CO <sub>2</sub> grid carbon intensity measures	Low
2	1b	“What we haven’t accounted for here – and this is actually a point you might want to consider – is what happens if we have fixed certain quantities or prices at a specific level? (...) That would be a very useful addition, for example. In other words, in the input parameters, you could include some kind of fixed price or fixed quantity.”	28:20	Data input of tariff-specific electricity prices (fixed/dynamic)	Low
2	1b	“Of course, it would be great if this system could also provide some kind of forecast. What could the expected load be today, based on past average values? Naturally, not every day will be like the past, not even on average, but we do have a rough idea of how the day is likely to develop.”	30:49	Data-driven forecasting of expected load	Medium
2	1b	“What just came to my mind is the topic of peaks. (...) There are grid usage fees (...) that are calculated based on two different components: One is the capacity charge, and peaks play a role in that. The higher the peak, the more expensive it gets. (...) And that’s the key issue here – when it comes to deciding whether to avoid the peak and charge later, potentially saving on peak costs but increasing CO <sub>2</sub> emissions or something else. (...) Also, the energy costs themselves – meaning what we actually draw from the grid in kilowatt-hours – but for peak minimisation, the first factor is what really matters. (...) It would be useful to add an aspect that shows what a peak actually costs us.”	34:17	Firm-specific peak pricing	Low
2	1a	“I also think it’s good that the CO <sub>2</sub> emissions are ultimately included there (...). However, it would be necessary to differentiate between what the actual CO <sub>2</sub> emissions are and what later appears as a calculated number, like the annual total.”	42:19	Analytical specification: CO <sub>2</sub> emissions (accounted vs. actually emitted)	Low
2	2a	“And what I would actually find really interesting: is that also dependent on the seasons, depending on what kind of strategy I might want to pursue at the time? And to actually simulate something like that?”	23:02	Seasonal effects / aggregated analytics	Medium

<sup>1</sup> DC = Design cycle

Table 11: Qualitative codes, categorised as ‘high priority’ for feature development (design cycle 3)

DC <sup>1</sup>	ID	Quote from interviews (round 2)	Timing (mm:ss)	Qualitative code(s)	Prio.
3	5b	<i>“I can’t really do much with the indication ‘energy consumption in kilowatt-hours’ in the diagram. What I would actually need is a power value – in other words, what is the actual power draw, not the consumption. (...) For usability, it would actually make more sense to me to have a power value there rather than the consumption.”</i>	17:00	Power (kW) on y-axis as additional visualisation output	High
3	5a/b	<i>“Tip: I think with Apple, for example, they have this kind of info button with just a very brief explanation behind it (...). I think something like that would help me a lot, especially if I don’t deal with these terms on a daily basis: Why this graph? What does it show me? What is the added value? So I think if you could integrate something like that, really understandable for everyone (...), then you’d know what it means and you’d have the information readily accessible.” [5a] “Or a small automatically generated summary text that says: if you had smart charging for peak minimisation, you could do xyz... And then in the end, you just have to link the elements from the diagram and the bar chart on the right, and then you basically already have what it’s supposed to be telling you. That’s already interpretation, and I think that would be helpful, because it would give us, in just one or two sentences, an explanation of what’s already in the diagram. (...) That would also help people who are a bit less familiar with the subject or are a bit further removed from it.” [5b]</i>	23:56	Auto-generated explanation text	High
3	5b	<i>“Yes, exactly, but I think something like absolute figures on an annual basis is good, because then I would immediately have something where I can say: OK, we’ve analysed one year – that would be roughly what we could save in a year with smart charging, which I could then also incorporate into my cost-effectiveness calculation for such a project. Because there’s always some kind of economic viability assessment behind these things, and so far, aspects like the economic component of smart charging don’t exist at all in this area for us. (...) And it doesn’t have to be a diagram on an annual level – there just needs to be an absolute figure on a yearly basis.”</i>	32:03	Aggregated analytics (annual)	High
3	8a	<i>“I’m not really that familiar with the whole topic, but I think it would’ve been kind of cool if the legend had been made a bit larger, and maybe if it had said something like ‘What is smart charging?’ – just a short definition, so I know exactly what it’s about.”</i>	20:00	Explanation text, larger legends	High

<sup>1</sup> DC = Design cycle

Table 12: Qualitative codes, categorised as ‘low-’ and ‘medium priority’ for feature development (**design cycle 3**) (1/2)

DC <sup>1</sup>	ID	Quote from interviews (round 2)	Timing (mm:ss)	Qualitative code(s)	Prio.
3	6c	<i>“So if I saw that correctly, when you switched from a day to a week view, the graph did change, but the bottom part (the x-axis) still ran from 00:00 to 24:00. (...) That wasn’t immediately clear to me at first glance. (...) Yes, because honestly I would have expected – since you said we’re now switching from a 24-hour view to a 7-day view – and while the graph did change, I still saw the labeling down there as 0 to 24:00, and so I instinctively switched back mentally to thinking it was only a single day again. (...) It was just that change in time frame from one day to one week: I had expected that the individual days would be displayed side by side, not layered on top of each other. That was my expectation – but it doesn’t have to be decisive. Once you know it, you can adjust to it.”</i>	10:15	Further explanation of weekly/monthly results related to timescale on x-axis	Medium
3	6a	<i>“In 2024, we didn’t yet have a PV system, but now we do – so for us, it would make sense both from a CO<sub>2</sub> emissions perspective and a cost perspective to make better use of that time window for charging. Do you have any way of visualising that?”</i>	14:52	Incorporating PV generation load	Medium
3	7a	<i>“I’d find it really cool if there were some kind of mix – like: ‘How can I maybe reduce the peak?’ But the actual magnitude of the peak doesn’t really matter to me, as long as it stays below the threshold P, because the peak is what gets expensive for companies. At the beginning of the year, you’re billed based on the peak rate, so it would be great if there were a fourth option [optimisation function] – the best of all of them. (...) And what would be interesting, perhaps, is to simply show that in the future you could also ask for the cost of the peak demand – like, what does the peak load cost per kilowatt?”</i>	12:17	Fourth objective function capping peaks	Medium
3	7a	<i>“What might be really cool is if the CSV or (...) the load profile that you import – it’s just numerical data that you’re displaying graphically here. Maybe a feature where you could add comments or set ‘flags’, so that you can briefly explain the peaks. Because as an energy manager, I look at it and it’s crystal clear to me. (...) Decision-makers don’t see it that way. And if I could take that from the export function and generate a small, simple visual report from it – that would be awesome. And if I could place ‘flags’ in those charts, so I could say: ‘Hey, here’s the first peak – employee clock-in, EV charging for the first shift, etc.’ Then the decision-maker can take that and go to facility management and say: ‘Look, here’s an export – you can see something here you could act on.’ ”</i>	21:04	Annotation function within graphs	Medium

<sup>1</sup> DC = Design cycle

Table 13: Qualitative codes, categorised as ‘low-’ and ‘medium priority’ for feature development (**design cycle 3**) (2/2) (cont’d)

DC <sup>1</sup>	ID	Quote from interviews (round 2)	Timing (mm:ss)	Qualitative code(s)	Prio.
3	8a	<i>“This diagram on the right side – it shows charging cost, how much you save. I find it doesn’t quite come across as convincing yet (...). Especially considering that – well, that’s actually the benefit you get in the end, that’s the outcome, and I think it could maybe be presented a bit more clearly. The reduced energy costs, the reduced carbon emissions – that kind of thing, so it’s immediately visible. (...) I mean, of course, this is a very technical view – which is also important to me if I’m working as a Sustainability Manager and want to pitch this to the board. (...) And yes, that’s what I mean with a different presentation: Maybe there are – I know it always sounds silly – but more ‘fancy’ ways to show it, like: this is how much cost you save, something that could also be exported into a presentation view that you can take into project meetings. But in general, this is the right kind of view, and I need it as well to do my calculations and to set up the project – so it is the right one.”</i>	24:35	Presentation export function (PPT)	Low

<sup>1</sup> DC = Design cycle

659 From all interview sessions across design cycles 2 and 3, we derived 29 concrete suggestions for further  
660 feature development, as well as 25 more general comments concerning usability, ease of use, and practical  
661 relevance. Since the six ‘*high-priority*’ feature requests identified in design cycle 2 have already been  
662 discussed earlier in §4.3, we focus here on the additional ‘*high-priority*’ requests that emerged during  
663 design cycle 3 with firms ID 5–8.

664 As part of design cycle 3, four further ‘*high-priority*’ feature enhancement requests were raised. First,  
665 interviewee 5b suggested a change in the way outputs are visualised: “*For usability, it would actually*  
666 *make more sense (...) to have a power value there rather than the consumption*” [ID: 5b]. This could be  
667 addressed by giving users the choice between two different visualisation types: power rate [kW] or electricity  
668 consumption [kWh]. Second, interviewee 5b proposed leveraging state-of-the-art ‘*generative Artificial*  
669 *Intelligence (genAI) Large-Language Models (LLMs)*’ to improve users’ understanding. Specifically, he  
670 suggested providing “*a small automatically generated summary text that says: ‘If you had smart charging*  
671 *for peak minimisation you could do xyz’*” [ID: 5b]. He explained that such an auto-generated explanation  
672 text would especially “*help people who are a bit less familiar with the subject or are a bit further removed*  
673 *from it*” [ID: 5b]. Third, and closely related to a previous feedback point from interviewee 1b in design cycle  
674 2 concerning aggregated analytics (cf. Table 9), interviewee 5b requested the computation of “*an absolute*  
675 *figure [of cost savings] on a yearly basis*” [ID: 5b] to improve understanding of the “*cost-effectiveness*  
676 *calculations for such a project*” [ID: 5b] involving smart charging. He justified this request by stating:  
677 “*Because there’s always some kind of economic viability assessment behind these things, and so far, aspects*  
678 *like the economic component of smart charging don’t exist at all in this area for us*” [ID: 5b]. This feedback  
679 underscores the practical importance of data-driven decision-support systems, such as our artefact, for  
680 simulating the economic outcomes of future smart charging investments. Fourth, and finally, interviewee  
681 8a expressed the wish for more ‘*rudimentary*’ explanatory texts, for instance related to “*‘What is smart*  
682 *charging?’ – just a short definition, so I know exactly what it’s about*” [ID: 8a].

683 Table 11 provides the complete set of interview quotes, linked to the respective qualitative code(s). All  
684 other ‘*low-*’ and ‘*medium-priority*’ feature requests can be accessed in Tables 12–13.

Table 14: Qualitative data pertaining to firms' decision context in the realm of energy management

DC <sup>1</sup>	ID	Characteristics of electricity load profile	Procurement strategy
2	1	- Production machineries as main demand sources (75%) - Cooling and compressed air (15%) - Remaining share attributable to facility management, incl EV charging	- Hourly time-of-use tariff - Certain share fixed via forward contracts - Remaining quantity sourced via spot market
2	2	- Small data centre with continuous load - EV charging, mainly during morning hours	- Variable fixed energy procurement (forward/spot)
2	3	- Facility operation	- Variable fixed energy procurement (forward/spot)
2	4	- Ventilation systems, cooling, production machineries	- Annual forward contracts (100% renewables)
3	5	- Production machineries	- Portfolio mix between short-, medium-, long-term products
3	6	- Compressed air generation, extraction, lighting, machineries	- Variable products (100% renewables)
3	7	- EV charging, AC during summer, canteen operations	- Variable products (100% renewables)
3	8	- Production machineries	- Variable products (100% renewables)
DC <sup>1</sup>	ID	Outlook: Future electricity consumption	Expected challenges
2	1	- Demand reduction through process optimisation and efficiency gains - No major uptake of EVs expected among employees	- Low-hanging fruits of process improvements have been realised already - Disproportionately high effort for further increase in energy efficiency
2	2	- Doubling of annual consumption due to electrification of heat production - Expansion of PV production on-site - Increase in annual demand by factor 2.5x	- High investment costs due to the adaptation of building services - Sensible integration and use of PV system(s) - Charging infrastructure - Reliability of electricity grid
2	3	- No future increase in demand from grid expected - Mainly due to expansion of on-site PV systems	- Flexible time-of-use tariff - Battery energy storage systems (BESS) for optimised load distribution
3	5	- +10-20% increase in demand due to electrification of processes	- Replacement of fossil-fuels (gas) remains challenging - Future technology remains uncertain (hydrogen vs. electrification vs. steam)
3	6	- More or less constant, possibly slight decrease	- Expansion of renewable energy production on-site - More efficient energy use, driven by ISO 50001
3	7	- +25% expected increase	- Managing higher peaks from increased EV charging demand
3	8	- Increased demand from expansion of production capacity	- Realising efficiency gains to lower overall electricity demand - Managing access to grid capacity

<sup>1</sup>DC = Design cycle

## F. In-depth quantitative data

Table 15: Tabular overview of respondents' individual SUS scores and their adjective ratings, differentiated by design cycles 2 and 3.

No.	System Usability Scale (SUS) Item <sup>1</sup>	Design cycle 2						Design cycle 3					Rating (Mean)
		1a	1b	2a	3a/b	4a	4b	5a	5b	6a	7a	8a	
1	I think that I would like to use this system frequently.	4	4	4	4	5	4	4	4	4	4	3	<b>4.00</b>
2	I found the system unnecessarily complex.	1	1	1	2	1	1	3	2	1	1	2	<b>1.45</b>
3	I thought the system was easy to use.	5	5	4	5	4	4	4	4	4	4	3	<b>4.18</b>
4	I think that I would need the support of a technical person to be able to use this system.	2	1	2	2	2	1	1	2	1	2	3	<b>1.73</b>
5	I found the various functions in this system were well integrated.	4	4	4	5	5	4	4	5	4	5	4	<b>4.36</b>
6	I thought there was too much inconsistency in this system.	2	1	1	2	3	2	2	1	2	2	2	<b>1.82</b>
7	I would imagine that most people would learn to use this system very quickly.	5	5	5	4	5	5	3	3	4	5	2	<b>4.18</b>
8	I found the system very cumbersome to use.	4	4	4	4	5	4	4	4	4	4	3	<b>1.36</b>
9	I felt very confident using the system.	5	5	4	3	4	4	4	4	3	5	3	<b>4.00</b>
10	I needed to learn a lot of things before I could get going with this system.	1	1	1	3	1	1	4	1	2	1	2	<b>1.64</b>
<b>Final individual SUS Score</b>		<b>90.0</b>	<b>95.0</b>	<b>85.0</b>	<b>77.5</b>	<b>87.5</b>	<b>87.5</b>	<b>70.0</b>	<b>82.5</b>	<b>80.0</b>	<b>87.5</b>	<b>57.5</b>	<b>81.8</b>
<b>Adjective rating <sup>2</sup></b>		(5*)	(5*)	(5*)	(3*)	(5*)	(5*)	(2*)	(4*)	(3*)	(5*)	(2*)	(4*)

<sup>1</sup> Likert scale: 1 = strongly disagree; 5 = strongly agree.

<sup>2</sup> Adjective ratings: (0\*) = Worst imaginable (0–25); (1\*) = Poor (25.1–51.6); (2\*) = OK (51.7–71.0); (3\*) = Good (71.1–80.7); (4\*) = Excellent (80.8–84.0); (5\*) = Best imaginable (84.1–100).

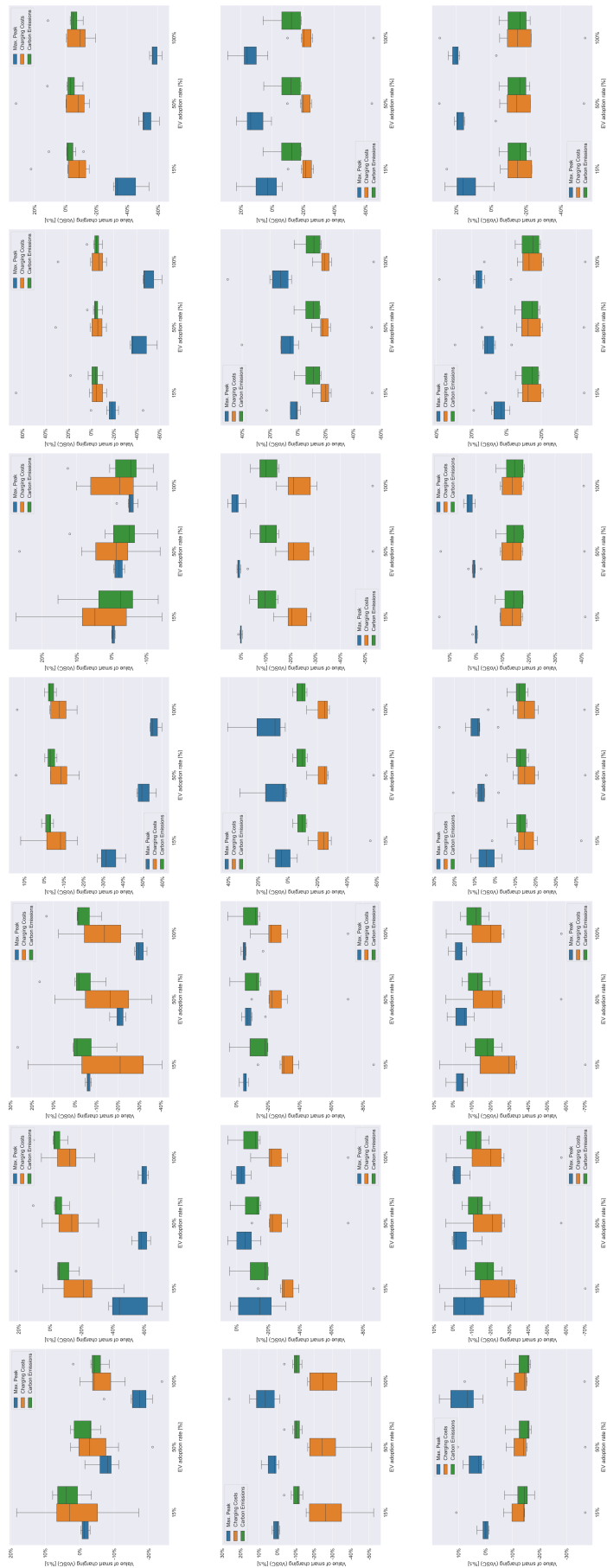


Figure 8: Visual summary of VoSC [%Δ] (y-axis) model results for increasing EV adoption rates of 15%, 50%, 100% (x-axis) w.r.t. each key metric *max. peak demand* (blue), *charging costs* (orange), and *carbon emissions* (green), differentiated by charging strategies *PM-VF* (top row), *CCM* (middle row), *CEM* (bottom row) and each participating firm (columns 1–7). Note that lower %Δ numbers refer to higher saving potentials.