BUSINESS VALUE OF THE INTERNET OF THINGS – A PROJECT PORTFOLIO SELECTION APPROACH

Research paper

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Abstract

The Internet of Things (IoT) counts among the most disruptive digital technologies on the market. Despite the IoT's emerging nature, there is an increasing body of knowledge related to technological and business topics. Nevertheless, there is a lack of prescriptive knowledge that provides organizations with guidance on the economic valuation of investments in the IoT perspective. Such knowledge, however, is crucial for pursuing the organizational goal of long-term value maximization. Against this backdrop, we develop an economic decision model that helps organizations determine an optimal IoT project portfolio from a manufacturer's perspective and complies with the principles of project portfolio selection and value-based management. For our purposes, IoT project portfolios are compilations of projects that aim to implement IoT technology in an organization's production process, products, or infrastructure. Our decision model schedules IoT projects for multiple planning periods and considers monetary as well as monetized project effects. On this foundation, it determines the project sequence with the highest value contribution. To evaluate our decision model, we discussed its real-world fidelity and understandability with an industry expert renowned for its proficiency in IoT technology, implemented a software prototype, and demonstrated its applicability based on real-world data.

Keywords: Internet of Things, economic valuation of IoT, value-based management, project portfolio management.

1 Introduction

Recent technological advancements made it possible to equip physical objects with sensors, actuators, information processing, and networking power, thereby enabling novel digitized functionality and capabilities (Yoo, 2010; Yoo et al., 2010). The resulting smart things connect to the Internet, can interact and communicate among one another, and thus form a network of smart things, commonly referred to as the Internet of Things (IoT) (Whitmore et al., 2015). The conjunction of physical things and the digital world gives rise to new business opportunities and has the potential to substantially transform business operations (Porter and Heppelmann, 2015). Generally, there is a strong trend towards integrating IoT technology into manufacturing contexts, a development referred to as industrial IoT (IIoT). The utilization of IoT technology in manufacturing enables information transparency within and across organizational borders through real-time monitoring, machine-machine, and human-machine interaction (Oberländer et al., 2017). IoT technology further enables new levels of organizing and managing industrial value networks as well as highly flexible production to individualize products at low cost. For example, the application of smart devices (e.g., smart wearables that support production workers) or so-called cyber-physical systems (e.g., systems of smart interconnected machinery) in manufacturing processes are expected to boost productivity (Kagermann et al., 2013; Lucke et al., 2008; Schuh et al., 2014). On top of that, the IoT enables organizations to offer innovative digital services to their customers (Anderl et al., 2015)). Such IoT-based services are enabled through smart products which can offer more sophisticated services than physical things (e.g., offering predictive maintenance to customers of IoT-enabled products). Consequently, the IoT is recognized as one of the most disruptive digital technologies (Manyika et al., 2013). It is estimated to generate $7.1 trillion in revenues by 2020 (Lund et al., 2014) and to have an impact of up to $11.1 trillion per year by 2025 (Manyika et al., 2015).

In the literature, the IoT is discussed with respect to two major streams: technological (e.g., Atzori et al., 2010; Borgia, 2014; Kortuem et al., 2010; Laya et al., 2014) and business research (e.g., Boos et al., 2013; Caputo et al., 2016; Dijkman et al., 2015). We can further distinguish between descriptive (e.g., Oberländer et al., 2017; Porter and Heppelmann, 2014; Püschel et al., 2016) and prescriptive IoT knowledge (e.g., Fleisch et al., 2015; Turber et al., 2014). Porter and Heppelmann (2014) show that the descriptive stream is especially important for understanding the IoT's transformative potential. They offer insights into IoT business applications, their implications for organizations and competition, as well as prospective business models. IoT application scenarios can be analyzed from two perspectives: the implementation of IoT technology in an organization's processes (e.g., Boos et al., 2013) and the equipment of products with IoT technology. The first perspective results in smart processes, while the latter leads to the production of smart things, i.e., smart products (e.g., Fleisch et al., 2015). Porter and Heppelmann (2014) highlight how companies can benefit from equipping products with IoT technology. However, this also leads to additional costs due to advanced technological requirements and associated security issues, among others. Hence, Porter and Heppelmann (2014) specifically emphasize the benefits and costs trade-off that results from manufacturing and selling smart products. Bucherer and Uckelmann (2011) investigate the creation of value by IoT business models, an investigation in line with the ideas of Rappaport (1986), who stated that all business activities and projects should be directed towards the goal of increasing the long-term firm value. As this includes the investment in IoT projects, organizations need means to assess their value contribution. On this foundation, Lee and Lee (2015) propose a

real-options-based analysis to value IIoT investments. However, they do not offer concrete decision support that manufacturing companies can use to determine the business value of IoT investments. To the best of our knowledge, Lee and Lee (2015) are, as of today, the only authors who offer any approach on estimating the business value of the IoT. Thus, our analysis of the extant literature revealed that there is a lack of prescriptive knowledge concerning the economic valuation of IoT investments. Against this backdrop, we examine the following research question: *How can manufacturing companies decide which IoT investments maximize their long-term firm value?*

To address the research question, we adopt the design science research (DSR) paradigm (Gregor and Hevner, 2013) and develop an economic decision model that enables the valuation of IoT project portfolios. As mentioned, IoT technology can be applied to processes (e.g., using smart gloves to enhance the production process (PROGLOVE, n.d.)) and products (e.g., a smart smoke detector that distinguishes between harmless and dangerous smoke development (Nest Labs, n.d.)). The economic impact of related IoT projects cannot be measured directly but becomes manifest in an organization's processes and products. Thus, our decision model covers projects that aim to implement IoT technology into an organization's processes and products. Complementarily, our model considers investments in an organization's IoT infrastructure, which may be necessary before making processes and products smart (Porter and Heppelmann (2014). In sum, our model assists manufacturing organizations in deciding which IoT investments maximize their long-term firm value by determining which IoT projects should be implemented in which sequence. As for justificatory knowledge, our decision model draws from value-based management (VBM) and project portfolio selection (PPS) (Archer and Ghasemzadeh, 1999; Buhl et al., 2011; Vom Brocke and Sonnenberg, 2015). We also build on the research of Linhart et al. (2015), and Lehnert et al. (2016), who combine VBM and PPS in their approach to value business process improvement projects, and extend it to the IoT context. Thereby, we expand a known solution and apply it to a new problem, which classifies our research as *exaptation* (Gregor and Hevner, 2013). Following the DSR reference process by Peffers et al. (2007), we specify design objectives, design the decision model, and evaluate its real-world fidelity, understandability as well as applicability via an expert interview and a software prototype demonstration based on real-world data. This approach is sensible as decision models are a valid design artefacts (March and Smith, 1995). It has also been shown that the adoption project portfolio management positively affects the success of investments in information technology (IT) (Reyck et al., 2005). Finally, value orientation is an accepted paradigm of organizational decision-making (Buhl et al., 2011; Vom Brocke and Sonnenberg, 2015).

Our paper is structured as follows: In section 1, we provide theoretical background on IoT, VBM, and PPS and derive design objectives. We then introduce our decision model in section 2 and report on our evaluation activities in section 3. In section 4, we conclude by summing up the key results, discussing limitations, and pointing out future research.

2 Theoretical Background and Design Objectives

2.1 The Internet of Things

The IoT is characterized by the conjunction of physical things and the digital world, which results in a network of smart connected things. In line with Oberländer et al. (2017), we define the IoT as a network of interacting physical objects, equipped with sensors and actuators, and connected to the Internet via data communication technology. The computing logic embedded in smart things enables smart things to act and decide ever more independently from human interference (Leonardi, 2013). It is vital to understand the domain of smart things to capture the scope of IoT projects. There are five different levels of value creation in IoT applications that can be used as guidance for IoT projects: *physical product*, if the product is still purely physical (e.g., a normal watch); *sensors / actuators*, if the product has already been equipped with sensor technology and actuating elements (e.g., a watch that can track a heartbeat or walking distance); *connectivity*, if sensors and actuators are connected to the Internet, which makes the product globally accessible (e.g., a watch able to track data and transmit the information via the Internet); *analytics*, if the product can add value by collecting, storing, and classifying data (e.g., a watch

that has the functionality of a fitness tracker, able to analyze and classify collected health and fitness data); *digital service*, if all the capabilities on all previous levels are structured into a digital service (e.g., a fitness tracker with a respective mobile application that shows all relevant health and fitness data and might even propose training and meal plans) (Fleisch et al., 2015; Püschel et al., 2016).

Due to novel functionalities, smart things are frequently integrated into industrial environments (e.g., production processes) (Sadeghi et al., 2015). In these environments, IoT technology assists humans by automatically performing certain tasks or improving decision-making via enhanced data provision and analytics (Anderl et al., 2015). This includes for example self-controlled material flows enabled by smart containers or entire smart factories that are able to collect and analyze real-time data on the whole production process and create the corresponding reports (Ulrich Kreutzer, 2014).

We conclude that IoT projects can either target an organization's production processes – in the following, referred to as *smart process projects* – or an organization's products – in the following, referred to as *smart product projects*. The implementation of IoT technology in processes and products poses new requirements for an organization's IT infrastructure (Porter and Heppelmann, 2014). Therefore, investments in necessary infrastructure – in the following, referred to as *IoT infrastructure projects* – need to be considered as well. To account for these three perspectives on IoT technology, we define the following design objective for our decision model:

(O.1) *Internet of Things*: When compiling the optimal IoT project portfolio, a decision model should capture the effects of different types of IoT projects, i.e., smart process, smart product, and IoT infrastructure projects.

2.2 Value-Based Management

Based on the work of Copeland et al. (1990), Rappaport (1986), and Stewart (1991), VBM aims to maximize the long-term firm value. According to Rappaport (1986), all business activities should be

directed towards this goal. Thus, the value contribution of specific activities and decisions – which include the selection and implementation of projects – needs to be considered. Further, decisions are to be based on cash flows, consider risks, and the time value of money (Buhl et al., 2011). Drawing from VBM, the value contribution of IoT projects can be assessed monetarily by means of an objective function based on discounted cash flows. This objective function accounts for the decision-maker's risk attitude (i.e., risk-neutral, risk-averse, or risk-loving) as well as the condition under which the decision is made (i.e., certainty or risk) (Berger, 2010). In case of risk and non-neutral decision- makers, decisions should be made based on the risk-adjusted expected net present value (NPV) which can for example be calculated via a risk-adjusted interest rate or the certainty equivalent method (Copeland et al., 2005). In case of risk and non-neutral decision- makers, decisions should be made based on the risk-adjusted expected net present value (NPV) which can for example be calculated via a risk-adjusted interest rate or the certainty equivalent method (Copeland et al., 2005). Therefore, we define the following design objective:

(O.2) *Value-based management:* When compiling the optimal IoT project portfolio, a decision model should consider cash flow effects of IT investment decisions, the decision-makers' risk attitude, and the time value of money in order to maximize the long-term firm value.

2.3 Project Portfolio Selection and Scheduling

Choosing from available project candidates, PPS aims to select a project portfolio that complies with an organization's objectives and does not exceed its resources (Archer and Ghasemzadeh, 1999). The extensive body of literature on PPS and project scheduling includes three major research streams: Quantitative modelling (e.g. Carazo et al., 2010; Perez and Gomez, 2016), empirical studies (e.g. Frey and Buxmann, 2011), and contributions of conceptual nature (Archer and Ghasemzadeh, 1999).

According to Archer and Ghasemzadeh's (1999) framework, the PPS process consists of the five stages *pre-screening*, *individual project analysis*, *screening*, *optimal portfolio selection,* and *portfolio adjustment*. In the *pre-screening* stage, decision-makers check the project candidates' fit with organizational

strategy and whether they are mandatory. During *individual project analysis,* each candidate is evaluated along pre-defined performance criteria. All projects that do not fit these criteria or violate performance thresholds are eliminated in the subsequent *screening* stage. From the remaining projects, decision-makers then determine the portfolio that best fits the performance criteria in the *optimal portfolio selection* stage. To ensure real-world fidelity, the PPS literature also requires the optimal project portfolio to consider interactions among projects as well as possible case-specific constraints (Lee and Kim, 2001; Yu et al., 2012). Finally, *portfolio adjustments* are possible, if the organization wants to further refine the selected project portfolio. Our decision model aims to guide organizations in the *optimal portfolio selection* stage of the PPS process. Hence, we define the following design objective:

(O.3) *Project portfolio selection:* When compiling the optimal IoT project portfolio, a decision model should consider the IoT projects' performance effects, interactions among pre-selected projects as well as further case-specific constraints.

3 Artefact Description

3.1 General Setting

In line with the principles of PPS and VBM, the aim of our decision model is to assist organizations in identifying which IoT projects they should implement in which sequence to maximize their long-term value. To transform the effects of individual IoT projects into the value contribution of an IoT project portfolio, we use two layers for structuring our decision model: an *IoT project layer* and a *valuation layer*. The IoT project layer covers the three aforementioned IoT project types (i.e., smart process projects, smart product projects, and IoT infrastructure projects). The valuation layer incorporates non-monetary process and product performance dimensions, as well as all relevant monetary and monetized performance indicators. These components are then integrated into periodic cash flow. The discounted sum of all periodic cash flows in the planning period builds the NPV of the IoT project portfolio, which in turn determines the portfolio's value contribution to the organization in line with VBM (Rappaport, 1986). To visualize the effects of the project types in the IoT project layer on the components of the periodic cash flow in the valuation layer, we use arrows with the corresponding polarity.
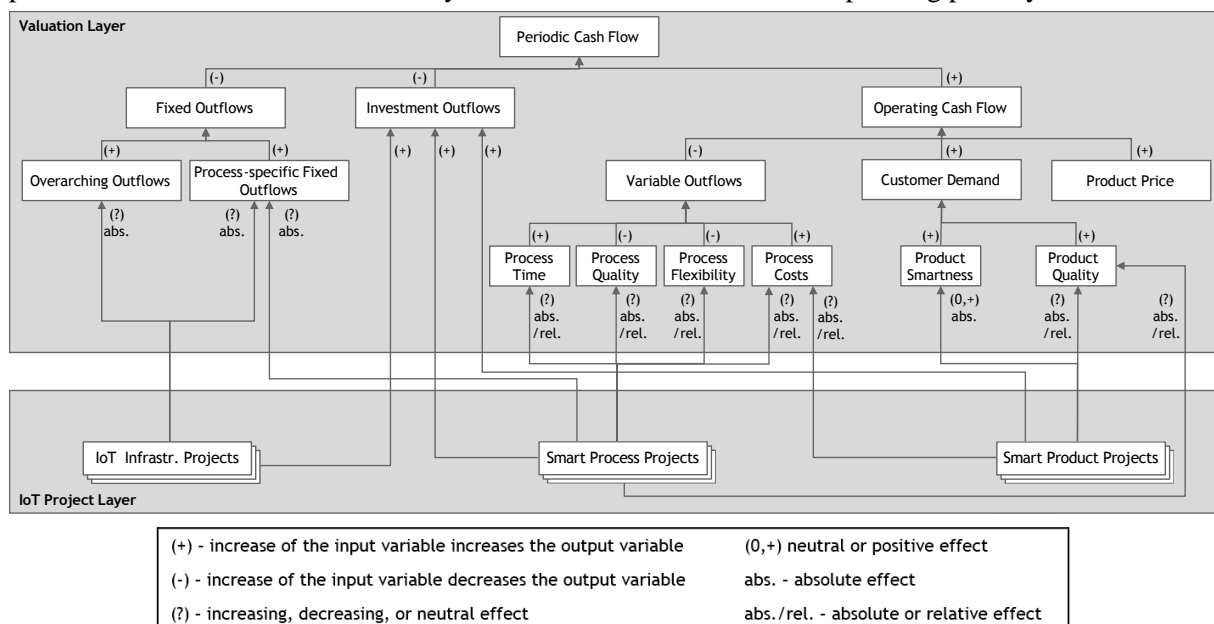

Figure 1. Performance effects of IoT projects for a single period

Figure 1 shows a high-level, single-period overview of the decision model's structure and its core components which are presented in detail below. Figure 1 also shows the connections between all layers as well as the polarity of each project effect, which can be relative, absolute, or both (Lehnert et al., 2016).

While absolute project effects (e.g., the savings through a cost decrease of 5,000 EUR) are independent of a performance dimension's current value, the absolute impact of relative effects (e.g., the savings through a cost decrease of 10%) depends on the effects of all previously completed projects. To enable a direct link between processes and products, the decision model considers a single production process with multiple product outputs of a distinct manufacturing company. Based on the extant literature on business process design, we draw that business processes can have different levels of granularity (e.g. Desel and Erwin, 2000; Knolmayer et al., 2000). Depending on the case and the level of abstraction, the production process in focus can for instance represent the entire organization-wide production, the production processes in a specific factory, or the production process of a specific product. Furthermore, the decision model allows for multiple projects and a multi-period planning horizon.

In line with previous work using PPS to assess the value contribution of project portfolios (Lehnert et al., 2016), the decision model allows for the execution of one project per period for the production process in focus. We assume that project effects become manifest immediately after a project has been completed, and that these effects can already be determined ex-ante in the individual project analysis stage of the PPS process. All parameters are assumed to be deterministic during the planning horizon. When assembling the IoT project portfolio, the decision model must account for intra-temporal, inter-temporal, and domain-specific constraints (Lehnert et al., 2016).

Below, we first introduce the objective function of the decision model. We then outline the different IoT project types and their effects, which we then integrate into the objective function. Finally, we sketch project interactions and domain-specific constraints that the decision model must cover.

3.2   Objective Function

The objective function of our decision model measures how a distinct project portfolio $r \in R$ contributes to the firm value in terms of its NPV, i.e., the sum of all discounted periodic cash flows based on a risk-adjusted interest rate z (Buhl et al., 2011; Damodaran, 2006). The valuation layer in Figure 1 illustrates the basic logic of the decision model's objective function in a single period. The mathematical expression of the objective function over all periods is depicted in Eq. (1). In each planning period y, the periodic cash flows are composed of *investment outflows*, *fixed outflows,* and *operating cash flows*. While the investment outflows and the fixed outflows are due at the beginning of each period, the operating cash flows are due at the end of each period (Lehnert et al., 2016). *Investment outflows* $O_y^{\text{inv.}}$ accrue for implementing projects in the respective period.

Fixed outflows can be divided into overarching outflows $O_y^{\text{O.fix}}$ and process-specific outflows $O_y^{\text{P.fix}}$. Overarching outflows occur independently from a specific process or product for the whole organization (e.g., costs for information system maintenance or expenditures for data security precautions – with data privacy and the robustness and integrity of the IoT system being one of the biggest organizational concerns (Borgia, 2014)). Process-specific outflows can be specifically mapped to the production process but occur independently from the number of process instances (Lehnert et al., 2016) (e.g., salaries or rent for the production facilities).

Operating cash flows are driven by a product price p_j, variable outflows $v_{j,y}$, and customer demand $d_{j,y}$ for a distinct product $j \in J$. For reasons of simplicity and clarity, we assume the product price to be constant. The variable outflows depend on the number of instances of the production process and are shaped by the process performance dimensions of the so called Devil's Quadrangle, i.e., throughput time t_y, quality $q_y^{\text{proc.}}$, flexibility f_y, and costs $C_{j,y}^{\text{P}}$ (Dumas et al., 2013). These performance dimensions are monetarily quantified and integrated into our decision model by estimating the costs they cause: We consider the additional costs which occur depending on throughput time (C_y^{T}; e.g., electricity costs), as well as shortcomings in process quality (C_y^{Q}; e.g., rework costs,) and flexibility (C_y^{F}; e.g., setup costs). Additionally, the process performance dimension cost is determined by performance-independent production costs, namely process operating costs ($C_{j,y}^{\text{P}}$; e.g., material costs). Customer demand is driven by product quality $q_{j,y}^{\text{prod.}}$ and product smartness $S_{j,y}^{\text{prod.}}$, which describes the level to which a product has been equipped with IoT technology. Typically, the demand increases with increasing product quality

(Anderson et al., 1994). In our model it further increases with product smartness and is bounded by the maximum number of process instances $ni^{\max}$, i.e., the maximum number of products producible.

$$r^* = \underset{r \epsilon R}{\operatorname{argmax}}\, NPV_r$$

$$= \underset{r \epsilon R}{\operatorname{argmax}} \sum_{y=0}^{Y} \left\{ \frac{-O_y^{\text{inv.}} - O_y^{\text{C.fix}} - O_y^{\text{O.fix}}}{(1+z)^y} + \sum_{j \epsilon J} \left[\frac{d_{j,y}\big(q_{j,y}^{\text{prod.}}, S_{j,y}^{\text{prod.}}, ni^{\max}\big) * \big(p_j - v_{j,y}\big)}{(1+z)^{y+1}} \right] \right\} \qquad (1)$$

where

$$v_{j,y} = C_{j,y}^{\text{P}} + t_y * C_y^{\text{T}} + \big(1 - f_y\big) * C_y^{\text{F}} + \big(1 - q_y^{\text{proc.}}\big) * C_y^{\text{Q}} \qquad (2)$$

3.3 Project Types and Performance Effects

Our decision model distinguishes between smart process projects, smart product projects, and IoT infrastructure projects: *Smart process projects* enhance the performance of the production process by implementing IoT technology. These projects intend to improve operating capabilities and therefore affect the process performance dimensions time, quality, flexibility, and cost. Smart process projects also affect process-specific fixed outflows, investment outflows, and – ultimately – product quality. The projects' effect on the process performance dimensions and on product quality can be absolute or relative while the effect on process-specific fixed outflows can only be absolute (Lehnert et al., 2016). All smart process projects cause investment outflows. For example, a smart process project can aim at equipping production machines with IoT technology (e.g., sensors, actuators, and connectivity) to track and analyze production data in real time and send accurate reports to the worker (Roberts, 2016).

Smart product projects have the goal to equip products with IoT technology and thereby address competition and meet market demand. In a smart product project, products can be enhanced from being merely physical – i.e., without any IoT technology – or from different levels of already developed product smartness. The goal of smart product projects should be to ultimately have products equipped with sufficient IoT technology to offer a digital service. Accordingly, a smart product project is not an all-or-nothing decision but can have varying impacts on a product's smartness. Besides product smartness, a smart product project also affects the product quality and – ultimately – process operating costs, depending on the complexity of the production process of the smart product. The projects' effect on product quality and process operating costs can be absolute or relative (Lehnert et al., 2016), while the effect on product smartness can only be absolute because of the level perspective. All smart product projects cause investment outflows. A practical example for a smart product project is the equipment of airplane turbines with sensors and actuators, which enables them to collect and analyze flight data and provide feedback to pilots and engineers (Rolls-Royce, n.d.).

IoT infrastructure projects principally have an enabling function as neither smart product nor smart process projects are possible without the appropriate infrastructure (Porter and Heppelmann, 2015). The projects affect overarching fixed outflows, as well as process-specific fixed outflows with absolute project effects (Lehnert et al., 2016). Due to the special character of IoT infrastructure projects, they do not necessarily require investment outflows: For example, the IoT infrastructure project of acquiring cloud space to enable subsequent smart process or smart product projects does not require an initial outflow at the beginning of the period. Rather, it requires regular periodical lease-like payments depending on the data storage space that is actually used (e.g., Amazon Web Services, 2018).

3.4 Integrating Performance Effects into the Objective Function

To investigate the value contribution of IoT projects, we integrate their effects into the decision model's objective function Eq. (1). We offer functions for determining process and product performance dimensions, as well as fixed and investment outflows in each period of the planning horizon.

Process time t_y is typically calculated as the sum of setup time, waiting time, and working time (Dumas et al., 2013). In our decision model, we consider the average throughput time of all production process instances in one period. The time of the production process in a given period depends on the throughput

time at the decision point and the time effects of all already completed smart process projects. The time effects can be either absolute ($\alpha_{y-1}^{\text{abs.}}$) or relative ($\alpha_{y-1}^{\text{rel.}}$) (Lehnert et al., 2016); see Eq. (3).

$$t_y = \begin{cases} t_0, \, if \, y = 0 \\ \left[max(t_{y-1} + \alpha_{y-1}^{\text{abs.}}; 0) * \alpha_{y-1}^{\text{rel.}} \right], \, else \end{cases} \tag{3}$$

Process quality $q_y^{\text{proc.}}$ can be viewed internally or externally (Dumas et al., 2013). While external process quality takes the customers' view, internal quality is measured from the process participants' point of view. As our objective function considers the costs which arise in the process due to shortcomings in process quality, we regard the internal quality which can for example be measured as the proportion of error-free output, i.e. the proportion of the output which does not require rework. Quality usually has an upper boundary (Leyer et al., 2015) which is incorporated in the decision model ($q^{\text{proc., max}}$). The quality of the process at a given period depends on the quality at the decision point and the quality effects of all already completed smart process projects. The quality effects can be either absolute ($\beta_{y-1}^{\text{abs.}}$) or relative ($\beta_{y-1}^{\text{rel.}}$) (Lehnert et al., 2016); see Eq. (4).

$$q_y^{\text{proc.}} = \begin{cases} q_0^{\text{proc.}}, if \, y = 0 \\ min(\left[max(q_{y-1}^{\text{proc.}} + \beta_{y-1}^{\text{abs.}}; 0) * \beta_{y-1}^{\text{rel.}} \right]; q^{\text{proc., max}}), \, else \end{cases} \tag{4}$$

Process flexibility f_y, measures a process's ability to react to changes and can be measured in many different ways (Afflerbach et al., 2013; Dumas et al., 2013). In our model, we consider flexibility analogously to process quality by estimating the costs which arise due shortcomings in the performance measure. Hence, we calculate process flexibility as the proportion of incoming demand which does not require special treatment, i.e., the standardization rate. Once the process is completely flexible and does not require any special treatment its flexibility cannot be increased any further. Process flexibility therefore has an upper boundary, which we incorporate in the decision model. The flexibility of the production process in a given period depends on the flexibility at the decision point and the flexibility effects of all already completed smart process projects. The flexibility effects can be either absolute or relative. Hence, flexibility is quantified analogously to process quality in Eq. (4).

Process operating costs $C_{j,y}^{\text{P}}$ depict performance-independent production costs which differ for each product $j \in J$ because, for example, different products require different materials. Process operating costs are therefore affected by both smart process projects and smart product projects. The process operating costs in a given period depend on the process operating costs at the decision point and the cost effects of all already completed smart process projects and smart product projects, respectively. The cost effects can be either absolute ($\gamma_{y-1}^{\text{abs.}}$ and $\delta_{y-1}^{\text{abs.}}$) or relative ($\gamma_{y-1}^{\text{rel.}}$ and $\delta_{y-1}^{\text{rel.}}$); see Eq. (5).

$$C_{j,y}^{\text{P}} = \begin{cases} C_{j,0}^{\text{P}}, \, if \, y = 0 \\ \left[max(C_{j,y-1}^{\text{P}} + \gamma_{y-1}^{\text{abs.}} + \delta_{y-1}^{\text{abs.}}; 0) * \gamma_{y-1}^{\text{rel.}} * \delta_{y-1}^{\text{rel.}} \right], \, else \end{cases} \tag{5}$$

Organizations can judge the *product smartness* $S_{j,y}^{\text{prod.}}$ level of their products by using existing IoT classification frameworks in IoT literature as guidance (e.g., Fleisch et al., 2015). Depending on the current functionalities, the product can be assigned a level of smartness based on the chosen framework. With smart product projects, companies can increase the product smartness by one or more levels – the effect can only be absolute and non-negative ($\varepsilon_{y-1}^{\text{abs.}}$). The product smartness in each period therefore depends on the smartness at decision point and the absolute effects of all already completed smart product projects; see Eq. (6).

$$S_{j,y}^{\text{prod.}} = \begin{cases} S_{j,0}^{\text{prod.}}, if \, y = 0 \\ \left[max\left(S_{j,y-1}^{\text{prod.}} + \varepsilon_{y-1}^{\text{abs.}} \right) \right], \, else \end{cases} \tag{6}$$

Product quality $q_{j,y}^{\text{prod.}}$ can be calculated analogously to process quality $q_y^{\text{proc.}}$ in Eq. (4) as it also has an upper boundary. It takes the customers' perspective and describes perceived product quality which is

independent from product smartness. For instance, it can be measured as the proportion of products without reclamations. The product quality in each period depends on the product quality at decision point and the quality effects of all already completed smart product projects. The quality effects can be either absolute or relative.

The *overarching fixed outflows* $O_y^{\text{O.fix}}$ in a given period depend on the overarching fixed outflows at the decision point and the absolute effects ($\zeta_{y-1}^{\text{abs.}}$) of related IoT infrastructure projects which have been completed up to that period; see Eq. (7). Analogously to Eq. (7), the *process-specific fixed outflows* $O_y^{\text{P.fix}}$ in a given period depend on the process-specific fixed outflows at decision point and the absolute effects of all already completed related IoT infrastructure and smart process projects.

$$O_y^{\text{C.fix}} = \begin{cases} O_0^{\text{C.fix}}, \text{ if } y = 0 \\ [max(O_{y-1}^{\text{C.fix}} + \zeta_{y-1}^{\text{abs.}}; 0)], \text{ else} \end{cases} \tag{7}$$

Lastly, the *investment outflows* $O_y^{\text{inv.}}$ in a given period are calculated as the sum of investment outflows for all smart process projects ($i \in process_y$), smart product projects ($u \in product_y$), and IoT infrastructure projects ($e \in infrastructure_y$) which are implemented in the current period; see Eq. (8).

$$O_y^{\text{inv.}} = \sum_{i \in PROCESS_y} O_i^{\text{inv}} + \sum_{u \in PRODUCT_y} O_u^{\text{inv}} + \sum_{e \in INFRASTRUCTURE_y} O_e^{\text{inv}} \tag{8}$$

3.5 Interactions and Constraints

The decision model helps organizations to choose the optimal IoT project portfolio from a set of admissible portfolios. To restrict the set of admissible IoT project portfolios, the decision model permits the formulation of project-, process-, period-, and product-specific constraints, which the respective project portfolios must not violate. We combined constraints which are popular in PPS literature (e.g., project exclusiveness, interdependencies, and precedence constraints) (Liu and Wang, 2011; Perez and Gomez, 2016) with constraints popular in the BPM context (e.g., critical time, quality, and flexibility boundaries) (Lehnert et al., 2016) and added smart product-specific constraints (e.g., maximum possible product smartness, minimum product quality, and a maximum supply capacity). The number of required interactions and constraints depends on the concrete context. For example, an organization's set of projects might include two projects which are mutually exclusive due to a shortage of staff. This and other case-specific constraints can be easily incorporated in our decision model. Lehnert et al. (2016) provide an extensive list of typical constraints. Furthermore, an example for the mathematical formulation can be found in Perez and Gomez (2016) and Liu and Wang (2011).

4 Evaluation

To evaluate our decision model, we adopted the evaluation framework by Sonnenberg and Vom Brocke (2012). This framework combines ex-ante and ex-post as well as artificial and naturalistic evaluation methods, and it comprises four evaluation activities EVAL1 to EVAL4 (Venable et al., 2012). Taking an ex-ante perspective, EVAL1 aims to derive design objectives and justify the research problem as a relevant DSR problem. We addressed EVAL1 in sections 1 and 2: First, we highlighted the research gap regarding the business value of the IoT, which stimulates the need to extend prescriptive knowledge in business-related IoT research. We also derived design objectives from justificatory knowledge related to the IoT, PPS, and VBM. EVAL2 also takes an ex-ante perspective and strives for validated design specification. To address this, we first perform an artificial evaluation by discussing the decision model against the design objectives via feature comparison (Siau and Rossi, 1998). Additionally, we validate the decision model's design specification naturalistically by conducting an interview with an industry expert. Taking an ex-post perspective, EVAL3 aims to validate artefact instantiations. We therefore first implement the decision model as a software prototype based on Visual Basic for Applications (VBA). We then demonstrate the decision model's feasibility with the application of the prototype to anony-

mized real-world data from our expert interview as a demonstration example. We confirm the applicability of the prototype by means of a scenario analysis. EVAL4 requires the validation of applicability and usefulness in practice. We plan to conduct this evaluation activity in future research.

4.1   Feature Comparison and Expert Interview (EVAL2)

To naturalistically validate our decision model's design specification and discuss its real-world fidelity, understandability, and completeness, we conducted a three-hour expert interview with a senior employee of a German industrial manufacturing company with an annual revenue of EUR 400m (fiscal year 2016) and 2,800 employees (September 2017). Our interview partner has a PhD in mechanical engineering and holds the position of Head of Smart Factory Engineering. The company is a renowned leader in IoT technology and had already implemented all IoT project types specified in our decision model. It acts as a leader in the manufacturing industry regarding IoT technology and pioneers in combining smart processes and smart products. We therefore consider it as a benchmark company. To artificially validate our decision model's design specification, we discuss the features of the decision model against the design objectives. We present the results of both steps structured along the design objectives and summarize general findings at the end of this section.

(O.1) Internet of Things: The decision model focuses on projects that aim to integrate IoT technology into an organization's production process and its products as well as to provide necessary IoT infrastructure. Thereby, the projects are conceptualized in a multi-dimensional manner by distinguishing between smart process, smart product, and IoT infrastructure projects. Performance measures for all three project types are captured in the decision model by quantifying how they contribute to the long-term firm value. Thereby, we provide organizations with a means for quantifying product smartness. The industry expert strongly agreed with our approach to take a multi-dimensional perspective on IoT projects. According to him, especially IoT infrastructure projects are of utmost importance in practice and their relevance tends to be underestimated in project planning. Furthermore, the expert explicitly agreed with measuring product smartness via a multi-level approach and put emphasis on the digital service being the ultimate goal of smart product projects.

(O.2) *Value-based management:* In line with the principles of VBM, the decision model complies with the goal of long-term value maximization by selecting the IoT project portfolio with the highest value contribution. Cash flow effects of IoT projects are incorporated in the decision model's objective function either directly, by translating them into monetary components, or indirectly, by first translating project effects into performance measures such as the dimensions of the Devil's Quadrangle. The time value of money is considered in the decision model by calculating the firm value in terms of discounted cash flows. Furthermore, the use of a risk-adjusted discount rate enables the consideration of the decision-maker's risk attitude. The industry expert agreed with our approach of using the NPV to quantify the value contribution of IoT project portfolios but pointed out that determining some of the parameters (e.g., process-specific fixed outflows) might be difficult in industry settings. In future research, we therefore plan to establish a profound knowledge base that facilitates data collection, provides benchmark data, and enables aligning the decision model's characteristics with the organizational peculiarities.

(O.3) *Project portfolio selection:* In line with the principles of PPS, the decision model uses multiple IoT projects, which have been pre-selected regarding strategic fit and organization-specific performance criteria, as input. It considers the performance effects of pre-selected IoT projects by quantifying their contribution to the long-term firm value. Further, the model can incorporate interactions among projects and consider case-specific constraints. The industry expert explicitly acknowledged this feature, as the model support a refinement against various case settings. The expert further agreed that it is sensible to use the PPS selection framework by Archer and Ghasemzadeh (1999).

The industry expert agreed with the general concept and design of our decision model. Nevertheless, we gained three key learnings, two of which we have incorporated in our model: First, in an earlier version of the model, process time had a decreasing effect on customer demand in line with (Anderson et al., 1994). However, the industry expert pointed out that this is impractical when considering production processes as manufacturers can warehouse smart products. Thus, customers are primarily influenced by

the throughput time of outbound logistics processes, such as delivery times. We agree with this rationale and, thus, removed process time as a demand driver in the final version of our decision model. Second, while collecting exemplary IoT projects during the interview, it became apparent that – contrarily to previous assumptions –not all IoT infrastructure projects cause investment outflows. This is due to the special character of IoT infrastructure projects. For example, investments might target an increase in server or cloud capacity, which mostly entails pay-per-use or rent-like payments. Consequently, we have incorporated this learning in our decision model by dropping the mandatory character of investment outflows for IoT infrastructure projects. At last, the industry expert indicated that our decision model seems to only consider cash flow-oriented projects, i.e., projects with which an organization aims to increase its long-term firm value. The expert's organization, however, is also confronted with the necessity of executing projects that primarily cause outflows but must be executed to keep up with current developments – especially in IoT technology. Our decision model is already able to consider such projects by using constraints (e.g., precedence constraints or mandatory projects). However, we find the notion of what happens if such projects are neglected very interesting and recognize this as an opportunity to conceptually further develop the decision model in future research, e.g., by including demand deterioration or process and product performance degeneration effects.

4.2   Artefact Demonstration (EVAL3)

To demonstrate the applicability of our decision model in a naturalistic setting, we implemented a prototype of our decision model and present a demonstration example based on data provided by the industry expert. This approach follows Sonnenberg and Vom Brocke's (2012) proposition to evaluate the model with respect to interaction with organizational elements that can comprise "subsets of 'real tasks', 'real system', and 'real users'". The data on process and product characteristics is deduced from the company's status quo for a specific product and its production process. Project effects and cash flows are deduced from forecasts for projects currently in planning. Owing to confidentiality, we anonymized and slightly modified the data using a constant factor. Additionally, we examine six potential IoT projects that cover smart process, smart product, and IoT infrastructure projects. A period in the organization's planning horizon lasts six months, and the organization can only implement one project per period for the process under investigation due to scarce resources. The organization plans to implement the IoT projects in the next four periods. To account for longer amortization periods, we use a planning horizon of eight periods, which leads to four further periods in which no projects will be implemented. Furthermore, we assume a risk-adjusted interest rate of 2.5% per period. The organization operationalizes process time as the average throughput time of the production process and uses the scrap rate as a proxy for process quality. As described above, process flexibility is calculated as the proportion of incoming demand which does not require special treatment, i.e., the standardization rate. The product has a basic demand, which captures all performance measures not incorporated by the decision model. On top of this, the demand is driven by the product's quality and its smartness level. In this example, we measure product smartness based on the IoT technology stack offered by Fleisch et al. (2015): We assign a smartness level to the product according to the offered functionality (physical product (1), sensors/actuators (2), connectivity (3), analytics (4), or digital service (5)). Product quality is measured as the percentage of reclamations that arise concerning the product's functionality. All input parameters regarding process and product characteristics are presented in Table 1. Moreover, we provide the input parameters for smart process, smart product, and infrastructure projects in Tables 2, 3, and 4.

Parameter		Status Quo
Process characteristics	Process time t_0	330 min
	Time dependent process costs C_0^{T}	0.33 EUR/min
	Process quality $q_0^{\mathrm{proc.}}$	98%
	Process costs that occur additionally due to errors C_0^{Q}	4 EUR
	Process flexibility f_0	95%

	Process costs that occur additionally due to lack of flexibility C_0^{F}	400 EUR
	Process operating costs C_0^P	20 EUR
	Process-specific fixed outflows $O_0^{\text{P.fix}}$	10,000 EUR
Product characteristics	Product price p	300 EUR
	Current product smartness $S_0^{\text{prod.}}$	3
	Product quality $q_0^{\text{prod.}}$	99.8%
	Basic demand d_0	200
Demand d_y		$d_0 + 0.3 \cdot \ln(q_y^{\text{prod}}) + 0.7 \cdot e^{S_y^{\text{prod.}}}$

Table 1.   Input parameters regarding the production process and the product

Project	Description and project effects	Investment Outflows	Constraints
(1)	*Integrating design and manufacturing* Decreases process-specific fixed outflows and increases flexibility	1,333 EUR	Requires prior execution of project (4)
(2)	*Introducing machine data analytics* Decreases process-specific fixed outflows	450 EUR	Requires prior execution of project (5)

Table 2.   Input parameters regarding pre-selected smart process projects

Project	Description and project effects	Investment Outflows	Constraints
(3)	*Introducing digital service* Increases product smartness	17,000 EUR	Requires prior execution of project (6)

Table 3.   Input parameters regarding pre-selected smart product projects

Project	Description and project effects	Investment Outflows	Constraints
(4)	*Improving hardware infrastructure* Increases overarching outflows	-	-
(5)	*Expansion of network infrastructure* Increases overarching outflows	7,600 EUR	-
(6)	*Increasing Cloud space* Increases overarching outflows	-	-

Table 4.   Input parameters regarding pre-selected IoT infrastructure projects

Using VBA, we constructed a Microsoft Excel based prototype of our decision model and applied it to the input parameters to generate the possible project portfolios and assess their contribution to the long-term firm value. We tested the prototype by means of a scenario analysis. For five scenarios, we provide the best and the worst project portfolio to provide insights into the sensitivity of the decision situation.[1] Scenario (A) serves as foundation for all other scenarios. In Scenario (B), we shorten the planning horizon by two periods. We then introduce project-specific constraints: First, we require project (3) to be completed within two years (Scenario (C)) and then, we make project (1) mandatory (Scenario (D)). In Scenario (E), we introduce a budget constraint of 10,000 EUR. The results of all scenarios are presented

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[1] Considering predecessor constraints, we get a total of 217 possible project portfolios in the general case, 217 in the case of a shortened planning horizon, 172 in the case of a completion time constraint on project (3), 54 in the case of a mandatory project, and 163 in the case of a budget constraint. Due to space restriction, we only show the best and the worst project portfolio in terms of the NPV in each scenario – a comparison which, in our opinion, delivers the most expressive interpretations.

in Table 5 showing which projects are implemented in which period, as well as value contribution of the respective IoT project portfolio in terms of its NPV.

Scenario	Description	Optimal project portfolio	Worst project portfolio
(A)	General case	({6},{3},{5},{2}) NPV: 186,230 EUR	({6},{4},{5},{}) NPV: 91,896 EUR
(B)	Shortened planning horizon	({6},{3},{},{}) NPV: 134,905 EUR	({6},{4},{5},{}) NPV: 69,727 EUR
(C)	Completion time constraint	({6},{3},{5},{2}) NPV: 186,230 EUR	({6},{4},{5},{}) NPV: 91,896 EUR
(D)	Mandatory project	({6},{3},{4},{1}) NPV: 181,440 EUR	({6},{4},{5},{1}) NPV: 101,649 EUR
(E)	Budget constraint	({5},{2},{},{}) NPV: 160,026 EUR	({6},{4},{5},{}) NPV: 91,896 EUR

Table 5.   Results of the scenario analysis

In Scenario (A), the optimal project portfolio includes four projects. These projects cover all IoT project types: smart process, smart product, and IoT infrastructure. The optimal portfolio yields a value contribution of 186,230 EUR. The worst project portfolio only consists of infrastructure projects. In fact, this portfolio is too long-term oriented, while neglecting short-term value creation. This scenario shows that implementing IoT technology in processes and products can lead to a higher value contribution. If the planning horizon is shortened, however, it proves to be more valuable to introduce only the smart product project (Scenario (B)). This follows from the fact that smart process projects often not do not yield direct cash inflows and thus have a longer amortization time. Due to a lower value contribution, project (1) and the corresponding infrastructure project (4) are only included in the optimal project portfolio if project (1) is mandatory. In general, the NPV in Scenarios (B) to (E) does not surpass the results of Scenario (A), which is reasonable, since a more restrictive scenario cannot logically result in a higher value contribution.

The demonstration example shows that the decision model yields interpretable results. It indicates the importance to consider all three types of IoT projects. In addition, the optimal project portfolios are relatively constant across the scenarios. This observation indicates the decision model's robustness against estimation errors. However, EVAL3 only strives for initially showing the artefact's feasibility, which we accomplish by performing a demonstration example based on a single expert interview. To generate more significant insights and to demonstrate decision model's applicability and usefulness in practice (EVAL4), we plan to apply the software prototype to data from different companies in future research.

5 Conclusion

In our paper, we examined which IoT projects a manufacturing company should implement in which sequence to maximize its long-term firm value. We addressed our research question by designing, instantiating, and validating an economic decision model in line with the principles of value-based management and project portfolio selection. The decision model contributes to the prescriptive knowledge on business-related IoT research by assisting organizations in the economic valuation of IoT project portfolios. Among possible IoT project portfolios, our decision model selects that with the highest contribution to the long-term firm value. For our purposes, we structured IoT projects into smart process, smart product, and IoT infrastructure projects, and we quantified their effects monetarily. To translate non-monetary effects of smart process and smart product projects, we relied on the process performance dimensions of the Devil's Quadrangle as well as the demand effect of product smartness and quality. Further, we specifically highlighted the necessity to consider projects that aim to provide the infrastructure required for the implementation of smart process and product projects. We evaluated the decision model in line with the framework as per Sonnenberg and Vom Brocke (2012). First, we justified our

research as a relevant problem and derived design objectives. We then compared its design specification with the design objectives, which we derived from the literature, and discussed them with an industry expert from a German manufacturing company that is a pioneer in combining smart processes and smart products. Further, we validated the decision model's feasibility by applying a software prototype on anonymized real-world data gathered from the expert interview.

Our decision model suffers from some limitations that encourage further research. First, some of the decision model's assumptions simplify reality. For instance, we assume all parameters of the model to be deterministic, while allowing for stochastic parameters would provide an increased real-world fidelity. Further, the product price is assumed to be constant. However, it might be worthwhile to investigate pricing issues with respect to customers' willingness to pay for smart products. In addition, to enable a direct link between processes and products, the decision model only considers a single production process with its multiple product outputs and can therefore currently not be applied to other types of business processes. As described above, the decision model can be refined conceptually by including degeneration and deterioration effects to better capture projects, which are mainly carried out to keep up with current developments. The decision model would also benefit from further evaluation. Especially further expert interviews, real-world case studies, as well as the application of the software prototype to real-world data in naturalistic settings will help to gain more insights and build up a profound knowledge base. Furthermore, the development of such a knowledge base in future research would facilitate data collection, provide benchmark data, and enable the alignment of the decision model's characteristics with organizational peculiarities. Despite these limitations, our decision model is an initial step toward an understanding of the business value of the IoT in industrial contexts. We hope it provides fellow researchers with a foundation for continuing their work in this important domain.

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