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Article

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Developing a Smart Energy Service Canvas Fostering Sustainable Manufacturing

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Abstract Rising energy and CO₂ prices are driving industrial companies to focus increasingly on energy efficiency and flexibility to remain competitive. Besides technical improvements, smart energy services like nonintrusive load monitoring (NILM) are promising approaches to increasing a company's energy efficiency and flexibility potential. Despite its advantages, smart energy services are not yet widely used in practice, and service providers are cautious. Existing research investigates almost exclusively technical aspects of smart energy service applications and systems, particularly for NILM, while a business model perspective is missing. This study addresses this research gap following a design science research approach with literature research and expert interviews, and develops a business model framework—the Smart Energy Service Canvas (SESC). The SESC is a practical and empirically validated tool to formalize, structure, and implement a business idea on smart energy services.

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1 Introduction

Due to the harmful effects of climate change, the United Nations' Paris Agreement declared ambitious climate goals and aims to decrease energy end-use below 1990 levels by 2030 (Boden et al. 2017). The industrial sector, accounting for more than 26% of the total energy consumption in the EU, holds great potential to reach climate goals (Agrawal et al. 2022; Mickovic and Wouters 2020). The industrial sector is motivated to reduce energy consumption due to rising energy prices, threatening competitiveness (Rusche et al. 2021). Additional economic pressure stems from the volatile electricity supply, leading to fluctuating energy prices (Scheubel et al. 2017). Therefore, energy efficiency and flexibility are increasingly important assets to counter rising economic pressure and get management's attention (Bauer et al. 2021; Glenk et al. 2021; Paukstadt and Becker 2021). Consequently, with advances in digitization, research has brought up new approaches like smart energy services to uncover the causes of energy consumption. Smart energy services go beyond core functions of energy consumption billing as they enable, for example, the optimization of energy consumption. Smart energy services are highly scalable as they require little to no customization. The large volumes of newly generated data offer the possibility for continuous optimization (Zhang et al. 2018). However, in practice, smart energy service usage to automatically identify and analyze industrial environments is not yet widespread (Knayer and Kryvinska 2022; Paukstadt and Becker 2021).

A prerequisite for energy efficiency and leveraging energy flexibility potentials with energy management systems is consumption transparency (Lindner et al. 2021; Seow and Rahimifard 2011). Still, transparency alone is not enough, as it is essential to derive concrete measures from the information gained. The value of making (production-related) energy consumption transparent is not limited to solely quantifying energy intake but to deriving additional estimates (Thiede et al. 2012). This transparency enables, for example, to monitor the overall condition of the systems and identify inefficient operating modes or impending failures to take proactive measures to reduce efficiency losses and downtimes. Still, the procurement of energy data with detailed consumption information at the appliance level is expensive and can only be generated with high technological effort (Yi et al. 2019). However, industrial environments are generally characterized by large quantities of consumers and complex wirings (Yi et al. 2019). Therefore, large-scale sub-metered energy monitoring systems applications are expensive and require considerable installation and maintenance effort (Hoyo-Montano et al. 2016). One exemplary technology is nonintrusive load monitoring (NILM). NILM allows identifying individual consumers in an aggregated power consumption load profile measured from a single meter using algorithms and machine learning (ML) (Ruano et al. 2019). Each device generates an individual load profile that suitable algorithms can identify and classify. NILM is already being offered by some service providers and has found its way into

residential households. It helps consumers identify the actual consumption of their household appliances just by letting the provider read their smart meter (Hosseini et al. 2017). The fact that NILM progresses significantly for private households, but industrial NILM service providers are rare again highlights this gap (Ruano et al. 2019). Industrial applications cannot simply transfer findings from the residential sector. These require a higher degree of reliability and stability, for example, influencing a business model's design (Zhuang et al. 2018). Nevertheless, research on smart energy services, particularly on NILM, in industrial applications almost exclusively investigates technical aspects such as optimizing different algorithms to achieve higher accuracy and identify appliances more accurately. Thereby, research from a business model perspective is missing to the best of the authors' knowledge. In other words, there is a gap between technical-oriented research and the usage of smart energy services not only limited to NILM in practice (Zhuang et al. 2018). From a practical perspective, this is supported by the fact that 80% of energy startups funded in 2010 at the height of the "cleantech boom" failed to meet their investors' expectations ten years later (Bennett et al. 2021). The failure of 80% of energy startups to meet investors' expectations highlights the critical need for robust business models when developing smart energy services. The predominant focus on technical implementation and incremental optimization in research does not address the market realities and the strategic planning necessary for commercial success. This gap is particularly evident in the application of smart energy services such as NILM in industrial settings, where the complexity and scale of operations necessitate more sophisticated business models. Furthermore, current research emphasizes the importance of aligning business models with technological innovations to enhance market adoption and sustainability. This alignment is crucial for the translation of technical advancements into viable commercial offerings that meet the evolving needs of industrial consumers. Concluding, to leverage the business potential of smart energy services in an increasingly digital manufacturing environment, a business model framework that enables structuring and developing a business model for NILM as a representative smart energy service for industrial applications is needed. Therefore, this work investigates the following research question:

How can business models for smart energy services like NILM be structured in an industrial context?

To answer the research question, we follow a design science research (DSR) approach and develop the Smart Energy Service Canvas (SESC) that enables structuring and developing a business model for smart energy services in the industrial sector. For an applied context we conceptualize the case of NILM. First, we examine the status quo in the existing literature regarding smart services, service-oriented business models, smart energy services and NILM to derive hypotheses for building the SESC. Then, we empirically evaluate these hypotheses and further refine them with the help of expert interviews to subsequently design the SESC. We argue that by providing a methodically sound and practical SESC, we contribute to literature and practice by complementing the ongoing, mainly technological-focused research activities. We thereby help to accelerate the introduction of smart energy services like NILM to the industrial sector supporting towards achieving climate goals.



Fig. 1 The steps of event-based disaggregation based on Zhuang et al. (2018)

The remainder of this study is structured as follows: In Sect. 2, the theoretical background provides an understanding of NILM and smart services and business models for the following steps. We then detail the methodological approach in Sect. 3. The SESC is presented in Sect. 4. In Sect. 5, we discuss learnings, theoretical contributions, and managerial implications. We then depict limitations and prospects for further research in Sect. 6.

2 Theoretical Background

2.1 Nonintrusive Load Monitoring

NILM is commonly understood as a computer-based technique because each device generates an individual load profile that can be identified and classified by appropriate algorithms (Kelly and Knottenbelt 2015). In other words, at a single point in the plant, load signatures can determine energy consumption by usage type or equipment type (IEC 2021). Commonly, NILM follows an event-based disaggregation adopted by numerous researchers (Zeifman and Roth 2011; Zoha et al. 2012) to identify appliances in an aggregated load profile. Following Zhuang et al. (2018), the event-based disaggregation covers four sequential steps (s. Figure 1): (1) data acquisition and processing, (2) event detection, (3) feature extraction, and (4) load identification.

In the first step, *data acquisition and processing*, key enablers for NILM are smart meters that deliver the needed data in real-time to disaggregate appliance-specific consumption data (Baechler and Hao 2015). Smart meters collect electrical data, including current, voltage, and power data (Ruano et al. 2019). Thereby, a higher sampling frequency generally leads to higher accuracy in appliance identification (Revuelta Herrero et al. 2018). In addition to measuring energy consumption, the collected data must be prepared for further processing. Data (pre-)processing typically covers steps such as data ingestion, data wrangling, and model-specific processing (e.g., converting units), as exemplarily described by Kaymakci et al. (2021). In the second step, *event detection*, events that are defined as any change in the state of an appliance over time are detected (Ruano et al. 2019)—Events, such as a simple turn on or off from an appliance, imply power consumption and current changes. Anderson et al. (2012) identified three approaches typically used to detect events in energy consumption data—expert heuristics, probabilistic models, and matched filters. In the third step, *feature extraction*, characteristic features must be extracted from the consumption data to identify unique appliance-specific load patterns or features that distinguish one from another (Ruano et al. 2019). These allow an unambiguous classification of a signal to a known appliance. Again, the resolution of the obtained data

determines the quality of the feature extraction. If low-resolution data is available, it enables the identification of simple features like voltage differences, classifying simple on-off-appliances (e.g., lamps) (Zoha et al. 2012). However, as the number of appliances, the rate of switch-on and -off events, and the occurrence of complex appliances with variable load profiles (e.g., computers) increases, it becomes more difficult to distinguish individual appliances with low-resolution data. The last step, *load identification*, the features previously identified, are used in a classification procedure to determine which appliances are operating at which time and at which state. The classification techniques are typically based on ML and differ in supervised, semi-supervised, or unsupervised approaches (Revuelta Herrero et al. 2018). Supervised approaches require prior training on extensive amounts of appliance-specific load usage data. Obtaining these is costly and limits practical applicability and scalability (Barsim and Yang 2015). By contrast, unsupervised approaches do not require learned patterns and consequently make time- and labor-intensive training obsolete (Zoha et al. 2012), as it autonomously classifies detected appliances (Bernard 2018). However, manual labeling of the identified clusters is necessary. The model learns from labeled and unlabeled observations using semi-supervised approaches, reducing training and manual effort. The methods proposed in research range from classical stochastic methods, such as Hidden Markov Models, to classifiers, such as Support Vector Machines or the Nearest Neighbor Heuristics, to deep learning approaches like Convolutional Neural Networks (Faustine et al.; Revuelta Herrero et al. 2018; Zeifman and Roth 2011; Zoha et al. 2012).

Despite the rising research interest and publications on NILM, research mainly focuses on residential household use cases which are already commercially offered by various service providers. The high maturity level of NILM systems in residential households enables sophisticated and scalable solutions. They allow utilities and third-party providers to propose detailed energy reports with user-friendly graphics, individualized budget plans, and high usage alerts (Baechler and Hao 2015). The main advantages that NILM products and services can achieve are reducing the cost of sub-metering, getting better-informed consumers, and enabling demand-side management and smart grid use cases (Baechler and Hao 2015). However, in contrast to the residential sector, NILM is—despite its great potential—not common in industrial applications. Besides reducing costs for extensive sub-metering devices and maintenance, identifying all appliances and systems and allocating consumption patterns can derive savings and energy costs according to cause (Armél et al. 2013). In addition, predictive utilization plans can be created to avoid peak loads and match volatile electricity supply, resulting in reduced energy expenses. NILM further allows monitoring the overall condition of appliances and enables identifying inefficient operating modes or imminent failures to take predictive measures to minimize efficiency losses and downtime. Efficiency measures can then be orchestrated holistically rather than solely replacing inefficient appliances. Research and practice are lagging in industrial NILM applications, mainly in the immense amount and higher complexity of industrial appliances, the technical shortcomings of available hardware, and a lack of available industrial data. While currently, available metering systems meet the requirements to disaggregate household appliances reliably, they fail to disaggregate complex industrial devices, as research has shown (Adabi et al.

2015; Bernard 2018). However, recently many of the predominant problems have been addressed by novel approaches. For example, new deep learning approaches (Barber et al. 2020; Zhang et al. 2018), semi-automated labeling tools (Völker et al. 2019), and the additional use of low-cost sensors (Giri et al. 2013; Roux et al. 2019) show that not only high-resolution data lead to good disaggregation results.

To summarize, research on NILM in industrial applications almost exclusively investigates technical aspects, even if the (economic) benefits are obvious. In addition to the above reasons why the use of NILM in industrial applications is not widespread, we see a clear indication in the one-sided perspective of research with a strong technical focus. Therefore, to leverage the potential of NILM, an economic perspective is necessary. This perspective should consider the technical aspects and allow practitioners to structure and develop NILM as a data-driven service for industrial applications.

2.2 Smart Services and Business Models

In industrial energy management, companies increasingly rely on the experience and offerings of external service providers, such as smart services. These so-called smart services are defined as data-based, individually configurable offerings consisting of products and digital services. Furthermore, they are organized and provided via integrated platforms and are a unique and complex service provision (Bullinger et al. 2017; Donnelly et al. 2021). Herein, especially the processing, analysis, and combination of data are the drivers for smart products and services (Jüttner et al. 2017). In this vein, smart energy products empower new services, so-called smart energy services (Paukstadt and Becker 2021).

Smart energy services are understood to be intelligent services in the energy sector (both residential and industrial) that provide a service (e.g., smart preheating) based on data from a smart energy product (e.g., smart thermometer) (Paukstadt 2019; Paukstadt and Becker 2021). Consequently, smart energy services are for example home energy management systems (e.g., intelligent lightning control) or demand-side management (e.g., load shedding) (Paukstadt 2019; Paukstadt and Becker 2021). For private households, Paukstadt (2019) mentions for example innovative energy supply tariffs. The range of different characteristics of smart energy services is shown by Fabri et al. (2024). In this vein, NILM is considered one of these smart energy services (Sintov and Schultz 2015). However, due to their novelty, only a little research supports the design of smart services in the energy sector and still lacks an economic perspective (Paukstadt and Becker 2021).

Nonetheless, there is transferable research in developing a business model: Therefore, we conducted a structured literature review (s. Table 1) following the approach by Webster and Watson (2002) and vom Brocke et al. (2009). Our initial search in

Table 1 Parameters of keyword search

Databases	ACM, AIS eLibrary, IEEEExplore, ScienceDirect
Search Fields	Abstract, Title, Keyword
Search Terms	Business model AND service AND (framework OR structure OR taxonomy)

Table 2 The eight reviewed frameworks of smart services and business models

Author	Application	Data-driven	Platform approach	Smart Energy Services	Focus on NILM	Value co-creation	Interface technology & business
Turetken et al. (2018)	Mobility Manufacturing	○	○	○	○	●	●
Pfeiffer (2018)	Electromobility	●	●	○	○	●	●
Pöppelbuß and Durst (2017)	Logistic & Transportation	●	●	○	○	●	●
Hakanen and Murtanen (2015)	Servitization cross-sectional	○	○	○	○	●	●
Viljakainen et al. (2013)	Media conglomerates	●	●	○	○	●	○
Zolnowski (2015)	Retail	●	●	○	○	●	●
Ojasalo and Ojasalo (2018)	Cross-sectional	●	●	○	○	●	●
Fabri et al. (2024)	Cross-sectional	●	○	●	○	●	●

● Covered
○ Not covered

January 2021 led to an initial set of 1170 articles. We searched for relevant articles across application domains, structured and analyzed the results. As proposed, we selected relevant articles by analyzing titles, abstracts, and full texts. With our focus on industrial applications, we removed frameworks that did not focus on an industrial context. Literature that did not focus on frameworks (e.g., case studies) was not considered for direct comparison, but only as a source of implicit knowledge. Finally, we synthesized an overview of the current body of knowledge. For the identified, relevant articles we did a forward and backward search. Furthermore, we updated the literature in our revision cycles in January 2024 and September 2024. This led to our final set of the eight reviewed frameworks in Table 2.

In general, appropriate business models are needed to exploit the potential of innovative technologies (Hofmann and zu Knyphausen-Aufseß 2022). Studies have developed various business model approaches and frameworks in the last decade, but multiple definitions have been proposed (Ojasalo and Ojasalo 2015). A well-known and widely accepted approach to business model development to this day is the Business Model Canvas (BMC), developed by Osterwalder and Pigneur (2010). It is characterized by practicality and provides executives with a coherent tool to operate confidently in uncertain, fast-moving, and unpredictable markets and environments (McGrath 2010). In addition, such corresponding frameworks serve as a visual tool for implementing such business models and analyzing, developing, communicating, implementing, and monitoring current or future business activities (Pfeiffer 2018).

An additional, important building block for developing a business model framework is the orientation in value creation. In this context, service orientation, which is derived from the so-called Service-Dominant Logic (SDL) of Vargo and Lusch (2004), is considered one of the most important contributions to the understanding of markets in recent years (Wilden et al. 2017). SDL assumes that the formal exchange processes do not so much determine value but instead emerge from the value provided by the product or service (Vargo and Lusch 2004). Here, customers drive the value and control the value creation of the service processes. The paradigm shift toward SDL has significant implications for the design of business models. The business model must consider both actors' changing roles and functions (Clauß 2014). To this end, several frameworks aim to integrate the SDL approach. However, as mentioned above, there is little research on smart services in the energy context. In this vein, we have conducted a literature review of these frameworks to draw from the existing research to provide a solid ground for developing our business model framework (s. Table 2).

Our identified frameworks reflect the abovementioned lack of research into smart services in the energy sector (e.g., Hakanen and Murtonen (2015), Turetken et al. (2018), Zolnowski (2015)). On the one hand, all frameworks consider value co-creation, a synergistic creating and exchanging of value with partners for benefits through symbiotic relationship. Furthermore, only one does not consider the interface between technology and business (i.e., Viljakainen et al. (2013)). In addition, most frameworks apply data-driven approaches and consider platform approaches. On the other hand, smart energy services are not considered. For example, the artifact of Ojasalo and Ojasalo (2018) neglects essential aspects such as the technical infrastructure or the synthesis of data from different sources (Ahle and Meyer

2012). Nevertheless, these are crucial for designing and delivering smart services, as addressed by Pöppelbuß and Durst (2017). The taxonomy of Fabri et al. (2024) identifies the essential characteristics of building-related smart energy services on a high-level perspective but does not include the business model perspective. In sum, the frameworks considered serve as a good starting point, and we include them in our developments for the SESC. To enhance our picture of a smart, data-based energy monitoring service, we derived 59 hypotheses, which should help to cover the practitioner's perspectives and provide a suitable basis for conceptualizing a service- and technology-oriented business model.

3 Study Design and Research Approach

In addressing our research question and building and evaluating our artifact, we adapt a DSR approach and define our study design based on Hevner's (2007) three cycle view of DSR (s. Figure 2). DSR draws from existing knowledge bases of scientific theories and experiences, expertise, and existing artifacts relevant to the design subject and application domain and the environment to design practical artifacts meeting the environment's actual needs and requirements. These three closely related cycles of activities thereby embody the process of DSR—rigor cycle, relevance cycle, and design cycle. With the rigor cycle, the research incorporates existing theories, methods, and experiences from the knowledge base and adds new knowledge generated by the research to the growing knowledge base. The relevance cycle provides the interface to the contextual environment to consider requirements and test developed artifacts in the environment. The central design cycle supports the (iterative) construction and evaluation of design artifacts (Hevner 2007). We choose DSR as a suitable research approach, since in line with Eisape (2019) and Hajishirzi (2023) we would refer our SESC as a model with knowledge as operational principle/architecture and therefore, according to Gregor and Hevner (2013) as nascent design theory.

In our study, we proceed in three main steps. We analyze the knowledge base in step one by conducting a literature review. We enrich literature findings with the authors' experience and expertise gained in (research) projects to have a solid basis for the development of the SESC. This step represents the *rigor cycle* at the intersection of building and evaluating the artifact. We follow an iterative approach to derive our hypotheses from the theoretical basis in combination with practical insights. First, we review the existing literature to create a solid theoretical background by deriving 59 hypotheses for the SESC. We deepen and test these initial hypotheses using practical insights with the author's experiences. The results flow into the further development of the hypotheses. According to the *relevance cycle* of the DSR, we must incorporate requirements from the contextual environment, so we verify and evaluate the hypotheses by the relevant application domain. For evaluation, considering the complexity of a business model with its many elements and the still rudimentary state of research regarding industrial NILM-applications and its practical relevance, we choose the method of expert interviews.

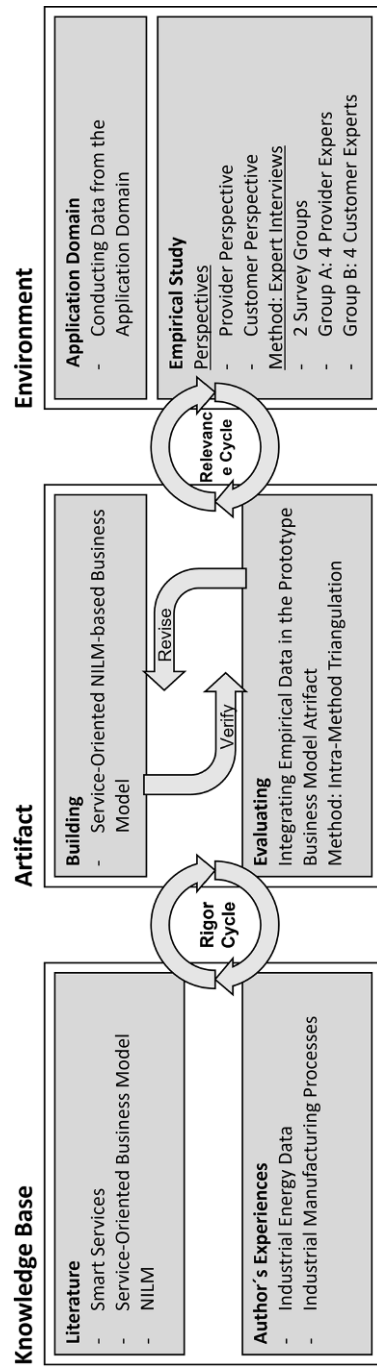


Fig. 2 Design Science Research Process (Source: Own figure based on Hevner 2007)

According to SDL in our evaluation, to meet the critical requirement of co-creation between the service provider and customer, we interview two survey groups to integrate a service provider and an (industrial) customer perspective in step two. We select the participants based on expertise in manufacturing-related energy data, smart energy monitoring systems and/or operational energy management, and service and business model design expertise. We choose to design semi-structured interviews for the qualitative study since they allow the interviewees to share their knowledge freely while maintaining the researchers' ability to navigate the interview (Helfferich 2011). Further, taking a multi-perspective approach into account, we develop two variants of interviews based on the respective survey group following the questionnaire design guidelines of Helfferich (2011). This approach includes opening questions for each topic, supported by several follow-up questions and corresponding vital points to check if topics are missing during the interview. We perform several pretests with researchers' backgrounds in the industry, digitalization, and the energy sector to ensure the questionnaire's practical suitability. For our evaluation, we consult eight experts (i.e., four providers and four customers). All our experts are located in Germany. Table 3 provides an overview of the experts interviewed, including the positions and industry to which the company of the respective expert belongs.

Ultimately, by combining the *rigor* and *relevance cycle*, we systematically compare our set of hypotheses to the empirical data we collected in a third step. A standard method of integrating two or more streams of research is triangulation, which combines data or theories within the same research question or phenomenon (Denzin 1978). Triangulation is often equated with the mixed-methods approach—the combination of qualitative and quantitative methods (Turner et al. 2017). The aim of the study is to enhance comprehension of the behaviour of the business model and to test the confidence regarding its practical suitability in a real system. Since both streams of our DSR approach are qualitative methods, i.e., literature review and expert interviews, we choose triangulation. To this end, we list our hypotheses in a matrix and listed the provider and customer perspectives from the interviews and checked them for consistency. In addition, we are able to identify issues that were only mentioned in the hypothesis but not by the experts and/or those that were mentioned by the experts but not included in the hypothesis. By including multiple perspectives and integrating both strands of research, the assumptions of the design-based concept could be systematically compared with the empirically collected data and additional categories identified. Table 4 represents a simplified example of this systematical comparison contributing to the relevance cycle. This approach allows us to conceptualize and assess the SESC in an iterative process.

4 The Smart Energy Service Canvas

To structure smart energy services using NILM as an example, we developed the SESC after evaluating our 59 hypotheses through expert interviews. Figure 3 graphically depicts a generic and smart energy service agnostic version of the SESC. The SESC is structured in four interrelated clusters—Smart Energy Service Value, Man-

Table 3 Overview of the interviewees

No.	Group	Industry	Position
E1	Provider	Service Provider, Manufacturer/Metering Operator, Smart Metering/B2B, B2C	Project Manager R&D
E2	Provider	Service Provider/Energy Management B2B	Managing Director
E3	Provider	Energy Utility, Service Provider/B2B, B2C	Customer Project Engineer
E4	Provider	Service Provider/Energy Management	Innovation Manager
E5	Customer	Manufacturer/Steel Goods	Head of Sustainable Manufacturing and Energy
E6	Customer	Manufacturer/Consumer Goods	Senior Engineer Production
E7	Customer	Manufacturer/Automotive	Project Engineer R&D Energy and Mobility
E8	Customer	Manufacturer/Chemicals	Production Manager

ufacturing Centricity, Enablement, and Economic Foundation—that contain nine elements relevant to model smart energy services: 1. Value Proposition, 2. Value Creation, 3. Customer Segments, 4. Interaction & Co-Production, 5. Technical Infrastructure & Digital Platform, 6. Key Partners, 7. Key Resources, 8. Revenue Streams, and 9. Cost Structure. The integration of the additional components—Value Creation, Interaction & Co-Production, and Technical Infrastructure & Digital Platform—into the SESC is driven by the need to address the specific complexities and requirements of smart energy services in industrial environments. Value Creation is essential to explicitly articulate how customers can derive practical benefits from the value propositions, encompassing aspects like energy cost reduction and operational efficiency improvements, which are critical for industrial applications. Interaction & Co-Production is included to emphasize the collaborative nature of implementing and operating smart energy services. Given the intricate nature of industrial environments, close cooperation between service providers and customers is necessary to tailor solutions effectively and ensure seamless integration and operation. Technical Infrastructure & Digital Platform is added to account for the significant technical requirements unique to smart energy services. The complexity of manufacturing systems, with their need for specialized hardware and robust digital platforms, necessitates a focused section to ensure all technical aspects are adequately addressed.

The following section presents and elaborates on each of the nine elements by considering the applied example of the smart energy service NILM. Figure 4 further presents a summary of the filled SESC for the NILM example.

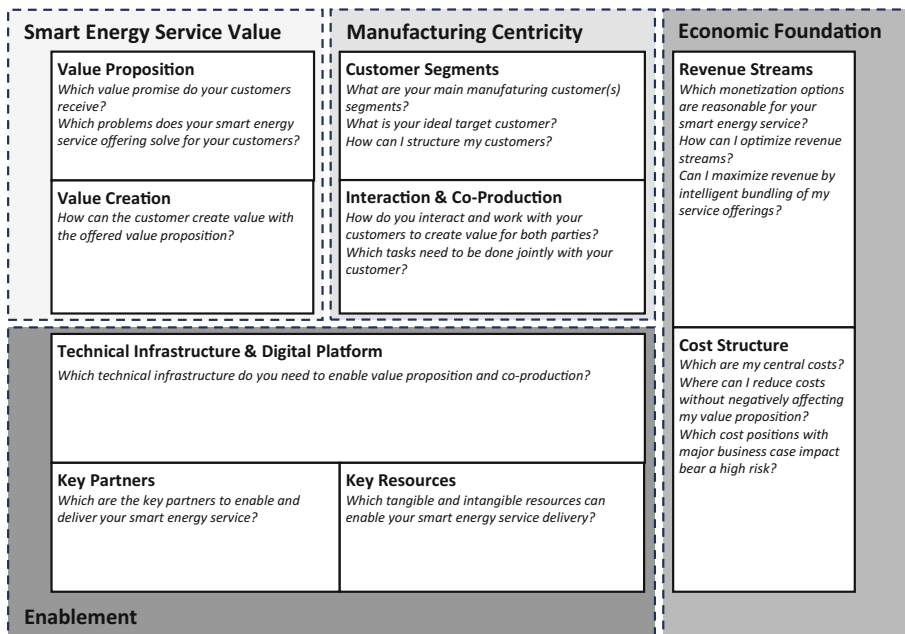


Fig. 3 Empirically verified and revised elements of the SESC

Table 4 List of the hypotheses categorized by the SESC elements including the results of the empirical study

Key Business Model Element	Hypotheses	Validated	Partially validated	Not validated
Customer	H1: Customer already has successfully implemented an Energy Management System according to ISO 50001	X	–	–
	H2: Customer has an energy management department with financial and operational authorities	–	–	X
	H3: Customer is aware of its energy saving potentials, but is not able to fully realize them	–	–	X
	H4: Customer is open-minded towards novel innovations and technologies	–	–	X
	H5: Customer already has some experience with AI and/or Data Science	–	–	X
	H6: Customer has energy and environmental goals that are part of its corporate strategy	–	–	X
	H7: Customer communicates its company values, such as sustainability & climate protection, with its own customer	–	–	X
Value Proposition	H8: Offering a NILM-based analysis of production-related electrical energy consumption	X	–	–
	H9: Enable an energy consumption transparency at appliance level	X	–	–
	H10: Implementing a production-related energy monitoring in real-time	–	X	–
	H11: Implementing and/or optimizing a peak load management system	X	–	–
	H12: Offering an internal and external energy benchmarking	X	–	–
	H13: Implementing an anomaly detection system including an alert system	X	–	–
	H14: Reducing energy costs	X	–	–
Value Creation	H15: Enabling the realization of an energy flexible production	–	–	X
	H16: Identifying energy efficiency potentials	X	–	–
	H17: Deriving operational energy efficiency improvement measures	X	–	–
	H18: Allocating energy costs in accordance with their cause	X	–	–
	H19: Enabling the certification or requalification of an energy management system according to ISO 50001	X	–	–
	H20: Integrating energy consumption data in energy, production and/or process related IT systems	X	–	–
	H21: Supporting the achievement of corporate environmental and climate goals	–	–	X
	H22: Enabling the identification of an “ecological footprint” of products and processes	–	–	X

Table 4 (Continued)

Key Business Model Element	Hypotheses	Validated	Partially validated	Not validated
Key Resources/Activities	H23:	Preprocessing raw data according to requirements (e.g. resampling, scaling, etc.)	X	–
	H24:	Disaggregating energy consumption on appliance level by using NILM-algorithms (e.g. event detection, feature extraction, load identification, etc.)	X	–
	H25:	Visualizing disaggregated data according to requirements	–	X
	H26:	Obtaining and using continuously measured power consumption data of the main metering point	X	–
	H27:	If available, obtaining and using continuously measured power consumption data of sub-meters	X	–
	H28:	If available, obtaining and using continuously measured sensor data	–	X
	H29:	If available, obtaining and using production-related documents and information (e.g. production plans, machine data, etc.)	X	–
Technical Infrastructure & Digital Platform	H30:	Deployment of an energy-data management system (EDMS) according to requirements	X	–
	H31:	Build and administration of server/s and databases to enable the deployment of the EDMS	X	–
	H32:	Installation of a local hub at the customer's facility to obtain and transfer the energy consumption data	X	–
	H33:	Build and administration of a ground-truth register for device specific reference load profiles	X	–
	H34:	Deployment of data protection arrangements	X	–
	H35:	Build and administration of a web-based interface to communicate between local hub, EDMS and customer	–	X

Table 4 (Continued)

Key Business Model Element	Hypotheses	Validated	Partially validated	Not validated	
Interaction and Co-Production	H36:	Personnel support of the customer by providing their mechanics and technicians for installing the local hub including a NILM-capable meter, a gateway, an industrial PC (IPC) and, if necessary, further sub-meters and sensors	–	X	–
	H37:	Participation of the customer on training programs to enable the customer to use the EnMS	X	–	–
	H38:	Assistance of the customer on the development of the NILM-models by handling incoming requests in the EdMS (e.g. labeling disaggregated energy data, etc.)	X	–	–
	H39:	Approval of the customer for obtaining energy related consumption data by reading meters and sensors	–	–	X
	H40:	Assistance of the customer by providing energy and production relevant information (e.g. historical energy consumption data, production plans, machine data, etc.)	–	X	–
Cost Structure	H41:	Main expenses that would be related to the implementation of this business concept are costs for the organizational structure, software development, IT infrastructure, measurement equipment, for building industry expertise, technical expertise, and data science expertise, for marketing and customer acquisition	X	–	–
	H42:	Suitable candidates for this business model are Start-Ups, Smart Home Service Providers, Energy and Technology Consulting or Research Institutes	–	X	
	H43:	Start-ups would face very high initial costs regarding the expected expenses compared to the other potential candidates	–	X	
	H44:	Smart Home Service Providers would face moderate initial costs regarding the expected expenses compared to the other potential candidates	–	X	
	H45:	Energy and Technology Consulting would face rather low initial costs regarding the expected expenses compared to the other potential candidates	–	X	
	H46:	Research Institutes would face moderate initial costs regarding the expected expenses compared to the other potential candidates	–	X	

Table 4 (Continued)

Key Business Model Element	Hypotheses	Validated	Partially validated	Not validated
Revenue Streams	H47:	Needling a two-phased sale process, consisting of an initial service phase and a use-based service phase to enable a suitable revenue stream	X	–
	H48:	Offering a customer specific fixed tariff price for the technical commissioning of the local hub based on the complexity of the customer's facility (depending on the number of appliances and metering points)	X	–
	H49:	Offering the customer three tariff stages (e.g. small, medium, and large project)	–	X
	H50:	Included in these tariffs are free preliminary studies and loan-based installation of addition equipment and sensors	–	X
	H51:	Offering the customer a service subscription model including three different packages to choose from	X	–
Key Partners	H52:	Selectable packages are either based on the customer's usage (e.g. on demand) or on the preferred service timespan (e.g. quarterly or yearly)	–	X
	H53:	Sourcing from manufacturers of measuring equipment and sensor systems*	X	–
	H54:	Collaborating with software developers*	–	X
	H55:	Sourcing the IT infrastructure from IT service providers (e.g. server hosting) *	–	X
	H56:	Having a marketing strategy set up by a marketing agency*	–	X
	H57:	Sourcing personnel support from a specialized personnel service provider or recruitment agency*	–	X
	H58:	Cooperating with universities and research institutes	–	X
	H59:	Cooperating with companies to work on pilot projects	–	X

*Note: The necessity depends on the resources already available

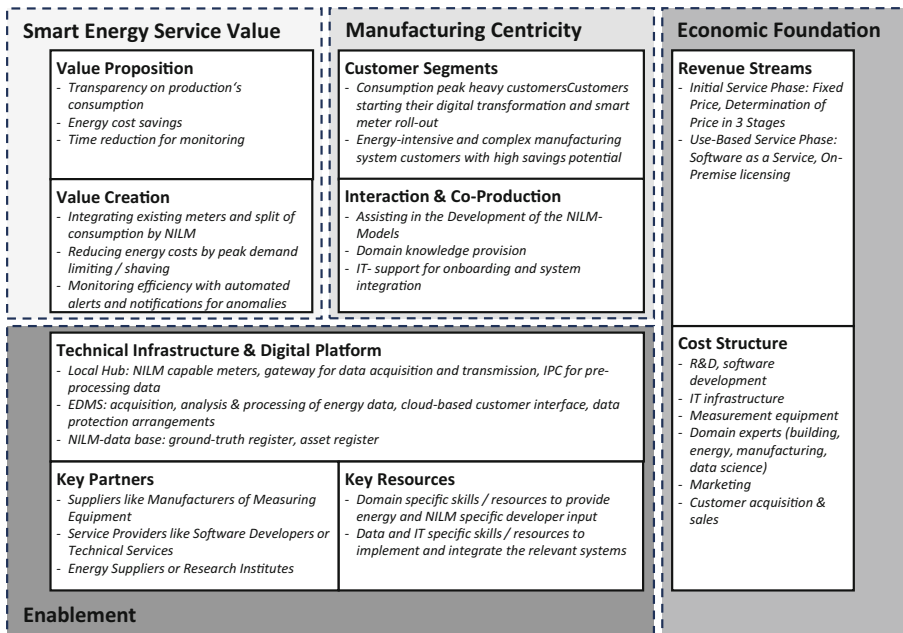


Fig. 4 Empirically verified and revised SESC for the example of the smart energy service NILM

The first cluster captures the smart energy service's value proposition and value creation. The **value proposition** element describes the promise of value from the company to the customers. The value proposition can often also be described by the problems solved for the customer. In other words: The value proposition describes the company's (i.e., service provider's) offer to the customer. According to the provider-side experts, the potential customer is described as inclined towards digitalization, experiencing high peak loads or energy consumption, and having fluctuating operating processes (s. H8). Expert 2 explains that "*customers who are subject to highly fluctuating, peak-heavy operating processes are particularly interested in such a service, as the potential savings in grid utilization costs are high*". Specifically for the NILM case, the main value propositions adopted include the following: First, enabling energy consumption transparency at the appliance level (s. H9), i.e., outputting the calculated energy consumption per appliance. Second, implementing real-time production-based energy monitoring (s. H10) and an anomaly detection system (s. H13), including alarms, which are used to notify the user of deviations from the standard consumption to check the deviations. Furthermore, the implementation or optimization of a peak load management system (i.e., defined switching off and on of electrical devices to prevent exceeding predefined power levels and make optimal use of the power margin) (s. H11) and the offer of internal and external energy benchmarking is made possible (s. H12). These lead to reduced energy costs, allocated according to cause.

The second element **value creation** describes how the customer can use the value propositions from above to create value. In our example, the company provides

the customer several possibilities of value creation: reducing energy costs (s. H14), derivation of operational energy efficiency measures (s. H17), enabling of certification or qualification of an energy monitoring system according to ISO 50001 (s. H19), and integration of device-specific energy consumption data into energy-, production-, and process-related IT systems (s. H20). Expert 3 sees value creation especially in the process efficiency of identifying energy efficiency potentials (s. H16), since “[...] *employees go to the plant with mobile measuring equipment and check the assumptions and hypotheses we have made beforehand. This process could be made more efficient.*” However, of our hypotheses, the proposed enabling of the realization of an energy flexible production (s. H15) could not be validated, as our experts rated this requirement as somewhat irrelevant in the interviews. Other aspects deemed appropriate by the experts, such as reducing the complexity of existing metering systems and the potential to verify the effectiveness of implemented technology and efficiency measures, were added.

The second cluster targets the manufacturing centrality by defining customer segments and structuring ways of (customer) interaction and co-production. The third focuses on the **customer segments** relevant for the smart energy service. During our research process and expert interviews, we identified the need for identifying customer segments as a crucial step since only one of our hypotheses on customer segments were validated. We further derived that even in the “niche” of smart energy services in a manufacturing context, customer segments might not be agnostic and hold across smart service offerings. For our NILM case, we investigated found literature and expert interviews to identify four different customer segments: Customer A can be characterized by its peak-heavy, fluctuating production processes and is thus particularly interested in the consumption of specific devices, which cause high electricity cost through grid charges for peak loads. Customer B is affected by the smart meter roll-out and aims to use its newfound potential. Customer C has already installed several sub-meters but would like to minimize the complexity of the monitoring system. Customer D is an energy-intensive and complex process manufacturer with extensive metering technology and high energy savings potential. Depending on the customer segment, the smart energy service NILM offering might have a different focus.

The fourth element, **interaction & co-production**, structures and defines the interaction with the customer along the service life cycle to subsequently create and deliver the value proposition. For the NILM example, this element summarizes the interaction with the customer from installation to processing during operation (e.g., provision of energy-relevant information) to generate value on both sides jointly. In essence, this element involves leveraging collective knowledge to generate value. For instance, the service provider contributes expertise in technical infrastructure and digital platforms for NILM but may require assistance from the customer in terms of domain knowledge or local specifics (s. H36). Consequently, respondents emphasized that collaborative interaction between supplier and customer must be as simple as possible for joint value generation. In this context, they suggested a web-based function for the customer to handle incoming standardized requests embedded in the proposed EDMS. In addition, the customer shall be supported by specialists (e.g., in training programs) with relevant expertise (s. H38). Concerning the SESC,

the distinction between customer tasks and contextual things and data, according to Pöppelbuß and Durst (2017), proved inappropriate since a clear differentiation was difficult and led to redundancies in content. Therefore, we generalized this element.

The third cluster ensures that the smart energy service can be enabled and delivered in its multiple facets being technically or non-technically. The fifth element, **technical infrastructure & digital platform**, basically summarizes the technical infrastructure and platform required to deliver the smart energy service. Depending on the smart energy service, the involvement of hardware vs. software components, as well as the setup of the infrastructure for a cloud-based vs. an on-premise option might differ depending on customer requirements, industry and intended service scalability. For the NILM case, we defined three core components (i.e., local hub, EDMS, NILM database) needed to build a coherent system for customer data. We found a consensus between the hypotheses and the empirical data regarding the technical specifications of the need for a central point of data acquisition (i.e., a local hub). Our evaluation confirmed that the local hub must include a high-resolution counter with a high sampling frequency, different transmission modes (e.g., LAN, cellular), and the option to process and compress the transmitted data according to the requirements (s. H30). This aspect makes an industrial NILM service much more complex than private applications since no standard hardware is available. In addition, the second key component is a web based EDMS. If the customer wants an on-premises solution, companies should offer local EDMS software instead of a web-based platform. The third key component considered necessary by many experts is the collection of data in a database (s. H31). This database should consist of two subcomponents: A ground truth register and an asset register. Almost all vendor-side experts shared our hypothesis about the importance of a ground truth register that serves as a platform for device-specific reference load profiles of industry-specific equipment (s. H33). The asset registry, which we incorporated into the final model based on our findings from the literature, is intended to support the NILM process. The customer selects their production-related equipment from the registry so that the provider can accurately map which equipment needs to be disaggregated and use that information when labeling and classifying energy consumption data (s. H32). Experts differed on the usage-based performance phase. Half of the respondents considered a cloud-based SaaS model. However, since almost all the experts interviewed wanted an on-premises solution, we added this option to the SESC. In general, an on-premises solution incurs a higher cost than a SaaS solution. However, due to the pronounced security concerns (s. H34), industrial customers are willing to pay a higher price to protect their data (Bibi et al. 2012).

We specify the **key partners** in the sixth element, as other frameworks have before (e.g., Pöppelbuß and Durst (2017)). This element describes which partners are essential to the delivery of the relevant smart energy service. In the case of NILM, Expert 2 confirms and justifies the importance of key partners in particular with the prevailing regulations, which “speak against self-build”, as it is a complex process to be allowed to operate your own smart meter. This must first be approved, which is left to the suppliers and is one of the reasons for the interest in cooperation in research and development processes (E2, E4, E5). On the one hand, suppliers are key partners since they deliver critical hardware for the technical infrastructure (s. H53, H54).

On the other hand, there is a need for service providers such as cloud providers for hosting computing capacities and providing information via dashboards. In addition, companies and customers need energy and building technicians for installation and maintenance. Finally, energy suppliers, consultancies, and research institutes can help generate added value for customers and companies from the information gained (H57, H58, H59). Expert 2 confirms and justifies the importance of key partners in particular with the prevailing regulations, which “speak against self-build”, as it is a complex process to be allowed to operate your own smart meter. This must first be approved, which is left to the suppliers and is one of the reasons for the interest in cooperation in research and development processes (E2, E4, E5).

The seventh element, **key resources**, outlines with tangible or intangible resources are required to deliver a smart energy service. Naturally, this element is closing connected with the key partners element as resources might not be available in-house which leads to make-or-buy decisions and dependencies on possible partners. For our NILM example, we distinguished—following Pöppelbuß and Durst (2017)—between analytical skills and data (i.e., a key resource in terms of co-creation, as the data can be accessed directly from the customer). However, most respondents emphasized the need for in-depth electrical engineering knowledge and industry-specific expertise, especially in terms of equipment-specific load profiles, as half of our experts addressed it as important (E1, E4, E5, E7). Therefore, the SESC now refers to technical skills and supplements the requirements mentioned by the experts accordingly.

The fourth cluster structures the financial aspects of a smart energy service considering revenue as well as costs. The eighth element, **revenue streams**, addresses monetization opportunities. In the context of monetization, there are a variety of options. However, for our example at NILM, we propose the following path identified from the literature and validated by experts: A customer-specific fixed price for initial technical commissioning (s. H48). For example, “*the complexity of the overall system, i.e., the number of devices and systems to be measured*” (E5) and the number of “*metering points*” (E1) are considered useful as reference variables for the formation of the fixed price. Offering our three-tiered rate based on assessing the complexity of the customer’s system, we intend to reduce planning risk for the customer and increase adoption (s. H49, H50, H51, H52). Studies show that complex, split pricing negatively affects the evaluation of the services offered (Bambauer and Gierl 2008), and customers generally prefer simpler pricing systems (Odlyzko 2001). However, experts have pointed out that there are financial risks for the provider, and that hourly or daily rates are more appropriate. However, the interviews also showed that the customer is generally unwilling to pay if the system could not successfully demonstrate its functionality and benefits in a pilot project. Subsequent charging for technical commissioning based on an hourly or daily rate would thus be difficult to implement. Therefore, we retained the proposed rate model.

The ninth element considers the smart energy service’s **cost structure**. The cost structure can be analyzed from different perspectives in combination with the other eight interrelated elements. Centrally, the different cost positions need to be identified, opportunities for cost savings without negatively affecting value proposition or service quality derived and risk management strategies for cost positions with

high risk defined. For the NILM example, the key cost drivers are organizational structure, software development, IT infrastructure, measurement equipment, industry expertise, technical expertise, data science expertise, and marketing and customer acquisition (cf. H41). The impact of the cost drivers might vary significantly for different smart energy services as our interviews revealed. According to the interviews, software development and IT infrastructure account for a large proportion of the expected cost (cf. H42–H46) as reported by multiple experts. In particular, the many years of experience and advantages (e.g., resources and expertise from the private customer sector, holistic approach as a full-service provider) were mentioned as essential by our experts. In contrast, costs regarding the organizational structure, customer acquisition, and marketing seem to be less critical as only a few experts only mentioned these costs.

In conclusion, we identified nine elements in the SESC that are not independent of each other but influence each other. Nevertheless, depending on the intention of use, it is possible to focus on individual areas. However, it is essential to consider the interfaces and effects on other elements. An example would be the connection between the services offered (i.e., value proposition) and the actual measures to create value. The concrete measures can then influence interaction and co-production, which can influence the element technical infrastructure & digital platforms in the technical area, for example.

5 Discussion

5.1 Derived Knowledge During the Research Process

Before deriving theoretical contributions, managerial implications and limitations and aspects of future research, we discuss learnings and knowledge gained alongside the research process. While conceptualizing the case of NILM, we developed 59 hypotheses based on a literature review and added project expertise what set a focus on an academic perspective in the first methodological steps. Results of the interviews showed that starting with an academic focus comes with drawbacks. This was particularly evident in the example of the customer segment, where almost all but one of the proposed hypotheses were rejected. Particularly interesting was the hypothesis “Customer has energy and environmental goals that are part of its corporate strategy”, which we identified as very necessary from an academic perspective due to its great importance for many companies. However, our experts rejected our hypotheses since they did not have a clear corporate strategy considering energy and environmental goals at the time of the interviews.

These insights from the experts demonstrate the advantage of the research approach taken, as we were able to dynamically incorporate practical expertise, validate and extend our theoretical findings during the canvas development. This was made possible by iterating and discarding assumptions that were not mentioned, but also by including knowledge from the interviews that were not covered in the hypotheses. This flexibility in development was important.

However, this dynamic also shows what we consider to be an important feature of the SESC: it is important that adaptations are possible in the future, as they will become necessary as the market and technologies change—with different dynamics and speed of adaptation in research and practice. We have therefore made sure that the canvas is modular, expandable and adaptable. For example, a change might occur in the area of marketing. Our hypothesis that a marketing strategy would be developed by a marketing agency was not confirmed by the expert interviews. At the time of the interviews, companies were not open to hiring external marketing agencies for their smart services, preferring instead to rely on internal expertise. This may change in the future if, for example, smaller service providers (e.g., start-ups) become more successful and do not have their own marketing department.

5.2 Theoretical Contribution

First, we contribute to the existing literature by consolidating two research streams: The technical research on smart energy services described above and the research on existing frameworks of value co-creation at the interface between technology and business. With the result that smart energy services such as NILM are not covered here, the existing frameworks from the second research stream were described in Sect. 2. Here, the scientific literature offers little evidence to support the adoption of smart energy services such as NILM, even though they offer an economic advantage over expensive sub-meters (Armel et al. 2013; Bucci et al. 2021; Hosseini et al. 2017; Yi et al. 2019). Today, the literature in the industrial sector studies almost exclusively technical aspects such as optimizing different algorithms to achieve higher accuracy (e.g., Li et al. (2021)). Allowing interdisciplinary solutions and leveraging technical and economic potentials, we merged previously separate research streams. In this vein, we offer a holistic (business) perspective on smart energy services with the SESC as an applicable, realistic, and practical model guiding business model development—confirmed by our experts (Sonnenberg and vom Brocke 2012).

Second, following up on the above business perspective, the SESC offers a two-fold view (i.e., customer and provider sides) for monetizing smart energy services. As our interviews confirmed, monetizing smart energy services is crucial as there is hardly any guidance. Existing works are mostly limited to payment/rate models (e.g., Paukstadt and Becker (2021)). However, especially for smart energy services in the industrial context, which encounter highly individual applications, it is crucial to quantify the economic potential individually. In this way, customer confidence is gained, and a mutually profitable business model with the potential for scale can be created. Consequently, we address this in the SESC.

Third, we extended existing frameworks, often limited to after-sales activities, by focusing on interaction and co-production in the sense of an SDL already at the beginning of cooperation. Existing research primarily addresses co-production in an already established customer relationship. Regarding the financial requirements, following on from the economic perspective, the SESC is also not just about enabling value creation and value proposition. Instead, as the interviews and the facts revealed, customers and providers should interact quantifying the potential of smart energy services such as NILM. As the interviewees explained, industrial production

environments are very heterogeneous. The effects/benefits of smart energy services are highly individual and require a high level of effort. In this way, the SESC creates transparency, and the provider and customer jointly evaluate the business case. In summary, interaction and co-production should begin with the initial discussion of energy efficiency and smart energy services, including the subsequent preparation of the business case.

Fourth, we found that other framework models to date neglect or do not sufficiently consider customer segmentation. However, customers differ significantly in how they use energy and thus have a correspondingly strong impact on energy consumption. For example, energy-intensive companies with significant potential for network charge reduction might have different requirements than a company with medium energy consumption and a higher proportion of flexible consumers that responds to price fluctuations. In this vein, smart energy services encounter a diverse and cross-industry customer base. Therefore, from customer to customer, the individual characteristics of the SESC may vary in importance. Translating the theoretical finding of diverse and cross-industry requirements into a managerial implication, we see potential for replicable solutions and scalability by targeting vertical markets with somewhat similar requirements. For example, the Food & Beverage vertical may have similar industrial processes of cooling and heating where patterns and learnings can be transferred from one customer to another. Thus, focusing on a specific vertical to gain rapid traction and scalability in one market before developing services across verticals. Consequently, it is essential that the SESC is not seen as a rigid document set in stone but leaves room for adjustments as experience grows.

In sum, our work contributes to the prescriptive knowledge of smart energy services, in general, and NILM-based services in the industrial sector, in particular. Since we bring an economic perspective to what is otherwise primarily technical and computer science-oriented literature, we provide guidance for implementing a NILM-based business model. Compared to the traditional business model canvas, which primarily focuses on generic business models, the SESC specifically adapts the structure to address the uniqueness and complexity of smart energy services. This adaptation is reflected in specialized dimensions such as “digital platform” and “technical infrastructure”, which are essential to capture the dynamic and data-driven aspects of smart energy services. By emphasizing these specific requirements and the need for platforms, we make a significant theoretical contribution that goes beyond the limitations of existing models and provides a sound basis for the development of business models in this sector.

5.3 Managerial Implications

Although NILM is recognized as a promising way to reduce energy costs in the industrial context, practical guidance for implementing NILM-based services is missing in the industrial context. Therefore, we provided prescriptive guidance through the SESC that helps practitioners implement NILM-based services. The SESC helps practitioners understand the elements needed for NILM-based services, thus increasing transparency. To enter the market as early as possible, generate a solid foundation for a long-term business model, and generate sales as quickly as possible should

generally be the short-term goal of a new business idea. The need and the enormous potential of NILM-based services in practice were also confirmed in the expert interviews (e.g., “only a matter of time until an established company offers a service, or a start-up specializes in it”).

We argue in line with Kampker et al. (2018) that novel providers often do not start with a completed, market-ready product. Instead, they offer a minimum viable product, gaining experience and constantly developing it further (Kampker et al. 2018). Therefore, the first step for smart energy services is building a database and understanding the individual customer’s needs. Consequently, we propose learning together with the customer, for example, in pilot and support projects (e.g., testing error-proneness and scalability). Especially the support of both sides in the consortium makes funding projects attractive at this point. The SESC can serve as a fundamental structuring aid in these projects by combining the necessary technical components (e.g., platform and infrastructure) with the economic perspective (e.g., revenue stream, cost structure).

However, the identified nine elements in the SESC influence each other. Nevertheless, depending on the intention of use, it is possible to focus on individual areas. Although, it is essential to consider the interfaces and effects on other elements. An example would be the connection between the services offered (i.e., value proposition) and the actual measures to create value. The concrete measures can then influence interaction and co-production, which can influence the element technical infrastructure & digital platforms in the technical area, for example. Therefore, we highly recommend a holistic view of the SESC for versatile smart energy services.

In the industrial context, however, as in private households, the provider needs to identify the potential with the customer. This circumstance requires comprehensive energy consulting in the sense of standard value co-creation. Therefore, the projects proposed above should elaborate a common advisory guide for providers and customers using the project’s findings and data.

Furthermore, we highly suggest using certified and standardized system components based on our findings. Data protection has shown itself to be one of the main customers’ concerns. However, there is currently little standardization regarding NILM-based systems. An interviewee explained that without standards, there is no definite trust in the reliability and accuracy of such a system. The IEC is currently addressing this problem. Recently, they released technical specifications for NILM (IEC 2021), which attempt to provide a classification of NILM sensing devices. However, standards on NILM analytics and performance indicators are to be awaited. One opportunity for trust and acceptance could be synergies with other services. Especially in the increasingly connected energy and production environment, it is crucial to avoid stand-alone concepts. Instead, companies should use the required resources for the possible services (e.g., predictive maintenance.) as synergistically as possible. For example, the infrastructure (e.g., cloud) could run with providers already in use. Since there is still no common language on that, the reliability of the overall system cannot be evaluated yet. Despite all these concerns, it can nevertheless be constituted that NILM services are already successfully marketed to private customers.

5.4 Limitations and Further Research

As with any research endeavor, our work is subject to limitations and offers prospects for further research. First, as research on NILM in industrial applications is still at an early stage, our research faced a lack of literature and an absence of available empirical data. Therefore, future studies should continuously improve the developed SESC in NILM research with experience gained in practical applications & research. Second, since we have acquired a relatively small sample size for the expert interviews, we suggest broadening the empirical database to strengthen the relevance and validity of the SESC in future studies. At the same time, from a methodological perspective, further research can run another iteration of *rigor*, *relevance*, and *design cycles* to obtain a more holistic and robust artifact. Thereby, alternative solutions to the SESC design will probably exist. However, we pose that these business model alternatives will converge into a similar or identical solution and lead to minor improvements. One option would be to conduct field tests and business model development workshops with the SESC in practice to strengthen the relevance cycle and identify flawed assumptions and uncertainties in a continuous learning process to optimize the SESC further. Third, since we sought to develop the SESC holistically for all aspects of an industrial NILM service, we considered each key business element (in the SESC) equally. However, we did not address the technical aspects to the extent that might have been necessary to provide a practical solution for a primarily technology-oriented business idea. We suggest detailing the key business elements of technical infrastructure and digital platforms to bridge the gap between engineers and business developers for further research. Also, in our study, we did not discuss the quantitative aspects of cost and revenues connected to a NILM business model. We identified and evaluated main expenses and defined multi-phased revenue streams. However, our paper lacks detailed support for further quantitative analysis like cost-benefit- and break-even calculations. These analyses would further assess profitability, confirm our qualitative findings, and support decision-making. Fourth, our research focused on the German market due to the origin of the authors. Especially regarding our proposed implications for practice, we considered prevailing regulations of the energy sector and market conditions in Germany, such as the progress of the smart meter roll-out for industrial consumers. Hence, further research should consider national specifics when using or adjusting the SESC in other countries. However, this would mainly affect strategic implications rather than key business model elements. Applying the business model outside of the German market affords considering this limitation. Fifth, our research is limited to NILM-based applications. However, further research could apply the SESC to other smart services in manufacturing. Therefore, further research could explore the cross-technology and cross-service applicability of the SESC to enhance its value to business developers in practice and researchers. Research might discuss applications such as data-driven anomaly detection in industrial energy consumption or other ML-based tasks that could be offered as a supplementary smart energy service (Kaymakci et al. 2022).

6 Conclusion

With the increasing impact of climate change and the tightening of climate policy, industrial companies face the challenges of becoming more sustainable. Nowadays and into the future, volatile electricity supply, the economic pressure for the industrial sector will rise (Bauer et al. 2021; Glenk et al. 2021; Paukstadt and Becker 2021). Consequently, the industrial sector sees its competitiveness threatened due to rising CO₂ and energy prices (Rusche et al. 2021). Hence, smart energy services are gaining importance as they help to improve energy efficiency and flexibility, which are becoming increasingly significant assets to counter rising economic pressure (Bauer et al. 2021; Glenk et al. 2021; Paukstadt and Becker 2021). However, research on NILM in industrial applications almost exclusively investigates technical aspects. Under these circumstances, we developed a business model framework that enables structuring and developing a business model for NILM as a representative smart energy service for industrial application. Thus, we contribute a practical and strategic framework for concretizing and implementing the business idea to complement the ongoing, mainly technological-focused research activities.

In conclusion, despite our limitations, we hope to provide a viable solution to structuring and developing industrial data-driven services with the practical and empirically validated Smart Energy Service Canvas.

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Availability of data and material The interviews that support the findings of this study are available but restrictions apply to the availability of these data, which were used under license for the current study, and so are not publicly available.

Code availability Not applicable.

Conflict of interest J. Günter, L. Fabri, S. Wenninger and C. Kaymakci declare that they have no competing interests.

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