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Driving Business Innovation and Sustainability through Internet of Things and Data Analytics: An Innovation Stage Model

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The ever-growing number of connected Internet of Things (IoT) devices, coupled with advances in data analytics, has created widespread opportunities for organizations to develop sustainable business and innovation solutions from the vast amounts of data generated by IoT devices. However, the innovation potential of IoT analytics to create sustainable business value out of IoT data remains largely unexplored, and organizations lack adequate support to determine the innovation stages of their IoT analytics solutions. Based on an analysis of various frameworks and maturity models of IoT analytics and interviews with practitioners, this article identifies four main dimensions that characterize the innovation potential of IoT analytics: 1) data source, 2) data target, 3) data analysis, and 4) data-based transformation. These dimensions are incorporated into an innovation stage model to help organizations identify the innovation stages of their IoT analytics solutions and realize the sustainability benefits offered by these solutions. The utility of this model is illustrated through two case studies from the energy and healthcare sectors. This article aims to bridge the conceptual gap with a model that provides insight into the value of IoT analytics to business innovation and sustainability. In addition, it provides a practical guidance to support management efforts in reorienting their businesses towards sustainable innovation and transformation driven by IoT analytics.

Key words: *Innovation Stage Model, Internet of Things, Industry 4.0, Maturity Models, Data Analytics, Business Innovation, Sustainability, Big Data.*

INTRODUCTION

The Internet of Things (IoT), which connects physical objects with the virtual world (Boyes, Hallaq, Cunningham, & Watson, 2018), is considered one of the most disruptive technologies of our time – with the potential to radically change how organizations and consumers interact with each other and with the surrounding infrastructure (Alexopoulos, Koukas, Boli, & Mourtzis, 2018; Brous, Janssen, & Herder, 2020). A whole range of physical "things" – from people and places to cars and computers to household appliances and industrial machines – are equipped with embedded IoT devices and sensors that continuously generate large amount of data. While data generated through IoT devices offers valuable opportunities for organization to create sustainable business and innovative solutions (Nagy, Oláh, Erdei, Máté, & Popp, 2018), it poses a tremendous challenge regarding data management, storage, and analysis. To ensure that organizations are not buried in floods of data, they need IoT analytics solutions capable of managing and analyzing these streams of sensor data and transforming them into actionable insights for creating innovative products and services that demand prompt and effective actions to meet consumer needs (Yassine, Singh, Hossain, & Muhammad, 2019). These IoT analytics solutions must also meet the growing demand for sustainability and the temporal granularity of decision making, whether offline or near real-time (Belhadi, Zkik, Cherrafi, Yusof, & El fezazi, 2019; Dai, Wang, Xu, Wan, & Imran, 2019).

With the growing demand for innovation and sustainability, coupled with the large-scale proliferation of IoT devices, IoT analytics has increasingly become an indispensable practice that many organizations are adopting for gaining knowledge and actionable insights from IoT data (Bibri, 2018; ur Rehman et al., 2019). IoT analytics provides powerful methods and tools for capturing, processing, and analyzing large volumes of data generated by IoT devices and sensors, enabling organizations to generate valuable insights by compiling the digital footprints of their customers into real-time intelligence for both business and technological innovations. These business-critical insights have the potential to build a sustainable competitive advantage and support customer-oriented innovation and services in several ways. Whether self-driving cars, smart houses, medical fitness trackers or networked production facilities, the disruptive power of the IoT analytics is expected to radically change the business logics of various industries (Yassine et al., 2019). This paves the way for new dimensions of innovation and sustainability with profound consequences for our society and economy (Braccini & Margherita, 2019). Therefore, IoT analytics solutions are increasingly intervening in product functionalities and thus not only influence entire value chains, but also transform products and services as well as their development and manufacturing processes (Vial, 2019). To keep pace with this transformation and to be able to develop their own smart products and services, organizations are increasingly relying on the use of IoT and advanced analytics technologies. This often leads to the development of proprietary IoT analytics solutions.

For most organizations, the adoption of an IoT analytics solution, which is usually not available "out-of-the-box" from a single provider, is a major challenge. The fact that they do not have a dedicated resources and capabilities for the development of enterprise-specific IoT analytics applications is challenging; small and medium-sized enterprises (SMEs) are particularly affected by this issue, since they typically have a small number of employees and limited resources to foster their innovation capability (Gherghina, Botezatu, Hosszu, & Simionescu, 2020; Matt & Rauch, 2020). There are also concerns about the potential benefits of IoT analytics for creating sustainable products and services due to several issues such as service availability, data security, and lack of interoperability between heterogeneous devices (Nagy et al., 2018). Organizations therefore lack the support they need to drive forward the systematic development of product and service innovations based on data from IoT analytics. Moreover, the costs of devices, platforms, data storage, connectively, security, and analysis technologies are often in an uncertain relationship with the potential benefits attained from the investment into IoT technologies and analytics (Bansal & Kumar, 2020; Brous et al., 2020; Matt & Rauch, 2020); including the effectiveness and efficiency of innovations creation processes as well as the development and market launch of innovative products and services (Ratten, Ramirez-Pasillas, & Lundberg, 2019). As a result, many organizations are reluctant to invest in IoT analytics technologies as the return on this risky yet strategic investment is usually uncertain and requires significant organizational transformations (Brous et al., 2020). Consequently, there is a great need to make it easier for decision-makers in organizations to understand the innovation potential of their IoT analytics solutions and realize the sustainability benefits associated with these solutions.

While previous research in the field of IoT analytics has mainly focused on technical approaches to capturing, processing, and analyzing data from connected IoT devices (Bansal & Kumar, 2020), limited research has investigated the potential benefits of IoT analytics for creating sustainable business and innovative products and services (Nicolescu, Huth, Radanliev, & De Roure, 2018). This article aims to investigate the potential benefits of IoT analytics for sustainable innovation management and, in particular, the innovation potential of different IoT analytics solutions for organizations (Brous et al., 2020). Enterprise IoT analytics solutions can eventually reach different levels of maturity, ranging from simple, local status queries of devices to global, distributed systems that process complex information. In practice, the maturity levels of IoT analytics solutions differ widely from each other. This also applies to the academic community involved in the development of maturity models for IoT analytics (Król & Zdonek, 2020; Nemeth, Ansari, Sihn, Haslhofer, & Schindler, 2018; Weber, Königsberger, Kassner, & Mitschang, 2017). An initial review of current IoT analytics maturity models raises several issues. Often, it is not clearly described what the term maturity level means and how it is measured. The dimensions describing the maturity level of IoT analytics are also not sufficiently defined. In addition, a closer look at the maturity models of IoT analytics shows that they do not adequately address the diversity of enterprise IoT analytics solutions or lack classification features. This article is therefore devoted to answering the following question: *How can organizations identify and promote the innovation potential and sustainability of their IoT analytics solutions using an easy-to-apply model?*

Based on an analysis of various frameworks and maturity models of IoT analytics and semi-structured interviews with IoT and data analytics practitioners, this article presents an innovation stage model consisting of four main dimensions that describe the innovation stages of IoT analytics: (1) data source, (2) data target, (3) data analysis and (4) data-based transformation. The innovation stage model presented in this article should help to evaluate IoT analytics solutions based on different stages with regard to their innovation potential. It thus provides a practical tool to support organizations in their efforts to develop innovative and sustainable products and services based on IoT analytics. The innovation stage model is designed to bring complex IoT and data analytics issues closer to the users in a simple way by restricting itself to central aspects, being clearly structured and easily applicable in an organizational context. The main contributions made in this article are as follows. First, this article presents an innovation stage model for identifying the innovation potential of IoT analytics solutions. Secondly, it identifies the key dimensions that characterize the innovation stages of IoT analytics solutions. Finally, it demonstrates the benefits of the innovation stage model using two IoT analytics applications from the energy and health sectors.

The remainder of this article is structured as follows. The next section gives an overview of research on innovation, sustainability and maturity models in the context of IoT analytics and defines key concepts. The following section presents the research methodology used to develop the innovation stage model. Subsequently, the innovation stage model and its practical application is presented using examples of two industrial cases. The next section discusses the implications for research and management practices resulting from the application of the innovation stage model. The final section concludes this article with a summary of the main findings and directions for future research.

INNOVATION, SUSTAINABILITY AND MATURITY OF IoT ANALYTICS

Before discussing existing frameworks and maturity models of IoT analytics, it is helpful and meaningful to separate the IoT analytics out and define the IoT, IoT analytics, business innovation and sustainability. A plethora of different definitions and interpretations for IoT can be found in science and practice (Boyes et al., 2018). In order to better understand the IoT, the definitions of Dorsemaine, Gaulier, Wary, Kheir, and Urien (2015), Rose et al. (2015), and Boyes et al. (2018) were aggregated. Based on the definitions of these scholars, IoT is an umbrella term for all technologies that enable the networking and collaboration of the physical and digital worlds –

objects, individuals and systems. It refers to the collection of all physical and digital components (i.e. hardware and software components) in the organization that enable the exchange and processing of data between objects, individuals and systems. In view of this, IoT analytics refers to the application of data analytics and machine learning tools and technologies to extract value from the vast amounts of data generated by connected IoT devices (Adi, Anwar, Baig, & Zeadally, 2020; Belhadi et al., 2019). It aims to assist organizations to achieve improved understanding of data, and thus, make efficient and well-informed decisions at both strategic and operational levels. With the help of IoT analytics solutions, organizations can appropriately expand their products and services (e.g. through condition monitoring) and make internal processes much more efficient (Brous et al., 2020). Thus, IoT analytics can be thought of as a driving force to increase the innovation potential of an organization (Belhadi et al., 2019). The innovation potential in this article refers to the possibility of increasing the number and quality of innovations by using an IoT analytics solution (Kneipp, Gomes, Bichueti, Frizzo, & Perlin, 2019; Ratten et al., 2019).

Innovation models designed to measure innovation usually focus on different levels, for example on an organizational or corporate level or even on an entire country (Bertolini, Esposito, Neroni, & Romagnoli, 2019). These models determine, for example, how innovative organizations behave based on research and development activities (Brous et al., 2020). However, such models are less likely to assess the impact of new technologies, such as IoT analytics, on the innovation potential of an organization. Innovation from a business perspective is usually described with models that attempt to measure the novelty of a product, service or process (Shakeel, Mardani, Chofreh, Goni, & Klemeš, 2020). This also applies to models that distinguish between incremental and radical innovation (Ringberg, Reihlen, & Rydén, 2019). These models are intended to provide support in assessing the effectiveness and efficiency of innovation processes on the outcome of an organization. They can also help to predict the success of new or improved product in the market. Above all, however, such models, which can also serve as a basis for characterizing the maturity of IoT analytics applications (Braccini & Margherita, 2019), enable the description of IoT analytics solutions in a structured way. Therefore, they not only promote a common understanding of these solutions, but also enable cross-company comparisons with peers (benchmarking).

With the knowledge of the innovation potential of IoT analytics, management seeks to be able to make better decisions and align strategies towards sustainable innovation and management (Ratten et al., 2019; Shakeel et al., 2020). Sustainability, as defined by the World Commission on Environment and Development (WCED) (Keeble, 1988), is a strategy that allows an organization to meet its current needs without losing its ability to meet future needs. While many scholars continue to view sustainability in terms of environmental issues, there is a growing consensus on the three dimensions of sustainability, often referred to in the literature as the "triple bottom line" (Evans et al., 2017; Saxena, Stavropoulos, Kechagias, & Salonitis, 2020). According to the "triple bottom line" theory proposed by Elkington (1998), there are three key dimensions of sustainability that organizations need to address, namely the economic, social and environmental dimensions. While the economic dimension relates to the ability of an organization to promote the growth and stability of businesses, the social dimension relates to the ability of an organization to improve the quality of life and promote community health and safety, and the environmental dimension relates to the organization's endeavors to conserve natural resources (land, water, and air) (Braccini & Margherita, 2019). An organization is considered truly sustainable if it simultaneously embraces all of these three pillars (Sivarajah, Irani, Gupta, & Mahroof, 2020)

Although IoT analysis is still in its infancy, it adds real economic value to organizations and offers numerous opportunities for both business innovation and sustainability (Bibri, 2018). The premise for sustainable success in IoT analytics is industry-specific business models that generate real customer value. The appropriate data analytics techniques bring IoT data and business models to life and ensure usability, reliable performance and security (Shakeel et al., 2020). From a technical point of view, there are three basic elements that pave the way for sustainable success in IoT and data analytics. First, the data analytics makes the IoT devices safe and energy efficient. Second, advanced data analytics and machine intelligence techniques enable the effective integration of IoT data while maintaining quality at the component, service and application levels. Third, data analytics techniques provide the framework and tools to move beyond analytics of real-time monitoring and automation use cases for IoT data to the seamless interaction of the entire IoT value chain (i.e., things, systems and services) (Goni et al., 2020; Mahdavinejad et al., 2018).

The stream of research on IoT analytics that has contributed to business innovation and sustainability management has gradually evolved over the years. Prior research (Grossman, 2018; Ratten et al., 2019; ur Rehman et al., 2019; Velosa & Kutnick, 2016) has provided descriptions of the maturity level of IoT analytics across multiple application scenarios, such as smart homes, car-sharing services, and smart thermostats. Püschel, Röglinger, Schlott, and Röglinger (2016) suggested a classification model for smart things based on a layered modular architecture, which is intended to distinguish between different technologies used in smart things. Paukstadt, Strobel, and Eicker (2019) distinguish four capability areas in IoT analytics solutions (monitoring, control, optimization and autonomy). Nevertheless, both models either consider only a certain range of IoT analytics solutions, such as smart things, or limit themselves to certain characteristics, such as descriptive analytics and reporting capabilities. A growing number of studies (e.g., He, Xue, & Gu, 2020; Jæger & Halse, 2017; Pradeep, Balasubramani, Martis, & Sannidhan, 2020; Tesch, Brillinger, & Bilgeri, 2017) have demonstrated the relevance of IoT analytics in the sustainable innovation research and have focused on examining the use of IoT analytics solutions in technological change (Kneipp et al., 2019), the role of IoT and data analytics in the innovation development process research (Brous et al., 2020), the importance of IoT analytics to innovation project leadership (Oláh et al., 2020), and the use of IoT analytics in sustainability development projects (Ratten et al., 2019). IoT analytics is characterized by new innovative capabilities, such as different analytical capabilities and sensors technology that conventional products and analytics do not have (Adi et al., 2020; Król & Zdonek, 2020). In order to gain a clear understanding of IoT analytics solutions and their innovation potential, it is necessary to investigate current maturity models and close the gaps in the current research combining the IoT analytics and business innovation and sustainability.

RESEARCH METHODOLOGY

The aim of this study is to develop an innovation stage model for IoT analytics solutions. The model is devoted to support organizations in determining the innovation potential of their IoT analytics solutions, and thus to plan further innovation stages. The research methodology used in this article is based on a deductive content analysis approach that consists of three main phases: (1) data collection, (2) data analysis, and (3) data synthesis (Carvalho, Rocha, & Abreu, 2016; Webster & Watson, 2002) (see Figure 1). Owing to the exploratory nature of the research, the evaluation and interpretation of the findings was more descriptive rather than statistically based.

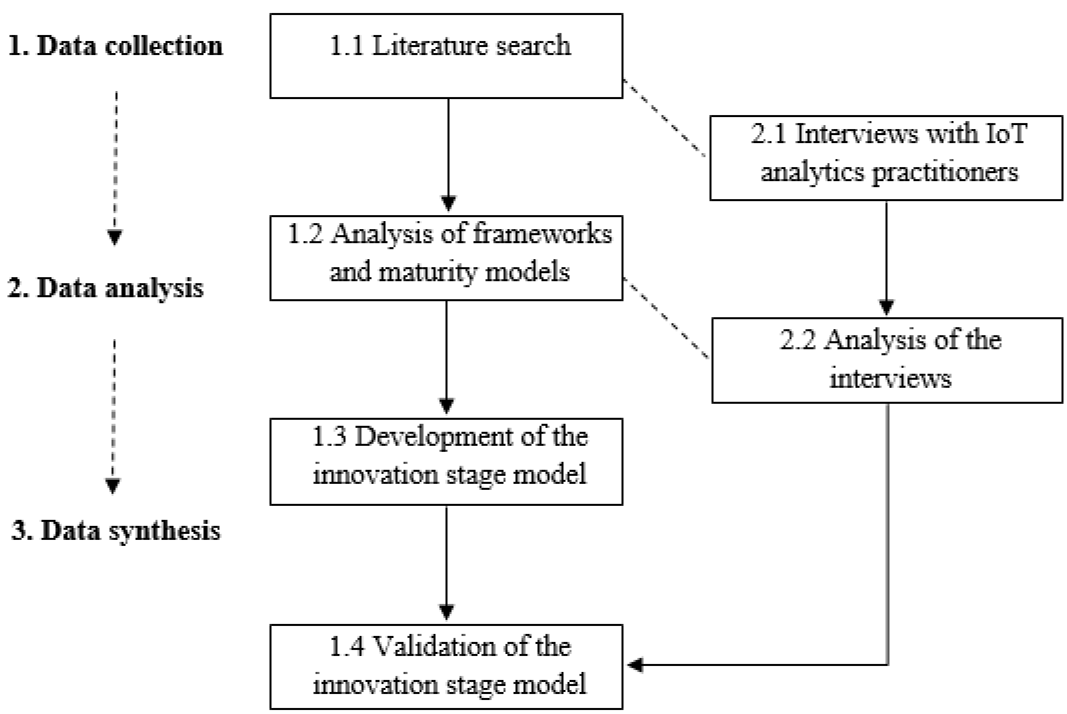

Figure 1: An overview of the research methodology.

Data Collection

In the first phase of the research process, both a literature research and semi-structured interviews with experienced IoT and data analytics professionals were conducted. The literature search was conducted based on the guidelines suggested by Webster and Watson (2002) and Carvalho et al. (2016). The focus of this research was to identify current frameworks and maturity models from research and practice that assign IoT analytics solutions to different classes and thus provide information about their innovation potential. In view of that, a topical approach is deemed more appropriate that a systematic one. In the literature search, the following search string: ("Product Maturity" OR "Product Capability" OR "Classification" OR "Taxonomy") AND ("IoT Analytics" OR "Internet of Things Analytics") were used. These search strings were used in several electronic search databases, including ScienceDirect, Scopus, IEEE Xplore, SpringerLink, ACM Digital Library, and AIS eLibrary. In addition, isolated sources from Google Scholar and Google searches were used to collect relevant research documents related to the topic under investigation. During the literature review, the title, abstract and keywords of academic papers, white papers and corporate publications published between 2010 and 2020 were considered. Table 1 provides an overview of the 31 models identified in the literature review.

Table 1: An overview of the maturity models and frameworks of IoT analytics from research and practice.

No	**Model**	**Reference**
1	Industrial IoT and Analytics Maturity Model	(Guilfoyle, 2020)
2	IoT Analytics Maturity	(Minteer, 2017)
3	Layered Taxonomy of IoT Analytics from Data to Application	(Siow, Tiropanis, & Hall, 2018)
4	IoT Big Data applications	(Biswas, Dupont, & Pham, 2017)
5	IoT Analytics Lifecycle	(Soldatos, 2017)
6	Microsoft Services IoT Maturity Model (IoTMM)	(Junco, 2018)
7	IoT Technological Maturity Assessment Scorecard	(Jæger & Halse, 2017)
8	Analytic processes maturity model (APMM)	(Grossman, 2018)
9	Big Data Business Model Maturity Index (BDBMMI)	(Schmarzo, 2016)
10	Gartner's maturity model for the Internet of Things	(Velosa & Kutnick, 2016)
11	Data Architecture for IoT Communications and Analytics	(Loshin, 2018)
12	Maturity Model for Data-Driven Manufacturing (M2DDM)	(Weber et al., 2017)
13	Industrial analytics maturity model (IAMM)	(O'Donovan, Bruton, & O'Sullivan, 2016)
14	TDWI Analytics Maturity Model	(Halper & Stodder, 2014)
15	Classification of IoT data analytics	(Adi et al., 2020)
16	The Temporal Big Data Maturity Model (TBDMM)	(Olszak & Mach-Król, 2018)
17	Life cycle of Big Data Analytics for Manufacturing Internet of Things (MIoT)	(Dai et al., 2019)

18	Secure IoT-requirement implementation maturity model (SIOT-RIMM)	(Hamza et al., 2020)
19	The Connected Enterprise Maturity Model	(Bradley, 2014)
20	Smart Factory Maturity Model	(Sjödin, Parida, Leksell, & Petrovic, 2018)
21	The 4 Stages IoT Solutions Architecture	(Pradeep et al., 2020)
22	PriMa-X –Three-Layer Portfolio Matrix	(Nemeth et al., 2018)
23	IoT-enabled supply chain in presence of big-data services	(He et al., 2020)
24	Taxonomy of BDA in industrial Internet of Things (IIoT)	(ur Rehman et al., 2019)
25	Classification of Big Data Analytics in the context of Manufacturing Process	(Belhadi et al., 2019)
26	Machine to machine (M2M) maturity model	(Oztemel & Gursev, 2020)
27	An organization's analytics maturity model	(Król & Zdonek, 2020)
28	Three–Stage Internet of Things Maturity Framework	(Banerjee & Woerner, 2017)
29	DELTA Plus Model & Five Stages of Analytics Maturity	(Davenport, 2018)
30	Digital transformation framework	(Ibarra, Ganzarain, & Igartua, 2018)
31	Functional model of IoT ecosystems	(Nicolescu et al., 2018)

In addition to the literature research, semi-structured interviews with experienced IoT practitioners were conducted to obtain feedback and validate the dimensions and idiosyncratic characteristics of the innovation stage model. Eight IoT analytics practitioners from different organizations were interviewed; in particular, two IoT consultants from a national state-owned company, three academic researchers specialized in IoT and data analytics, two production managers responsible for IoT infrastructure and services for SMEs, and one IoT analytics consultant from a consulting firm. The interviews followed a guideline based on the four key dimensions of the innovation stage model identified during the review and analysis of the maturity models of IoT analytics.

Data Analysis

In order to derive the dimensions and idiosyncratic characteristics of the innovation stage model from the identified maturity models and eight interviews, a qualitative analysis was carried out in two steps.

In the first step, the differences between the maturity models were first examined in terms of dimensions. In order to identify these dimensions, the identified maturity models were analyzed with respect to their analytical capabilities and their applicability in sustainable innovation practices using two detailed concept-centered matrices as recommended by Webster and Watson (2002) and Król and Zdonek (2020). In particular, the analytical capabilities of existing IoT analysis models were evaluated in the areas of decision support, levels of analytics, connectivity, data generation, integration, and data security. In the analysis of maturity level models, the main focus was on identifying dimensions that directly and indirectly affect the innovation potential of IoT analytics solutions. As the innovation stage model presented in this article is aimed at supporting management practice in decision making and innovation management, the applicability of the maturity models of IoT analytics has been evaluated in a second concept matrix, as recommended by Webster and Watson (2002). At this point, differences in the structured representation, design and logic between the models were observed. Some models only had descriptions of the individual maturity levels, but did not support them graphically (e.g. models 5, 9, and 23). Other models and their classification characteristics were not sufficiently defined (or not logical) to analyze the innovation potential of IoT analytics solutions (e.g. models 7, 11, and 14). Furthermore, the development of the models is explained in a partially transparent manner. Figure 2 summarizes the analysis results of the two concept matrices in aggregated form and shows that none of the identified maturity models has pronounced analytical capabilities (x-axis) or a high degree of applicability in practice (y-axis).

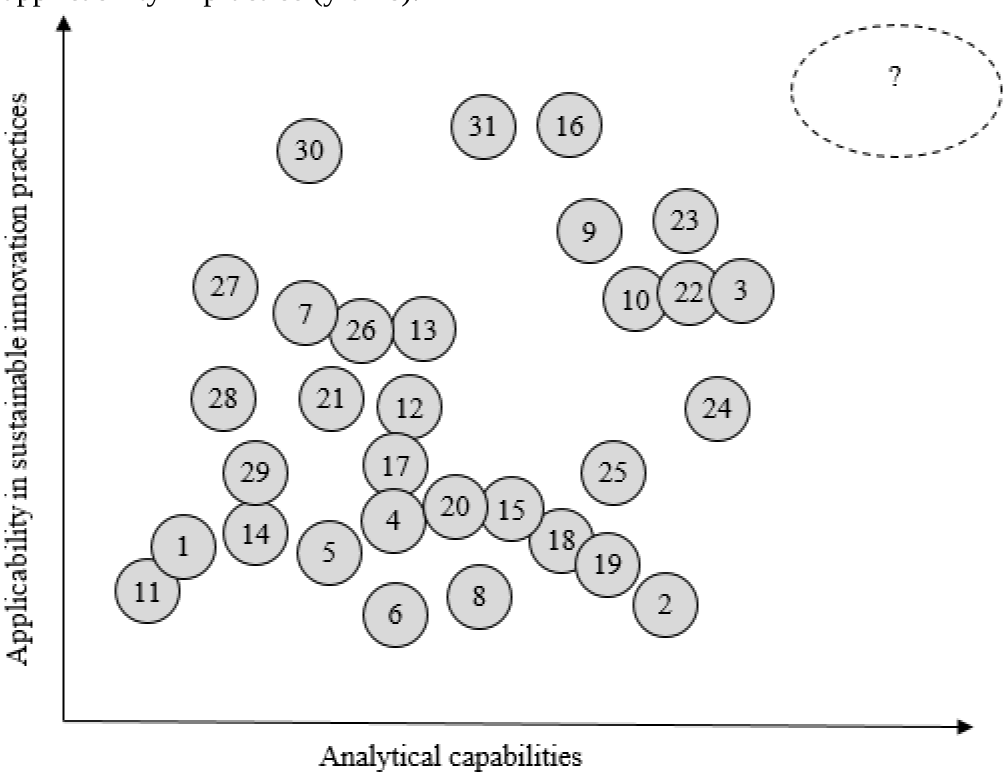

Figure 2: Evaluation of frameworks and maturity models of IoT analytics in terms of analytical capability and applicability in sustainable innovation practices.

Based on this analysis and focusing on the analytical capabilities of maturity models, four key dimensions were identified, namely: 1) data source, 2) data target, 3) data analysis and 4) data-based transformation. In a second step, the analysis of the key dimensions was extended by identifying their unique characteristics. These characteristics were also developed based on the maturity models identified in the literature research. Initially, it was possible to derive most characteristics for each of the four key dimensions through the related models 3, 9, 10, 16, 22, 23, 24, 30 and 31. On the one hand, these models were characterized by important analytical capabilities. On the other hand, they clearly identified the specific features behind the individual characteristics of each dimension. During the content analysis, attention was paid to the influence that individual characteristics can have on the innovation potential of IoT analytics solutions. This was followed by an analysis of interviews with practitioners of IoT analytics to verify the dimensions and characteristics of the innovation stage model. All interviews were transcribed prior to content analysis. As the four main dimensions have already been identified, opinions on the individual characteristics of each dimension were sought from the practitioners interviewed. The practitioners, in turn, have also developed concepts similar to those used in maturity models. After two assessments, four unique (or exclusive) characteristics were finally identified for each dimension, as shown in Figure 3.

Development and Validation of the Innovation Stage Model

In the final phase of the research process, the innovation phase model was developed as a synthesis of the literature (or the analysis of existing maturity models of IoT analytics) and expert interviews. The development process followed the approach of Becker, Knackstedt, and Pöppelbuß (2009), which distinguishes between four different strategies for the development of maturity models for IT management: 1) the construction of a completely new model, 2) the extension of an existing model, 3) the combination of existing models into a new one, and 4) the transfer of content or structures into a new model. While these strategies have been suggested to develop maturity models in business informatics (Bertolini et al., 2019), they can be applied to the process of developing the innovation stage model presented in this article. To this end, the innovation stage model was developed by combining existing maturity models, mainly focusing on the most closely related models (3, 4, 6, 13, 16, 22, 23, 24, and 31). As a result, the innovation stage model consists of four key dimensions, each of which has four distinct characteristics. The ensemble of these characteristics determines the innovation potential and stages of IoT analytics.

The dimensions and characteristics of the innovation stage model were validated through qualitative interviews with experts and two case studies from energy and healthcare sectors. The aim of the innovation stage model is to assign IoT analytics solutions to an innovation stage and thus create a tool that enables organizations to better assess or compare the innovation potential of their IoT analytics solutions. This model is described in detail in the following section.

THE INNOVATION STAGE MODEL AND ITS DIMENSIONS

Based on the research process described in the previous section, four stages of innovation for IoT analytics solutions were identified. The innovation stage model shown in Figure 3 represents successive stages, whereby all the characteristics of a stage must be fulfilled in order to assign an IoT analytics solution to that stage. The higher the innovation stage, the greater the innovation potential of the IoT analytics solution. The model allows the assignment of an IoT analytics solution to an innovation stage based on its characteristics within the four dimensions: data source, data target, data analysis and data-based transformation. The totality of characteristics in the four dimensions determines the stage of innovation and thus the innovation potential of the IoT analytics solution. If an IoT analytics solution achieves at least all characteristics of an innovation stage, it can be assigned to that stage. An IoT analytics solution that could be assigned to the third stage, for example, has the potential to promote the development of new products and services, but can also be used for use cases from lower stages such as the monitoring and descriptive analysis of processes. The innovation stages therefore build on each other. The four key dimensions and their idiosyncratic characteristics are discussed in the following points.

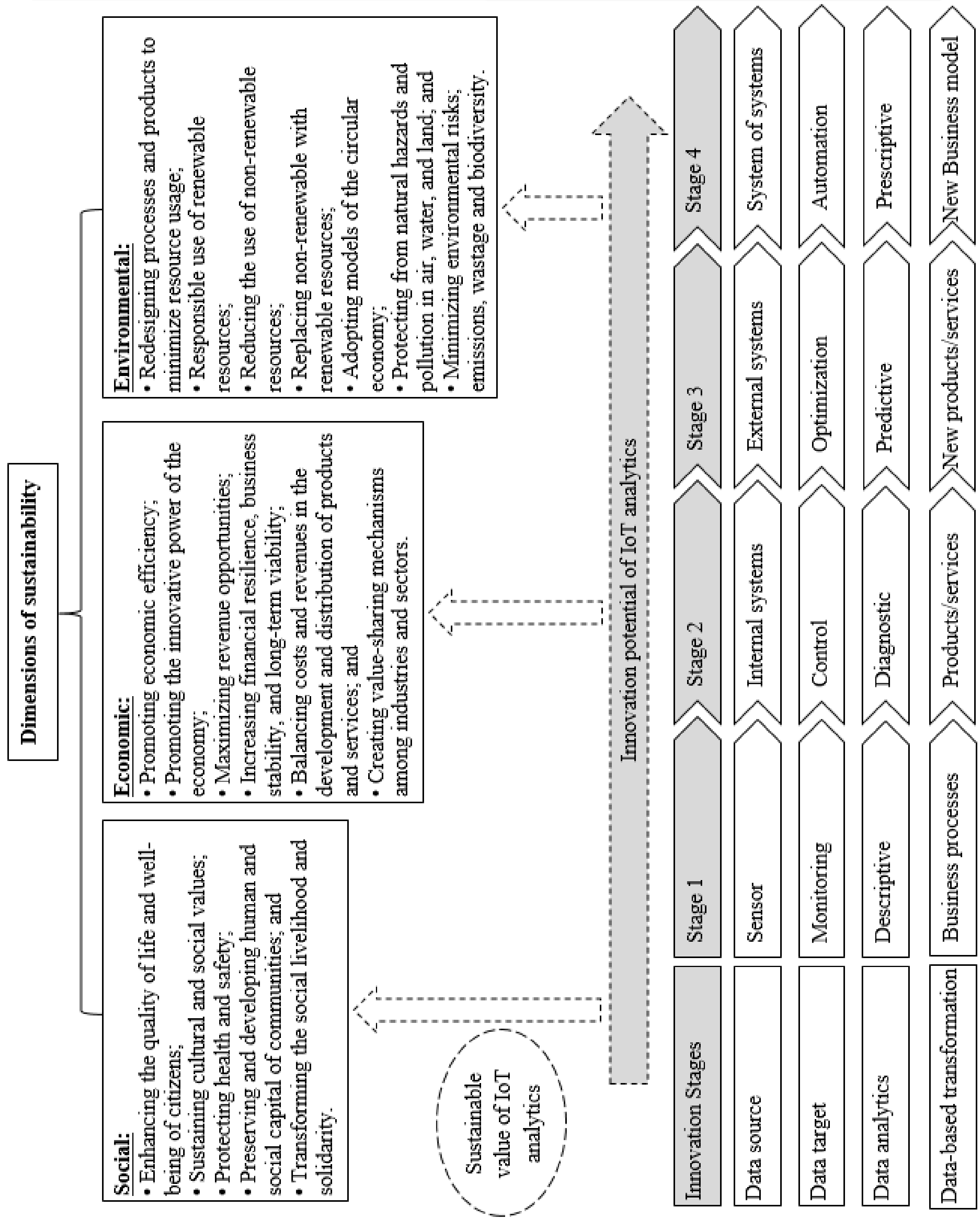

Figure 3: Innovation stage model.

1. Data source: The data source specifies the scope and quality with which an IoT analytics solution generates relevant data. In the context of IoT analytics, data collection devices sense and capture data and transmit these data using embedded IoT devices and sensors. While sensors account for a large part of the collected data volume, data can also be generated by people working in production; usually in conjunction with proprietary digital tracking devices or mobile applications. However, in practice, even if simple sensors provide information about the condition and service life of a machine, they do not make the information or production process smart. Companies usually supply their internal systems and processes with additional data sources. Examples of this are the inclusion of transactional data from enterprise resource planning (ERP) systems or other internal company information systems. The integration of external third-party systems has the potential to provide an even more comprehensive analysis. Data from social networks can also provide additional useful information to support organizational decision-making and innovation processes. These data sources can also come from partners, suppliers and customers, creating an ecosystem of useful data sources. In this context, the term 'System of Systems' (SoS) is usually used to describe such configurations. This term is even more strongly emphasized when the IoT analytics solution integrates interdependent systems or information from other industries (e.g. Siemens MindSphere IoT analytics system). According to the practitioners interviewed, the IoT-based networking can exploit its full potential through SoS configurations. Therefore, it is important for organizations to identify their data sources and specify what they need to take advantage of their IoT analytics applications to create innovative and sustainable products and services.

2. Data target: The data target indicates the economic value and innovation potential that the organization is pursuing through data insights from IoT analytics applications. In the case of simple sensors technology, machine states can be monitored in an industrial context (monitoring). In the event of a machine failure, service technicians are then immediately sent to a machine to repair it. A networked factory can also control the entire production process (control). IoT analytics solutions that enable use cases such as condition monitoring and predictive maintenance make the factory and its products smarter; they help maintenance technicians work smarter and enable organizations to spot potential machine failures in advance by detecting early signs of potential downtime and component problems (Yassine et al., 2019). This saves companies considerable costs that would be incurred by stopping production. Through optimization, companies seek to make their innovation processes more efficient and possibly more effective, e.g. by redesigning them. This often involves a combination of internal and external data. According to the practitioners interviewed, automation is related to the complete networking of the value creation processes and two-way communication from devices to a cloud platform and, after appropriate analysis, back to devices for automated and intelligent production (Olszak & Mach-Król, 2018).

3. Data analysis: After IoT data is captured and integrated, it is transmitted through a gateway to a central database or cloud platform so that it is available for analysis in a structured and prepared format. In the context of Industry 4.0, organizations rely heavily on methods and tools of data analytics to make their production processes more efficient, further develop products and enable innovative analysis-based services. In the literature, a basic distinction is made between four primary types of data analytics: descriptive, diagnostic, predictive and prescriptive analytics (Siow et al., 2018; Soldatos, 2017). IoT analytics solutions with descriptive methods are used to monitor the current status of IoT devices, machines, and products (ur Rehman et al., 2019). Diagnostic analytics techniques work deductively on IoT data. They combine current and historical IoT data with visualizations to identify problems and repair or improve a service, product or process. Predictive analytics is distinguished by inductive techniques and data mining algorithms that enable organizations to predict what will happen and identify the likelihood of future outcomes based on existing data. Prescriptive analytics is the final frontier of analytic capabilities. It entails the application of mathematical and computational sciences and aims to find the best course of action for a given set of scenarios based on the results of descriptive and predictive analytics (Minteer, 2017). These four levels of data analytics were confirmed by the interviews with the IoT analytics practitioners.

4. Data-based transformation: According to the interviews with the IoT analytics practitioners, the critical step after a thorough data analysis, in which correlations and patterns in the data are identified, is to take concrete measures for further development of products and services. As previously mentioned, the innovation stage model is intended to help organizations to identify the innovation potential of their IoT analytics solutions and thereby drive possible changes or transformations of their businesses and services. For example, an organization that sells fire extinguishers can offer additional services that improve predictive maintenance by installing pressure sensors and corresponding pressure data. In this way, the organization can expand its business from a pure product provider to a service provider by enriching its products with innovative service features; offering customers unique and sustainable value propositions that enable organizations to differentiate themselves from their competitors. Thus, the last dimension of the innovation stage model provides information about the (data-based) transformation of business processes and services. In principle, the more advanced the IoT analytics solution, the greater the innovation potential of a company. In the first stage, data are collected by sensors that carry out simple machine status queries. With the help of the current status information of machines, new insights can be gained into a process, so that it can be made more efficient and possibly more effective. Through process recording and analysis, it can be recognized that the relocation of a factory to another location or similar measures lead to time savings and a higher production output. In the second innovation stage, an IoT analytics can positively influence existing products and services. In the fire extinguisher example, an existing product has been improved. Adding external systems and their data sources can completely create new products and services. For example, insights into the customer usage behavior of machines can be incorporated into the rapid product improvement of machines. A new machine generation or a machine enhanced by new services could be the result. These services are often provided as (mobile) applications. The usage data generated there is then used by the manufacturer for product improvements or further developments (Sjödin et al., 2018). Moreover, the use of IoT analytics can also lead to a transformation of parts or the entire business model. One possible application of IoT analytics for manufacturing companies is the development of new billing models, such as the pay-as-you-use of machinery. Further intelligent algorithm-based applications using data generated in real time would be possible at this stage of innovation. In addition, companies could also decide to set up an IoT analytics platform, thereby significantly transforming their business model (e.g. Siemens MindSphere IoT analytics system). Through a platform strategy, providers of IoT analytics platforms become a central hub between supply (developers of IoT analytics solutions) and demand (Consumer companies). However, this market is fiercely competitive.

APPLICATION OF THE INNOVATION STAGE MODEL

In this section, the application of the innovation stage model to identify the innovation potential of IoT analytics solutions is illustrated. To this end, two IoT analytics solutions from MASE Ltd. (MASE, 2020) and Cochlear (Cochlear, 2020) are presented, who participated in the "IoT Analytics & Mobile Business Award 2020" as part of a hackathon to find innovative and sustainable solutions to the challenges facing the energy and healthcare sectors in Jordan (UNDP, 2020).

MASE

MASE (Modern Arabia For Solar Energy) is a leading solar energy and automation technology company headquartered in Jordan (MASE, 2020). As MASE's mission is to provide innovative solar energy solutions for the electricity needs of low-income families in Jordan and the Middle East, the company has sought to optimize operations using an IoT analytics solution to create sustainable value and maintain long-term competitiveness. The IoT analytics solution deployed in MASE is a Bluetooth-communicating sensor that can be easily attached to different solar panels, gathering information on operating and state parameters such as vibration, temperature, energy consumption or overload. The data is either read out by the installation and maintenance employees using a mobile application or sent to the MASE's cloud via a gateway. The data is then analyzed using specially developed analytics-based system to provide the plant operator with usable information for maintenance operations. This enables engine downtimes to be reduced by up to 70%. At the same time, the service life of the solar panels is extended by up to 30% and energy consumption is reduced by up to 10% (MASE, 2020). This IoT analytics solution—from smart sensor installation, Bluetooth or gateway communication, MASE's cloud to data analysis—can also be adopted and expanded by other solar energy companies to offer more sustainable products and services to low-income families. Figure 4 shows the classification of this IoT analytics solution in the innovation stage model.

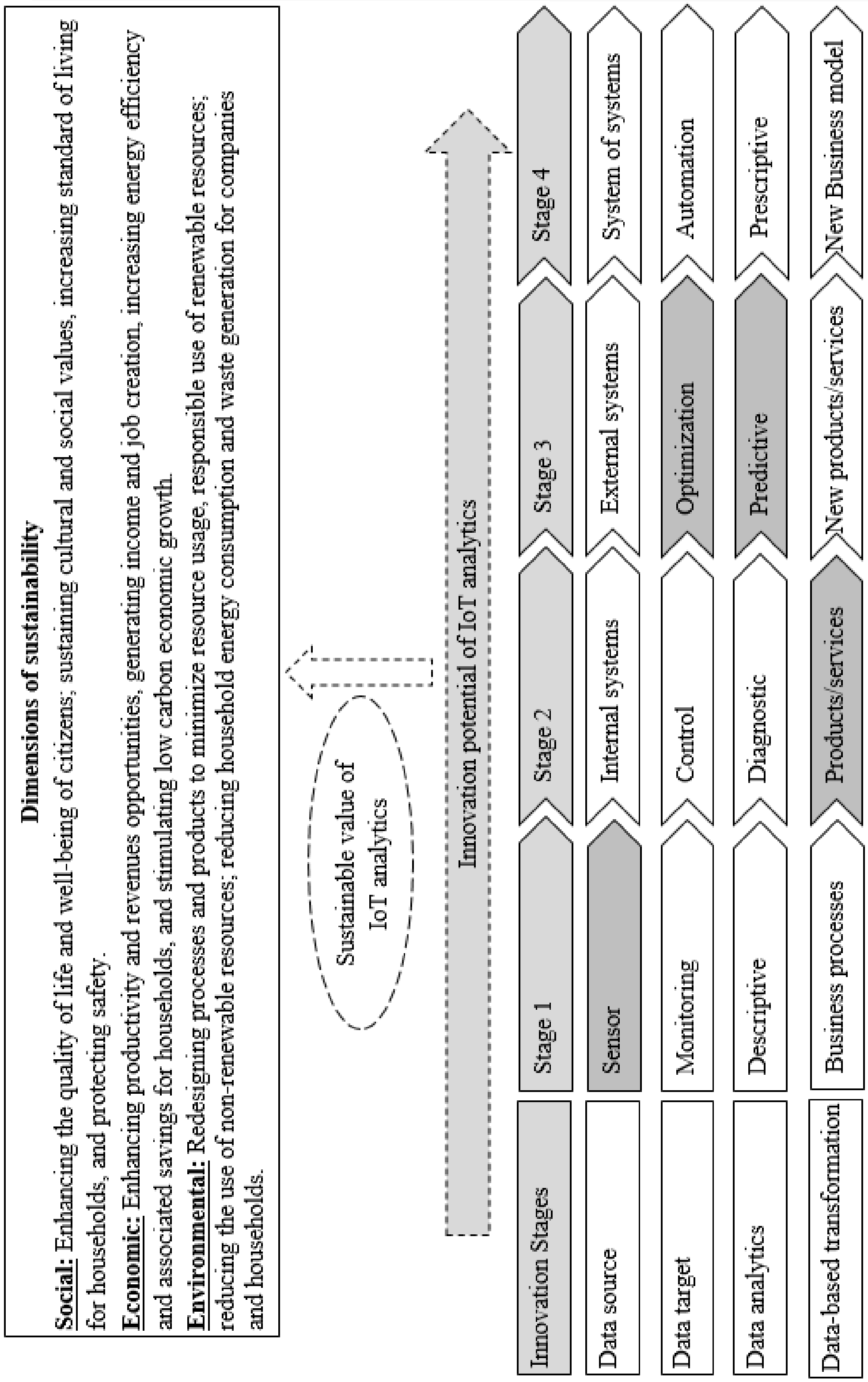
Dimensions of sustainability
Social: Enhancing the quality of life and well-being of citizens; sustaining cultural and social values, increasing standard of living for households, and protecting safety.
Economic: Enhancing productivity and revenues opportunities, generating income and job creation, increasing energy efficiency and associated savings for households, and stimulating low carbon economic growth.
Environmental: Redesigning processes and products to minimize resource usage, responsible use of renewable resources; reducing the use of non-renewable resources; reducing household energy consumption and waste generation for companies and households.
Sustainable value of IoT analytics
Innovation potential of IoT analytics
Innovation Stages
Stage 1
Stage 2
Stage 3
Stage 4
Data source
Sensor
Internal systems
External systems
System of systems
Data target
Monitoring
Control
Optimization
Automation
Data analytics
Descriptive
Diagnostic
Predictive
Prescriptive
Data-based transformation
Business processes
Products/services
New products/services
New Business model

Figure 4: Applicability of the innovation stage model for MASE's IoT analytics solution.

A key advantage of MASE's IoT analytics solution is the easy installation of the IoT sensor. Thus, the smart sensor is assumed to be the main data source of this IoT analytics solution. The data objectives (targets) of MASE in implementing the smart sensor are to monitor, control and optimize their own production machines and the solar panels it sells to customers. To ensure a long-term improvement of all machines, the MASE's IoT analytics solution must have diagnostic and, depending on the use case, predictive analytics capabilities. With the help of predictive analytics, use cases such as predictive maintenance, energy storage optimization, and service quality assessment can be applied to solar power station equipment. In this way, MASE can identify at an early stage at which point a machine could fail with a certain probability. The implementation of such a use case would not only lead to a more sustainable production process, but could also enable MASE to offer and deliver innovative services that improve the quality and performance of its products; this would lead to significant energy savings in both private and economic contexts, reduce household energy consumption and support the generation, storage and distribution of energy.

Cochlear

Cochlear is an international Australian company that develops, manufactures and supplies hearing aids devices to treat sensorineural hearing loss (SNHL) (Cochlear, 2020). The hearing aids devices combine a surgically inserted implant and an external "sound processor" worn behind the ear. The latest generation of the "Nucleus 7" product line has a classification function that analyzes the user's surroundings (e.g. quiet living space vs. busy street) and automatically adjusts the settings of the processor in order to achieve the best performance for the respective environmental conditions. As Cochlear is under pressure to ensure constant cost and quality improvements, it has sought to improve operational efficiency and drive innovation in products and services by adopting and using an IoT analytics solution. The proprietary IoT analytics solution includes three portable IoT sensors that capture 16 digital signals and 8 analog signals. The gateway communicates the data generated by IoT sensors via Open Platform Configurations Unified Architecture (OPC-UA) to a Microsoft Azure cloud platform for data analytics. The data is then supplemented with additional information; e.g. the product to be produced, the number of employees per line, the room temperature, room humidity and sensor data of different rollers. After the data is available in the cloud in a structured manner, the predictive analytics method follows, which was implemented with machine learning technology. With the help of machine learning algorithms, Cochlear can predict the number of production interruptions. The algorithm currently uses only locally generated data, including environmental data and plan data from the ERP system. Currently, the Cochlear IoT analytics solution enables a prediction accuracy of the number of expected production stops of 90% (Cochlear, 2020). Figure 5 shows the classification of the solution in the innovation stage model.

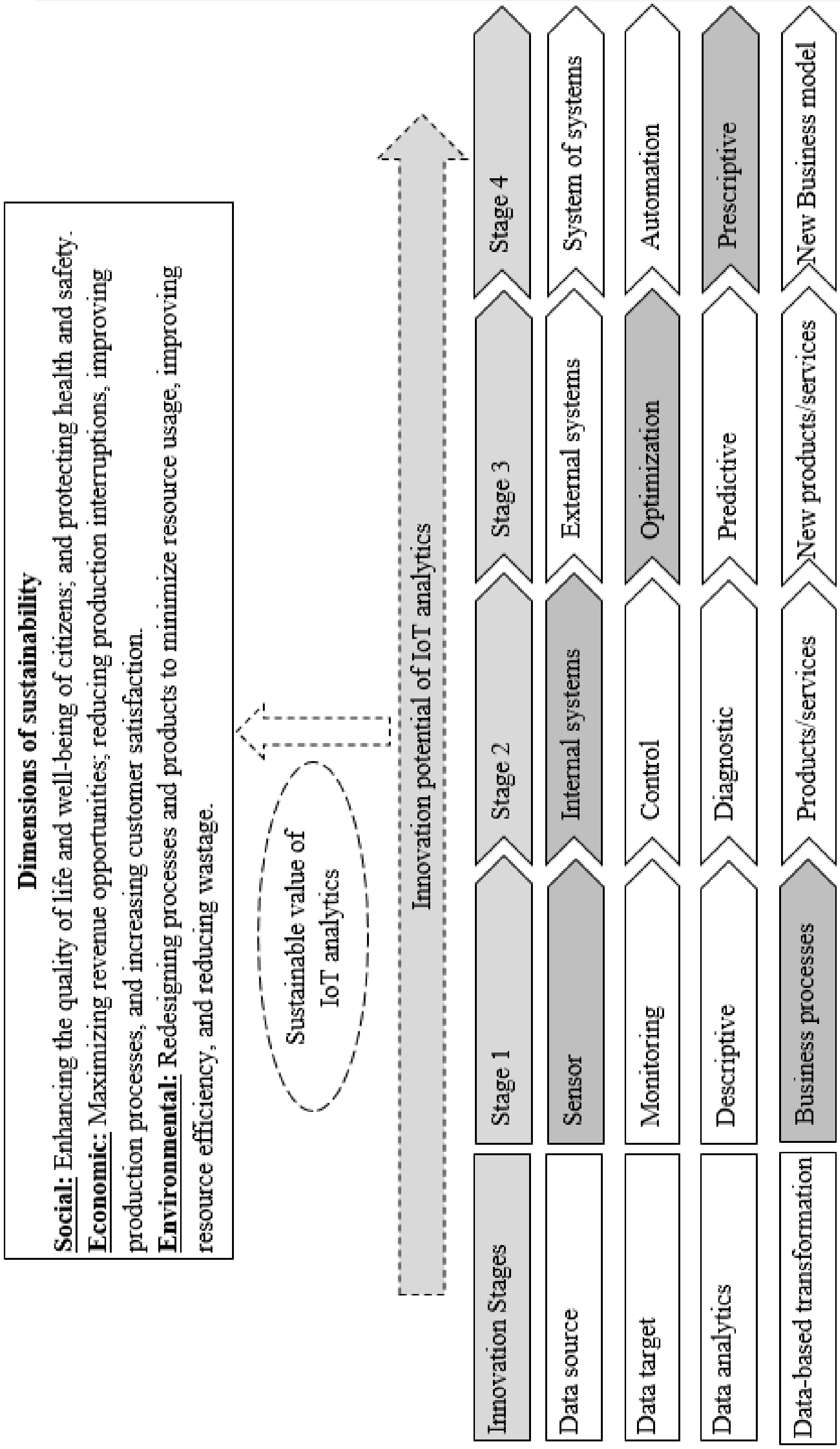

Figure 5: Applicability of the innovation stage model for Cochlear's IoT analytics solution.

The data sources from which Cochlear's IoT analytics solution feeds its analytics applications are manifold. On the one hand, various sensors are used to provide status information about the production rollers or the room temperature. On the other hand, other internal systems, such as ERP transaction data, are used to enrich production processes with additional data. The goal is to use the data to make the production process of hearing aids more effective, so that fewer production stops and thus less material waste are generated (optimization). To achieve this data target, Cochlear uses machine learning algorithms on the Microsoft Azure platform (predictive analytics). With the help of IoT analytics, Cochlear is able to identify different situations and automatically make customer-specific adjustments using the IoT analytics-based service. The use of its IoT Analytics solution has thus significantly reduced production interruptions and led to an improvement in its own production processes of hearing aids and implants.

IMPLICATIONS FOR BUSINESS PRACTICE

As IoT analytics is an emerging and challenging field for both scholars and practitioners, the innovation stage model presented in this article should both make theoretical contributions and provide support to management in creating sustainable and innovative products and services based on IoT analytics practices. The identification of the four key dimensions, along with their unique characteristics, to describe the innovation stage model is an important step towards developing a deeper and more detailed understanding of the role that IoT analytics can play in the development of the innovation capacity of organizations. It is therefore important to transfer the results of this research to sustainable innovation management and service engineering. To date, there is a dearth of tools that demonstrate the innovative potential of IoT analytics solutions in organizations (Brous et al., 2020). The combined visualization of the innovation stage model with its four dimensions provides an intuitive presentation that is easy to grasp, communicate and use for reporting and early approval processes. This also makes it possible to show the development progress over time or to juxtapose solutions in one's own organization or in a competitive environment. Therefore, the innovation stage model presented in this article can serve as a means to promote the innovation and competitiveness of organizations based on IoT analytics applications.

As the innovation stage model presented in this article describes the capabilities of IoT analytics solutions in a systematic way, it can easily be applied to innovative service design and business models. It helps to identify the skills required to design and develop an IoT analytics solution at an early stage within the organization, especially in the early stages of service development. The well-structured description of the key dimensions of the innovation stage model serves as a guideline for the individual understanding and learning of complex IoT analytics solutions and their innovative potential. Especially in the hype of concepts - such as data analysis, smart IoT, artificial intelligence and machine learning - there is a wide range of thoughts in people's minds, which makes effective communication quite challenging. This model not only shows the spectrum and range of innovative possibilities, but also explains the unique characteristics of each innovation stage.

In general, the innovation stage model offers organizations with a methodological tool to support and reconsider the development of their IoT analysis solutions. In the coming years, it can be expected that sustainability goals will become an integral part of many commercial IoT analytics solutions. Sustainability will no longer be just a by-product on the way to economizing and living smartly. IoT analytics solutions will increasingly be designed not only with regard to business and technological requirements, but also with regard to their sustainability. Nevertheless, IoT analytics solutions with high levels of innovation require considerable investments and therefore require top management support and decision making (Brous et al., 2020). The step-by-step presentation makes management more aware of whether decision making requires very long steps and whether it is better to gain more experience and build skills or whether many levels of innovation can be skipped without significant risk. If successful practical cases are incorporated into the model, the potential advantage of IoT analysis solutions for innovation and sustainable development can also be demonstrated to skeptical management. Typically, decision-making in digitization initiatives requires the coordination of decentralized innovation projects or in some cases sub-strategies. As Wulf, Mettler, and Brenner (2017) explain in their remarks on the digital services capability model, such models also serve to build consensus. Both the uniform terminology mentioned above, and the shared assessment of the current situation, make it possible to consolidate heterogeneous and conflicting perspectives. This is imperative not only in larger companies or globally distributed companies, but also when the IoT innovations lead to business ecosystems involving more coordinated stakeholders and partners.

LIMITATIONS

The research process used in this article to develop the innovation stage model imposes a number of limitations, which in turn open up several possibilities for future research. The methodology for developing the innovation stage model follows the philosophy of design science, which provides an effective approach to a given problem (Hevner, March, Park, & Ram, 2004). However, this methodology does not necessarily provide an ideal solution, and other studies and maturity models not addressed in this research may lead to completely different results. Furthermore, it should be acknowledged that the results of the analysis are limited in their generalization. Therefore, applying the innovation stage model to a number of cases used to verify the model and its key dimensions only shows its usefulness for the classification of services based on IoT analytics. This opens new horizons for further future research to evaluate the model and its four key dimensions.

In view of the application examples used to verify the innovation stage model, customer references publicly available on the software vendors' websites were used to support the development of the innovation stage model and its four main dimensions. Although, the two applications represent a broad cross-section of the use cases of IoT analytics, there are still many applications that were not considered in this research. It may be useful to consider customer references from smaller and more specialized software vendors to identify use cases of IoT analytics-based services. This leads to an increase in data and application diversity, for example by increasing the number of SMEs offering innovative IoT analytics-based solutions.

CONCLUSION

Driven by technology trends such as IoT and cheaper sensor technology, businesses across various industries are increasingly striving to create sustainable innovation solutions from the large volumes of IoT data and analytics applications. The use of connected devices and corresponding analytics tools often leads to individual IoT analytics solutions with which organizations can differentiate themselves in the market. Given that the literature provides only limited insights into the main differences between different IoT analytics solutions and their innovation potential, this article offers an innovation stage model that helps organizations to identify the innovation potential of their IoT analytics solutions and further expansion stages.

The innovation stage model presented in this article was derived based on an analysis of the existing frameworks and maturity models of IoT analytics, supported by interviews with IoT and data analytics practitioners. The model consists of four key dimensions: 1) data source, 2) data target, 3) data analysis, and 4) data-based transformation, which with their four characteristics, describe the innovation potential of IoT analytics solutions. The practical application of the model was demonstrated using two IoT analytics solutions from industrial companies. On the one hand, this article closes the conceptual gap with a model that allows conclusions to be drawn about the influence of IoT analytics on business innovation. On the other hand, it provides a concrete tool support management's tasks in creating sustainable and innovative products and services. The extent to which the model is adopted by management and its implications for research and application provide a fruitful direction for further research. As innovation endeavors are not only top-down, but also originate from the core of the organization, the model could be used to improve visibility at the top management level and company-wide, thus promoting a more centralized, forward-looking approach.

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