Critical Success Factors for AI-driven Smart Energy Services

Jana Gerlach
Information Systems Institute, Leibniz Universität Hannover, gerlach@iwi.uni-hannover.de

Sarah Kristin Lier
Information Systems Institute, lier@iwi.uni-hannover.de

Paul Hoppe
Information Systems Institute, Leibniz Universität Hannover, paul.hoppe@gmx.net

Michael H. Breitner
Leibniz Universität Hannover, breitner@iwi.uni-hannover.de

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Jana Gerlach
Leibniz Universität Hannover
gerlach@iwi.uni-hannover.de

Sarah K. Lier
Leibniz Universität Hannover
lier@iwi.uni-hannover.de

Paul Hoppe
Leibniz Universität Hannover
paul.hoppe@stud.uni-hannover.de

Michael H. Breitner
Leibniz Universität Hannover
breitner@iwi.uni-hannover.de

Abstract

Artificial Intelligence (AI) can significantly contribute to decentralizing and digitalizing the energy sector and environmental sustainability. Integrating AI-driven smart energy services (SES), such as energy production forecasting, building energy management, and predictive maintenance, remain in an early phase for plant providers or energy utilities. However, the knowledge regarding key factors determining the design of AI-driven SES is limited in the literature. Therefore, we derive critical success factors (CSFs) for the design of AI-driven SES in a design science research (DSR) approach in connection with the design thinking process. We identified ten CSFs and 31 CSF categories by iteratively combining the knowledge of interviewed AI business experts, scientific literature, and results of AI programming projects with students. Based on this, we developed a further research agenda containing six research demands and direct further research questions.

Keywords

Artificial intelligence, energy sector, critical success factors, design thinking, design science research.

Research Needs and Motivation

AI solutions in the energy sector can be deployed for various tasks, such as energy generation forecasting, demand side management, building energy management, weather forecasting, predictive maintenance, plant and storage management, and energy price forecasting (Li et al. 2022). A forecast for the year 2025 predicts that the AI software market will generate annual revenue of 126 billion US dollars (Omdia 2020). Reasons for the increasing integration are the development of technologies for the collection and storage of big data and the constantly evolving computing power (Haenlein and Kaplan 2019). According to Nishant et al. (2020) AI systems in the energy sector contribute threefold: to task automation, gaining insights from data, e.g., documents, videos, and e-mails, and solving complex problems through computing capabilities. Automation tasks include the automated usage of drones for inspection and safety purposes. Gaining insights from data involves image analysis to provide predictive maintenance for power lines or energy production forecasting for energy planning. Solving complex problems includes planning efficient and multiple usages of battery storage (Nishant et al. 2020; Quest et al. 2022). Therefore, AI solutions, here AI-driven SES, can significantly impact energy efficiency and contribute to environmental sustainability, decarbonization, and decentralization of the energy sector (Antonopoulos et al. 2020; Nishant et al. 2020). Environmental sustainability, one of the three dimensions of sustainable development, concerns climate change and the measures required to quantify and reduce its impacts. Sustainability must be understood as consuming natural resources only so that future generations are not exposed to natural resource depletion (Purvis et al. 2019). Current literature on AI-driven SES addresses AI and Machine Learning (ML) models (Li et al. 2022), application areas and business models (Antonopoulos et al. 2020; Li et al. 2022; Quest et al. 2022), and advantages and disadvantages (Ahmad et al. 2021; Benbya et al. 2020). However, knowledge of key factors critical for the design of AI-driven SES is limited in the literature. Moreover, Benbya et al. (2020) stated that AI models remain for most organizations in an "experimental" phase, and a minority of organizations have integrated AI into their value chain processes due to economic risks, the potential bias of the algorithms, and lack of accountability and explainability. Therefore, Nishant et al. (2020) call for developing design guidelines for real-world problems of new sustainability practices, like SES (Antonopoulos et al. 2020). They recommend a design thinking process (Denning 2013) in a DSR approach (vom Brocke et al. 2020). We aim to derive CSFs for designing AI-driven SES. CSFs determine the competitiveness of organizations and identify characteristics that require special attention to reach the organization's goals (Boynton and Zmud 1984). The design thinking process allows the integration of user expectations of a system in the first step of the research design, but also the integration of the designer's intention (Denning 2013). This leads to our research question (RQ): *What are critical success factors for the design of AI-driven smart energy services?*

To address our RQ, we conducted four programming projects with students tasked to develop AI-based predictive models addressing energy-relevant issues. The results are analyzed, and initial CSFs can be derived. Then, we conducted a literature review and iteratively extended the set of CSFs. To evaluate all CSFs, we interviewed AI startup managers in the smart energy domain and finalized our CSFs. We derived implications and recommendations for theory and practice based on our results and findings and developed a further research agenda. Our CSFs can contribute to theory and practice by providing a knowledgebase on how AI-driven SES can be designed and help stakeholders to determine which factors to be targeted in an AI model development and integration process.

Theoretical Background

AI aims to sense, perceive, innovate, solve problems, support decision-making, and automate physical processes (Benbya et al. 2020). The definition of AI is diverse, so Haenlein and Kaplan (2019, p.5) define AI as "a system's ability to interpret external data correctly, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation" and Berente et al. (2021, p.1433) stated that "AI is not a technology or a set of technologies, but a continually evolving frontier of emerging computing capabilities." The computing power and handling of big data, at its core ML and deep learning (DL), have the potential to facilitate people's lives in areas such as medicine, living, and education (Berente et al. 2021). ML models are utilized to detect patterns and solve classification tasks from experience (reinforcement learning), labeled data (supervised learning), and unlabeled data (unsupervised learning). DL models have the ability to learn from labeled and unlabeled data without human supervision in application areas of image and speech recognition. Neuronal networks (NN) are modeled on the structure of the human brain, which algorithm can discover relationships in large data sets, leading to application areas of weather predictions and credit score evaluations (Benbya et al. 2020). With the increasing development of technologies for collecting, processing, and storing big data, AI can generate many business opportunities (Haenlein and Kaplan 2019; Omdia 2020). Thus, many AI startups have been founded and funded recently (Omdia 2020). These include, for example, AutoGrid and Myst AI in the energy sector. According to Quest et al. (2022), AI in the energy sector can be divided into the application areas of planning, robotics, ML, and computer vision. Planning includes tasks for scheduling problems, e.g., electronic vehicle charging point routing or battery storage management. AutoGrid is an AI startup that offers an energy storage management system. This allows optimizing the energy storage according to predefined purposes and values for power system stability optimization, profit maximization in dynamic energy price markets, or demand response maximization (AutoGrid 2023). The application area of robotics targets maintenance, security, and inspection services through drones (Quest et al. 2022). Skyqraft is a startup offering predictive maintenance services for utility companies by analyzing aerial images of electrical transmission lines. This enables the reduction of maintenance costs and greenhouse gas emissions (Skyqraft 2023). ML-based application areas include energy consumption optimization, market trading, electric grid management, and failure prediction (Quest et al. 2022). Bidgely offers AI-driven load monitoring services to manage the energy consumption of individual devices (Bidgely 2023), and Myst AI provides a forecasting model platform for energy markets, weather, and human behavior (Myst AI 2023). The application area of computer vision includes automated image classification and fault detection (Quest et al. 2022). The startup SYNC analyzed satellite images to identify or predict grid outages (SYNC 2023). This analysis highlights that many AI-driven services within the energy field are explicitly offered for grid operators, power plant operators, and energy utilities and also positively impact environmental sustainability. Current literature on CSFs for AI supported services concerns organizational, technological, environmental, and human-related aspects (Dora et al. 2022; Hamm and Klesel 2019). Hamm and Klesel (2019) deduced CSFs for the adoption of AI in organizations by conducting a literature review. CSFs are, e.g., top management support, resources, strategy, security, reliability, compatibility/IT infrastructure, trust, and public funding. Mir et al. (2020) derived through a literature review and focus group discussion CSFs for the integration of AI and robotics, that are governance, data, manpower, capital, software, utility, and hardware. Dora et al. (2022) identified CSFs in the domain of AI-driven supply chains, e.g., proper training for staff and end-users, ethics in data collection, sufficient privacy and security, and AI provider commitment and support.

Research Design and Methods

To develop CSFs for designing AI-driven SES, we conducted a five-step research design combining the DSR approach (vom Brocke et al. 2020) with a design thinking process (Denning 2013; Thoring and Müller 2011). This combination aims to generate design knowledge and a solution for a real-world problem (e.g., improve software design), iteratively combining computational intentions with user expectations (Denning 2013). We include the design thinking process because integrating user experiences and expectations play a major role in the effective and successful design of AI systems (Ho and Wang 2021). The design thinking process allows the inclusion of insights from case studies at the beginning of the research process in form of our programming projects. In this regard, we derive CSFs for designing AI-driven SES to better understand factors that influence successful implementation and usage. We are guided by the CSF definition of Rockart (1979) “[…] the limited number of areas in which satisfactory results will ensure successful competitive performance for the individual, department or organization. CSFs are the few key areas where “things must go right” for the business to flourish and for the manager’s goals to be attained” (Rockart 1979, p. 84-85). Table 1 shows our research design which is based on the DSR steps as well as the design thinking steps.

DSR steps	*Problem identification*		*Gathering knowledge*	*Build design artifact*	*Evaluation*
Design thinking steps	*Empathize*	*Define and ideate*	*Prototype*		*Test and iterate*
Steps and Method	**Step 1:** Programming project	**Step 2:** Initial CSF development	**Step 3:** Literature search	**Step 4:** CSFs development	**Step 5:** Expert interviews
Tasks	1.1 Define scenarios 1.2 Observe the process of programming project 1.3 Understand occurring problems 1.4 Collect source material (insights and experiences)	2.1 Analyze source material and programming project output 2.2 Conduct a brainstorming session to deduce potential CSFs from the programming project results 2.3 Derive initial CSFs	3.1 Define search scope 3.2 Conduct a keyword-based literature search 3.3 Conduct forward, backward, and Google Scholar similarity search 3.4 Process exclusion criteria	4.1 Develop a concept matrix 4.2 Consolidate initial CSFs on theory and programming project 4.3 Deduce and formulate CSFs	5.1 Contact experts 5.2 Develop interview guidelines 5.3 Conduct interviews 5.4 Transcript and analyze interviews 5.5 Evaluate and adjust CSFs 5.6 Develop a further research agenda
References	Denning (2013); Thoring and Müller (2011)	Denning (2013); Thoring and Müller (2011); vom Brocke et al. (2020)	vom Brocke et al. (2015); Webster and Watson (2002)	vom Brocke et al. (2020)	Watson and Webster (2020)
Output	Source material and programming project output	Initial set of CSFs	Knowledge base and concept matrix	Literature-based CSFs	Final set of CSFs and further research questions

Table 1. Research Design

As suggested by Thoring and Müller (2011), in the first step of our research design, we conducted four programming projects with students tasked to develop different AI-based forecasting models using a self-sourced dataset. In the empathize phase of the design thinking process, source material in the form of "background knowledge, insights, and experiences" needs to be collected to define the problems and goals of the prototype and to generate design ideas (Thoring and Müller 2011, p.141). The source material collected during the programming project through observations and student experience reports relates to the particular challenge. For example, in the first programming project, AI-based forecasting models for wind energy generation have to be developed. The programming projects 1-4 lasted six months and involves the following forecasting tasks (1: wind energy generation, 2: energy prices, 3: photovoltaic energy generation (with an additional task to integrate explainable AI (XAI) methods), 4: photovoltaic energy generation). The source material from all programming projects was consolidated in the second step. In connection with the source material, potential CSFs were derived, which led to a first list of initial CSFs (Thoring and Müller 2011), see Figure 1.

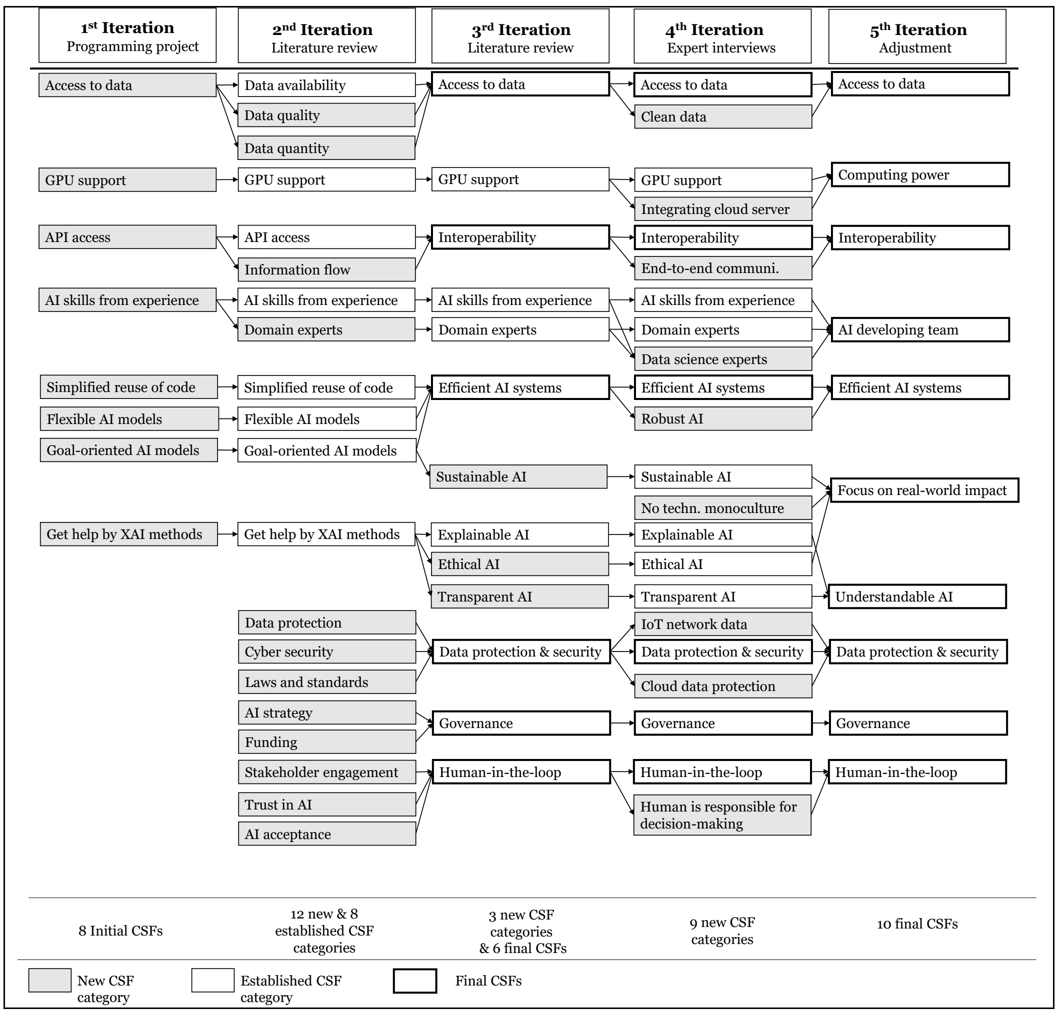

Figure 1. Iterative Development Process of the CSFs

To gather knowledge from scientific literature, we performed in the third step a keyword-based literature search according to vom Brocke et al. (2015) and Webster and Watson (2002). Based on this, we extracted the key topics in AI applications in the context of SES. For this purpose, we defined the search string ("artificial intelligence" OR "AI" OR "machine learning" OR "ML") AND ("renewable energy" OR "energy efficiency" OR "smart energy") AND ("management" OR "service") included in the abstract. To obtain a comprehensive literature base, we searched the academic databases ScienceDirect, IEEExplore, SpringerLink, and AIS eLibrary. The search yielded 96 results, which were reduced only considering articles published in academic journals and conferences. The full texts were then screened, and 24 publications were selected, after which a backward-, forward, and author search of the selected publications included five additional publications (Webster and Watson 2002). A similarity search followed this in Google Scholar, leading to one additional selected article. Based on the initial set of CSFs, derived from the programming project results, we built a concept matrix in the fourth step and analyzed the 30 papers. We iteratively expanded the CSF categories and built overall CSFs and associated subcategories. With an open coding system, we could change and rename the categories in each iteration, see Figure 1. In the fifth step, we evaluated and extended our initial set of CSFs by interviewing four experts who are founders or managers of AI-driven SES startups. Our expert selection refers to the perspective of entrepreneurs who successfully introduced an AI-driven SES. The interviews aimed to increase the usefulness and level of detail of the CSFs and obtain insider knowledge from the experts regarding applied AI models, customer relationships, value propositions, and successes and failures in the startup (Denning 2013; vom Brocke et al. 2020). We conducted semi-structured interviews with a prepared interview guideline. For preparation, the guideline was sent to the experts in advance. Expert 1 founded an AI-driven optimization company for photovoltaic power plants (founded 2017). Expert 2 is a business development manager at a company for AI-driven analysis of customer data for energy providers (founded 2011). Expert 3 is a company's chief executive officer for AI-driven building energy management (founded 2008). Expert 4 is the founder and chairman of a company offering AI-driven solar asset analysis (founded 2015). The interviews took 35-60 minutes and were transcribed afterward. These transcripts were then coded and analyzed using the coding procedure from the fourth step. The coding system was based on the CSFs and their categories, as shown in Figure 1. We analyzed and coded the literature as well as the interview transcripts via the coding tool MAXQDA. All authors independently conducted the coding process in the fourth and fifth steps.

Results and Findings

After every programming project was finished, we analyzed the source material and the reports. Most students had the same experiences during the programming project, such as limited data availability, graphics processing unit (GPU) support, and application programming interface (API) support. The following initial CSFs were derived: access to data, GPU support, API access, AI programming skills just come with AI experience, simplified code reuse through AI framework support and efficient maintenance, high model flexibility, goal-oriented models with low training and prediction times and low error values, and add XAI methods, see Figure 1. The final set of CSFs is explained in detail in the following section and visualized in Table 2.

Information privacy and security: Expert 2 stated that data protection is a major challenge for their business. Expert 1 stated that its business cooperates with cloud providers for data storage. As a result, they have to provide a data protection guarantee for the provider's data storage. Specific authentication processes and control mechanisms must be implemented to ensure information security. Additionally, recovery processes must be applied to handle data losses (Rani et al. 2021). Cyberattack scenarios are conceivable in energy systems and can interrupt the energy supply, resulting in economic and societal risks (Yu et al. 2018). Transparency must be ensured regarding what data is used, whether and for how long it is stored, and whether external third parties have access (Expert 1). To identify and document security vulnerabilities, regulations such as threat reporting must be obeyed (Ponnusamy et al. 2021).

Access to data: Data access is a major entrance challenge. Expert 3 mentioned, "If there is enough data, the vision of the control strategy can also be implemented well. The combination of control strategy, use case, and the plant is implicit in the energy data because it directly results from what happens in the building." Expert 1 stated, "So the basic work for an AI application is first of all clean data." The performance depends on the quality of the input data (Al-Othman et al. 2022; Rangel-Martinez et al. 2021). The data generated by plants, sensors, and other devices often exist in different formats and exhibit high heterogeneity (D'Amico et al. 2020). Expert 1 noted, "We have implemented over 150 different data formats, which we then normalize via our pipeline and send to the front end via an interface. This process has nothing to do with AI, but 90 percent of the product would be inconceivable without this entire process because no AI can understand this diversity, this diversification in the raw data."

Effectiveness of AI models: Goal-oriented AI models are necessary to achieve a high performance, which implies low training time at many training cycles, lean programming, and low error scores (Quest et al. 2022; Sharma et al. 2021). The performance of AI models must be continuously monitored to evaluate the validity of the results. AI models require flexibility to improve algorithms while conserving resources

(O'Dwyer et al. 2019). Expert 1 also stated, "So, in our case, the AI would recommend action. If the recommendation is wrong, then there is a problem. So false positive is a huge problem. We must be careful that we first calibrate things correctly, and we need certain training cycles."

Focus on real-world impact: To integrate AI-driven SES, the carbon footprint and energy efficiency must be monitored and optimized (Benbya et al. 2020). A possible approach is using green computing to reduce power consumption and thus decrease emissions (Ahmad et al. 2022). Ethical considerations in AI models can help systems to be more accepted in society and set moral frameworks to ensure safety and correctness in decision support systems (Yu et al. 2018).

CSF	CSF category	References	E	P
Data protection and security	IoT network data protection	Rani et al. (2021)	2	
	Cloud data protection	Rani et al. (2021)	2	
	Cybersecurity	Rani et al. (2021)		
	Regulatory laws and standards	Ahmad et al. (2021)	1,2,3	
	Data protection	Kaur et al. (2022)	2	
Access to data	Clean data and data quality	Al-Othman et al. (2022); Rangel-Martinez et al. (2021)	1, 3, 4	+
	Data availability and quantity	Shi et al. (2020)	3	+
	Data integration	D'Amico et al. (2020); Rani et al. (2021)	1	+
Effectiveness of AI models	Goal-oriented development	Sharma et al. (2021)	2, 3	+
	Flexibility and responsiveness	O'Dwyer et al. (2019)	1, 3	+
	Robustness	Currie et al. (2020)	2	+
	Simplified reuse of code			+
Focus on real-world impact	Energy efficient AI models and environmental impact awareness	Ahmad et al. (2021); Ismail et al. (2022)	1, 2	+
	Ethical considerations	Yu et al. (2018)	3	
	No technological monoculture		1, 4	
Interoperability	Seamless information flow between heterogeneous systems	Kuguoglu et al. (2021); Ponnusamy et al. (2021)	1, 2	+
	End-to-end solutions		1	
	API support			+
AI developing team	AI programming skills	Ahmad et al. (2021); Kuguoglu et al. (2021); Ponnusamy et al. (2021)		+
	Data science skills		3, 4	+
	Integration of domain experts	Shi et al. (2020)	2, 3	+
Human-in-the-loop	Stakeholder engagement	Ahmad et al. (2021); Langer et al. (2021)	3	
	Human-centered development	Ho and Wang (2021)	3	
	Trust and acceptance in AI systems	Ahmad et al. (2022)	1	
	Humans are accountable for decision-making, AI for decision-support		4	
Governance	AI strategy	Ahmad et al. (2021); Kuguoglu et al. (2021)		
	Funding	Rani et al. (2021); Wang et al. (2021)	1	
Understandable AI	Explainability	Verhagen et al. (2021)	3	+
	Transparency	Ahmad et al. (2022); Verhagen et al. (2021)	3	+
Computing power	GPU support		1	+
	Integrating cloud server		1, 3	

Table 2. Critical Success Factors

**E = Expert, P = Programming project*

Interoperability: AI-driven SES contain information flows from multiple plants, devices, and subsystems from organizations not designed to operate together. This leads to a disrupted flow of information and a loss of efficiency, which can affect the operation of services (Kuguoglu et al. 2021). It is critical to ensure the efficient exchange of data as well as programming interfaces (Ponnusamy et al. 2021). Expert 1 stated that end-to-end solutions must be created to capture, process, visualize, and add value to data.

AI developing team: AI algorithms are complex, especially DL. In many cases, the accuracy of the AI systems output increases with algorithmic complexity (Rani et al. 2021). In organizations, training measures to build up and improve AI programming skills must be offered. Next to AI programming skills, data science skills are essential to identify a potential bias or error in the data set and to interpret results

(Expert 3, 4). Additionally, to the programming AI skills required for training, integrating, monitoring, and adapting the models, domain experts from the specific domain must be integrated, and collaboration between technical and domain professionals must exist (Shi et al. 2020).

Human-in-the-loop: All stakeholders, such as users, developers, and governmental agencies, must be involved in AI development. Technology acceptance can be achieved if AI systems' benefits are understood and the applications are easy to use. Trust deficits can be caused by a lack of fairness in decision-making or biases within the data (Yigitcanlar et al. 2021). Expert 4 stated, "Sometimes humans with their unique experience solve unique problems. In medicine, AI does not replace the doctor. It helps them quickly find the relevant and right picture in the database. And it may be pictures one or two. However, the doctor will make the decision. So, we call it decision support. They do not replace people."

Governance: AI strategy is a well-defined plan for implementing AI applications. According to a study conducted by Ahmad et al. (2021), two-thirds of the companies surveyed, which operate in the energy sector, state that the development of a clear AI strategy and AI funding (Rani et al. 2021) is necessary to successfully integrate AI and realize business values (Ahmad et al. 2021). When defining the AI strategy, it is important to align it with the business goals (Kuguoglu et al. 2021).

Understandable AI systems: If the user of incomprehensible AI systems is not the developer, explainability and transparency are needed (Verhagen et al. 2021). Expert 3 also stated that "[...] transparency is everything. So, we explained many of our simpler algorithms to our clients, for example, how do we know if it is occupied or not occupied? Look at the ratio of the two k-means of consumption during the day. An unoccupied building will typically have high times of consumption and low times of consumption." Programming project three adds XAI models to a photovoltaic generation forecasting model. It assists in opening the black box of the model, but further explanation is still necessary for a client.

Computing power: Is a CSF primarily based on programming projects and expert interviews. In the programming projects, the support of the GPU was essential for frictionless calculation. It was impossible to make forecasts more detailed than the hourly level of input data, e.g., weather data. In the interviews, computing power was an issue that the startups solved using cloud servers (Expert 1).

Discussion, Implications, Limitations, and a Further Research Agenda

To address our RQ, we developed ten CSFs and 31 CSF categories for designing AI-driven SES in a design thinking-oriented DSR approach. By combining literature from energy services and the AI domain with experiences from real-world applications in the form of programming projects and expert knowledge, we contribute to AI-driven SES theory. The experts provided insights from the business perspective and shared experiences with their clients, data processing, regulatory issues, and the importance of algorithmic transparency. We identified that the expert's clients' have misguided expectations of AI systems. Expert 3 stated, "One of the disadvantages of AI is that people confuse the terminology and think it can solve problems for people or companies, and it cannot. So, the disadvantage for me, the most obvious one, is that people like to think it is their magic wand. We buy an AI system, and it will give us a business intelligence solution." Expert 1 also highlighted that their product's AI model only describes the last five percent of the product. Nevertheless, these five percent are supposed to contribute significantly to differences in margins and distribution opportunities. Our CSFs enhance the understanding of how AI-driven SES can be designed and help stakeholders to determine which factors to be targeted. Therefore, our CSFs can also be used as a checklist for AI system integration, thus facilitating information technology project work. Based on our analysis and the five iterations, we identified the CSFs access to data, interoperability, data protection and security, and focus on real-world impact as the most important. In the expert interviews, access to clean data and data format heterogeneity were major barriers. Thus, practice and governmental institutions must provide an improved and free-of-charge database, such as a platform for weather data or energy prices. Furthermore, data and information standards must be enhanced to facilitate interoperability and information flow between heterogeneous devices. Another important CSF is data protection and security, as critical infrastructure is a special target for cyber attackers. In particular, due to the increasing collection of private energy data, e.g., smart meter data, cybersecurity threats, such as data breaches or threats against the availability and integrity, can cause serious harm to individuals, companies, and governments (European Parliament 2022). The focus on real-world impact is another important CSF, as it connects other CSFs and CSF categories, such as ethical AI, XAI, transparent AI, and the human responsibility of decision-making, and the AI systems capability of decision support. However, next to the advantages of AI, their disadvantages, e.g., biased decision-making and human rights violations due to not understandable AI models, have to be considered equally (Seppälä et al. 2021). Potential rebound effects reducing the positive impact of AI systems on environmental sustainability (Nishant et al. 2020) have to be considered through the development of energy-efficient algorithms and continuous evaluations.

A limitation of our study is the subjectivity of our literature survey. To mitigate this limitation, all authors independently reviewed the literature. The low number of expert interviews is another limitation that we mitigate with the diversity of application areas of the companies. Another limitation results from the programming projects and the selection of the experts. If other students with different Master majors and AI programming skill levels were asked, other initial CSFs would be derived, the same applies to the selection of the experts. Nevertheless, our CSFs provide an extendable framework that further quantitative and qualitative research can build on. The next step is further developing our CSFs into design principles, according to Gregor et al. (2020) (Nishant et al. 2020). The definition of design principles must target concrete action guidelines for the design of AI-driven SES (Gregor et al. 2020). The design principles can be evaluated by user-testing of commercially offered AI-driven SES. A potential further RQ (fRQ) is *fRQI: How design principles can be derived for the design of AI-driven SES?* As Benbya et al. (2020) proposed that AI system integration into corporate environments remains in an early phase, thus, requiring a process model. This enables a shift in AI integration and foster collaboration between AI developers and domain experts. *fRQII follows: What requirements must be considered regarding the integration of AI-driven SES into a corporate environment and how these requirements can be integrated into a process model?* A process model for the integration of XAI methods, as utilized in the third programming project, is another research need with the *fRQIII: What requirements must be considered regarding the integration of XAI methods to AI-driven SES and how these requirements can be integrated into a process model?* As explained in the theoretical background section, the market for AI-driven SES is growing, which calls for a taxonomic analysis of design elements with the *fRQIV: What are the conceptually implicated and empirically validated design elements of AI-driven SES and what business model archetypes can be deduced?* During the programming project, we identified the complexity of selecting the best suitable hyperparameter, the weighting, and the combination of the layers. A decision support system in a decision tree helps AI developers find the best suitable input and model parameters. This leads to the *fRQV: How can a decision support system for AI developers be designed?* Expert 3 said, “People need to understand that they need a collection of tools to solve a problem they face.” This statement enables the last *fRQVI: How can a combination of different tools and technologies achieve optimal impact?*

Conclusions

To address our RQ, we identified ten CSFs and 31 CSF categories. We iteratively included knowledge from AI framework users, literature, and business experts, managing startups offering AI-driven SES. The CSFs serve as a multi-perspective knowledge base for further research and as a guide to strategically planning the integration of AI systems. In addition, we developed a further research agenda with six research topics and suitable research methods to address the research needs.

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