Design of Data-Driven Decision Support Systems for Business Process Standardization

Zur Erlangung des akademischen Grades eines Doktors der Wirtschaftswissenschaften

Dr. rer. pol.

von der KIT-Fakultät für Wirtschaftswissenschaften
des Karlsruher Instituts für Technologie (KIT)

genehmigte

DISSERTATION

von

Christian Fleig, M.Sc.

Tag der mündlichen Prüfung:	28. Februar 2020
Referent:	Prof. Dr. Alexander Mädche
Korreferent:	Prof. Dr. Gerhard Satzger

Dissertation, genehmigt von der KIT-Fakultät für Wirtschaftswissenschaften des Karlsruher Institut für Technologie (KIT), 2020.
Referent: Prof. Dr. Alexander Mädche, Korreferent: Prof. Dr. Gerhard Satzger

Abstract

Increasingly dynamic environments require organizations to engage in business process standardization (BPS) in response to environmental change. However, BPS depends on numerous contingency factors from different layers of the organization, such as strategy, business models (BMs), business processes (BPs) and application systems that need to be well-understood ("comprehended") and taken into account by decision-makers for selecting appropriate standard BP designs that fit the organization. Besides, common approaches to BPS are non-data-driven and frequently do not exploit increasingly available data in organizations. Therefore, this thesis addresses the following research question: *"How to design data-driven decision support systems to increase the comprehension of contingency factors on business process standardization?"*.

Theoretically grounded in organizational contingency theory (OCT), this thesis addresses the research question by conducting three design science research (DSR) projects to design data-driven decision support systems (DSSs) for SAP R/3 and S/4 HANA ERP systems that increase comprehension of BPS contingency factors. The thesis conducts the DSR projects at an industry partner within the context of a BPS and SAP S/4 HANA transformation program at a global manufacturing corporation.

DSR project 1 designs a data-driven "Business Model Mining" system that automatically "mines" BMs from data in application systems and represents results in an interactive "Business Model Canvas" (BMC) BI dashboard to comprehend BM-related BPS contingency factors. The project derives generic design requirements and a blueprint conceptualization for BMM systems and suggests an open, standardized reference data model for BMM. The project implements the software artifact "Business Model Miner" in Microsoft Azure / PowerBI and demonstrates technical feasibility by using data from an educational SAP S/4 HANA system, an open reference dataset, and three real-life SAP R/3 ERP systems. A field evaluation with 21 managers at the industry partner finds differences between tool results and BMCs created by managers and thus the potential for a complementary role of BMM tools to enrich the comprehension of BMs. A further controlled laboratory experiment with 142 students finds significant beneficial impacts on subjective and objective comprehension in terms of effectiveness, efficiency, and relative efficiency.

Second, DSR project 2 designs a data-driven process mining DSS “KeyPro” to semi-automatically discover and prioritize the set of BPs occurring in an organization from log data to concentrate BPS initiatives on important BPs given limited organizational resources. The project derives objective and quantifiable BP importance metrics from BM and BPM literature and implements KeyPro for SAP R/3 ERP and S/4 HANA systems in Microsoft SQL Server / Azure and interactive PowerBI dashboards. A field evaluation with 52 managers compares BPs detected manually by decision-makers against BPs discovered by KeyPro and reveals significant differences and a complementary role of the artifact to deliver additional insights into the set of BPs in the organization. Finally, a controlled laboratory experiment with 30 students identifies the dashboards with the lowest comprehension for further development.

Third, OCT requires organizations to select a standard BP design that matches contingencies. Thus, DSR project 3 designs a process mining DSS to select a standard BP from a repository of different alternative designs based on the similarity of BPS contingency factors between the as-is process and the to-be standard processes. DSR project 3 thus derives four different process model variants for representing BPS contingency factors that vary according to determinant factors of process model comprehension (PMC) identified in PMC literature. A controlled laboratory evaluation with 150 students identifies significant differences in PMC. Based on laboratory findings, the DSS is implemented in the BPM platform “Apromore” to select standard BP reference models from the SAP Best Practices Explorer for SAP S/4 HANA and applied for the purchase-to-pay and order-to-cash process of a manufacturing company.

Table of Contents

List of Figures

List of Tables

List of Abbreviations

ANOVA	Analysis of variance
BI	Business intelligence
BM	Business model
BMC	Business Model Canvas
BMM	Business Model Mining
BM-Miner	Business Model Miner
BMT	Business Model Transformation
BP	Business process
BPM	Business process management
BPMN	Business Process Model and Notation
BPMS	Business process management system
BPS	Business process standardization
CT	Contingency theory
DD	Design decision
DP	Design principle
DS	Design cycle
DSR	Design science research
DSS	Decision support system
EPC	Event-driven process chain
EPM	Enterprise process model
ERP	Enterprise resource planning
Friedman's ANOVA	Friedman's Analysis of Variance test
HANA	High Performance Analytic Appliance
IS	Information systems
IT	Information technology
KeyPro	Key Process Miner
KPI	Key performance indicator
M	Mean
Max	Maximum
Min	Minimum
MR	Meta requirement
N	Sample size
OCT	Organizational contingency theory
PMC	Process model comprehension
SAP	Systeme, Anwendungen, Produkte [German company name]
SARFIT	Structural adaption to regain fit
SD / Std.Dev	Standard deviation
SEQUAL	SEmiotic QUALity [framework]

SIQ	Simple, integrated, quality [framework]
SLR	Structured literature review
UML	Unified Modeling Language
VAR	Variance

1 Introduction[1]

The notion of organizations fitting to the environment and adapting to changes traces back to the seminal “survival of the fittest” evolutionary theory by Charles Darwin. Success, survival, and extinction in evolution are neither the result of strength nor intelligence, but of the (in)ability to “transform” in response to changed environmental conditions. Disruptive and gradual changes in internal and external environments of organizations stem from a multitude of sources, including technology, business and industry, macroeconomics, financial markets as well as the political, legal or even the natural environment (Aldea, Iacob and Quartel, 2018; Moustaka *et al.*, 2019; Niemimaa *et al.*, 2019; Sammut-Bonnici and Galea, 2015). In particular, technological advances, innovation and dynamics increasingly accelerate the pace of change for organizations (vom Brocke *et al.*, 2018) and provide tremendous potential for new business models (BMs). For instance, in technology environments, changes and trends such as digital transformation (Al-Debei, El-Haddadeh and Avison, 2008; Botzkowski, 2018), the internet of things, or big data (Acharya *et al.*, 2018; de Camargo Fiorini *et al.*, 2018; Loebbecke and Picot, 2015). In business environments, individualized customer requirements (Del Giudice, 2016) and servitization with a shift from product-oriented to service-oriented BMs alters the competitive situation in markets and provides possibilities for economic growth (Ferràs-Hernández, Tarrats-Pons, & Arimany-Serrat, 2017; Athanasopoulou, de Reuver, Nikou, & Bouwman, 2019).

In sum, these environmental changes exert high pressure on organizations to adopt business strategies and orientation to effectively leverage these future possibilities (Chen *et al.*, 2017; Hinkelmann *et al.*, 2016; Reynolds and Yetton, 2015). Therefore, decision-makers need to fundamentally rethink their organizations on all layers, including strategy, BMs, business processes (BPs), and application systems (Bharadwaj *et al.*, 2013; Khanagha, Volberda and Oshri, 2014).

[1] This chapter builds on content from previous publications in Fleig (2017), Fleig, Augenstein and Maedche (2018a, 2018b, 2018c, 2018d).

Particularly, BPs are core elements of organizations with significant economic impact (Polpinij, Ghose and Dam, 2015) and need to adapt to changing conditions for the organization to remain competitive and economically successful (Măruşter and van Beest, 2009). Thus, business process management (BPM) has been increasingly recognized as a successful approach to achieve and foster strategic goals on the operational level of BPs (Trkman, 2010).

Within BPM, a strategy that has been found successful in complex and rapidly changing organizational environments is business process standardization (BPS) (Gepp, Khomut and Vollmar, 2012). BPS has increasingly gained in attention throughout the last two decades (Manrodt and Vitasek, 2004; Münstermann, Joachim and Beimborn, 2009; Wurm *et al.*, 2018) and Venkatesh (2006) perceives process standards as one of three "broad future research directions", and Imai (1997) finds BPS to be "*the best, easiest, and safest way to do an activity*". The increased interest in BPS can be traced back to numerous advantages for the organization and BPs in particular. On the level of the organization, BPS improves the organizational manageability in terms of flexibility and agility (Münstermann, Joachim and Beimborn, 2009; Schäfermeyer and Rosenkranz, 2011), and is linked to improvements in operational performance (Münstermann, Eckhardt and Weitzel, 2010; Wurm *et al.*, 2018). Besides, BPS allows organizations to achieve competitive advantage (Naveh and Marcus, 2005), to realize cost savings associated with the management of fragmented applications landscapes (Sedera and Dey, 2007) and to harmonize the "face" to customers (Kundu, Datta and Vyas, 2012; Wurm *et al.*, 2018) or to increase transparency while reducing organizational complexity (Kampker *et al.*, 2014; Wurm *et al.*, 2018). On the level of BPs, BPS possibly results in scalability or reductions in operational costs (Williams and van Triest, 2009; Wurm *et al.*, 2018), errors (Lei, Naveh and Novikov, 2016) or throughput times (Münstermann, Eckhardt and Weitzel, 2010). Romero, Dijkman, Grefen and van Weele (2015) associate BPS with benefits in terms of responsiveness, reduced times and costs required for BP executions, increased effectiveness and efficiency of BPs, as well as higher quality of BP outputs. In Romero, Dijkman, Grefen and van Weele *et al.* (2015), the authors find that harmonized BPs allow organizations to realize significant benefits in terms of economies of scale. For example, the authors in Stetten *et al.* (2008) conduct a case study to demonstrate the value of BPS combined with an underlying application system in recruiting processes in terms of overall process performance, and "cost, time and quality" in particular. Likewise, Beimborn *et al.* (2009) show how BPS might contribute to process performance measured by "*efficiency, quality, control, and processing time*".

However, BPS depends on a variety of contingency factors, which results in a general difficulty in measuring the extent of BPS (Romero, Dijkman, Grefen and van Weele, 2015; Wurm *et al.*, 2018) as well as to select appropriate standard processes which take into account organizational contingencies. Therefore, there is a call for research exploring measures, interdependencies, and antecedents of BPS (Münstermann, Eckhardt and Weitzel, 2010; Schäfermeyer, Grgecic and Rosenkranz, 2010; Zellner and Laumann, 2013). As a consequence of the large number of BPS contingency factors, initiatives in BPS are inherently complex (Manrodt and Vitasek, 2004; Münstermann and Weitzel, 2008), and impose a multitude of challenges to organizations, which requires artifacts to support decision-making (Bala and Venkatesh, 2007; Harmon, 2015).

Besides, BPS gains in complexity due to a close interdependence of BPs and application systems such as enterprise resource planning (ERP) systems (Gattiker and Goodhue, 2005; Harmon, 2015; Lee and Lee, 2000; Seethamraju and Krishna Sundar, 2013). BPS allows to optimize ERP systems and is a necessary step before ERP implementation projects. Abundant research finds BP initiatives such as BPS as a fundamental prerequisite step before the actual ERP implementation (Botta-Genoulaz, Millet and Grabot, 2005; Kocaoglu and Acar, 2015; Loh and Koh, 2004; Umble, Haft and Umble, 2003). For example, if similar BPs are executed by multiple organizational units, the design, implementation, and maintenance of ERP systems to support these processes might be easier (Romero, Dijkman, Grefen and van Weele, 2015). However, ERP implementation projects impose significant monetary and non-monetary challenges to organizations (Fischer *et al.*, 2017). ERP implementations are inherently complex, time-consuming, and involve high investments, managerial challenges, risks, and a large number of employees (Hwang and Min, 2015; Laughlin, 1999). As a consequence, ERP implementation projects frequently fail and failures impose substantial tangible and intangible costs to both large and small to medium-sized enterprises alike (CIO, 2017). Although numbers vary significantly, practitioners classify implementation projects as a failure in twenty-one (Panorama Consulting Solutions, 2015) to seventy-five percent of cases (Deloitte, 2015).

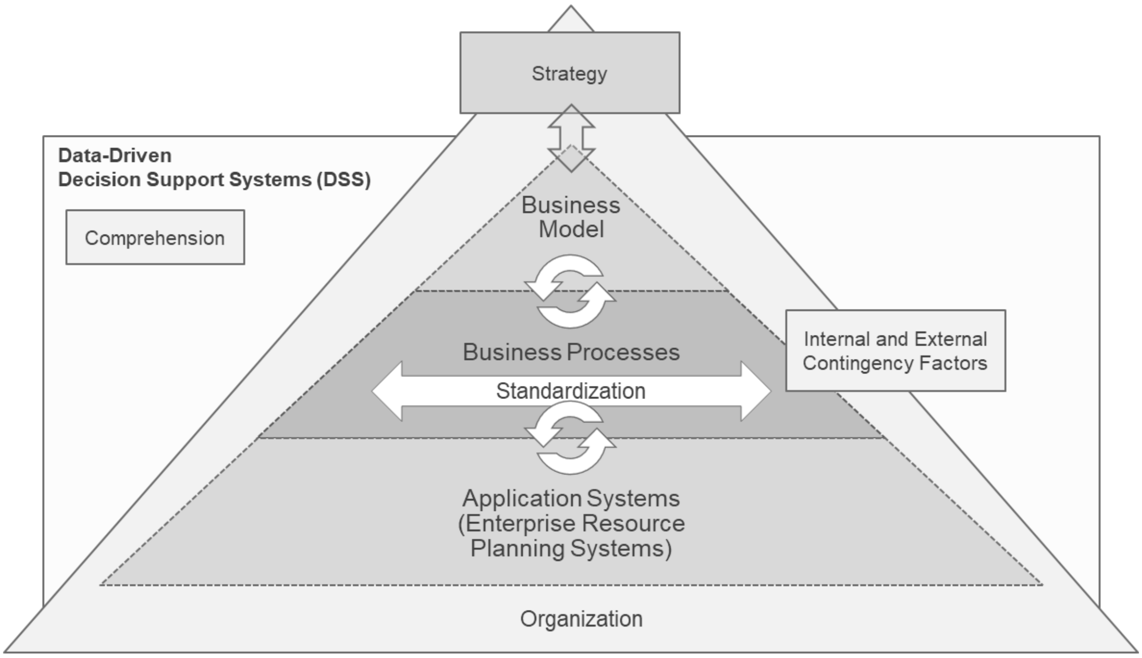
ERP systems such as the SAP R/3 Business Suite, S/4 HANA, or Oracle provide numerous alternatives for possible standard process designs. In workshops performed at the industry partner in the context of a BPS and SAP S/4 HANA implementation project, it was discovered that organizations are frequently challenged by the selection of the most appropriate standard process design which matches the organizational contingencies.

Besides, the complexity, significance of BPS for the organization, and the number of contingency factors requires organizational decision-makers to have a profound understanding and comprehension of the contingencies (cf. section 2.6). Lindland, Sindre and Solvberg (1994) highlight the importance of comprehension by saying that “*not even the most brilliant solution to a problem would be of any use if no one could understand it*“.

To contribute to these outlined challenges, the amount of data available for decision-making in organizations has increased tremendously in the last few years, and organizations increasingly adopt “big data” technologies (Santos *et al.*, 2017). A chance to overcome the challenge in decision-making in BPS is to utilize the increasing availability of process data from numerous information sources in organizations (Loebbecke and Picot, 2015). Contemporary application systems such as WfM, ERP, CRM, SCM, and B2B systems record business events in so-called event logs, which serve as foundations for process mining (van der Aalst *et al.*, 2007; van der Aalst and Weijters, 2004). These large amounts of “big data” might enhance decision-making processes (de Camargo Fiorini *et al.*, 2018) by collecting and interpreting large data sets (Davenport, 2014), building on and extending concepts such as decision support systems (DSSs) (Goes, 2014). For example, application systems store process events in large event log tables (van der Aalst *et al.*, 2007) which provides the possibility to improve decision-making by data-driven approaches such as process mining (van der Aalst, 2014). For example, the SAP R/3 ERP Business Suite or S/4 HANA store executed transactions and actions in the system which significantly improves the ability to derive BPS decisions. For instance, process mining delivers descriptive and positive "de-facto" process analyses based on data (van der Aalst, 2014). Process Mining aims to automatically discover BPs from transaction data (Schönig *et al.*, 2016; van der Aalst *et al.*, 2007) and offers a spectrum of techniques to perform automatic process discovery, monitoring, and improvement activities using system data in event logs (van der Aalst, 2011). In particular, process mining retrieves process models, which graphically and analytically represent BPs (Fischer *et al.*, 2017) and depict the course of activities and their dependencies (Agrawal, Gunopulos and Leymann, 1998). These process models derived from data might be closer to reality than non-data-driven models based on human perceptions (de Weerdt *et al.*, 2012). However, “a *prerequisite for an* *effective usage of process models is that stakeholders can readily understand them*" (Petrusel, Mendling and Reijers, 2017).

In addition to the complexity of decision-making in BPS, decision-relevant contingency factors on BPS originate from different sources in the organization. Organizations consist of several layers including strategy, BMs, BPs, and application systems, which interact with each other (Bonakdar *et al.*, 2013; Di Valentin *et al.*, 2012). For instance, Bask, Tinnilä and Rajahonka (2010) describe the layers of strategy, BMs, and BPs in a connected framework of increasing level of detail. First, the strategy layer encompasses the corporate group-level perspective. All other layers such as the BM or process layer are to be designed according to the strategy of the organization (cf. sections 2.2 and 2.3). Second, the BM layer covers the architecture levels of the organization with a focus on business units. While strategy contains a high-level focus, BMs translate the organizational strategy into tactical guidelines on how the organization intends to create value (Osterwalder and Pigneur, 2013). The literature further acknowledges the role of BMs as a linking element between strategy and BPs (Al-Debei and Avison, 2010; Andersson, Bergholtz and Gregoire, 2006; Bask, Tinnilä and Rajahonka, 2010). In particular, BMs in Al-Debei and Avison (2010) serve as the foundation for the derivation of the operational BP level in a more detailed perspective. Third, the BP layer represents concepts for the actual implementation in a functional perspective and translates and executes the BM by concrete operational guidelines (Al-Debei and Avison, 2010; Bask, Tinnilä and Rajahonka, 2010). Finally, the application systems layer of the organization provides the technological fundament to execute BPs and is therefore linked to the BP layer (Bass, Allison and Banerjee, 2013; Botta-Genoulaz, Millet and Grabot, 2005; Michalik *et al.*, 2013; Ross, 2003; Seethamraju, 2006; Steinfield, Markus and Wigand, 2011; Vries *et al.*, 2011). Thus, this thesis applies the following pyramid framework in figure 1 to structure the content.

Figure 1: Organizational pyramid framework to structure constructs and DSR projects



1.1 Structure and DSR Projects of Thesis

To contribute to decision-making by increasing the comprehension of decision-relevant BPS contingency factors and by supporting the selection of standard process designs that fit the organization under consideration of BPS contingency factors, this thesis addresses the following main research question:

RQ: "How to design data-driven decision support systems to increase the comprehension of contingency factors on business process standardization?"

In alignment with the organizational pyramid in figure 1 and the research gaps in figure 5, the main research question will be addressed in three interconnected design science research (DSR) projects which address each of the organizational layers and research gaps, respectively, to increase the comprehension of the BPS contingency factors by data-driven DSSs. To take into account the close intertwining between BPS and application systems and to address calls for practical relevance of IS research by authors such as Benbasat and Zmud (Benbasat and Zmud, 1999), an industry cooperation with the IT service provider of a German small to medium-sized manufacturing corporation was formed to conduct the DSR projects in the context of a real-life BPS and SAP S/4 HANA ERP implementation project. In 2018, the corporation consisted of five sub-companies operating globally with more than 8.200 employees and about 1.4bn Euro in turnover in 22 countries.

1.1.1 Problem Awareness and Motivation of DSR Project 1

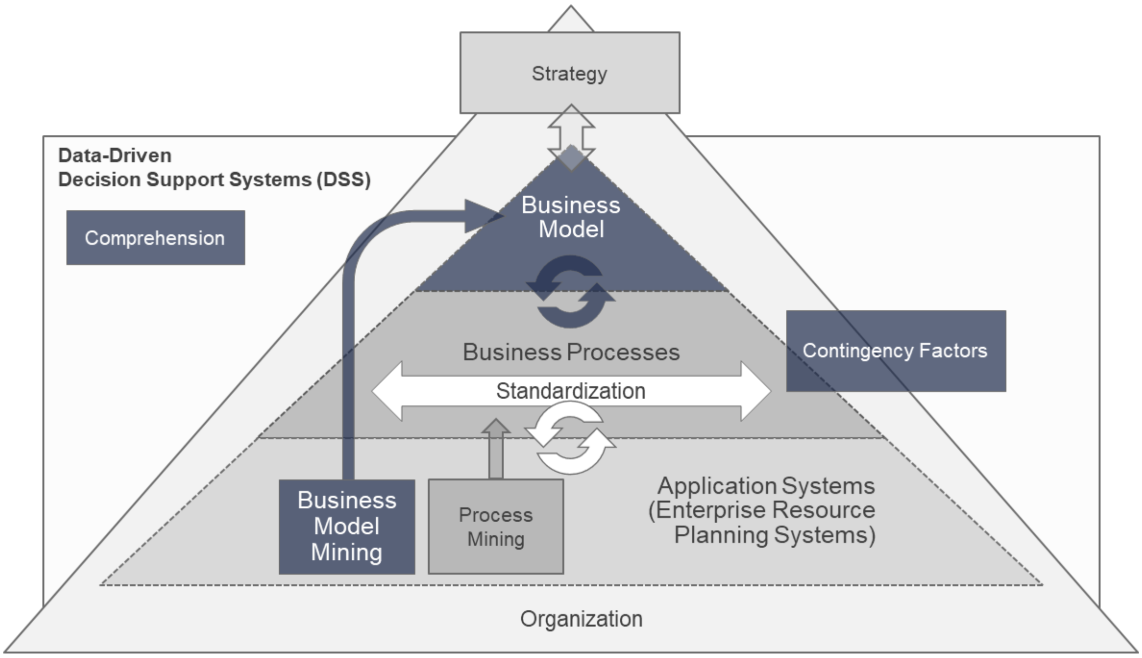
First, resulting from the requirement of strategic alignment between BPs and BMs (cf. section 1), (Trkman, 2010) BMs contain numerous decision-relevant contingency factors. Traditional, non-data-driven approaches to business modeling such as the "BM Canvas" (BMC) by Osterwalder and Pigneur (2010) typically follow a data-independent, manual approach involving one ore many participants. To model how an organization executes its business, several BM methods such as the widely accepted BMC have been developed to support a commonly shared understanding of the BM in the organization. However, these traditional non-data-driven approaches suffer from several drawbacks, which limit their usefulness in BPS decision-making. Traditional approaches are decoupled from the operational layer of an organization (Di Valentin *et al.*, 2012). Therefore, non-data-driven approaches deliver rather higher-level and strategic inputs in BPS and rely on human inputs instead of "de-facto" data from application systems. Besides and in addition to potentially arising biases and subjectivity, traditional non-data-driven approaches to business modeling might be more expensive, time-consuming, prone to errors by human decision-makers, and superficial compared to data-driven analyses of BMs (Augenstein and Fleig, 2017; Fleig, Augenstein and Maedche, 2018d).

As a consequence, research proposes to link non-data-driven approaches to the operational layer, such as BPs to improve the contribution of business modeling tools for decision-making (Di Valentin *et al.*, 2012). Thus, the need for data-driven BM tools has been recognized by both research (Szopinski *et al.*, 2019) and practice (Szopinski *et al.*, 2019; Terrenghi *et al.*, 2017). To contribute to these research gaps, DSR project 1 aims to increase comprehension of the organizational BM and to retrieve BM-related BPS contingency factors by providing a data-driven "Business Model Mining" (BMM) system. The research question for DSR project 1 is formulated as follows:

RQ DSR Project 1: "How to design a data-driven decision support system to retrieve business models from application systems automatically?"

Within the structure of this thesis, DSR project 1 is located as illustrated in figure 2.

Figure 2: DSR Project 1 in the organizational pyramid framework



1.1.2 Problem Awareness and Motivation of DSR Project 2

Following an understanding of the status quo BM and BM-related contingency factors of BPS in DSR project 1, the question which BPs should be standardized given limited resources arises. Organizations possibly consist of several hundreds of BPs (Garretson and Harmon, 2005; Margherita, 2014). Nevertheless, a large number of organizations does not have an exhaustive understanding of how BPs behave in reality (Caron, Vanthienen and Baesens, 2013; Gopal, Marsden and Vanthienen, 2011; van der Aalst *et al.*, 2007), and of which of the BPs can be considered as "important" (Fleig, Augenstein and Maedche, 2018b). Furthermore, existing approaches to process discovery and prioritization rely on surveys and interview-based techniques, which are not funded by data in the application systems or the operational layer of the organization (Fleig, Augenstein and Maedche, 2018b; van der Aalst, 2018; vom Brocke and Rosemann, 2015). As discovered by Imgrund *et al.* (2018), organizations usually exhibit a "short head" of actively managed BPs, which receive a significant share of managerial attention and organizational resources, and a high number of hidden BPs in the "long tail" (Imgrund *et al.*, 2018). These BPs in the "long tail" might receive less attention, resources, and are possibly unknown to and unmonitored by decision-makers.

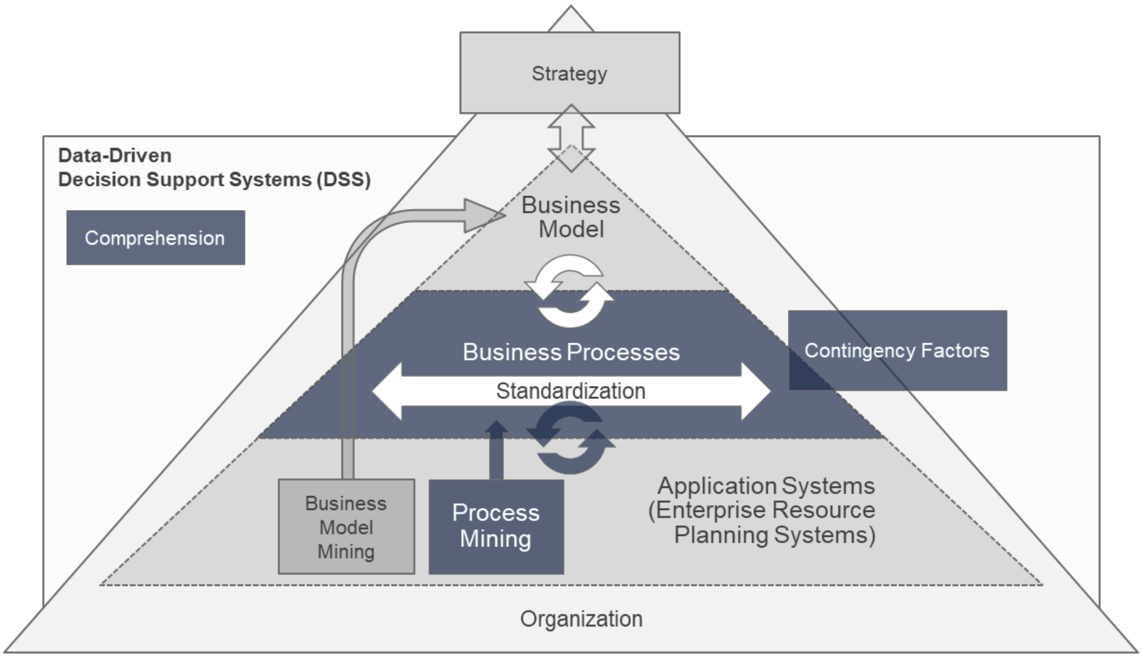
Organizational decision-makers frequently do not have a clear or exhaustive comprehension of the real-world process landscape (Fleig, Augenstein and Maedche, 2018a, 2018b;

Imgrund *et al.*, 2018; van der Aalst *et al.*, 2007) with non-data-driven, to-be process documentations of BPs differing substantially from actual as-is behavior (Tiwari, Turner and Majeed, 2008). First, before decision-makers can launch a BPS project, the one or the set of BPs to be standardized needs to be known and selected. Thus, the BP selection decision requires a complete list of all BPs executed in the organization, including the hidden "long tail" (Imgrund *et al.*, 2018). Second, the understanding of which of the BPs are "key" to an organization enables decision-makers to focus BPS projects on the "important" BPs, as well as to improve investment decisions or resource management by allocating limited BPM resources to value-creating processes. For instance, before the start of a process mining project, organizations are required to prioritize processes to make informed decisions concerning which of these BPs should be implemented in a process mining application. Besides, application systems in organizations might be inherently complex due to a large number of different application systems involved in BPs, which are further characterized by a high degree of organization-specific individual developments, addons, customizing, or interfaces (Fleig, Augenstein and Maedche, 2018c), which possibly limits the understanding and overview of decision-makers over the set of BPs in the organization. However, the comprehensive discovery, understanding of the entire set of BPs occurring in an organization, as well as the data-driven prioritization of BPs according to their relative importance to the organization, is essential for decision-making in BPS projects (Fleig, Augenstein and Maedche, 2018b). Besides, contributions on process importance and quantifiable metrics for BP importance are fragmented across numerous contributions. To the best of my knowledge, no contribution previously investigated which BPs are most important to organizations and how such processes can be discovered automatically in a data-driven approach by relying on data from application systems (Fleig, Augenstein and Maedche, 2018b). Therefore, DSR project 2 aims to support decision-making in BPS projects by providing a data-driven DSS to retrieve and prioritize the set of BPs in the organization. DSR project 2 addresses the following research question:

RQ DSR Project 2: "How to design a data-driven decision support system to discover and prioritize existing business processes from application systems automatically?"

Within the pyramid framework of this thesis, DSR project 2 is located, as illustrated in figure 3.

Figure 3: DSR project 2 in the organizational pyramid framework



1.1.3 Problem Awareness and Motivation of DSR Project 3

In BPM, process models serve as the foundation for decision-making in initiatives such as BPS. However, the number of process models in organizations is continually growing, and requirements in more and more areas of application (Figl and Recker, 2016a) from an increasingly heterogeneous set of expert and non-expert users arise (Koschmider, Kriglstein and Ullrich, 2013; Rosemann, 2006). Besides, the complexity of BPs has sharply increased throughout the last decades, which increasingly challenges organizations in managing BPs (Caron, Vanthienen and Baesens, 2013; Gopal, Marsden and Vanthienen, 2011; van der Aalst, 2016). Models of BPs are thus becoming increasingly important for organizations (Haisjackl *et al.*, 2017; van der Aalst, 2011).

Despite the outlined importance, organizations frequently possess only limited insights into BPs (van der Aalst and Weijters, 2004) and BPS contingency factors in particular. Traditional non-data-driven approaches to standardizing BPs rely on manually created "de-jure" process models, which are potentially distorted, error-prone, simplistic, and deviating from process reality in the organization and application systems. For instance, “de-jure" process documentations usually only contain idealistic process executions such as the ideal to-be process (“happy path”), while most process variants and deviations from the ideal target specification are ignored (van der Aalst, 2014). In addition to content-related insufficiencies, non-data-driven process modeling itself is a time- and resource-consuming task (Indulska *et al.*, 2009). In sum, van der Aalst finds that the currently prevailing approaches of process modeling are “disconnected” from process realities (van der Aalst, 2013), which implies that human-centered, non-data-driven approaches provide only an insufficient base for decision-making in BPS.

At the same time, BPs allow for different standard process design that can be implemented (Fleig, 2017; Fleig, Augenstein and Maedche, 2018c). Process-oriented initiatives such as BPS projects require a solid comprehension of BPs as a fundamental prerequisite for decision-making (Reijers, Mendling and Recker, 2010). To unleash the potential of process models, users need a profound model understanding (Mendling, Strembeck and Recker, 2012) and the both the correct and fast comprehension of the model is particularly important to support communication of a BP and use its functionality (Turetken *et al.*, 2019) for the selection of a standard process design which matches the organizational contingencies from the BM, the organization, BPs and application systems.

Despite the vast potential of data-driven approaches such as process mining to retrieve complete process models and contingency factors of BPS from increasingly available data in application systems (DSR projects 1 and 2), the numerous contingency factors of BPS need to be displayed appropriately to increase the comprehension of decision-makers. Nevertheless, although research identified a rich pageant of determinants and antecedents of PMC, the question of how to display a large number of process attributes such as BPS contingency factors in process models and to select a to-be standard BP design based on these process models remains a rather unresolved research area. Besides, a significant research gap refers to the absence of contributions on the “post-mining” phase, with only a few contributions exploring the question of how to turn the insights gained by process mining into actual process transformation decisions (Fleig, Augenstein and Maedche, 2018a) such as BPS.

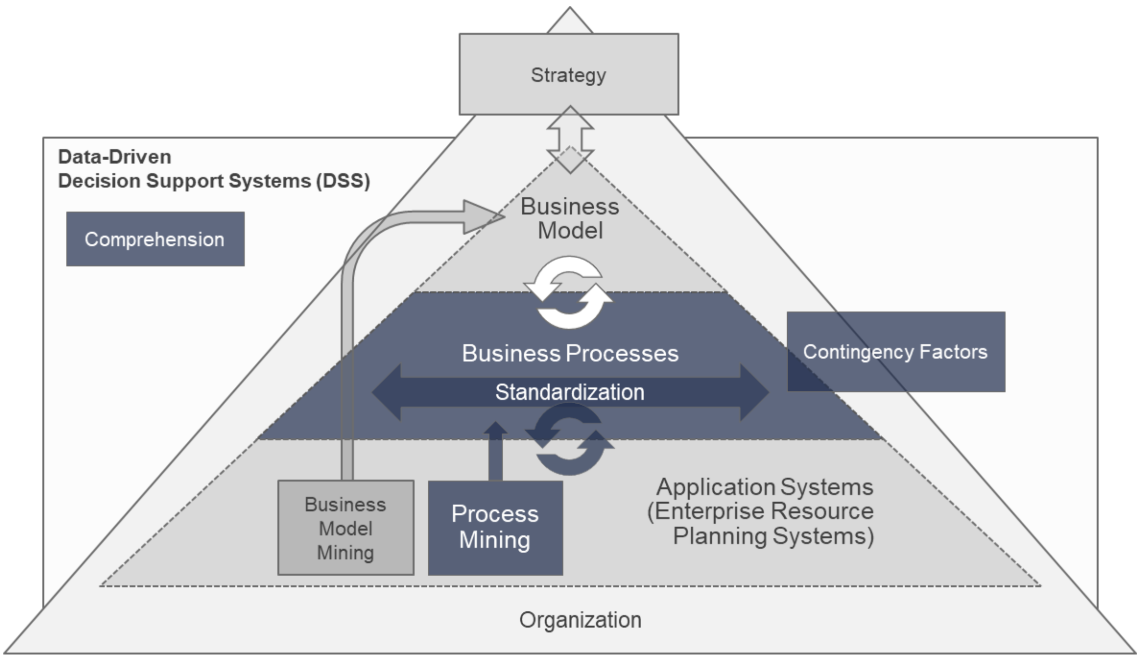
BPS literature reports evidence for impediments to achieving perfect standardization, and finds variability in BPs to be unavoidable (Wurm *et al.*, 2018). For instance, process variants allow for individual treatment of different cultures and customers (Romero, Dijkman, Grefen and van Weele, 2015) or the avoidance of micro-management due to sufficient autonomy at individual departments (Manrodt and Vitasek, 2004). Thus, while the standardization of BPs achieves certain organizational benefits (cf. section 1), the possible drawbacks of overly homogeneous BPs require a well-balanced strategy between individualization and standardization (Romero, Dijkman, Grefen and van Weele, 2015; Tregear, 2010), which leads to a "standardization dilemma" (Tregear, 2015).

In sum, DSR project 3 designs a data-driven DSS which combines process models from process mining with additional BPS contingency factors to semi-automatically recommend a standard process model from a repository of standard process designs based on BPS contingency factors. DSR project 3 thereby addresses the following research question:

RQ DSR Project 3: "How to design a data-driven decision support system to increase comprehension of process models for BPS contingency factors from application systems, and to select a standard business process from process design alternatives?

Within the organizational pyramid framework, DSR project 3 is located as illustrated in figure 4.

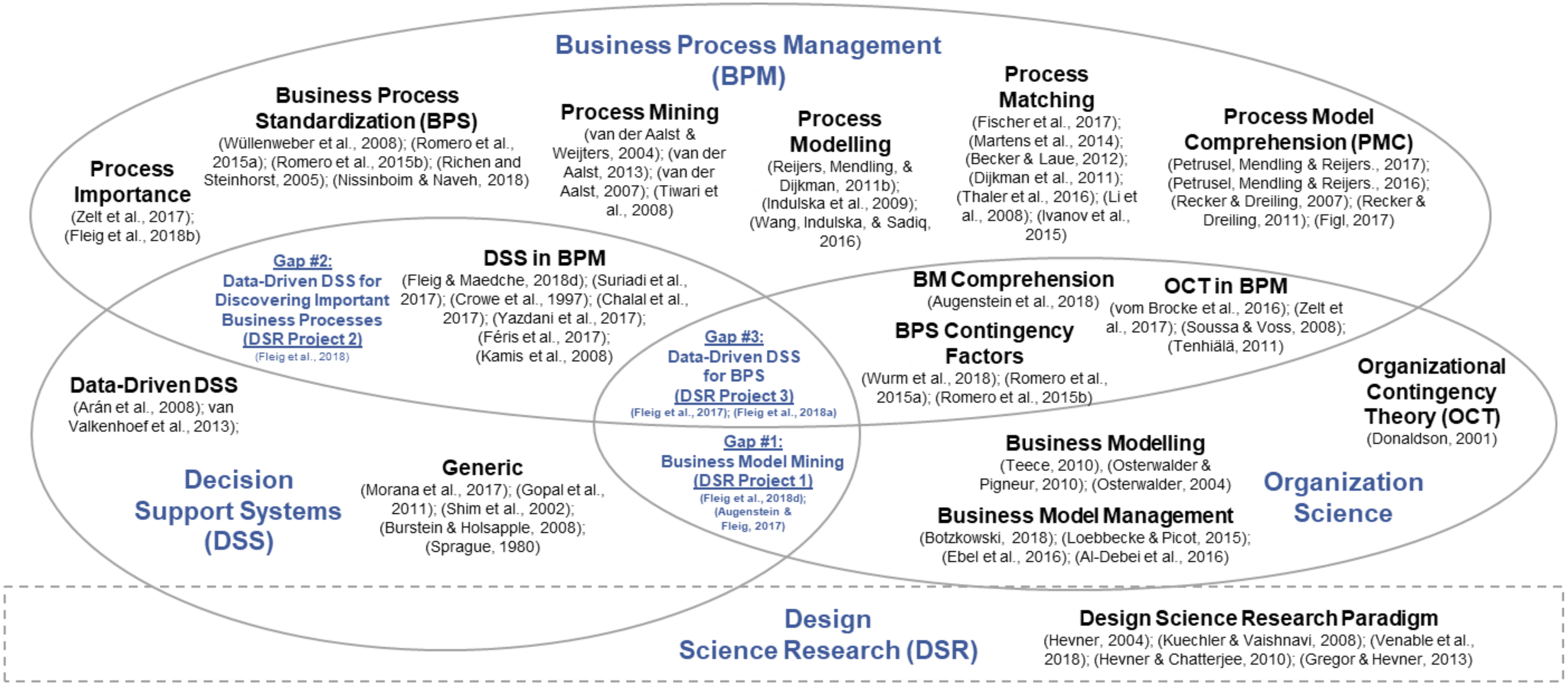
Figure 4: DSR project 3 in the organizational pyramid framework



1.2 Research Gaps and Streams

The DSR projects within this thesis draw on and combine different streams of literature to contribute to research gaps at the intersections between these disciplines. Figure 5 summarizes the different literature branches and allocates the DSR projects to research gaps.

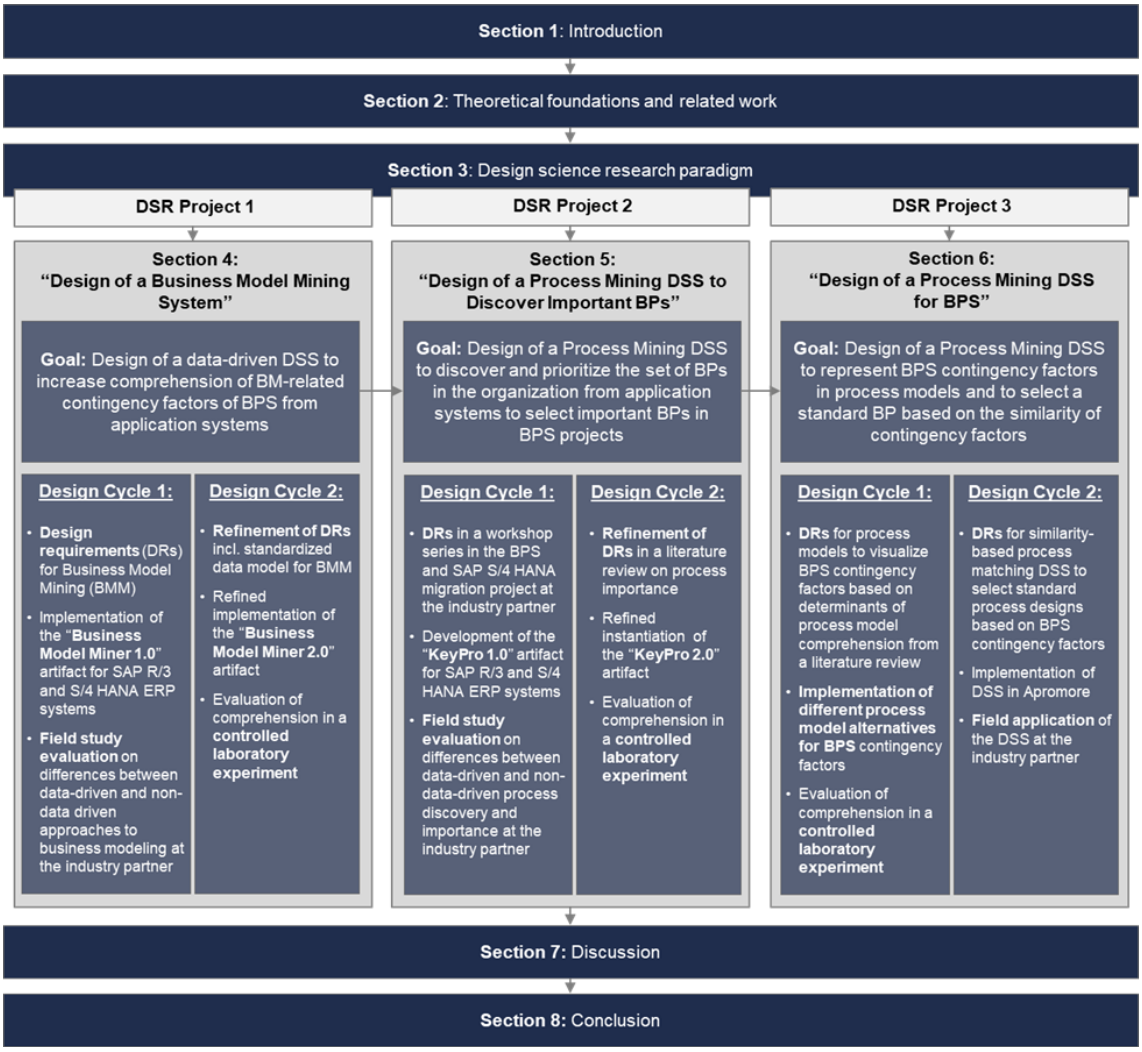
Figure 5: Overview of research streams, gaps, and allocation of DSR projects



1.3 Structure and DSR Projects of Thesis

The remainder of this thesis is structured according to the DSR projects and proceeds as illustrated in figure 6.

Figure 6: Overview of sections and contents



Section 2 introduces conceptual foundations. Section 2.1 presents the concept of organizations, including the necessity to align the organization and strategy with the environment as required by organizational contingency theory (OCT) (2.1.1). Section 2.2 links the strategic layer of the organization with the architectural and tactical levels and introduces fundamental concepts from the area of BM management such as BMs (2.2.1), BM mining (BMM) (2.2.2), business modeling and BM development tools (2.2.3) that lay the foundations for DSR project 1. In section 2.3, constructs from BM management are connected to the operational levels of the organization in business process management

(BPM). Central BPM constructs include BPs (2.3.1), business process change (BPC) (2.3.2), BP standardization (BPS) (2.3.3), BP modeling (2.3.4), process mining (2.3.5), and process importance (2.3.6) required for DSR projects 1 and 2. Regarding the over-arching research goal of this thesis to provide data-driven decision support for BPS, section 2.4 explains enterprise resource planning (ERP) systems which serve as both the data source for the DSR projects, as well as the context of BPS in the industry BPS project. Section 2.5 introduces decision support systems (DSSs) as the type of artifacts designed throughout this thesis. Section 2.6 defines comprehension as the dependent variable of interest.

Section 3 presents the employed DSR approach (3.1), research design (3.2), evaluation strategy (3.3) as well as the BPS and SAP S/4 HANA industry project context (3.4) of this thesis.

Section 4 conducts the first DSR project on designing a BMM system in two design cycles. Section 4.1 provides an outline of the DSR project, while section 4.2 presents the first design cycle including design requirements for BMM applications (4.2.1), the implementation of a prototype “Business Model Miner 1.0” (BM-Miner 1.0) in Microsoft PowerBI for mining a BMC from SAP R/3 and S/3 HANA ERP systems (4.2.2), and a field study evaluation on differences between manually created and data-driven BMCs (4.2.3) at a manufacturing corporation. Section 4.3 conducts design cycle 2 with a refined problem awareness (4.3.1), additional design requirements (4.3.2), the final implementation of the “Business Model Miner 2.0” (4.3.3), and a controlled laboratory experiment on comprehension (4.3.4).

Afterward, section 5 presents the execution of DSR project 2. Section 5.1 outlines the contents of the two design cycles. Section 5.2 conducts the first design cycle by suggesting design requirements based on literature and expert workshops at the industry partner (5.2.1), by instantiating the prototype “KeyPro 1.0” in Microsoft PowerBI for SAP R/3 and S/4 HANA ERP systems (5.2.2), and by conducting a field study evaluation on the differences between human and data-driven process discovery of the set of BPs in organizations (5.2.3). In section 5.3, the second design cycle conducts additional expert interviews (5.3.1) for further problem awareness, further develops design requirements (5.3.2), and implements the final instantiation in “KeyPro 2.0” (5.3.3). A laboratory experiment on comprehension as a validity check closes DSR project 2 (5.3.4).

In section 6, DSR project 3 designs a process mining DSS to visualize BPS contingency factors in process models and to automatically select a BP from different alternative designs. Section 6.1 outlines the DSR approach, while section 6.2 conducts the first design cycle to design BPMN process models to visualize BPS contingency factors for comprehension of decision-makers, including a derivation from literature on process model comprehension (PMC) (6.2.1), the implementation of the process models in design alternatives (6.2.2) and a controlled laboratory experiment on comprehension (6.2.3). In section 6.3, the second design cycle implements the BPMN process models in a data-driven process mining DSS to select a standard process from a repository of alternative process designs based on process similarity in the BPM platform Apromore for SAP R/3 ERP and S/4 HANA ERP systems. The second design cycle justifies the use of process similarity for decision-making (6.3.1) and derives design requirements (6.3.2) for the implementation of the final data-driven DSS for decision-making in BPS (6.3.3) while technical feasibility is demonstrated in a field showcase in section (6.3.4).

Finally, section 7 discusses the findings of the DSR projects in this thesis. In section 7.1, findings in DSR project 1 are discussed, including theoretical (7.1.1) and practical (7.1.2) implications, as well as limitations and future research (7.1.3) for BMM. The same structure is applied for the remaining DSR projects with theoretical contributions in sections 7.2.1 and 7.3.1 and practical contributions in 7.2.2 and 7.3.2, respectively. Avenues for future research are provided in sections 7.2.3 and 7.3.3.

The conclusion in section 8 reflects main contents of the thesis.

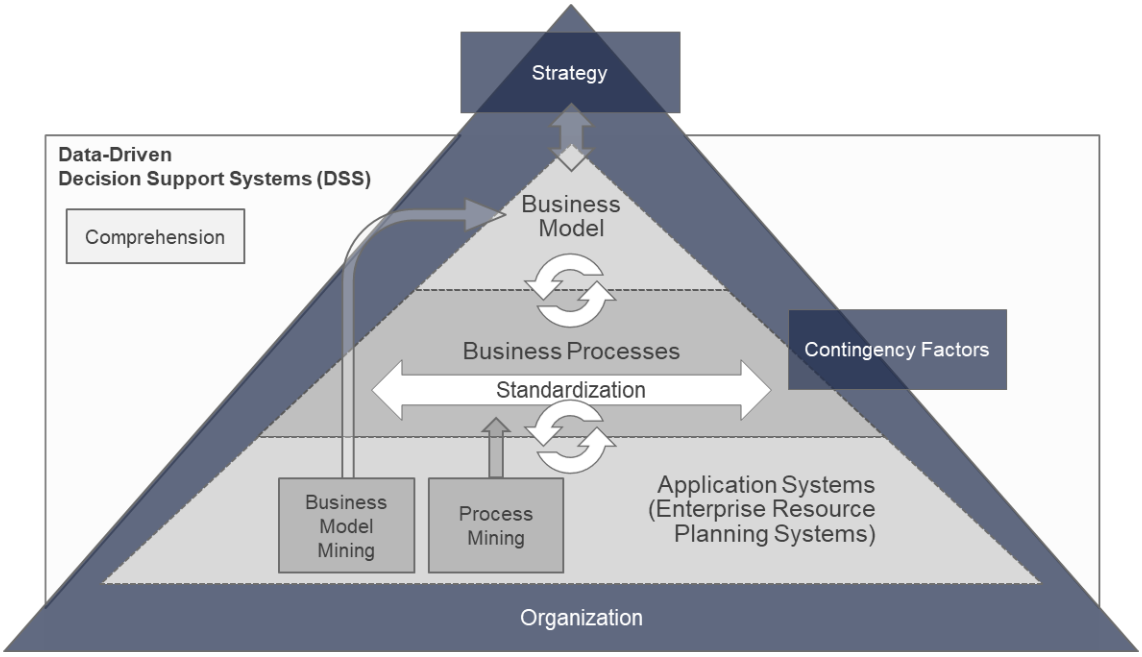
2 Conceptual Foundations[2]

This chapter introduces conceptual foundations for this work according to the previously introduced framework of the organizational pyramid to structure the DSR projects.

2.1 Organizations

Organizations provide the framework conditions for BPS with contingencies from different layers, such as strategy, BMs, BPs, and application systems.

Figure 7: Organizations in the organizational pyramid framework



Organizations are complex sets of rules to structure different activities of collaborating and interacting agents (Fox, Barbuceanu and Gruninger, 1996). In particular, organizations bring resources together to pursue and achieve various organizational goals, to produce outputs such as goods and services, to foster innovation in order to ultimately create value for different stakeholder groups (Daft, Murphy and Willmott, 2010). Thus, successful organizations require a strategy to achieve the intended organizational goals, such as customer satisfaction or performance (Lockamy and Smith, 1997). The strategy contains

[2] This chapter builds on content from previous publications in Fleig (2017), Fleig, Augenstein and Maedche (2018a, 2018b, 2018c, 2018d).

the plan of actions for the organization to compete in markets (Casadesus-Masanell and Ricart, 2010) and is usually defined "*as a contingent plan of action designed to achieve a particular goal*" (Casadesus-Masanell and Ricart, 2010). Besides, organizations are open systems that consist of interdependent parts in constant interaction with the greater environment (Donaldson, 2001, 2006; vom Brocke, Zelt and Schmiedel, 2016).

This dissertation, therefore, follows the widely accepted definition by Daft, Murphy and Willmott (2010) who perceive organizations as "*(1) social entities that (2) are goal-directed, (3) are designed as deliberately structured and coordinated activity systems, and (4) are linked to the external environment*".

2.1.1 Organizational Contingency Theory

Following the definition of organizations (cf. 2.1), the characteristics of organizations include goal-orientation, a deliberate structure, and coordination of the layers as well as links to the environment.

This thesis adopts the definition as proposed by (Sarkis, Zhu and Lai, 2011) and by other works such as (de Camargo Fiorini *et al.*, 2018) which perceives an organization theory as "*a management insight that can help explain or describe organizational behaviors, designs, or structures*" (Sarkis, Zhu and Lai, 2011). In particular, organization theories seek to explain all kinds of organizations and organizational environments, including processes (de Camargo Fiorini *et al.*, 2018; Hatch and Cunliffe, 2013). Thus, organization theories explain phenomena in multiple functional areas of organizations (de Camargo Fiorini *et al.*, 2018).

Contingency theory is a "fundamental" (de Camargo Fiorini *et al.*, 2018) concept in organization theories. Contingency theory by Lawrence and Lorsch (1967) perceives organizations as systems that continuously interact with the external and internal environment, such as markets or technology. For example, the authors in (Waller and Fawcett, 2013) propose to use contingency theory to adjust the organization to changes in the supply chain environment to explain how internal needs of the organization can be met by big data and supply chain processes (de Camargo Fiorini *et al.*, 2018).

Thus, as stated by the seminal contribution by Donaldson (2006), "*the most effective organizational structural design is where the structure fits the contingencies*". The arising need of organizational responsiveness to changes in environmental contingencies has long been recognized by research (Woodward, 1970) and has inspired numerous research disciplines such as IS research (David, McCarthy and Sommer, 2003) or BPM (Trkman, 2010; vom Brocke, Zelt and Schmiedel, 2016; Zelt, Schmiedel and vom Brocke, 2018). BPM, in particular, has been recognized as "*a matter of contingencies*" (Niehaves *et al.*, 2014) and research calls for more research on the "context" of BPs (van der Werf, Verbeek and van der Aalst, 2012). In particular, Niehaves *et al.* (2014) criticize existing maturity model approaches which imply that organizations are predictable with the development of BPM capabilities following a linear and predetermined, irreversible pathway.

From a theoretical perspective, the requirement to align an organization with contingencies from the internal and external environment is motivated by organizational contingency theory (OCT) (Donaldson, 2001, 2006; Trkman, 2010; vom Brocke, Zelt and Schmiedel, 2016). In OCT, the effectiveness of the organization is determined by the fit between organizational characteristics and contingency (context) factors of the environment (Sousa and Voss, 2008). In more detail, the seminal contribution by Sousa and Voss (2008) in the discipline of Operations Management distinguishes among contextual as well as response and performance variables. Contextual factors are environmental factors with a low degree of control of organizational decision-makers over these variables. Response variables are measures over which the organization has a higher degree of control, while performance variables are the output measures of the alignment constellations.

In Donaldson (2006), adaptations of the organization are continual, incremental, and small-stepped adaptions instead of large-scale adaptations of the organization ("Cartesianism"). Although these small-stepped adaptations themselves are unlikely to result in a perfect alignment, organizational performance might be increased in imperfect quasi-fit states. However, this argumentation further implies the necessity of continuous repetition of transformative activities. Furthermore, according to the model by Donaldson (2006), the contextual fit is a temporary state of the organization, as contextual fit might be disturbed by a change in the contingency factors or by the mere implications of fit itself. For instance, Donaldson (2006) reasons that once an organization achieves a state of fit, the increased performance leads to a change in contingency factors such as growth in firm size due to economic success, which then ultimately implies a state of misalignment. Thus, in order to realign the organization, a "*Structural Adaption to Regain Fit* (SARFIT)" (Donaldson, 2006) is required. However, this requires the knowledge of the set of contingency factors that are decision-relevant.

In a BPM context, Trkman (2010) acknowledges that challenges in BPM might stem from different sources, including organizational, managerial, or social causes in the organization. Thus, the contribution by Trkman (2010) combines three theories to determine critical success factors, which further motivates the need for a contingency approach to BPS. First, OCT requires a fit between processes in the organization and the environment. Second, dynamic capabilities theory requires to improve processes to ensure benefits for the organization continuously. Third, processes and application systems need to be in fit, as stated by task-technology fit theory. This, however, implies that BPS requires a holistic and continuous approach which includes the entire set of contingency factors on BPS.

Besides, the need for data-driven BPS in alignment with strategy and application systems has been acknowledged in CT research. Within the domain of business analytics, Cao and Duan (2017) highlight the importance of data-driven environments for organizations. Especially, Cao and Duan (2017) hypothesize that high-performing organizations rely more on data-driven decision-making and that in high-performing organizations, there is a higher degree of fit between the organizational strategy and business analytics. Besides, Morton and Hu (2008) apply OCT to examine the fit between organizational structure and ERP systems and assume that the fit between characteristics of the ERP system and organizational dimensions influences the success of an ERP implementation. In particular, Morton and Hu (2008) highlight BPS as an essential characteristic of the ERP system. In line with this argumentation, Petruzzi and Garavelli (2007) find a positive correlation regarding the degree of fit between BPs and IT and the organizational performance in an OCT contribution.

Nevertheless, research acknowledged the inconclusive state of research on which contingencies need to be considered for decision-making, and why some of these contingency factors are successful in decision-making while the same contingencies fail in other contexts or organizations (Sousa and Voss, 2008; Trkman, 2010). For example, the seminal contribution by Donaldson (2006) only identifies company size and diversification as contingency factors. Thus, table 1 provides an overview of the studies which employ a contingency theory perspective from a literature review in the context of BPM since 2010 and presents discovered contingency factors and outcomes. Notably, none of the studies explores contingency factors in the context of BPS. Therefore and regarding the research aim of supporting BPS in a data-driven DSS, which takes into account the contingency factors of standardization, the entire set of contingency factors with a specific focus on BPS is derived in a structured literature review in section 2.3.3.3.

Table 1: Overview of studies in contingency theory in BPM (excerpt after 2010)

Contribution	Study Motivation	Contingency Factors		Outcomes
		Contextual variables	Response variables	
Cao and Duan (2017)	The study examines the impact of business analytics on the performance of organizations in a survey of UK manufacturing organizations.	• Strategy • Structure • Process	• *The Application of Business Analytics:* Either descriptive, predictive, or prescriptive	Organizational Performance
Marciniak *et al.* (2014)	The study examines how strategies in ERP systems implementations are influenced by cross-functional awareness, and how this relationship is influenced by the contingency factor of organization size in French organizations.	• Organization size	• *Strategies in ERP implementations*: Flexibility, the vision of the organization, business process reengineering, core functions coverage and speed of deployment	Cross-functional awareness
Morali and Searcy (2013)	The study explores the implementation of practices of sustainability in supply chain management in a structured literature review and an interview-based case study in Canadian organizations to discover sustainability-specific contingency factors. OCT serves as an explanatory theory to describe decisions to implement practices of sustainability.	• The pressure exerted by stakeholders on the organization		Sustainability practice implementation and triple-bottom-line results
Pero and Lamberti (2013)	The study explores the management of interfaces between supply chain management and marketing in organizations in multiple case studies.	• *Firm-level*: intra-firm (organization) trust, absorptive capacity, and market orientation of the organization • *Development of new products on the project level*: phase and uncertainty	• Supply Chain Marketing • Interface archetype: pooled, sequential, reciprocal interdependence (mediated or without disintermediation)	Project performance (success)
Pratono (2016)	The study explores the impact of technological turbulence and competitive intensity in the context of strategic orientation in a survey in Indonesian small- and medium-sized organizations.	• Technologic turbulence • Organization size • The competitive intensity of the industry	• *Strategic Orientation*: Resources and opportunities • *Market orientation*: Proactive or responsive	Organizational performance

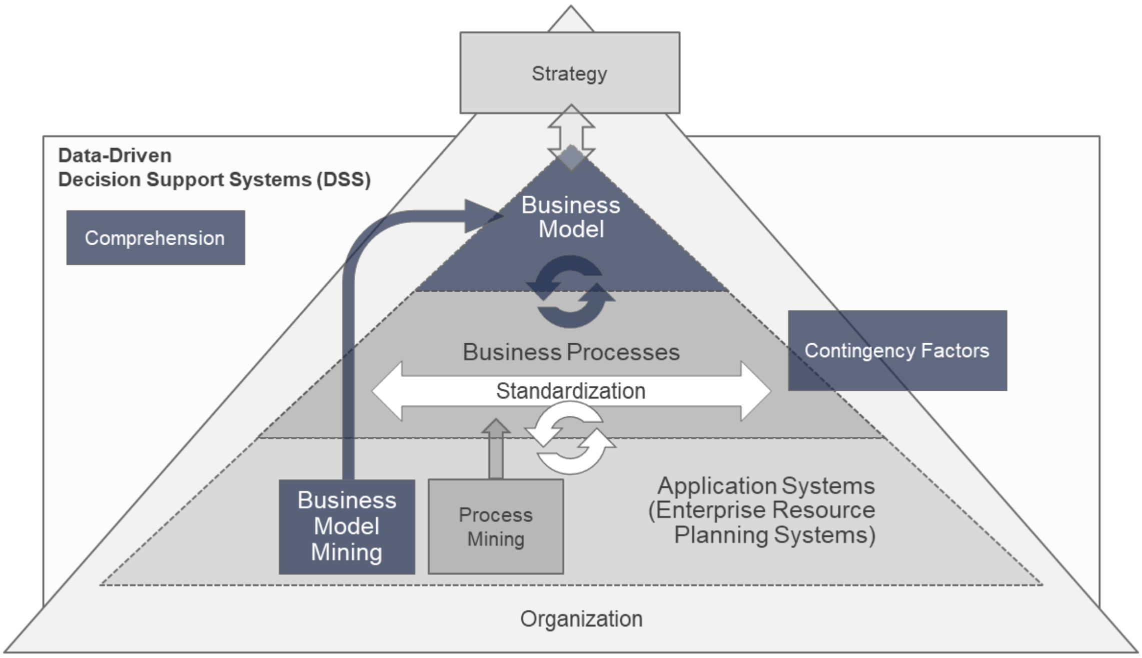
Contribution	Study Motivation	Contingency Factors		Outcomes
		Contextual variables	Response variables	
Taylor and Taylor (2014)	The study seeks to explore contingency factors in the context of the implementation of performance management systems (PMS) in operations management in small- and medium-sized and large organizations in a survey.	• National culture • Strategic context • Organizational size (small- and medium-sized organizations vs. larger organizations)		PMS implementation success
Trkman (2010)	The study addresses the lack of a research framework to explain the critical success factors of BPM through a case study in banking. Multiple different theories, such as dynamic capabilities or task-technology fit, need to be merged to create a research model. OCT is required as the fit between BPs, and the environment needs to be tailored and customized to each organization individually.	• Industry structure • Markets • Suppliers and customers • Characteristics of the organization • The strategy of the organization	• Strategic alignment • Level of IT investments • Performance measurement • Level of employee specialization	BPM success
van Looy and van den Bergh (2018)	The study builds on the context model introduced in Rosemann, Recker and Flender (2008) to explore how organization size and sector impact BPM adoption to achieve contextual fit and performance by employing a maturity model in West-European organizations.	• Organization size • Sector	• The degree of BPM adoption • Degree of capabilities related to BPM of the organization	Fit (Performance)
vom Brocke, Zelt and Schmiedel (2016)	The study seeks to explain "context" for the determination of BPM adoption success factors and to provide a framework of contextual factors from a literature review.	*Dimensions:* • *Goal*: Focus • *Process*: Value creation, repetitiveness, knowledge-intensity, creativity, interdependence, variability • *Organization*: Scope, industry, size, culture, resources • *Environment*: Competitiveness, Uncertainty		BPM success

Contribution	Study Motivation	Contingency Factors		Outcomes
		Contextual variables	Response variables	
Wong, Lai and Cheng (2011)	The study explores information integration in the Supply Chain Management context and perceives organizations as a system of inputs, processes, and outputs. Previous studies did not sufficiently address interplays between internal/external contingencies and the moderating role of information sharing on organizational performance.	• Munificence • Uncertainty, • Product type • Complexity	• Information integration	Operational performance (customer orientation) and cost performance
Yu and Kittler (2012)	Examination of the reasons for the success or failure of organizational change programs in the context of IS program strategies. OCT serves to explain the program structure.	• *Organizational structure*: formalization, standardization, autonomy, and centralization of authority • *Organizational environment*: size, state of technology, environmental change; *effectiveness*: efficiency, work satisfaction, innovation, profitability; Business Process homogeneity; Program authority	• Program organization or structure (centralized vs. decentralized)	Program success
Zelt *et al.* (2018)	The study seeks to research the customized and context-specific design of BPs and to provide contingency factors for successful BPM in terms of performance based on the organizational information processing theory (OIPT).	• *Process requirements*: Uncertainty and equivocality • *Process characteristics* as in (Zelt, Schmiedel and vom Brocke, 2018)	• BP documentation • BP standardization • BP monitoring • IS • Lateral relations	Process performance by efficiency (time and costs) and effectiveness (quality and customer satisfaction)
Zelt, Schmiedel and vom Brocke (2018)	The study is based on (vom Brocke, Zelt and Schmiedel, 2016) and seeks to provide a systematic classification of process characteristics derived in a systematic literature review to foster the understanding of the “nature” of BPs.	• *Process uncertainty:* BP importance, BP interdependence, BP variability • *Process equivocality:* BP importance, BP analyzability, BP differentiation		

2.2 Business Model Management[3]

Wirtz (2018) perceives the BM as the link between strategic and operational levels of an organization. In particular, BMs reflect the organizational strategy, which serves as the basis for the BM (Al-Debei and Avison, 2010). In particular, managers consider changes to organizational BMs as a possibility to differentiate their organization from competitors (Pohle and Chapman, 2006; Wirtz, 2018). Research in BMs with various research foci has gained a significant degree of both academic and practical attention (Aspara *et al.*, 2013; Teece, 2010; Zott, Amit and Massa, 2011). The success of the BM approach is related to the provision of "*powerful ways to understand, analyze, communicate, and manage strategic-oriented choices*" (Al-Debei and Avison, 2010).

Figure 8: Business Model Management in the organizational pyramid framework



2.2.1 Business Models

Resulting from ever-changing organizational environments, BMs are "*continuously or periodically changing in terms of components, relationships, and structure*" (Andreini and Bettinelli, 2017). Therefore, Demil and Lecocq (2010) propose to use *"the concept*

[3] This chapter contains content previously published in Fleig, Augenstein and Maedche (2018d).

as a tool to address change and innovation in the organization" (Demil and Lecocq, 2010) such as BPS.

Although BM research has evolved rapidly in the past (Foss and Saebi, 2017; Massa, Tucci and Afuah, 2017; Zott, Amit and Massa, 2011), research on BMs and their definition, in particular, remains highly fragmented, which results in a missing common understanding of the term (Al-Debei and Avison, 2010; Bagnoli *et al.*, 2018; Botzkowski, 2018; Schneider and Spieth, 2013; Zott, Amit and Massa, 2011).

BMs illustrate how the organization creates value (Timmers, 1998). "*A business model explains how a company works [...]*" (Di Valentin *et al.*, 2012). For instance, Demil and Lecocq (2010) perceive a BM as "*the description of the articulation between different BM components or 'building blocks' to produce a proposition that can generate value for consumers and thus for the organization*" (Demil and Lecocq, 2010). In more detail, Massa, Tucci and Afuah (2017) categorize existing definitions into (1) BMs as descriptive attributes of real organizations, (2) BMs as cognitive and linguistic schemata, or (3) BMs as formal, conceptual representations and descriptions of how an organization works. Due to both the broad applicability as well as the acceptance and popularity, the thesis adopts the definition by Osterwalder and Pigneur (2010) and defines BMs as "*the rationale of how an organization creates, delivers, and captures value*" (Osterwalder and Pigneur, 2010).

The term "BM" further entails different elements and purposes (Peters, Blohm and Leimeister, 2015), goals, business levels, constituent components, or interactions (Wirtz, 2018). Besides the relevance of these BM components for the comprehensive definition of BMs, changes in the environment or in the organization itself need to be reflected in the BM to restore the fit in the outlined OCT argumentation. Regarding the close interconnection of the BM with BPs in the organization, these components serve as contingency factors for decision-making in BPS (cf. section 2.2.3).

2.2.2 Business Model Mining

Currently prevailing non-data-driven approaches to business modeling suffer from limitations such as limited executability (Veit *et al.*, 2014; Zott, Amit and Massa, 2011) or proneness to errors, subjectivity, a high consumption of organizational resources as well as a disconnection to the operational layers of organizations including application system

(Fleig, Augenstein and Maedche, 2018d). As a consequence, planning and execution of changes in the organization and BMs are often based on non-data-driven managerial knowledge, which might imply erroneous decision-making (Gassmann, Frankenberger and Csik, 2014) in BPS projects.

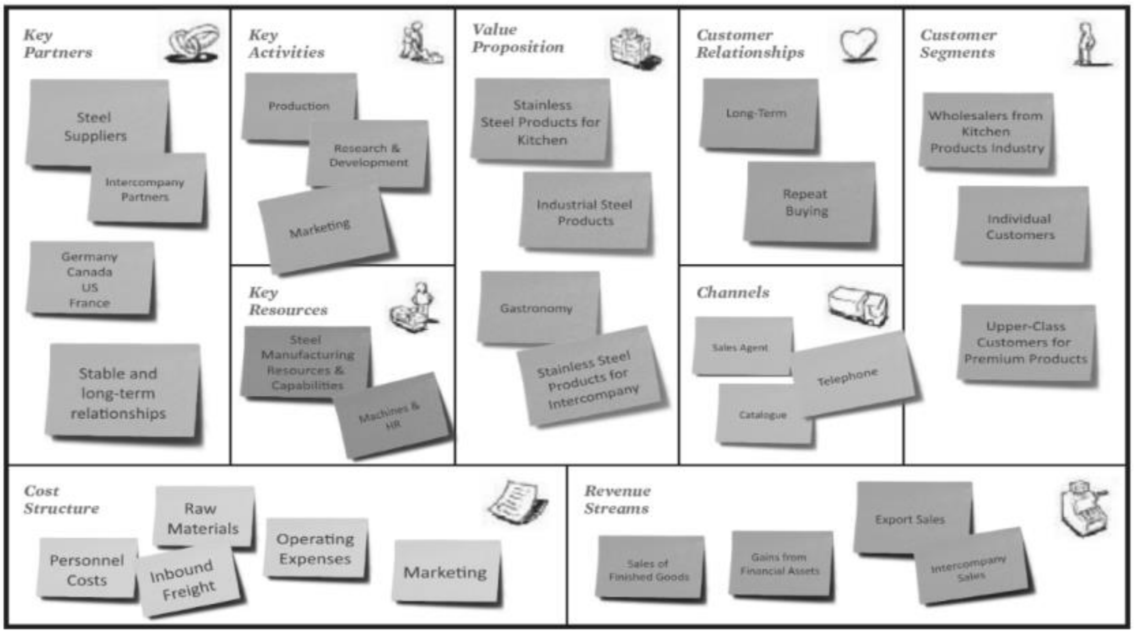
However, BMs are implemented in organizational application systems to a large degree (Al-Debei and Avison, 2010; Veit *et al.*, 2014) and organizations increasingly use data from various sources for BM-related activities such as business modeling (Osterwalder and Pigneur, 2013), BM development (Fan and Gordon, 2014), or BM visualizations (Täuscher and Abdelkafi, 2017). For instance, van der Aalst (2013) coined the term "*Mine Your Own Business*" with the proposal to use "Big Data" technologies such as process mining in organizational decision-making. Therefore, to overcome these weaknesses of decision-making, research proposed BMM as a data-driven BM visualization technique to retrieve BMs automatically from organizational application systems.

Regarding the need to increase the understanding and comprehension in BPS, which includes contingency factors from the BM, visualization provides "*a way to improve understanding of business models can be to use visual means such as graphs and diagrams*" (Financial Reporting Council, 2018; Havemo, 2018). Täuscher and Abdelkafi (2017) define visual BM representations as "*as self-contained, purposefully designed, two-dimensional images that contain graphic and textual elements to convey information about a BM understanding or a specific BM*". BMM complements existing non-data-driven approaches to BM visualization (Augenstein and Fleig, 2017; Augenstein, Fleig and Dellermann, 2018; Fleig, Augenstein and Maedche, 2018d) and is defined as a data-driven approach to automatically identify, retrieve, and visualize organizational BMs in data-driven analyses from data in different organizational application systems.

2.2.3 Business Modeling and Business Model Development Tools

For the development and visualization of BMs, academia, and practice developed a rich spectrum of different BM development tools (Ebel, Bretschneider and Leimeister, 2016). BM development tools aim to represent BMs for decision-makers in a complete, easily understandable, and transparent mode (Kley, Lerch and Dallinger, 2011). In particular, BMC is a predominant method and a "shared language" (Osterwalder and Pigneur, 2010) to describe, analyze, assess and design, and to finally change BMs (Osterwalder and Pigneur, 2010). The BMC illustrates the logic of how the business is intended to make money with the inputs in nine building blocks that cover customers, offers, infrastructures of the organization, as well as financial viability (Osterwalder and Pigneur, 2010). In particular, the BMC captures customer segments and relationships, value propositions, channels, revenue streams, resources, activities, partnerships, and the cost structure of the BM (Osterwalder and Pigneur, 2010). "*Customers and Suppliers*" captures people and organizations targeted by the BM. Further, "*Value Propositions*" comprises the products and services through which the BM creates value for the customer segments. "*Channels*" collects the different ways of how the organization communicates and how the value propositions are delivered to customers. "*Customer Relationships*" defines the type of customer relationships such as customer retention and acquisition. "*Revenue Streams*" gathers the different types of revenue generated by the BM. "*Key Resources*" represents the assets that are vital for the BM. "*Key Activities*" is the building block of the BMC which captures the "most important actions" which need to be done. "*Key Partnerships*" comprises the pool of suppliers and partners in the value chain of the organization to enable the BM through resource acquisition (e.g., purchasing materials). "*Cost Structure*" captures the essential expenditures incurred for carrying out the BM.

Figure 9 - Exemplary Business Model Canvas from an industry partner company in manufacturing (template taken from (Osterwalder and Pigneur, 2010))



In addition to the BMC, the "BM Cube" is another widely accepted representation and tool for BM innovation based on ontologies (Heikkilä *et al.*, 2016). The BM Cube depicts constituent elements of BMs such as competences, networks, value chain functions, value proportions, value formulas, customers and users in a multi-dimensional form (Lindgren and Rasmussen, 2013). Also, the “Triple-Layered BM Canvas” (TLBMC) extends the original cube with a sustainability and a stakeholder perspective (Joyce and Paquin, 2016). Finally, (França, 2017) combine the BMC with a five-level framework of the “Framework of Strategic Sustainable Development” (FSSD) which elaborates on coordination of BM development and value creation and which illustrates the interdependencies between stakeholders, activities, resource flows, as well as social-ecological issues of sustainability (França, 2017).

Furthermore, several techniques and tools for business modeling have been proposed and implemented based on these foundational concepts. First, online tools such as Strategyzer, Canvanizer, or BMFiddle provide computer-supported versions of the BMC. Second, the “Value Delivery Modeling Language” (VDML) provides different diagram types to model value creation, organizational relationships, capabilities, and value exchange (Capecchi and Pisano, 2014). VDML is the basis for tools like the Neffics platform (Berre Arne- Jørgen, de Man Henk and Lindgren, 2013), which allows linking different dimensions of BMs to different VDML diagrams through relations. VDMbee provides another modeling tool based on the BM cube (Heikkilä *et al.*, 2016). In VDMbee, each BM has a participant network, which defines the participants who create, deliver and exchange values. Participants might either be partners, customers, or the company which owns the BM. Each of the participants can be assigned one or more roles, and values are exchanged between the different participants via their respective roles. Customers can be either organizations, entire segments or individuals. Activities are the processes carried out to create value. Competencies are skills of companies such as abilities and resources.

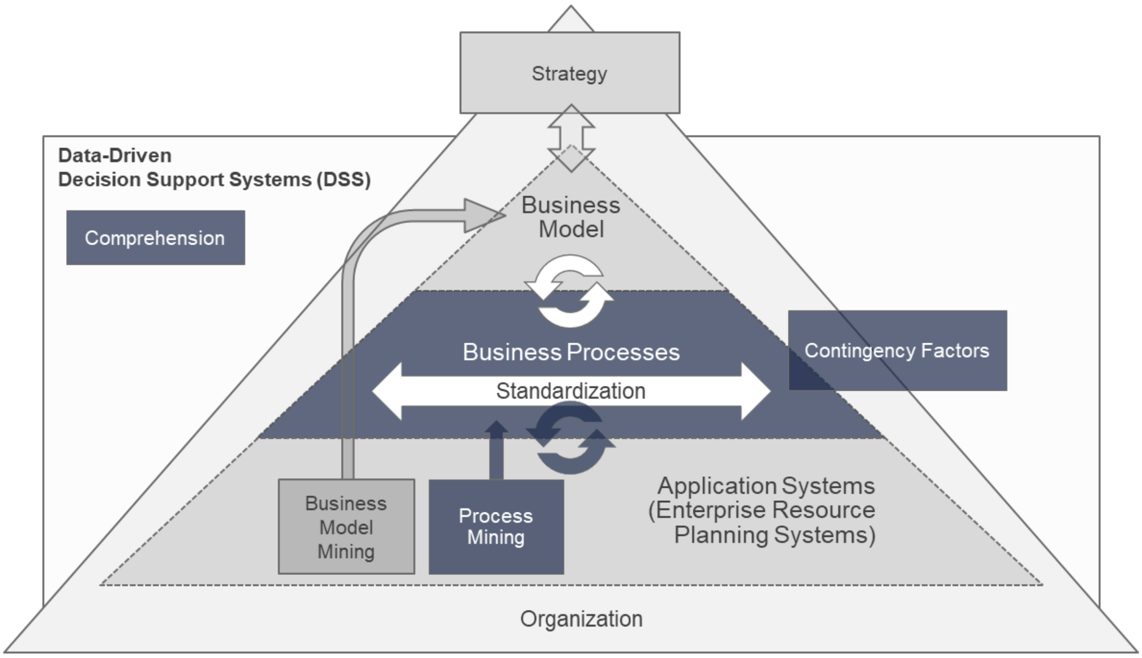
2.3 Business Process Management[4]

“*The notion of BPM is among the key trends regarding business processes*” (Vergidis, Turner and Tiwari, 2008) and the increasing orientation of organizations on BPs and the subsequent improvement of BPs offers a vast potential to both innovate (Davenport,

[4] This chapter contains content previously published in Fleig (2017), Fleig, Augenstein and Maedche (2018a, 2018b, 2018d, 2018c), Wurm *et al.* (2018).

1993) and to increase success variables such as performance of the organization (Škrinjar, Bosilj-Vukšić and Indihar-Štemberger, 2008). Formally, BPM is the discipline concerned with the establishment of a process view on organizational operations and the performant management of BPs (vom Brocke, Zelt and Schmiedel, 2016). BPM plays a significant role as a bridge between strategy, the organizational BM and the underlying application systems as it is the discipline to "*translate a firm's strategy into specific needs and enable the execution of the strategy*" (Trkman, 2010). However, the critical role of BPs in BMs is often neglected or underestimated (Caspar *et al.*, 2013). For example, if BPs change, organizations might need to adjust the BM subsequently (Bonakdar *et al.*, 2013; Caspar *et al.*, 2013) and vice-versa.

Figure 10: Business Process Management in the organizational pyramid framework



As proposed by van der Aalst, ter Hofstede and Weske (2003), BPM comprises a field of knowledge which entails a set of methods, adjacent techniques, and different tools for the design, enactment, control, and analysis of organizational BPs (Vergidis, Turner and Tiwari, 2008). BPM intends to identify, discover, analyze, redesign, implement, monitor and control BPs (Dumas *et al.*, 2013).

In contrast to BP reengineering from the 1990s, BPM does not target only a "one-off" revolutionary change to a BP but intends an iterative evolution of BPs (Vergidis, Turner and Tiwari, 2008). Literature generally perceives BPM in cycle models such as the model by Hammer (2010) or by Dumas *et al.* (2013). In Hammer (2010), BPM activities for a

BP start with an initial design, documentation and process implementation. Second, process compliance ensures the establishment of performance targets which are themselves created by measuring process performance and by understanding customer needs or by benchmarking competitors. Third, the model by Hammer (2010) requires the development of an intervention plan once the cause of a deviation between design and execution is understood by the organization. The intervention plan might either be executed by finding and fixing the execution problem in the as-is process, or by improving the design of the to-be process with design modifications or a complete replacement of the design. Following the implementation of the intervention plan, the cycle restarts with measuring results for ensuring process compliance. In contrast to Hammer (2010), in Dumas *et al.* (2013), BPM activities start with the identification of the respective BP which yields the process architecture. Second, the as-is process model is identified during the process discovery phase. Third, insights into process weaknesses and their performance impact are identified during the process analysis phase. Fourth, a new and improved to-be process model is developed during the process redesign phase based on the results of the previous process analysis. Fifth, the executable process model is implemented. Sixth, once the new to-be process is successfully implemented, process monitoring and controlling ensure the conformance of the new process with specifications and generates insights about process behavior. Finally, the BPM lifecycle returns to process discovery. Alternatively, Hassani and Gahnouchi (2017) perceive BPM as a four-step lifecycle that comprises design, execution, management and supervision, as well as analysis and optimization.

BPM covers six factors and capability areas, including strategic alignment, governance, methods, information technology, people, and organizational culture (de Bruin and Rosemann, 2007; Rosemann and vom Brocke, 2015). First, strategic alignment concerns the alignment of organizational priorities and BPs to achieve strategic goals and requires that "*processes have to be designed, executed, managed, and measured according to strategic priorities and specific strategic situations*" (vom Brocke and Rosemann, 2015). Thereby, strategic alignment ensures that benefits from the BPs are realized together with the expectations of "process customers", i.e., the ones who expect and consume the outcome of the process. The strategic alignment of BPM further defines how BPs are positioned in the organization and how they are aligned in the global process landscape. In particular, the category of strategic alignment allows for prioritizing BPs, e.g., regarding projects such as BPS, investments, and improvement activities as well as their contribution to the organizational goals. In particular, strategic alignment entails "process improvement planning" to capture the overall BPM approach of the organization, "strategy and process capability linkage" or strategy maps (Kaplan and Norton, 2004), "enterprise process architecture" in enterprise process models (EPMs) (Garretson and Harmon, 2005), process measures such as the evaluation of output and BP performance in performance indicators, and "process customers and stakeholders" to whose interests BPM initiatives need to be aligned. Second, governance concerns the establishment of both proper and transparent accountability for BPs, as well as decision-making processes for rewards and guiding actions of actors. Particularly, governance of BPM needs to establish appropriate decision-making processes, compliance structures, change management practices, and management concepts for performance for multiple processes and process types simultaneously. Third and fourth, the categories of methods and information technology comprise all the approaches and techniques to support and enable consistent process actions and outcomes, which implies that BPM methods and IT need to be designed in such a way that they allow for contextual ("contingent") BPs. Fifth, the people category encompasses all BPM activities concerning individuals and groups in the organization who continually improve and apply knowledge and expertise of BPs. Employees in the organization need to be "literate", i.e., have a deep understanding of BPs. Such processual literacy covers the contingencies to strategy, BMs, other BPs and application systems. In particular, Rosemann and vom Brocke (2010) highlights the importance of employees being familiar with methods of data analytics such as BI to get data-driven process insights. Sixth, culture comprises the set of values and beliefs which are commonly shared by people in the organization that shapes attitudes and behaviors related to BPs (de Bruin and Rosemann, 2007; Rosemann and vom Brocke, 2015).

2.3.1 Business Processes

BPs are at the heart of BPS. Numerous definitions for BPs and classification schemes exist in research (Ko, 2009; Melcher, 2012). In a widely accepted definition, Davenport and Short (1990) define a BP as *"a set of logically related tasks performed to achieve a defined business outcome"*. Likewise, in Houy, Fettke and Loos (2015) a process is *"a sequence of activities which are undertaken to produce a certain output*".

In particular, events are defined as an atomic occurrence without duration, while an activity represents tasks or work units. Actors represent active elements within a BP such as humans, entire organizations, or systems. Objects comprise tangible or intangible elements of a BP. Process customers are special actors who consume the output of the BP (Dumas *et al.*, 2013).

Davenport and Short (1990) propose that BPs have "*defined business outcomes*" and internal or external organizational customers as recipients of process outcomes. Further, BPs are "independent" of organizational boundaries, structures, and are implemented "*across or between organizational subunits*". These interrelated activities are undertaken to convert inputs into outputs to achieve business objectives, and to create overall value for the organization (Mani, Barua and Whinston, 2010; Rai *et al.*, 2012).

In early seminal contributions, Davenport (1993) describes a BP as "*the specific ordering of work activities and clearly identified inputs and outputs*". Davenport (1993) differentiates between a BP and a product perspective, with BPs focusing on the way of how work is performed, while products emphasize the outcome of processes. Alternatively, the authors in Hammer and Champy (1993) perceive a BP as "*a collection of activities that takes one or more kinds of input and creates an output that is of value to the customer*". The authors in Ray, Barney and Muhanna (2004) further reinforce the goal-oriented perspective on BPs by perceiving BPs as *"actions that firms engage in to accomplish some business purpose or objective"*. Besides, building on the seminal work by Ould (1995), Ko (2009) extends these views on BPs by actors involved in the BP and actor collaboration. In a more recent definition, Weske (2012) defines a BP as *"a set of activities that are performed in coordination in an organizational and technical environment. These activities jointly realize a business goal. Each business process is enacted by a single organization, but it may interact with business processes performed by other organizations"*.

However, Vergidis, Turner and Tiwari (2008) highlight two major concerns concerning existing definitions of BPs in literature: first, definitions might be overly simplistic and generic by not sufficiently incorporating problem specificities, or second, existing definitions might be bound to a specific application domain. Regarding the research question of this dissertation and the interdisciplinary focus on organizational aspects and application systems, the definition by Dumas *et al.* (2013) is adopted. Dumas *et al.* (2013) perceive BPs as "*a collection of inter-related events, activities and decision points that* *involve a number of actors and objects, and that collectively lead to an outcome that is of value to at least one customer*".

2.3.2 Business Process Change

Organizational BPs are subject to constant change and not limited to particular industries or contexts (Sharma, 2015). "BP change" (BPC) considers either the redesign of an individual BP, a set of BPs, or the redesign of an entire organization. BPC refers to a methodological process that involves information technology to achieve critical business goals by overhauling BPs (Kettinger and Grover, 1995).

BPC subsumes existing approaches for changing BPs which have been proposed by research in different flavors and decades. As structured by Christin Jurisch *et al.* (2014), "central elements" to BPC include revolutionary approaches such as BP "reengineering" (BPR), BP "transformation" (BPT), or BP "innovation" (BPI) as well as evolutionary approaches such as total quality management (TQM), Six Sigma and continuous process improvement (CPI). Both revolutionary and evolutionary approaches target the improvement of BPs and often complement each other (Christin Jurisch *et al.*, 2014; Grover and Markus, 2016).

Among the revolutionary approaches, BPR refers to "*the fundamental rethinking and radical redesign of BPs to achieve dramatic improvements in critical, contemporary measures of performance, such as cost, quality, service, and speed*" (Hammer and Champy, 1993). BPR requires significant changes (Limam Mansar and Reijers, 2007), and focuses on the fundamental and radical redesign of the organizational structure by first implementing and afterward continuously reengineering the set of BPs to achieve dramatic performance improvements (Hammer and Champy, 1993). As a minor difference between the concepts, BPT highlights the importance of IT and the implementation of "*new approaches, methodologies, and tools*" (Grover and Markus, 2016). However, the concepts of BPR, BPT, and BPI are closely related and frequently used as a synonym for "one-time undertakings" (Christin Jurisch *et al.*, 2014).

2.3.3 Standardization in Business Processes

2.3.3.1 Standardization

Organizations try to achieve increased returns of scale through standardization (Wurm *et al.*, 2018). Already in 2006, Lyytinen and King (2006) recognized the importance of standardization independently from processes in IS research and acknowledge a lack of research on standardization in information and communication technologies (ICT). In general, standards are designed and implemented by administrative authorities (Gepp, Khomut and Vollmar, 2012). According to the ISO/IEC GUIDE 2:2004 by the International Organization for Standardization (ISO), standardization refers to the "*activity of establishing, with regard to actual or potential problems, provisions for common and repeated use, aimed at the achievement of the optimum degree of order in a given context*". In Schäfermeyer, Grgecic and Rosenkranz (2010), "*a standard is established through consensus by a recognized body and is providing rules, characteristics and guidelines for repeated activities and their results*". In addition, Vries, Slob and van Zuid-Holland (2006) derive an alternative definition of standardization as "*the activity of establishing and recording a limited set of solutions to actual or potential matching problems, directed at benefits for the party or parties involved, balancing their needs, and intending and expecting that these solutions will be repeatedly or continuously used, during a certain period, by a substantial number of the parties for whom they are meant*".

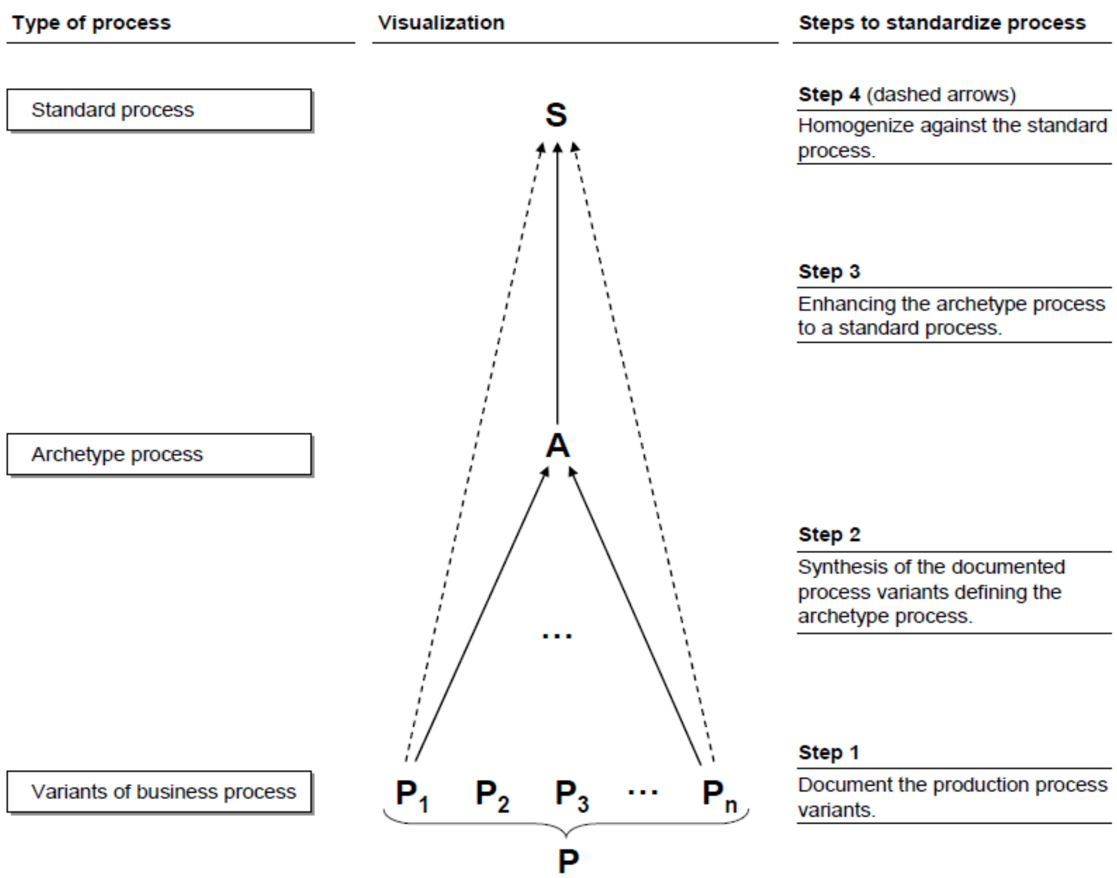
2.3.3.2 Business Process Standardization

BPS targets a situation in which the same or similar activities in different organizational units are conducted identically or similarly (Fleig, Augenstein and Maedche, 2018a; Harmon, 2010). In a widely accepted definition, Jang and Lee (1998) perceive BPS as "*the degree to which work rules, policies, and operating procedures are formalized and followed*". In a more narrow interpretation, the phenomenon of BPS comprises the alignment of business process variants with a defined-meta-process (Münstermann and Weitzel, 2008; Wurm *et al.*, 2018). For example, Wüllenweber *et al.* (2008) define the objective of BPS as "*to make process activities transparent and achieve uniformity of process activities across the value chain and across firm boundaries*". As in earlier work (Wurm *et al.*, 2018), this work will adopt the widely accepted definition by Davenport (2005) with extensions by (Schäfermeyer, Grgecic and Rosenkranz, 2010) and define BPS as "*the* *unification of BPs and the underlying actions within a company […]*" due its broad applicability.

Besides, adjacent research interprets BPS as similar to "business process harmonization" (Romero, Dijkman, Grefen and van Weele *et al.*, 2015). Process harmonization is defined as an activity performed to design and implement process standards across the different regions and units of the organization to realize the benefits of BPS while ensuring process acceptance across stakeholders (Fernandez and Bhat, 2010; Romero, Dijkman, Grefen and van Weele *et al.*, 2015). Harmonization captures common elements across processes and therefore aligns different variants and specifications of processes while still accounting for differing and conflicting interests and requirements (Romero, Dijkman, Grefen and van Weele *et al.*, 2015). Therefore, harmonization highlights the uniformity-variability tradeoff (Fernandez and Bhat, 2010; Girod and Bellin, 2011; Romero, Dijkman, Grefen and van Weele, 2015). In contrast, BPS is aimed at the uniformity of BPs (Romero, Dijkman, Grefen and van Weele, 2015) while harmonization provides for a higher degree of variation to achieve more harmonious standard acceptance (Richen and Steinhorst, 2005).

In Münstermann and Weitzel (2008), the authors distinguish between homogenization and standardization as follows. BP homogenization requires the selection of an archetype process A as "*a business process that serves as master or prototype process*" (Münstermann and Weitzel, 2008). Regarding a BP with an array of process variants $P_1, P_2, \dots P_n$ and the archetype process with the identical process outcome, homogenization refers to the procedure of homogenizing "*the business process P against the archetype process A*" (Münstermann and Weitzel, 2008). In particular, the homogenization step does not necessarily involve improvement of the performance of the process variants $P_1, P_2, \dots P_n$. Second, BPS is the following step, which additionally involves an enhancement of the archetype process A to a standard process which satisfies four criteria. First a standard process in implies Münstermann and Weitzel (2008) the documentation of the standard process S. Second, the standard process S needs to be modularized and subdivided into meaningful (sub-)processes and constituent steps. Third, specificities of S need to be reduced "*to the lowest number of process activities possible*" (Münstermann and Weitzel, 2008). Fourth, standard processes need to "ensure process excellence" by incorporating "knowledge and experience" into the standard process (Münstermann and Weitzel, 2008). Thus, "*to standardize processes, either an archetype process has to be enhanced to a* *standard process internally or a standard process has to be chosen externally*" (Münstermann and Weitzel, 2008) from an external reference model or "best practice" or "best in class" process libraries (Münstermann and Weitzel, 2008).

Figure 11: Approach to BPS (for a production process) (taken from (Münstermann and Weitzel, 2008))



BPS is often interpreted as the one end of the spectrum in the dichotomy of BPS and process diversity (Wurm *et al.*, 2018). On the other end of the spectrum, process diversity comprises the generation of a series of process variants from a standard or meta-process. For example, standard processes might be adapted to suit local legislations (Mocker, Ross and Ciano, 2014) or to adapt products or services to local needs of markets (Weill and Ross, 2005; Williams and van Triest, 2009; Wurm *et al.*, 2018). BPS is not a binary and black-and-white decision, but the degree of BPS ranges on a continuum with adjacent decisions and trade-offs between standardization and variation and flexibility on the other end of the continuum (Manrodt and Vitasek, 2004; Tregear, 2015).

Thus, literature differentiates between different types of BPs regarding the extent of BPS (Harmon, 2010; Seidel, 2009; Tregear, 2015; Wurm *et al.*, 2018). Lillrank (2003) distinguishes between standard, routine and non-routine processes. While pure standard processes are most effective from an economic view, these are unable to address scenarios that deviate from the predefined standard schema. On the other end of the spectrum, non-routine processes are non-repetitive and cannot be defined before the actual execution of the process occurs.

2.3.3.3 Contingency Factors on BPS in BPM Literature

Research developed several procedure models to align BPs with standards (Kettenbohrer, Beimborn and Kloppenburg, 2013; Münstermann and Weitzel, 2008). While procedure models for BPS are relatively well-researched, a fundamental gap in research refers to the contingency factors which determine the extent of BPS (Wurm *et al.*, 2018). In particular, BPS for processes with a high degree of variation in the environment is difficult (Lillrank, 2003). Thus, existing research primarily focuses on the relationship between BPS and process performance (Laumer, Maier and Eckhardt, 2015; Münstermann, Eckhardt and Weitzel, 2010) with BPS being operationalized through the execution perspective. For example, in these studies, BPS is determined by the way activities are performed and executed and the structuredness of the process flow (Münstermann, Eckhardt and Weitzel, 2010; Schäfermeyer and Rosenkranz, 2011; Wurm *et al.*, 2018). However, these studies do not incorporate other contingency factors including governance (Tregear, 2010), process documentation (Ungan, 2006) or the strategic process focus (vom Brocke, Zelt and Schmiedel, 2016). Thus, regarding the problem of selecting appropriate standard BPs, organizations require knowledge on the contingency factors as decision variables on the "business context" (vom Brocke, Zelt and Schmiedel, 2016) of BPs.

For example, in a literature review under the title of "*Factors that Determine the Extent of Business Process Standardization [...]*", Romero, Dijkman, Grefen and van Weele (2015) identify 11 contextual factors (contingency factors), namely cultural differences, different regulations, power distance, number of different locations, IT governance centralization, product type, maturity level, organizational structure centralization, number of mergers and acquisitions, level of process structuredness, and personal differences. Also, the authors identify 6 categories which determine the extent of standardization. These are activities, resources, data, control-flow, information technology, and management.

To further derive the set of contingency factors that determine decision-making in BPS, a structured literature review was conducted in Wurm *et al.* (2018) with adjacent field expert interviews to identify measurement items and substrata of BPS. The literature review was conducted according to the guidelines by (Kitchenham, 2004; Kummer and Schmiedel, 2016) for the search string “Process Har-moni*” OR “Process Standardi*” to select journal articles and conference contributions within 4 widely accepted academic databases in the fields of IT, IS, and BPM in particular. Identified contributions were filtered in a selection process (Grant and Booth, 2009) which resulted in the identification of 529 items of BPS in 100 articles. To further cover the phenomenon of contingency factors in BPS, results from the literature review were further enriched with candidate items in 8 semi-structured interviews with BPM experts. Following the literature and expert interviews, candidate items were sorted into eleven substrata (contingency factors) of BPS. These contingency factors mostly relate to the “core elements” of BPM (de Bruin and Rosemann, 2007; Rosemann and vom Brocke, 2010) described in section 2.3. Contingency factors further include 7 to 14 individual measurement items (112 items in total) (Wurm *et al.*, 2018). Table 2 contains an overview of the contingency factors identified in the literature review. For each BPS contingency factor in table 2, the contribution by Wurm, Mendling, Schmiedel and Fleig (2018) provides a series of measurement items which can be rated on a Likert scale from 1-7 to objectively measure the BPS contingency factors.

Table 2: Contingency factors in BPS (taken from Wurm, Mendling, Schmiedel and Fleig (2018))

Contingency Factor	Description	Selected references as in Wurm *et al.* (2018)
Process Execution	Degree of structure of process activities and process sequence	(Beimborn *et al.*, 2009; Harmon, 2010; Laumer, Maier and Eckhardt, 2015)
Inputs & Outputs	Stability of input and output factors of the business process	(Hall and Johnson, 2009; Wüllenweber *et al.*, 2008; Zellner and Laumann, 2013)
Documentation	Rigor and completeness of documentation materials and trainings	(Hammer and Stanton, 1999; Tregear, 2010; Ungan, 2006)
Data	The extent to which process data is consistent across the business process and IT systems employed	(Bass, Allison and Banerjee, 2013; Michalik *et al.*, 2013; Seethamraju, 2006)
Information Technology	Availability of a common technological platform to support the business process	(Ross, 2003; Steinfield, Markus and Wigand, 2011; Vries *et al.*, 2011)
Governance	Embedding of rules and formal control mechanisms in the business process	(Dijkman, 2007; Lillrank and Liukko, 2004; Manrodt and Vitasek, 2004)

Contingency Factor	Description	Selected references as in Wurm *et al.* (2018)
People & Knowledge	Knowledge and skill intensity, which the business process requires	(Kettenbohrer and Beimborn, 2014; Seidel *et al.*, 2007; Siriram, 2012)
Culture	The degree to which corporate and national culture is supportive of standardization	(Finestone and Snyman, 2005; Hofstede, 1997; Williams and van Triest, 2009)
Legal	Differences and commonalities in governmental regulations across countries	(El Kharbili, 2012; Mocker, Ross and Ciano, 2014; Neubauer, 2009)
Collaboration & Communication	Common patterns of collaboration within and among work teams	(Curiazzi *et al.*, 2016; Kanter, 1994; Kwak, Lee and Lee, 2016)
Strategy	The strategic focus of the process with regards to standardization	(Griffith, Chandra and Ryans, 2003; Mocker, Ross and Ciano, 2014; Wagner and Weitzel, 2012)

2.3.3.4 Contingency Factors on BPS in BM Management Literature

In a literature review, 8 component categories of BMs were identified. First, “customers” comprises constructs such as customers (Magretta, 2002), customer needs (Ebel, Bretschneider and Leimeister, 2016), customer segments (Osterwalder, Pigneur and Tucci, 2005), networks of customers (Zott, Amit and Massa, 2011) as well as the “*value communication and transfer to the service consumer*” (Peters, Blohm and Leimeister, 2015). Second, “governance” concerns “*the way flows of information, resources and goods are controlled by the relevant parties, the legal form of organization, and the incentives to the participants*” (Villani, Greco and Phillips, 2017). Besides, governance comprises actors (Bolton and Hannon, 2016), the prioritization of activities in the organization, and the “*integrative leadership, government-led legal framework, and risk mitigation planning*” (Villani, Greco and Phillips, 2017). Third, “revenues and costs” entails revenue and costs (Osterwalder, Pigneur and Tucci, 2005), adjacent revenue and cost models which determine payment and financing (Bohnsack, Pinkse and Kolk, 2014; Demil and Lecocq, 2010), generated revenue streams (Ebel, Bretschneider and Leimeister, 2016; Teece, 2010) as well as the associated revenues, costs and profits architecture (Teece, 2010). Fourth, BMs contain “networks and partnerships” of related entities with components such as the generic business environment (Osterwalder and Pigneur, 2013), ecosystems and institutional arrangements (Wieland, Hartmann and Vargo, 2017), value networks (Al-Debei and Avison, 2010), communications (Teece, 2010), competitors (Ebel, Bretschneider and Leimeister, 2016) as well as vendors, partners or financiers (Amit and Zott, 2015). Fifth, BMs determine the “organizational structure” in a contingency theory argumentation, which comprises the structure (Amit and Zott, 2015), architecture (Hedman and Kalling, 2003) and upstream- and downstream activities within the organization (Autio, 2017; Bolton and Hannon, 2016). Sixth, "products and markets" entails products and services (Bohnsack, Pinkse and Kolk, 2014), market segments (Chesbrough, 2002; Teece, 2010), product markets (Zott and Amit, 2008) and target segments (Bohnsack, Pinkse and Kolk, 2014). Seventh, the component "resources and skills" encompasses resources (Hedman and Kalling, 2003; Osterwalder and Pigneur, 2010), capabilities (Zott and Amit, 2008), skills knowledge, competencies (Amit and Zott, 2015; Jacobides and Winter, 2012; Villani, Greco and Phillips, 2017). Eighth, BMs specify the organizational value proposition (Augenstein, Fleig and Dellermann, 2018; Chesbrough, 2002; Giessmann and Legner, 2016; Osterwalder and Pigneur, 2010) or related terms such as value capturing (Ebel, Bretschneider and Leimeister, 2016), value creation (Wieland, Hartmann and Vargo, 2017). Table 3 provides an overview of the BM components.

Table 3. Business model components (BM-related BPS contingency factors)

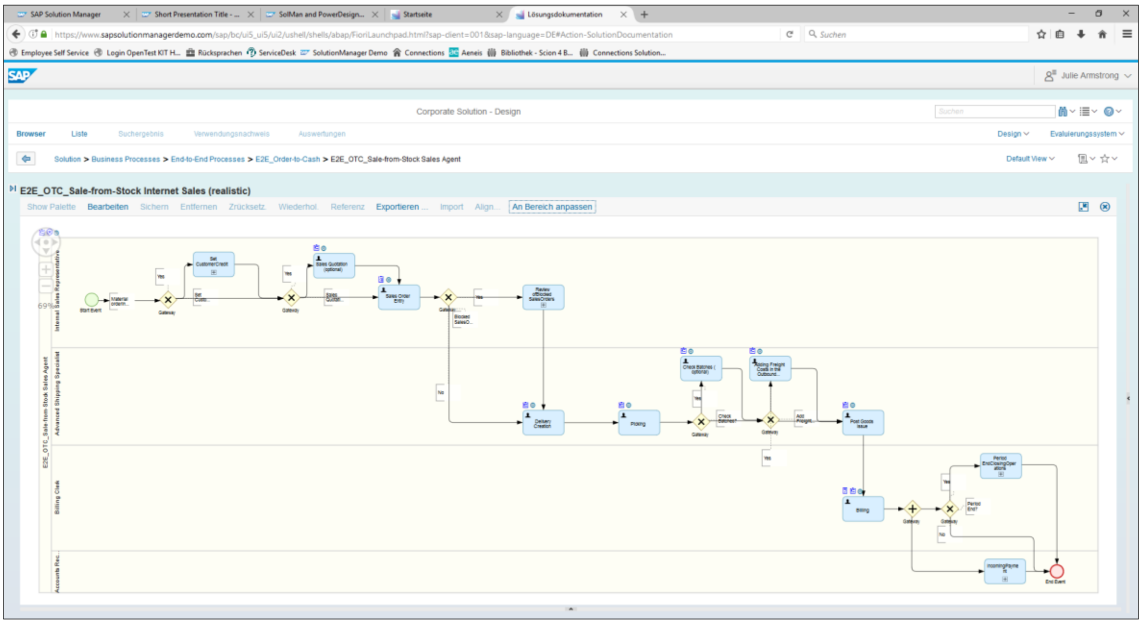
Contribution	Component (BM-related contingency factors)							
	Customers	Governance	Resources & Skills	Costs & Revenues	Networks & Partnerships	Products and Services	Value Proposition	Organizational Structure
(Al-Debei and Avison, 2010)				x	x	x	x	x
(Amit and Zott, 2015)	x		x		x		x	x
(Autio, 2017)		x		x	x		x	x
(Bieger and Reinhold, 2011)					x		x	
(Bohnsack, Pinkse and Kolk, 2014)	x			x	x	x	x	
(Bolton and Hannon, 2016)	x	x			x		x	x
(Chesbrough, 2002)	x			x	x	x	x	
(Ebel, Bretschneider and Leimeister, 2016)	x			x	x	x	x	x
(Giessmann and Legner, 2016)	x		x	x	x		x	
(Hedman and Kalling, 2003)	x		x		x		x	x
(Jacobides and Winter, 2012)			x	x				x
(Magretta, 2002)	x			x			x	
(Osterwalder and Pigneur, 2013)					x		x	

Contribution	Component (BM-related contingency factors)							
	Customers	Governance	Resources & Skills	Costs & Revenues	Networks & Partnerships	Products and Services	Value Proposition	Organizational Structure
(Osterwalder, Pigneur and Tucci, 2005)	x		x	x	x	x	x	x
(Peters, Blohm and Leimeister, 2015)	x				x		x	
(Rosenkopf and McGrath, 2011)	x	x			x		x	x
(Teece, 2010)	x			x	x	x	x	x
(Villani, Greco and Phillips, 2017)		x	x	x	x		x	x
(Wieland, Hartmann and Vargo, 2017)			x	x	x	x	x	
(Zott and Amit, 2008)	x		x		x	x		
(Zott, Amit and Massa, 2011)	x			x	x	x	x	x

2.3.4 Process Modeling

Process models can serve as a powerful means to increase the comprehension of users by displaying process information such as BPS contingency factors in a structured representation of reality. In process modeling, process models are created to model process realities to conduct BPM activities such as analyses (Green and Rosemann, 2000; Hwang and Yang, 2002). Process models graphically notate and represent BPs (Reijers, Mendling and Dijkman, 2011) for a variety of purposes (Curtis, Kellner and Over, 1992; Dikici, Turetken and Demirors, 2018) to visualize flows of activities and interdependencies occurring in a BP (Agrawal, Gunopulos and Leymann, 1998). In order to visualize process models, notations such as Petri nets, heuristic nets, fuzzy models, causal nets, event-driven process chains (EPCs) or the BP model and notation (BPMN) have been developed with different degrees of ease of interpretation and popularity (de Weerdt, van den Broucke and Caron, 2015). Purposes of process models range from communicating BPs to supporting the understanding and improvement activities (Indulska *et al.*, 2009) or to reducing the cognitive effort required in BPM activities (Wang, Indulska and Sadiq, 2016).

Figure 12: Example of a real-life BPMN process model for a sales process from the industry partner in SAP SolutionManager with 12 tasks and 7 gateways



Researchers distinguish process models from a procedural and imperative and a declarative perspective (Fahland *et al.*, 2009). In the imperative perspective, process models depict the entire set of decision alternatives. In contrast, process models in the declarative perspective illustrate the set of constraints but disregard deviations from the ideal specification such as variants or execution alternatives (Fahland *et al.*, 2009; Figl, 2017).

Process models, therefore, serve as a means to support decision-makers in understanding the contingency factors of BPS. For instance, process models provide an abstract representation of the BP with reduced complexity (Rodrigues *et al.*, 2015) as an input in decision-making. Besides, adequate process models set the focus of decision-makers on items of interest (Rosemann, 2006). Process models might thus increase comprehension in BPS and understandability of processes taking into account additional contingency factors. Researchers call for comprehensible process models as a requirement for organizations (Becker, Rosemann and von Uthmann, 2000; Reijers *et al.*, 2011). In Figl, Recker and Mendling (2013), process models are proposed to address the complexity and are defined "*as a means of abstraction for fostering understanding, transparency and communication of such complex processes*".

2.3.5 Process Mining

BPM distinguishes between normative “de-jure” process models that rely on the tacit knowledge of decision-makers and descriptive “de facto” process models based on actual process data in organizational application systems which might capture process realities more comprehensively (van der Aalst, 2014, 2016). BPs in organizations might differ profoundly concerning the intended to-be design in process models and the actual as-is process execution (Hwang and Yang, 2002). Traditional, non-data-driven process models might inadequately capture BPs and depict idealized or subjective representations of BPs or lack flexibility in the abstraction of process levels and details (van der Aalst, 2016).

Organizations frequently do not meet the prerequisites for BPS in terms of sufficient comprehension of BPs and possess only limited insights and a narrow understanding of existing processes and BPS contingency factors (van der Aalst and Weijters, 2004). Traditional non-data-driven approaches to BPS rely on "de-jure" process analyses instead of "de-facto" data-driven approaches, which suffer from a number of insufficiencies as they are based on handmade process models which are often biased compared to process reality (van der Aalst, 2011). For instance, “de-jure" process documentations usually only contain idealistic process executions such as the to-be process, while most process variants and deviations from the ideal target specification are ignored (van der Aalst, 2014).

In addition to content-related insufficiencies, non-data-driven process modeling itself is a time- and resource-consuming task (Indulska *et al.*, 2009). Further, “de-jure” process models are error-prone due to their manual creation. In sum, van der Aalst finds that the currently prevailing approaches of process modeling are “disconnected” from process realities (van der Aalst, 2013), which implies that human-centered non-data-driven approaches provide only an insufficient base for decision-making in BPS.

A chance to overcome these weaknesses of decision-making in process transformation is to utilize the increasing availability of process data from numerous information sources in organizations (Loebbecke and Picot, 2015). For example, application systems store process events in large event log tables (van der Aalst *et al.*, 2007) which provides the possibility to improve decision-making by data-driven approaches such as process mining (van der Aalst, 2014). For example, process mining delivers descriptive and positive "de-facto" process analyses based on data (van der Aalst, 2014). Hence, “de-facto” process analyses provide a valuable complement to decision-making in BPS.

At the same time, data-driven technologies such as "process mining" (van der Aalst and Weijters, 2004) provides the potential for data-driven analyses of BPs (Lederer *et al.*, 2017; van der Aalst, 2018). Although process mining originated several decades ago, the technique still emerges at an unprecedented speed and increasingly gains in popularity in both academia and practice (van der Aalst, 2011). Process mining provides the potential to complement non-data-driven process analyses, and to contribute to the solution of organizational challenges (van der Aalst *et al.*, 2007) such as BPS. In particular, process mining serves as the bridge and the missing link for the gap between traditional, non-data-driven or model-based analysis and decision-making in BPs and evolving data-driven techniques such as data mining (Mans *et al.*, 2013; Reijers, Vanderfeesten and van der Aalst, 2016; van der Aalst *et al.*, 2007). Therefore, process mining offers a promising technique to retrieve contingency factors of BPS from data in application systems to enrich existing non-data-driven knowledge of decision-makers.

The fundamental and basic idea of process mining is to retrieve BP knowledge such as "*process, control, data, organization, and social structures*" (van der Aalst *et al.*, 2007) data-driven and automatically from process-related data and information stored in organizational application systems (van der Aalst, 2011). In their seminal manifesto, the authors in van der Aalst *et al.* (2011) describe process mining as a lifecycle which includes planning and justifying, data extraction, creating control-flow models and connecting event logs, creating integrated process models, and providing operational support.

Formally, process mining refers to a set of techniques to extract knowledge from event logs containing process-related data in order to discover, monitor, and to improve BPs (van der Aalst *et al.*, 2011). Other definitions in the literature focus on different aspects of process mining. For example, Kudo *et al.* (2013) define process mining as a technology for the analysis of different classes of BPs by examining event logs generated in different types of IT systems.

The discipline of process mining is generally divided into process discovery, process conformance checking, and process enhancement (Brandão, Santoro and Azevedo, 2015). In particular, process discovery serves to create process models automatically from data in event logs (van der Aalst *et al.*, 2011; van der Aalst, 2016). In conformance checking, process mining compares the mined processes in terms of whether the observed as-is process behavior complies with a specified to-be process model to discover deviations (van der Aalst, 2016). In process enhancement, process mining tries to actively interfere with BPs using event-log information (van der Aalst, 2016) or to provide process-related analysis information such as key performance indicators (“KPIs”).

In order to retrieve BPs from data in application systems, events are logged in process event logs. Process events are elements such as tasks or activities which define the process (van der Aalst *et al.*, 2011). Event logs containing process-related data serve as the basis for process mining analyses (Hutchison *et al.*, 2005). In a most basic form, event logs contain information about an activity (e.g., a process step or a transaction in the ERP system such as mm01 to create a new material in the SAP R/3 ERP system), a case identifier to which the process activity belongs to (e.g., the material number), and a timestamp for each of the process events (van der Aalst *et al.*, 2007). Information in event logs is usually connected to additional process data to enrich process analyses with additional information (Graupner, Urbitsch and Maedche, 2015; van der Aalst *et al.*, 2003).

Further, in order to analyze BPs, process mining relies on different algorithms which perform analyses on event logs such as the “Alpha-Miner” (van der Aalst *et al.*, 2011), the “Heuristics Miner”, GLS-Miner”, or the “ACO-Miner” (Chinces and Salomie, 2013).

However, process mining focuses on a and data-centric perspective on BPs. Thus, process mining encounters several limitations in its application and the ability to automatically retrieve process knowledge. For example, process mining does not capture “shadow processes” (van der Aalst, 2016) and non-data-driven process information which is not stored in data in organizational application systems, and not all possible BP behaviors might be captured in event logs (van der Aalst, 2018). Additionally, due to the reliance on event logs, process mining also suffers from incompleteness or noise (van der Aalst, 2016).

2.3.6 Process Importance[5]

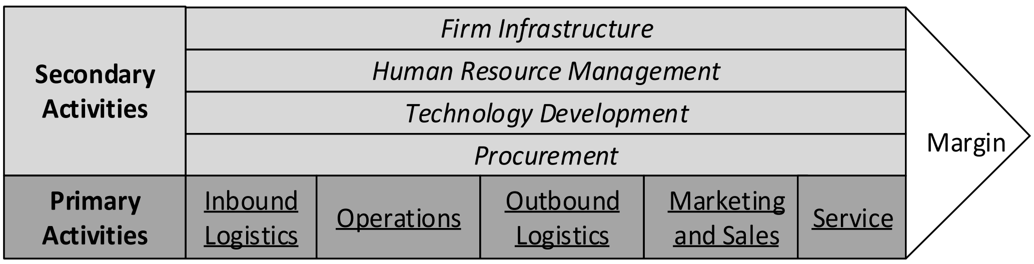
Research identified a strong significance and the necessity of strategic alignment of BPs as a critical success factor for BPM initiatives (McLean, 2016; Trkman, 2010; vom Brocke and Rosemann, 2015) (cf. section 2.3). However, organizations possibly consist

[5] This chapter contains content previously published in Fleig, Augenstein and Maedche (2018b).

of hundreds of BPs (Dumas *et al.*, 2013; Imgrund *et al.*, 2018). At the same time, organizational resources are limited such that, the prioritization of BPM activities to "important" BPs becomes crucial (Fleig, Augenstein and Maedche, 2018b; vom Brocke and Rosemann, 2015).

With a focus on the need for BPs to contribute to strategy and competitive advantage, the frequently cited contribution by Ould (1995) distinguishes processes into core processes such as the service of external customers, into support processes for the service of internal customers and the support of core processes, as well as management processes to administer the organization (Gibb, Buchanan and Shah, 2006). Likewise, the seminal contribution by Porter and Millar (Porter and Millar, 1985) distinguishes BPs into primary and secondary activities. The value chain by Porter and Millar (1985) is often used to analyze the organizational value creation process (Wirtz, 2018). Primary activities are comparable to core processes in Ould (Ould, 1995) to clearly distinguish the organization from the competition. According to Duan et al., (Duan, Grover and Balakrishnan, 2009) primary activities are activities such as physical creation, logistics, sales, and pre- and after-sales (Duan, Grover and Balakrishnan, 2009). In contrast, secondary processes are similarly performed across organizations, thus adding little uniqueness to the particular organization (Gibb, Buchanan and Shah, 2006; Porter, 1985). These supportive processes merely support primary activities by providing necessary inputs such as resources (Duan, Grover and Balakrishnan, 2009).

Figure 13: Value chain by Porter (Porter, 1985) with primary and secondary processes



In BPM-focused literature, the identification of "important" BPs is crucial in the identification phase of the BPM lifecycle (cf. section 2.2.3) due to limited organizational resources in BPM activities and the arising need to be cost-effective (Dumas *et al.*, 2013). To prioritize BPs in process redesign, Dumas *et al.* (2013) introduce three criteria in terms of importance, dysfunction, and feasibility. First, importance refers to "*assessing the* *strategic relevance of each process*" (Dumas *et al.*, 2013) and the "centrality" of a BP to the business strategy under the consideration of profitability, continuity, as well as the "*contribution to the public cause*" of the organization. Following this importance perception, BPs which contribute to the organizational goals and value creation might be termed "important". Second, dysfunction targets the maturity level of the BP in a "*capability maturity model integrated framework*" and the current health status and necessity to revise and rework the BP. Third, feasibility prioritizes BPs according to "*how susceptible they are to process management initiatives*" (Dumas *et al.*, 2013) with a particular focus on culture and politics (Dumas *et al.*, 2013).

Besides, a further BPM-centric contribution by Zelt, Schmiedel and vom Brocke (2018) derives 36 dimensions of in 5 main categories to distinguish diverse BPs in their "nature" formally. Among these categories, "process importance" characterizes a BP according to the impact on the organizational competitiveness and includes criticality and value creation as dimensions.

To synthesize these previously existing definitions, "process importance" is therefore defined as in Fleig, Augenstein and Maedche (2018b) "*as the degree to which a business process impacts the ability of the organization to create value, achieve organizational goals, and ultimately performance*".

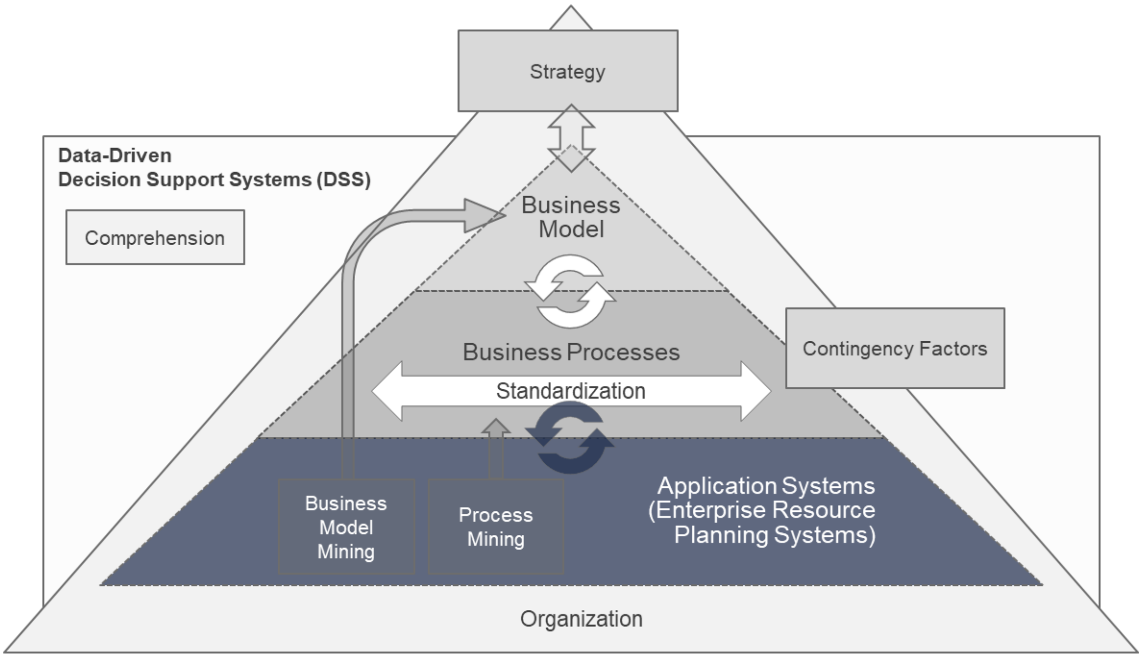
2.4 Application- and Enterprise Resource Planning Systems[6]

Standardization and homogenization of BPs have been recognized as an essential step prior to any ERP implementation project (Botta-Genoulaz, Millet and Grabot, 2005). ERP systems are closely linked to BP management initiatives such as (data-driven) BPS. On the one hand, data mining techniques such as BMM or process mining require data from organizational application systems for data-driven analyses and decision-making. On the other hand, organizations increasingly utilize application systems such as Enterprise Resource Planning (ERP) to support operations (Fischer *et al.*, 2017) in their daily operations. Furthermore, abundant practical experiences and academic contributions reveal the

[6] This chapter builds on the previously published contribution by Fleig, Augenstein and Maedche (2018c).

significant potential of ERP systems for BP improvement and reengineering (Finney and Corbett, 2007; Salazar, Rivera and Vázquez, 2013; Scheer and Habermann, 2000).

Figure 14: Application systems (in particular ERP systems) in the organizational pyramid framework



ERP systems are commercial application systems to achieve automation and integration throughout organizational BPs (Gattiker and Goodhue, 2005) to provide holistic overviews over businesses (Ehie and Madsen, 2005). Thereby, ERP systems allow organizations to streamline BPs, and to efficiently and effectively share information both within and across organizations (Lee J., Siau and Hong, 2003).

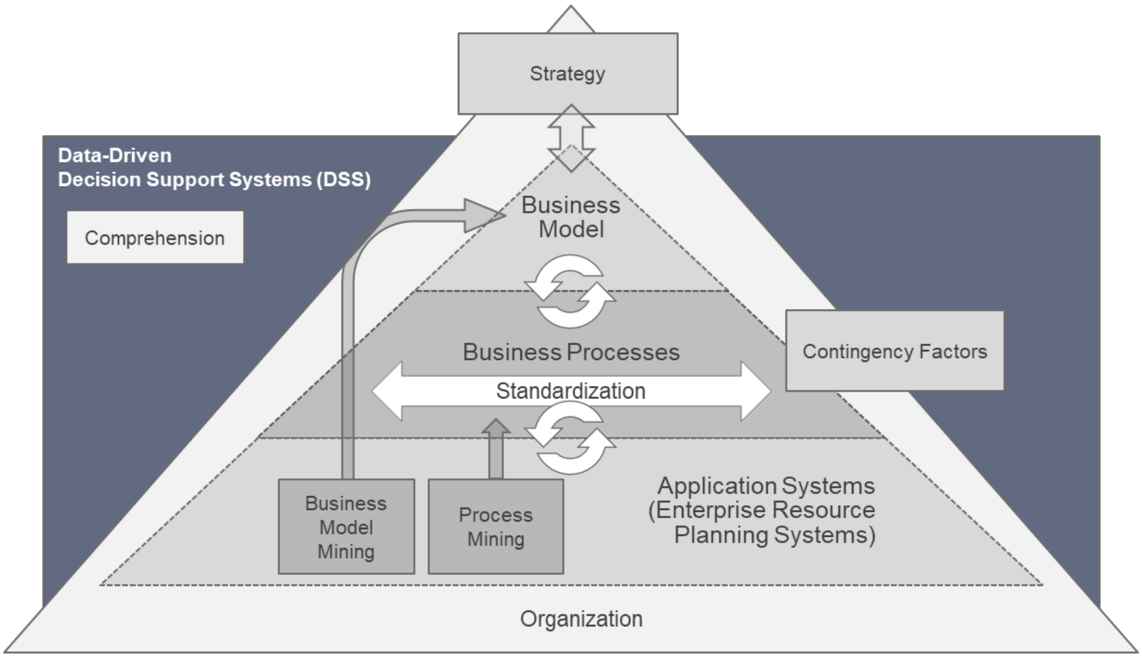
Therefore, ERP systems allow to integrate and to standardize BPs by implementing them in one common and harmonized underlying architecture (Benders, Batenburg and van der Blonk, 2006), which avoids both duplication and redundancies. ERP systems require organizations to adhere to formalized BPs and to "*to move away from a function-based organizational structure in favor of an integrated, process-oriented structure*" (Morton and Hu, 2008). In the context of ERP implementations, BPS might either be pursued actively by the organization before an ERP system is realized with only standardized BPs being implemented in the system (Harmon, 2015; Seethamraju and Krishna Sundar, 2013), or passively as the result of the ERP system which provides and requires own standard or reference processes (Gattiker and Goodhue, 2005; Lee and Lee, 2000).

Organizations link substantial efficiency improvements and increases in customer satisfaction (Poston and Grabski, 2001) and cost reductions to investments in ERP systems (Laughlin, 1999). Organizations pursue a large number of different goals and benefits when deploying ERP systems (Benders, Batenburg and van der Blonk, 2006). Among the most important implementation goals, organizations expect increases in overall performance (Poston and Grabski, 2001; Rajagopal, 2002), cost reductions (Hwang and Min, 2015), the enablement of new BMs (Poston and Grabski, 2001) and the reengineering of BPs in reaction to environmental change (Rajagopal, 2002). Organizations further implement ERP systems to integrate and consolidate informationally, geographically (Benders, Batenburg and van der Blonk, 2006) or functionally separated units (Hwang and Min, 2015; Laughlin, 1999). Besides, ERP systems are implemented to reduce redundancies, incompatibilities, and inconsistencies in information (Benders, Batenburg and van der Blonk, 2006; Poston and Grabski, 2001; Rajagopal, 2002). Besides, information in centralized databases is entered only once in the ERP and distributed enterprise-wide to other units close to real-time (Benders, Batenburg and van der Blonk, 2006; Laughlin, 1999; Poston and Grabski, 2001), which allows for faster information transactions and item tracking (Hwang and Min, 2015). ERP systems also support changes with increased technological capabilities and reduce the degree of errors due to higher automation (Laughlin, 1999). Besides, ERP implementation projects provide the ability to replace legacy application systems (Laughlin, 1999). Further, organizations introduce ERP systems to increase compliance (Poston and Grabski, 2001). Finally, ERP systems are further associated with benefits in organizational decision-making (Hwang and Min, 2015; Poston and Grabski, 2001), and improved overviews over the organization (Benders, Batenburg and van der Blonk, 2006).

2.5 Decision Support Systems

Data-driven DSSs such as cloud-based and service-oriented DSSs gain in importance due to the increasing amount of data available in organizations for decision-making (Demirkan and Delen, 2013). DSS research has been around "*over the past four decades*" (Hosack *et al.*, 2012) but originates from the seminal contribution by Simon Herbert in 1947 (Hosack *et al.*, 2012). Despite its maturity, DSS research "*is as relevant now, if not more so, than ever before*" (Hosack *et al.*, 2012).

Figure 15: Decision support systems in the organizational pyramid framework



DSS are widely accepted as a means to improve and support decision-making in organizations across a spectrum of application areas such as medicine or energy (Arán Carrión *et al.*, 2008; Sim *et al.*, 2001; van Valkenhoef *et al.*, 2013) and the discipline of BPM in the domain of supplier selections (Yazdani *et al.*, 2017), quality management (Féris, Zwikael and Gregor, 2017), online purchasing (Kamis, Koufaris and Stern, 2008) or BMs (Fleig, Augenstein and Maedche, 2018d).

As revealed by the set of contingency factors on BPS identified in table 2 in section 2.3.3.3, BPS depends on factors which might be contained in and retrieved by data-driven approaches such as process execution, inputs and outputs or data, while other contingency factors refer are intangible such as culture, governance, or legal factors. In the era of big data, DSSs are still relevant and extended with data-driven elements such as business intelligence (BI) or analytics (Hosack *et al.*, 2012; Pourshahid *et al.*, 2014). DSSs provide a view over data contents (Gopal, Marsden and Vanthienen, 2011; Hosack *et al.*, 2012) for decision-makers to get insights (Bousquet, Fomin and Drillon, 2011).

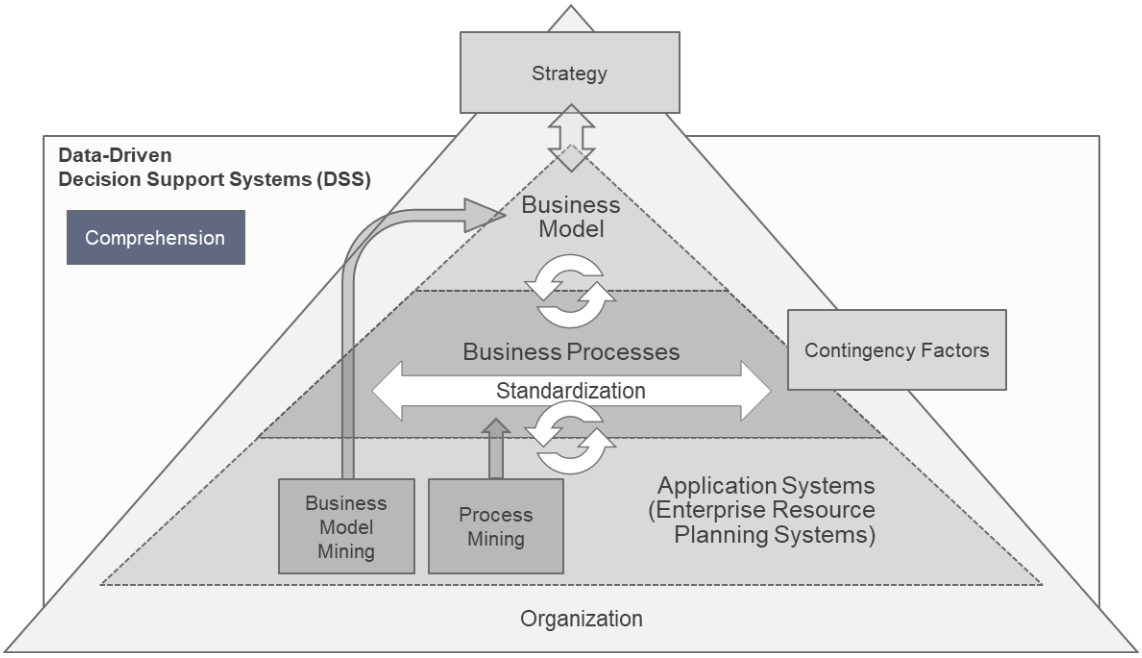
DSSs are an important type of organizational ISs that provides advice for decision-making (Morana *et al.*, 2017; Turban *et al.*, 2005). A DSS aims to improve decision-making in several attributes such as time, quality or difficulty (Morana *et al.*, 2017). In a seminal definition by Turban *et al.* (2008), a DSS is referred to as a computer-based type of IS for decision-making activities. Besides, in an early definition, Ford (1985) "*a DSS helps* *decision-makers utilize data and models to solve unstructured or semi-structured problems*". Hosack *et al.* (2012) highlight the intention of DSS *"to facilitate better decision making for difficult and complex structured, semi-structured, and unstructured decisions*". In particular, a DSS "*enables users to understand ["comprehend"] a large number of parameters and relationships that are stable but nevertheless limit the decision maker's ability to process all aspects of the decision*" (Hosack *et al.*, 2012) and is thus a suited type of IS for the addressed research problems and DSR projects. Synthesizing from the definitions above and according to a definition in previous work (Fleig, Augenstein and Maedche, 2018b), a DSS is defined as an IS to address semi-structured and unstructured decision problems to support decision-making and the comprehension of users in organizations (based on (Shim *et al.*, 2002; Sprague, 1980)).

Nevertheless, DSSs and the models these systems create vitally depend on the comprehension and understanding of users. In the context of decision aids (broader class of IS which also includes DSSs), Morana *et al.* (2017) highlight the importance of different variables such as "model / system understanding", "knowledge acquisition", "accuracy", or "time, speed" in the design of DSS.

2.6 Comprehension

Within the context of BPM, the construct of comprehension provides an established research domain to support the understanding of decision-makers in organizations.

Figure 16: Comprehension in the organizational pyramid framework



Several contributions such as Arnott (2006) investigate how to prevent comprehension problems in artifact application and development. Besides, the contribution by Arnott (2006) argues that the removal of comprehension errors is more difficult due to the nature of comprehension errors, which increases the relevance of research on comprehension in DSR artifacts.

Models such as visual notations of BMs or BPs as designed throughout the DSR projects of this thesis are "*human-oriented representations […] to facilitate […] communication and problem-solving*" (Harel, 1988; Moody, 2009). Thus, model comprehension is perceived as the "*primary measure of pragmatic model quality*" (Figl, 2017) as opposed to syntactic or semantic model quality (Figl, 2017).

The construct of "comprehension" is widely used across various fields such as healthcare where Kim *et al.* (2009) perceive it as the "actual knowledge acquisition" (Kim *et al.*, 2009) or within the domain of BPM (Figl, 2017). Despite its focus on process models and as shown in previous research, comprehension from BPM can also be used in the context of BM research (Augenstein and Fleig, 2018) to determine the comprehension of BMs.

2.6.1 Process Model Comprehension

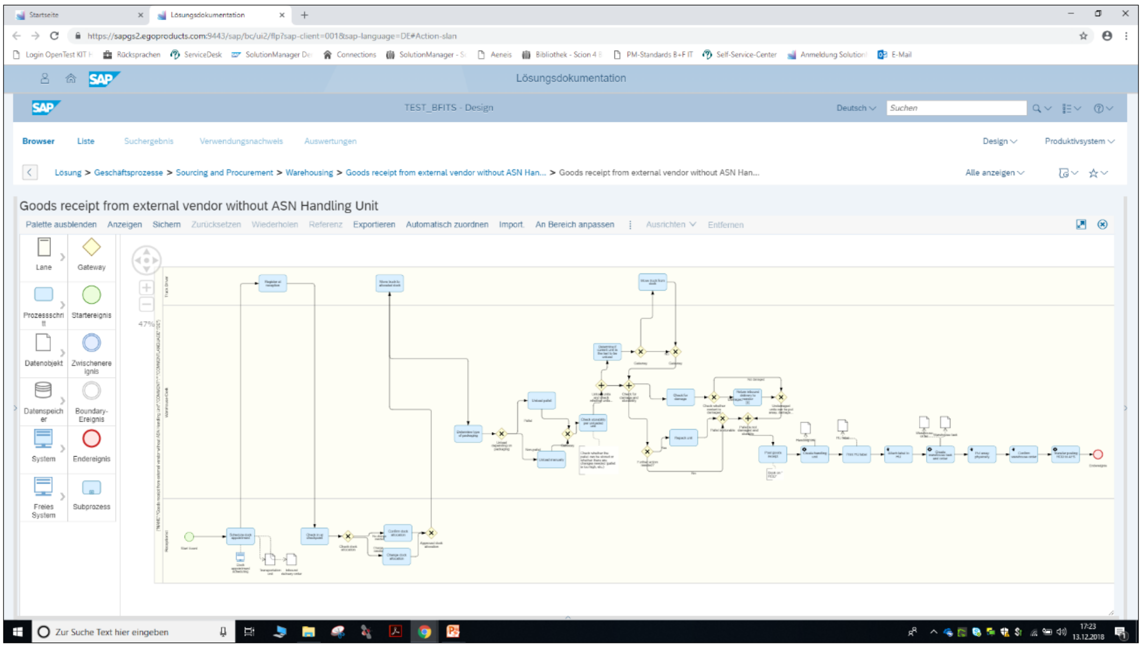
Resulting from the growth of process models in organizations (cf. 2.3.3.4), process model comprehension (PMC) has received increasing scholastic attention from different disciplines. Nevertheless, research has not arrived at a conclusive and commonly accepted definition of PMC, which results in ambiguity over the term of PMC (Houy, Fettke and Loos, 2012). Besides, the concept of PMC is often used as a synonym for "comprehensibility" or "understandability" (Dikici, Turetken and Demirors, 2018; Houy, Fettke and Loos, 2012).

Process models need high quality to optimally achieve the intended purpose (Houy, Fettke and Loos, 2014). Thus, research developed numerous frameworks to conceptualize process model quality such as SIQ (Reijers, Mendling and Recker, 2010) or SEQUAL (Krogstie, 2012). As stated by Reijers, Mendling and Recker (2010), the SIQ framework serves as a further development of the initial SEQUAL framework by Lindland, Sindre and Solvberg (1994). In the SIQ framework, process models are differentiated according to syntactic, semantic and pragmatic model quality. First, syntactic model quality refers to the notational correctness and is defined as the compliance of a given process model with the specifications of a modeling language in terms of vocabulary and syntax. Second, semantic quality encompasses the correspondence of the process model to the real-world behavior of the BP (Reijers, Mendling and Recker, 2010). Third, pragmatic quality expresses the comprehension and understandability of the process model for the user (Dikici, Turetken and Demirors, 2018).

Besides, Reijers and Mendling (2011) refer to PMC as "*the degree to which information contained in a process model can be easily understood by a reader of that model*". Alternatively, Sánchez-González *et al.* (2010) define PMC as "*ease with which business process models can be understood*". Besides and with a focus on domain information, Recker, Reijers and van de Wouw (2014) define comprehension as "*the ability of a user to retain domain information from the elements in a process model*" (Mayer, 2009). In more detail, the authors in Aysolmaz and Reijers (2016) require a comprehensible process model to satisfy three requirements. First, comprehension requires the reader to be able to build a mental model from the presented information which corresponds to the meaning of the creator of the model. Second, the model needs to enable the reader to transfer the information to other contexts and activities. Third, model creation needs to be as fast as possible. Besides, the authors in Bodart *et al.* (2001) distinguish between different levels and deepness of comprehension. First, a superficial comprehension enables users to answer comprehension questions that do not require a deeper problem understanding. Second, deeper comprehension also enables users to apply the information for answering problem-solving questions. This thesis will adhere to the widely accepted definition by Reijers and Mendling (2011).

Also, research identified a vast array of determinants and antecedents of PMC (Dikici, Turetken and Demirors, 2018; Figl, 2017) (cf. section 6.2.1 and table 43). Among these impact factors, Petrusel, Mendling and Reijers (2017) distinguish among model-related characteristics, model language as well as personal characteristics of the user of the process model. Furthermore, Mendling, Strembeck and Recker (2012) take into account the problem domain to increase PMC. Model characteristics include aspects such as size and complexity (Recker, 2013) as the number of elements in the process model (Petrusel, Mendling and Reijers, 2017). Figure 17 illustrates a complex real-life process model from the industry partner for a goods receipt process from an external vendor in a logistics center in SAP SolutionManager 7.2.

Figure 17: Example of a real-life BPMN process model from the industry partner of a goods receipt process from an external vendor (in SAP SolutionManager 7.2)



Personal characteristics comprise, for instance, the modeling experience of the user (Mendling, Strembeck and Recker, 2012), while language comprises linguistic descriptions of the BP such as notational symbols, acronyms or formal concepts such as process grammar (Petrusel, Mendling and Reijers, 2017).

2.6.2 Operationalization of Comprehension in the DSR Projects

As cognitive processes like the interpretation of a BM are tacit (Gemino and Wand, 2004), comprehension cannot be measured or observed directly (Patig, 2008). Further, the literature on comprehension proposed a wide variety of possible comprehension metrics (Houy, Fettke and Loos, 2012). In their contribution, the authors in Dikici, Turetken and Demirors (2018) two forms of comprehension, namely subjective comprehension such as a self-evaluation of users on a Likert-scale (Weber *et al.*, 2015), and objective comprehension, which can be calculated objectively (Genero, Poels and Piattini, 2008).

Objective measurement metrics for comprehension include effectiveness and efficiency. For example, effectiveness (Reijers, Mendling and Dijkman, 2011) and frequent synonyms such as correctness (Aranda *et al.*, 2007) or accuracy (Reijers *et al.*, 2011) can be determined by the number of correctly answered questions in a survey task (Mendling, Strembeck and Recker, 2012). Besides effectiveness, efficiency is further used to proxy for comprehension and refers to the speed and time required to complete a particular comprehension task (Recker and Dreiling, 2007). Thus, *effectiveness* is measured as the number of correct answers given by subjects. *Efficiency* is the time (in minutes) required to answer the comprehension questions. *Relative efficiency* links both constructs and is defined as effectiveness divided by time (Dikici, Turetken and Demirors, 2018).

Subjective measures for comprehension include the perceived ease of understanding (Burton-Jones and Meso, 2002) as well as the perceived ease of interpretation (Gemino and Wand, 2005). Besides, adjacent literature captures related constructs including technology acceptance variables such as perceived ease of use or perceived usefulness (Mturi and Johannesson, 2013) or the user's perceived subjective confidence in understanding (Aranda *et al.*, 2007), cognitive load (Figl, Mendling and Strembeck, 2013), mental effort (Zugal *et al.*, 2015), or difficulty (Kummer, Recker and Mendling, 2016).

3 Research Methodology[7]

For decades researchers have called for contributions that are practically applicable to foster the relevance of IS research (Benbasat and Zmud, 1999; March and Smith, 1995). In the recent past, DSR has experienced a significant increase in acceptance as a research paradigm in IS (Gregor and Hevner, 2013) due to the strength in solving real-world problems by delivering effective IS artifacts (Peffers *et al.*, 2014). This thesis employs a DSR approach to systematically justify, derive, develop and evaluate data-driven DSSs for increasing the comprehension of BPS contingency factors. Thus, in the following the underlying DSR approach is introduced in more detail.

3.1 Design Science Research

The paradigm of DSR can be traced back to the fundamental contribution by Simon (1969) which builds on the idea to enrich natural science by a science of the artificial. “Design” refers to “*a plan for arranging elements in such a way as to best accomplish a particular purpose*” (Eames, 1972) and can be interpreted both as a noun (object interpretation), as well as a process (verb interpretation), which focuses on form and function of the artifact. DSR creates artifacts with the aim of solving significant social or organizational problems (Hevner *et al.*, 2004) to contribute to the scientific body of knowledge (Hevner and Chatterjee, 2010) and has been defined as *“knowledge in the form of constructs, techniques and methods, models, well-developed theory for performing the mapping [from functional spaces to attribute spaces] – the know-how for creating artifacts that satisfy given sets of functional requirements. DSR is research that creates this type of missing knowledge using design, analysis, reflection and abstraction”* (Vaishnavi, Kuechler and Petter, 2004).

Therefore, the DSR paradigm is located at the interplay between science and technology. While science provides descriptive knowledge and theories on natural phenomena or human behavior, technology delivers prescriptive knowledge, design theories, or design artifacts.

[7] This chapter contains content previously published in Fleig (2017), Fleig, Augenstein and Maedche (2018d, 2018a).

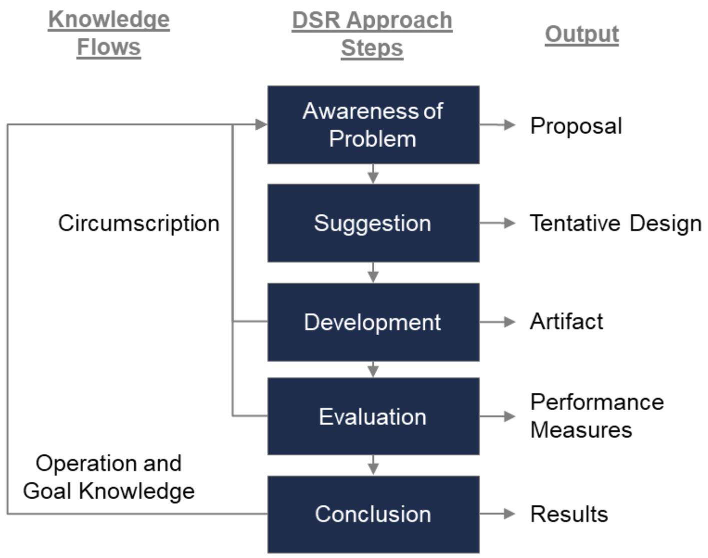
Following the application in the IS discipline, DSR produces different types of outputs, including artifacts such as methods, models, constructs, or instantiations (March and Smith, 1995), which vary according to abstractness, design knowledge maturity, and completeness (Gregor and Hevner, 2013). To this end, the authors in Hevner *et al.* (2004) distinguish among constructs, models, methods, and instantiations. Constructs refer to the vocabulary or symbols to define research problems and adjacent solutions. Models are built on these constructs while methods allow for building models. Instantiations are the concrete implementation of design knowledge within an IT solution or piece of software. Design knowledge creation in the IS domain ranges from an artifact-centric to a theory-centric focus (Peffers *et al.*, 2007). For instance, artifact-centric approaches focus on the design of applicable or problem-solving artifacts (Peffers *et al.*, 2007; Sein *et al.*, 2011), while theory-centric contributions focus on the delivery of a design theory (Jones and Gregor, 2008) or the investigation of artifact features (Baskerville and Pries-Heje, 2010).

Researchers following the DSR paradigm are required to adhere to a rigor application of methods when developing and evaluating artifacts (Hevner *et al.*, 2004). Therefore, DSR provides different procedural frameworks on how to execute DSR projects (Hevner *et al.*, 2004; Hevner, 2007; Kuechler and Vaishnavi, 2008; Peffers *et al.*, 2007; Venable, Pries-Heje and Baskerville, 2014). The seminal works by Hevner (Hevner *et al.*, 2004) and Kuechler and Vaishnavi (Kuechler and Vaishnavi, 2008) propose to perform DSR projects in sequential design cycles in a "build-and-evaluate loop" (Hevner *et al.*, 2004) to iteratively arrive at an optimized artifact instantiation.

3.2 Research Design

The following chapter describes the structure of the DSR projects to derive, develop, and evaluate the artifacts. Within each of the three DSR projects, the DSR approach comprises two design cycles. Each design cycle consists of a problem awareness, suggestion, development, evaluation, and a conclusion phase (Hevner *et al.*, 2004) as illustrated in figure 18.

Figure 18: Steps in the DSR projects according to (Kuechler and Vaishnavi, 2008)



The problem awareness phase, identifies the research problem, defines the scope of the project, justifies the value of the designed artifact (Féris, Zwikael and Gregor, 2017) and raises awareness for a research problem. In particular, "a*n awareness of an interesting research problem may come from multiple sources including new developments in industry or in a reference discipline*" (Vaishnavi, Kuechler and Petter, 2004). Following the problem awareness, "*suggestion is essentially a creative step wherein new functionality is envisioned based on a novel configuration of either existing or new and existing elements*" (Vaishnavi, Kuechler and Petter, 2004). The suggestion phase proposes a solution on how the research problem is solved and formulates generic design requirements in the form of meta requirements (MRs) and associated design principles (DPs) and design decisions (DDs) on the conceptual design of the artifact and the solution (Féris, Zwikael and Gregor, 2017). MRs define classes of problems for the artifact (Walls, Widmeyer and El Sawy, 1992) which are further addressed by DPs (Koppenhagen *et al.*, 2012). DPs capture "*knowledge about instances of a class of artifacts*" (Sein *et al.*, 2011), communicate critical knowledge on the to-be designed artifact and abstract from a singular setting. From abstract DPs, concrete DDs are taken during artifact instantiation (Koppenhagen *et al.*, 2012). Therefore, design requirements are derived in a semantic flow of MRs, DPs, and finally, DDs. The development phase instantiates and develops a prototype implementation regarding the requirements formulated in the previous suggestion phase in concrete design decisions.

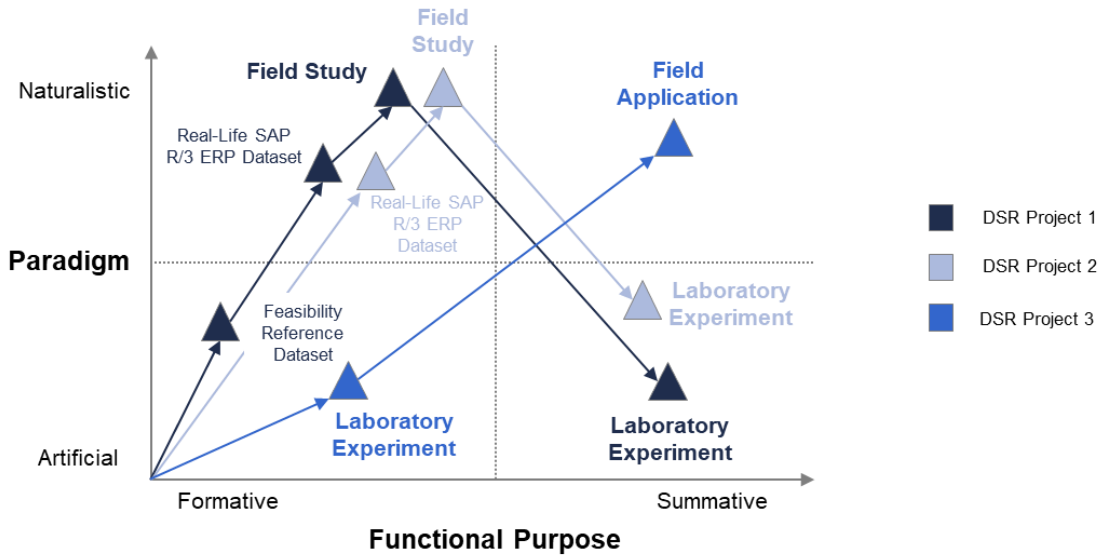
3.3 Evaluation Strategy

Besides the actual creation phase of the artifact, the evaluation phase is by authors such as (March and Smith, 1995) and (Venable, Pries-Heje and Baskerville, 2014) considered to be of top-most importance in DSR projects. It is important to highlight that since DSR seeks to contribute not only by developing artifacts but further by generating new insights to the knowledge base, both artifact utility as well as the knowledge quality need to be evaluated (Venable, Pries-Heje and Baskerville, 2014).

Venable, Pries-Heje and Baskerville (2014) provide a methodological framework for DSR evaluations. They define formative evaluations as a consequence-focused type of evaluation in which "empirically-based interpretations" are delivered to allow for improvements of the evaluand. Summative evaluations are empirical evaluation procedures to form "shared meanings" in various contexts. Therefore, they propose to locate the evaluation on a continuum between formative and summative. The formative end aims for successful action following the evaluation, while evaluations on the summative end of the continuum provide interpretations of shared meanings of the artifact. Besides, the framework by Venable, Pries-Heje and Baskerville (2014) distinguishes among artificial or naturalistic evaluations. Artificial evaluations are defined as positivist and reductionist procedures which may be either empirical or non-empirical and include theoretical argumentation, mathematical proofs, experiments in a laboratory setting, or simulations. Thus, artificial evaluations are characterized by a higher degree of scientific reliability due to repeatability and falsifiability. However, the rigor in artificial evaluation is achieved through a reductionist nature with unreal users, systems, and problems. In contrast, naturalistic evaluations explore the performance of the DSR artifact in real environments such as the organization and comprise case and field studies, field experiments, surveys, or action research among others. The strength of naturalist evaluations lies within the ability to capture the artifact amid the complexities of "human practice" (Venable, Pries-Heje and Baskerville, 2014).

This thesis employs different evaluation strategies for evaluating the designed artifacts in the different DSR projects which are summarized in figure 19.

Figure 19: Evaluation strategy for the DSR projects



In DSR project 1, technical feasibility is demonstrated by implementing and applying the prototype for an open reference dataset and three real-life SAP R/3 ERP systems at three companies of the industry partner. Besides, the first design cycle conducts a field study evaluation at the industry partner (external validity) to validate differences between human and data-driven BMCs and thus the need for data-driven mining of BPS contingency factors from the BM. In order to ensure internal validity, the second design cycle conducts a laboratory experiment to demonstrate that the artifact increases comprehension among non-expert (novices) students in a controlled environment. In DSR project 2 to design a Process Mining DSS to discover and prioritize the set of BPs in the organization, the first design cycle develops and implements the prototype based on real-life data from three different SAP R/3 ERP systems and evaluated in a first field study to demonstrate differences in the comprehension between data-driven and non-data-driven perceptions of the set of BPs occurring in the organization and their relative importance across four different manufacturing companies of the industry partner. In the second design cycle of DSR project 2, a controlled laboratory experiment examines in an interim evaluation which dashboards of the designed prototype provide improvement potential in terms of comprehension for the future artifact development in a third design cycle. However, to limit the scope of this thesis, the laboratory experiment in the second design cycle will be excluded from this thesis and not be presented in-depth. Finally, the evaluation strategy for DSR project 3 to design a Process Mining DSS to visualize the BPS contingency factors in process models and to recommend a standard process design based on the similarity of

BPS contingency factors between the as-is process implementation and to-be standard process design alternatives, conducts a controlled laboratory experiment to evaluate the comprehension of alternative process model designs for BPS contingency factors. The second design cycle conducts a field showcase of the Apromore instantiation of the DSS to the SAP order-to-cash ("sales") and the purchase-to-pay ("procurement") processes in an SAP R/3 ERP system of a manufacturing corporation at the industry partner to select standard process designs for the future SAP S/4 HANA solution.

The conclusion phase transfers the generated knowledge throughout the DSR project to the audience (Peffers *et al.*, 2014).

3.4 Research Context: BPS and SAP S/4 HANA Migration Project at the Industry Partner[8]

DSR projects need to achieve both rigor and relevance of research (Hevner, 2007). The industry partner serves to identify real-world problems in decision-making in BPS projects. Besides, to increase relevance, the DSR projects are conducted within the context of a large-scale BPS project at a German manufacturing group, which comprises the standardization of BPs across three different companies as well as the replacement of the current multi-system SAP R/3 ERP systems landscape by the future SAP S/4 HANA Business Suite in a single-system landscape. In 2018, the corporation consisted of five sub-companies operating globally with more than 8.200 employees and about 1.4bn Euro in turnover in 22 countries.

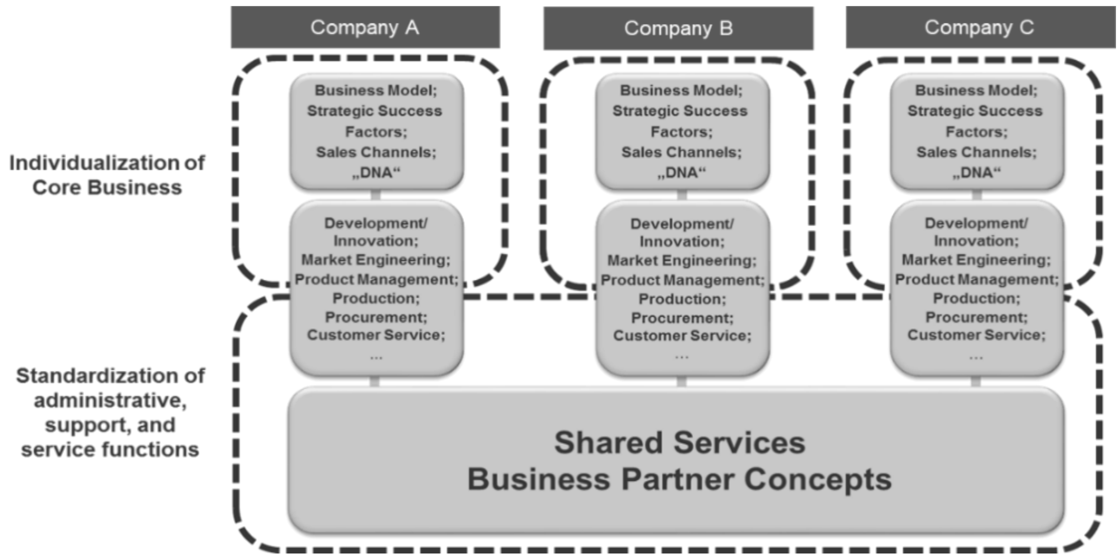
ERP systems are strategically important assets in organizational process change and BPS (cf. section 2.4) with a systemic impact on the organization (Besson and Rowe, 2012). The aim of the project is to develop a holistic approach for the introduction and use of the new SAP S/4 HANA ERP Business Suite for the entire group of companies, which standardizes as many processes as possible, provided this is economically and organizationally possible regarding the individual BMs of the different companies. At the same time, the project also regards the trade-off between standardization and business-critical

[8] This chapter contains content previously published in Fleig, Augenstein and Maedche (2018c, 2019).

individualization for the individual companies, and allows for individual non-standard process designs if these are decisive for business success.

Figure 20 illustrates the standardization-individualization framework. At the one end of the spectrum, processes suitable for corporate-wide standardization such as administrative, support or service functions are located in a “shared services” sphere without any deviations from the corporate standard. At the other end of the spectrum, business-essential processes such as the production of individual products or sales processes which are part of the BM and individual “DNS” of a company and which may not be standardized without threatening the ability of a company to serve markets are located in the individualization sphere. In between, processes which are neither suitable for perfect standardization, but which offer the potential for some degree of harmonization are located in the harmonization sphere between standardization and individualization.

Figure 20: Process standardization vs. individualization across the companies at the industry partners in the new SAP S/4 HANA ERP system



4 DSR Project 1: Design of a Business Model Mining System[9]

BMM intends to provide a more comprehensive data-driven "understanding" of the BM-related contingency factors in BPS. DSR project 1 therefore designs a BM Mining (BMM) system to automatically identify, retrieve, and visualize BMs from data contained in application systems such as ERP systems.

4.1 Outline of DSR Project 1: Design Cycles

The DSR project to design the BMM system consists of two iterative design cycles in a "build-and-evaluate-loop" (Hevner *et al.*, 2004). In the first design cycle, the first prototype of the BM-Miner is designed. In the problem awareness phase, a series of expert workshops within the context of the BPS and SAP S/4 HANA project at the industry partner and a literature review on BM development tools is conducted to validate the observed research gaps and practical needs for data-driven BMM in application systems (Augenstein and Fleig, 2017; Fleig, Augenstein and Maedche, 2018d). Based on the literature review and the expert workshops at the industry partner, the first set of design requirements and a generic blueprint conceptualization are derived in the suggestion phase. In the development phase, a prototype of the BM-Miner is instantiated (Augenstein and Fleig, 2017) for mining organizational BMs from existing SAP R/3 and S/4 HANA ERP systems in Microsoft SQL Server, Azure and Microsoft PowerBI (Fleig, Augenstein and Maedche, 2018d). Technical feasibility is demonstrated by applying the BM-Miner on three different types of SAP ERP systems in the organization of the industry partner. First, the BM-Miner is applied based on data from an open educational SAP S/4 HANA IDES demo system of a fictitious bicycle company and an open reference dataset ("AdventureWorks"). Second, the BM-Miner is applied for three different real-life BMs for the manufacturing corporation from three individual SAP R/3 ERP systems. A formative field study with a gold standard evaluation at the industry partner in a series of 21 employee interviews tests for differences between data-driven and non-data-driven business

[9] This chapter contains content previously published in Fleig, Augenstein and Maedche (2018d); Augenstein and Fleig (2017).

modeling approaches and gathers feedback on the intermediate prototype of the BM-Miner 1.0 for further development in a naturalistic setting.

In the second design cycle, an artificial and summative laboratory experiment demonstrated artifact utility in terms of comprehension of the final BM-Miner 2.0 instantiation.

Findings from the first design cycle are incorporated into the artifact refinement in the second design cycle. Besides, the suggestion phase refines design requirements and provides an open standardized reference data model for BMM to combine data from multiple different application systems existing in an organization beyond SAP R/3 and S/4 HANA systems. The data model and more sophisticated dashboards including more BM contingency factors (cf. 2.3.3.4) are implemented in the final prototype implementation. In the final evaluation phase, an artificial summative laboratory experiment with 142 students evaluates whether the artifact increases the comprehension of the organizational BM in terms of effectiveness, efficiency, relative efficiency, as well as subjective comprehension. Figure 21 summarizes the main contents of each design cycle within the first DSR project.

Figure 21: Overview over contents of design cycles in DSR project 1

Process Iteration

	First Design Cycle	Second Design Cycle
Problem Awareness	• Expert workshops at an industry partner in an SAP S/4 HANA and process standardization project • Literature review on business model development tools	• SAP expert workshops • Literature research on BM comprehension
Suggestion	• Design requirements on business model mining • Synthesis into blueprint conceptualization	• Refinement of design requirements • Standardized data model for business model mining
Development	• Prototype instantiation of design principles in “Business Model Miner 1.0”	• Instantiation of design principles in “Business Model Miner 2.0”
Evaluation	• Field study evaluation on differences between top-down and bottom-up BM(C)s	• Controlled laboratory experiment on comprehension
Conclusion	• Results analysis	• Results analysis

4.2 Design Cycle 1: Business Model Miner 1.0

4.2.1 Suggestion: Design Requirements

4.2.1.1 Meta Requirements

In the first design cycle, three meta-requirements (MRs) and associated design principles (DPs) for BMM are derived (cf. (Augenstein and Fleig, 2017; Fleig, Augenstein and Maedche, 2018d)).

First, BMM requires data from application systems and the software artifact needs knowledge on which data provides the relevant inputs for which of the components of the BM. Thus, MR1 demands:

MR1: "*To mine BMs from application systems, BM-related data needs to be identified and retrieved*".

Second, BMM extracts large amounts of data from various sources such as multiple ERP-systems, which store BM-related data across numerous data tables. Furthermore, BMM systems encounter a challenge imposed by the broad diversity of application systems in organizations. Landscapes of organizational application systems are fragmented and consist of numerous different types such as Enterprise Resource Planning (ERP), Workflow Management, Customer Relation Management, or Supply Chain Management systems, which create large amounts of BM-related data dispersed across multiple sources in different forms and formats (van der Aalst *et al.*, 2007).As a consequence, BMM systems need to consolidate and prepare data from possibly different application systems for later mining and visualization of the BM. Thus, MR2 imposes the following requirement on BMM:

MR2: "To mine BMs from application systems, different sources of BM-related data need to be consolidated."

Regarding the purpose of BMM to increase comprehension, visual representation of models is crucial for users to decode models effectively and efficiently and has been determined as a critical determinant (Figl, Mendling and Strembeck, 2013; Figl, Recker and Mendling, 2013; Mendling, Strembeck and Recker, 2012; Petrusel, Mendling and Reijers, 2017; Recker, Reijers and van de Wouw, 2014). For example, models need to be designed to attract user attention to important components (Figl, Mendling and Strembeck, 2013).

Thus, the BM needs to be aggregated, visualized and presented to the user in a uniform template for a shared understanding (Osterwalder and Pigneur, 2013). Therefore, MR3 requires:

MR3: "To mine and analyze different BMs from application systems, BMs need to be visualized in a predefined template."

4.2.1.2 Design Principles

Based on these three meta-requirements, the first design cycle introduced three associated design principles.

First, to be able to retrieve the components of a BM from an IS, the relevant data tables in the system need to be identified, extracted, and connected via primary keys. Thus, BM-related data in one or more application systems is identified and extracted in individual files to account for MR1 in an "Application Systems Layer". The first design principle demands accordingly:

DP1.1: "BMM requires an application systems layer including a BMM algorithm to extract and identify relevant data."

Second, BM data needs to be merged in one central database and preparatory steps and scripting need to be performed to account for MR2. Thus, the "Data Consolidation, Scripting, and Preparation Layer" merges for later visualization of the BMs. Therefore, the second design principle requires as follows:

DP2.1: "BMM requires a data management layer to consolidate and prepare BM-related data."

Third, MR3 requires the visualization in a predefined template. The goal of BM tools is to provide a complete, transparent, and easy-to-understand visual representation of the BM (Augenstein and Fleig, 2017; Kley, Lerch and Dallinger, 2011). Besides, research proposed various BM approaches to describe the business logic visually and to support managers in planning and developing BMs (Zott, Amit and Massa, 2011). In general, these visual representations of BMs are subsumed under the term of BM "representations" (Täuscher and Abdelkafi, 2017) or BM "frameworks" (Lindgren and Rasmussen, 2013). Visual representations of BM might in general be classified into an elements view, which visualizes a BM with a collection of predefined elements, a transactional view to represent transactions with objects connected to actors, as well as a causal view which illustrates causal relationships between objects with arrows (Täuscher and Abdelkafi, 2017). For the purpose of BM analysis, users need to be provided with the possibility to interactively explore BMs by data operations such as filtering, aggregating, or drill-downs into different components of the BM. Thus, the "BM Presentation Layer" visualizes the BM in a predefined template and provides additional functionality for analysis of the BM. Design principle 3.1 thus requires:

DP3.1: "BMM requires a presentation layer to present BMs in a predefined BM template and provide additional analysis functionality."

In order to select an appropriate template for visualization, different possibilities were discovered in a literature review and presented in section 2.2.3 in the conceptual foundations. In particular, the BMC by Osterwalder (Osterwalder and Pigneur, 2010) has gained significant popularity in both academia and practice and was thus selected for visualization (DP3.2). In a recent literature review on BM development tools, Szopinski *et al.* (2019) find the BMC by Osterwalder and Pigneur (2010) to be "*the quasi-standard for representing BMs*". Thus, design principle 3.2 is imposed as follows:

DP3.2: "The BMC is selected as a template for visualizing the BM in the presentation layer."

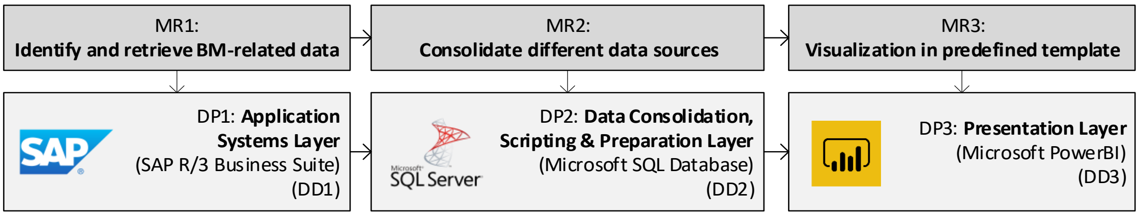
4.2.2 Development: Instantiation of the BM Miner Prototype (Design Decisions)[10]

The following paragraph presents results from the implementation of the BM Miner based on the design requirements derived in section 4.2.1. The prototype retrieves data from an SAP R/3 ERP system in the application systems layer (DP1.1). A BMM algorithm was developed for SAP R/3 and S/4 HANA ERP systems in the SAP programming language ABAP to identify and extract BM-related data in the application systems layer (DD1). The program recognizes data tables that contain data on the building blocks of the BMC and the associated lookup tables. Data from the tables is extracted as individual .csv files and is consolidated in a Microsoft SQL Server database (DD2) in the data management

[10] This chapter builds on the previously published contribution by Fleig, Augenstein and Maedche (2018d).

layer (DP2.1). Finally, the BM is visualized graphically in Microsoft PowerBI (DD3) in the presentation layer (DP3.1). The presentation layer with the BMC (DP3.2) is implemented in Microsoft PowerBI due to the free availability of the solution and the ability to connect to many different database formats. Further, it can process large amounts of data and provides a large standard selection of different visualizations.

Figure 22: Design requirements (meta requirements and design principles) in the first design cycle



The BMC contains 9 building blocks that try to capture and structure the BM into a predefined template (cf. section 2.2.3). A series of expert workshops with SAP consultants and developers was conducted at the IT service provider of the industry partner to identify suitable proxies for the building blocks of the BMC. For each of the building blocks, one or several proxies which reflect the definition of the building block and which can be computed from data stored in ERP systems in accordance with the contribution by Osterwalder and Pigneur (2010) is implemented in the prototype. Contents of the data model in the following and the required data tables for the instantiation in the SAP system are derived from Osterwalder and Pigneur (2010).

First, organizations operate within networks upstream and downstream in the supply chain. For example, several elements of the BM such as activities or resources can be outsourced to partners to which the organization is connected. Examples for key partnerships include competitors, strategic alliances such as joint ventures, or buyer-supplier relationships. In the BM-Miner, partnerships are proxied from the SAP ERP system by supplier master data including industries, networks, classifications, types, regions, languages, date information of the relationships and procurement transaction data including purchase value and volumes (DD4).

Second, organizations execute a number of key activities that transform inputs into outputs to create value. In particular, the importance of BP for the BM of an organization is often underestimated (Caspar *et al.*, 2013). Further, BMs and processes need to be aligned to execute the BM. Information on key activities is obtained by implementing the mining algorithm in the "KeyPro" tool from DSR project 2 (Fleig, Augenstein and Maedche, 2018b) (cf. section 5) into the BM-Miner. KeyPro is a tool automatically determining “important” BPs in ERP systems by matching executed transactions in the ERP system to a library of BPs. For each BP, KeyPro calculates or provides importance metrics such as the number of executions, employees involved, customer and supplier involvement, or a primary versus secondary process classification (Fleig, Augenstein and Maedche, 2018b) (DD5).

Third, the execution of BMs requires key resources as inputs to realize value propositions and value delivery. Key resources include physical, intellectual, human, or financial key resources. Thus, the BM-Miner proxies resources from the SAP ERP system by executing balance sheet reports which comprise both tangible and intangible assets from accounting data (DD6).

Fourth, the creation of value is at the heart of any enterprise. Value propositions solve customer problems or satisfy demands to create value for a customer segment. Value propositions comprise bundles of products and/or related services for which the customer is willing to pay. Examples for value propositions include quantitative constructs such as product price or speed of service, or qualitative constructs such as design or customer experiences. For the data-driven discovery of the value proposition from application systems, the BM-Miner extracts sales data and related information on the product hierarchy (DD7).

Fifth, different customers expect different treatments and different kinds of relationships. The organization needs to establish, maintain and nurse relationships with customer segments to acquire or to retain customers or to improve sales. Examples of customer relationships include personal assistance, self-service, automated services, communities, or co-creation. Information on customer relationships is contained in SAP ERP systems for example in the form of sales organizations, customer classifications, customer contact points, or the duration of customer relationships (DD8).

Sixth, channels bridge the gap between customer segments and value propositions. Channels are the pathways through which value propositions are delivered to the customer segments and include communication as well as sales and distribution channels. These interfaces “provide customer touchpoints” (Osterwalder and Pigneur, 2010) to create awareness for the value propositions or to interact with customers. An organization can deliver value propositions through its own channels (e.g., webshops or retail stores), partner channels (e.g., wholesale distribution), or a combination of both. The BM-Miner retrieves the information on channels from delivery data including sales organizations, delivery types, channels, and routes (DD9).

Seventh, BMs need to serve the demands of at least one customer segment. Osterwalder and Pigneur (2010) propose to improve the ability to satisfy customer segments through the distinction among different segments in terms of customer needs, behaviors, and additional attributes. Examples include segmentation in terms of mass or niche market customers. In SAP ERP systems, customer segments are proxied by the classification of customers and the order information via sales organizations (DD10).

Besides and eighth, the execution of BMs incurs costs in the form of the cost structure. Thus, the data model provides data tables and associated lookup tables to store and identify the cost structure. The BM-Miner retrieves the cost structure of the organization via the purchase information and accounting information on the outflow of resources in balance sheets (DD11).

Ninth, successful BMs create revenue streams from the delivery of the value propositions to customers. Revenue streams include the different possible pricing mechanisms such as asset sales, usage or subscription fees, lending, renting, leasing, or other forms of licensing. Comparably to the cost structure, the BM-Miner retrieves the revenue structure by the inflow of incoming payments and balance sheet data in the SAP ERP system (DD12).

Table 4 contains an overview of the proxies chosen for each building block in the BMC.

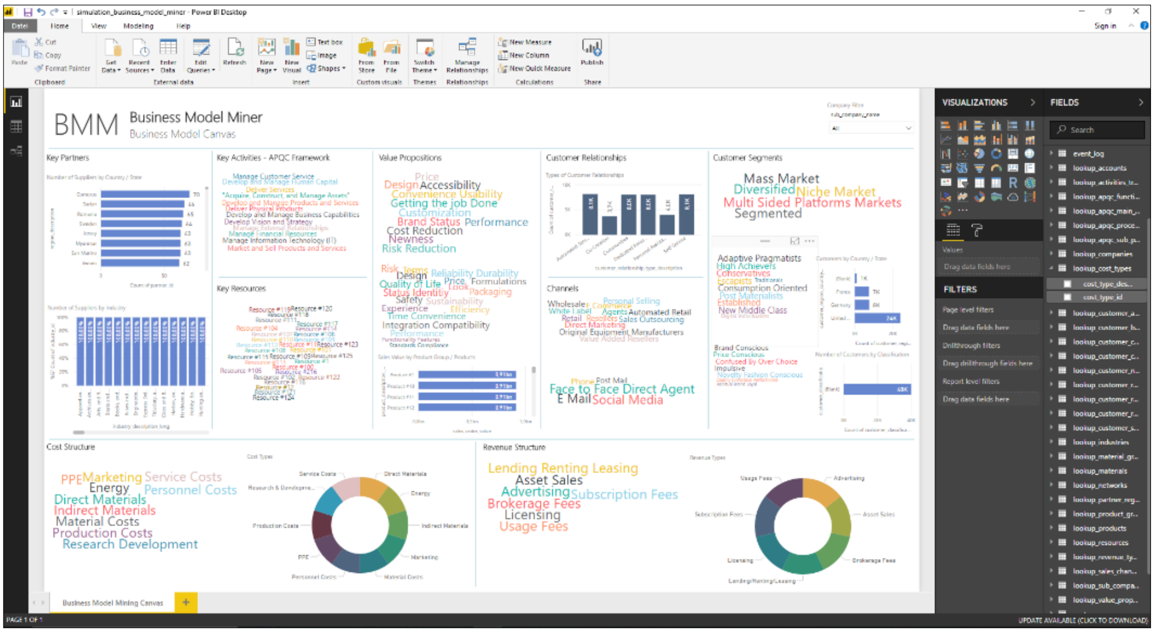
Table 4: Proxies from ERP systems for the BM-related contingency factors

Contingency factors	Proxies (“Design Decisions”) for the BM Components in the BMC
Key Partners (DD4)	Supplier industries, networks, classifications, types, regions, languages geographic supplier information, duration of supplier relationships, procurement transaction data
Key Activities (DD5)	KeyPro-matching of executed transactions in the ERP-system („event log“) to the APQC process framework (APQC, 2017) and importance metrics such as counting the number of executions, human users related to process execution, the involvement of a customer or supplier in the transaction, or a primary versus secondary process classification
Key Resources (DD6)	Tangible and intangible assets from balance sheets
Value Proposition (DD7)	Amount and value of products and services sold (product groups and hierarchies)
Customer Relationships (DD8)	The value generated with customers, repeat buying / single transactions, duration of customer relationships, sales organizations, customer classifications, customer contact points
Channels (DD9)	Amount and value of products and services sold over distribution channels, sales organizations, delivery types, channels, and routes

Contingency factors	Proxies ("Design Decisions") for the BM Components in the BMC
Customer Segments (DD10)	Customer industries, customer classifications, geographic customer information, order information via sales organizations
Cost Structure (DD11)	Procurement data, expenditures from balance sheets
Revenue Structure (DD12)	Sales data, revenues from balance sheets

Data for the prototype implementation in the first design cycle contains BM-related data for three companies in the corporation for a period between 2010 and 2017. Each company is implemented on one SAP R/3 ERP system, such that the BM of the particular company can be distinguished along with the organizational units of the respective SAP systems. Figure 23 contains the instantiation in Microsoft PowerBI based on the randomization of values for reasons of company compliance.

Figure 23: BM Canvas dashboard of the Business Model Miner 1.0 in the first design cycle



For each building block of the BMC, the tool presents word clouds and diagrams. The size of the tags in the word clouds is scaled according to values such as sales or purchase values or numbers such as the volume of products sold or purchased. Users can adjust the level of details and specify the number of elements to be displayed in the word clouds and dashboards (e.g., the top N for each of the proxies). Besides, the screen contains a company code to filter to select the BM of one or more individual companies. Further, the date filter allows selecting BMs over a specific period of time. Each of the dashboards provides the ability of Microsoft PowerBI to filter distinct elements and associated data. For each of the building blocks, an additional detailed analysis dashboard page with further visualizations and drill-down possibilities is provided.

4.2.3 Evaluation: Field Study on Differences between Data-Driven and Non-Data-Driven Approaches to Business Modeling

Gold standard evaluations are frequently used to compare results of technological data-driven solutions against human, non-data-driven solutions. For example, in the context of BPM, “process model matching contests” conduct gold-standard evaluations (Antunes *et al.*, 2015; Cayoglu *et al.*, 2013). Manual approaches to deriving the current BM suffer from several drawbacks, such as user bias and subjectivity, high time expenditure and susceptibility to errors, which ultimately limit their usefulness for decision-making (cf. section 1 and 2.2.3). Therefore, a field evaluation at a manufacturing company at the industry partner was performed to evaluate whether differences exist between human and data-driven perceptions of organizational BMs in the first design cycle. To this end, a non-data-driven BMC created by human business experts and the data-driven BMC provided by the BM-Miner is compared to a "golden standard" BMC created by senior managers at the executive level of the organization. Further, a round of feedback interviews was conducted with managers to receive qualitative feedback on the prototype of the first design cycle as well as directions for future research from business experts. Thus, the evaluation setup contains three groups, i.e. a baseline group for the golden standard, group A for manual non-data-driven creation of BMCs, and group B for feedback.

In the field evaluation, it is expected that differences can be identified between the BM, which is derived using traditional methods, and the data-driven approach, which underlies the "BM-Miner. For that purpose, the BMCs created by group A and the BMC created by the BM-Miner are investigated with regard to 1.) the information contained (‘informativeness’), 2.) the accurately determined BM characteristics (‘accuracy’), 3.) the number of elements commonly identified in both approaches (‘common elements’), and 4.) the number of correct elements in a BMC multiplied by the level in a BM taxonomy (‘taxonomy-valued informativeness’) to value responses according to their informative value to account for the different levels of detail of responses. For example, in the building block “key partners”, interviewees could give only a high-level and superficial response “supplier” or cite the actual name of a supplier, which implies a more in-depth knowledge on the BM of the organization. In order to evaluate the degree of *informativeness* of a BMC, the number of correctly identified elements was compared to the golden standard BMC. *Accuracy* was defined as the percentage of correct elements in the BMC in relation to total elements (evaluated by an independent third person). *Common elements* described the number of identical elements contained in two BMCs. Besides, *taxonomy-valued informativeness* is defined as the sum of correct elements multiplied with their respective levels in the BM taxonomy.

4.2.3.1 Interview Execution

In total, 21 business experts (23.8% female, 76.2% male) from the manufacturing corporation and its IT service provider participated in the field evaluation. The participants had an average working experience of 8.5 years in the manufacturing corporation (Min = 1, Max = 28 years, Std.Dev = 7.36 years). The field study was conducted at the workplace of the participants. Participants in all groups were given an introduction into BMs, Business modeling and the BMC concept. Interviewees were then presented with an abstract definition of each of the building blocks from the BMC by Osterwalder and Pigneur (2010). Afterward, interviewees were shown an exemplary BMC for Apple iTunes from Osterwalder and Pigneur (2010) to clarify the concept with the example of a commonly known enterprise. Interview partners then had to confirm they understood the concept and the meanings of the building blocks.

First, the golden standard BMC (baseline group) for the company was created by four senior managers with at least 10 years of working experience in the company (Average = 13.75 years, Std.Dev = 6.24 years). Each member of the baseline group had to create the BMC individually. All BMCs of the baseline group were then merged into one comprehensive BMC for the company by the authors of this paper. Second, group A who had to create a BMC manually for the company comprised of 12 managers and employees (33.3% female, 66.6% male) with an average working experience of 7.82 years (Std.Dev = 8.69 years). Third, the BM-Miner was applied in an SAP R/3 ERP system for one company of the manufacturing corporation to create the data-driven BMC. Fourth, interviews with the members of group B were conducted to receive additional feedback on the concept of BMM, the BM-Miner prototype, and to derive possible directions for improvement of the concept as well as for the software instantiation in the second design cycle. On average, the interviews lasted 23 minutes per interview partner. Group B contained 5 experts (20% female, 80% male) with an average working experience of 5.8 years (Std.Dev. = 1.1 years) in the organization. They were presented with the results of the BM-Miner for their company. Interviewees were presented the BMC dashboard delivered by the BM-Miner for their company and asked to comment on the entries in the dashboard in the first part of the semi-structured interviews. In the second part, interviewees were asked in an open interview part to state their opinion on the concept and the BM-Miner freely.

4.2.3.2 Hypotheses Formulation

Accordingly, the following hypotheses were formulated in the field study:

H1: Using the BM-Miner leads to a higher degree of informativeness of the created BM.

H2: Using the BM-Miner leads to higher accuracy regarding the BM elements.

4.2.3.3 Data Analysis and Interpretation

The analysis of the BMCs created by baseline group, group A and the BM-Miner was performed individually by the authors to prevent an author bias. First, the taxonomy for the construct taxonomy-valued informativeness was created. All responses per building block were merged into one list which was sorted into a hierarchical taxonomy by two different persons independently to create the taxonomy. The final merging of the two taxonomies was then performed by a third person. The final taxonomy contains a branch for each of the building blocks with a total of 330 non-data-driven and 33.080 data-driven elements. Detailed results are reported in table 5.

Table 5: Descriptives of the items in the BM taxonomy for taxonomy-valued informativeness

Building block	No. non-data-driven	No. data-driven	Common	Total	Levels
Key Partners	52	32113	15	32150	4
Key Activities	32	37	11	58	3
Key Resources	33	45	9	69	3
Value Propositions	44	17	7	54	3
Customer Relationships	23	1	4	20	2
Channels	21	78	10	89	3
Customer Segments	35	18	0	53	5
Cost Structure	58	689	27	720	4
Revenue Structure	32	82	12	102	3
Total	**330**	**33080**	**95**	**33315**	**-**

Results reveal several differences in terms of accuracy, informativeness and taxonomy-valued informativeness among the BMCs created. While the software performs better against both the gold standard and the non-data-driven BMC in building blocks which depend on operational data and a large number of individual elements such as cost and revenue structure, partners, channels, or resources, the artifact achieves comparably lower results in customer relationships, customer segments and the value proposition that are harder to get from data due to a higher degree of qualitative elements which cannot be captured by data (such as “high quality”, “intense relationships”, “young customers”).

Table 6: Evaluation results (average values) for (1) = accuracy; (2) = informativeness; (3) = taxonomy-valued informativeness

	Golden Standard (Baseline)			Manual BMC (Group A)			Data-Driven BMC (BMM)		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Channels	1.00	11.00	18.00	0.97	5.61	9.13	1.00	78	156
Cost Structure	1.00	15.00	40.00	0.95	9.48	20.69	1.00	689	1148.33
Customer Rel.	1.00	8.00	11.00	0.97	4.70	6.48	1.00	1	2
Customer Seg	1.00	12.00	41.00	0.99	6.79	20.92	1.00	18	36
Key Activities	1.00	8.00	20.00	1.00	6.08	11.54	1.00	37	68
Key Partners	1.00	20.00	42.00	0.92	10.36	20.39	1.00	32.113	64226
Key Resources	1.00	12.00	26.00	1.00	7.23	13.11	1.00	45	135
Revenue Structure	1.00	2.00	5.00	0.99	2.56	4.49	0.60	49	136.67
Value Prop.	1.00	18.00	38.00	1.00	9.34	18.36	0.88	15	34

Thus, findings in table 6 are interpreted as partial support for H1 and H2 and as evidence for a complementary role of BMM which provides insights into BMs in addition to human, non-data-driven knowledge on BMs.

In the feedback interviews lead with group B, the structure of some building blocks such as the cost and revenue structure were found to contain too many information entries and thus were perceived confusing. The experts therefore proposed to focus on visualizing only the most critical information according to value and volume-based constructs, and to additionally provide a drill-down functionality that allows for further exploration of the building blocks if required. Besides, experts wished for implementation of the BM-Miner to mine BMs in real-time for monitoring in daily operations and to immediately discover deviations from a to-be BM. In addition to the functionality to filter parts of the BM in the BM-Miner interface, experts further proposed to implement a real-time business simulation function for demonstrating the effects on the BM when a component, for example the price of a product, is changed or a product is removed from the portfolio.

4.3 Design Cycle 2: Business Model Miner 2.0

4.3.1 Problem Awareness

Components of a BM are interconnected to each other (Osterwalder and Pigneur, 2013). For example, a sold product of the organization might impact the BMC as follows: the product (e.g., kitchen sink) requires inputs (e.g., stainless steel) purchased from partners (e.g., suppliers), which are then processed via the key activities (e.g., manufacturing processes) into the final product using key resources (e.g., production machinery and employees) of the organization. The product provides a value proposition (e.g., high-quality kitchen sinks) to the customer segments (e.g., wealthy individuals) and is delivered via channels (e.g., direct shipment via online purchasing) in a particular relationship (e.g., one-time buying), which creates cost (e.g., costs of goods sold) and revenues (e.g., sales of goods) for the organization.

4.3.2 Suggestion: Additional Design Requirements

BMM systems require a generic reference data model which is able to consolidate BM-related data irrespective of the underlying application systems and to connect data from different BM component to each other to reflect these relationships between different components of the BM in a data perspective. Thus, an additional meta requirement MR4 was introduced in the second design cycle. The fourth meta requirement requires a universally applicable BMM data model including data tables and relationships between the data and BM components.

MR4: "To mine BMs from application systems, a reference data model including data tables, lookup tables, and relationships is required."

Following MR2 which calls for the provision of a data management layer, a further design principle was introduced to account for the data model in the data management layer (DP2.1):

DP2.2: "The data management layer needs to provide a reference BMM data model to store data from multiple source application systems."

In combination with DP3.2 which selects the BMC as a visualization template for the BM, the data model needs to adhere to the structure and the requirements of the building blocks in the BMC. DP4.1 consequently demands:

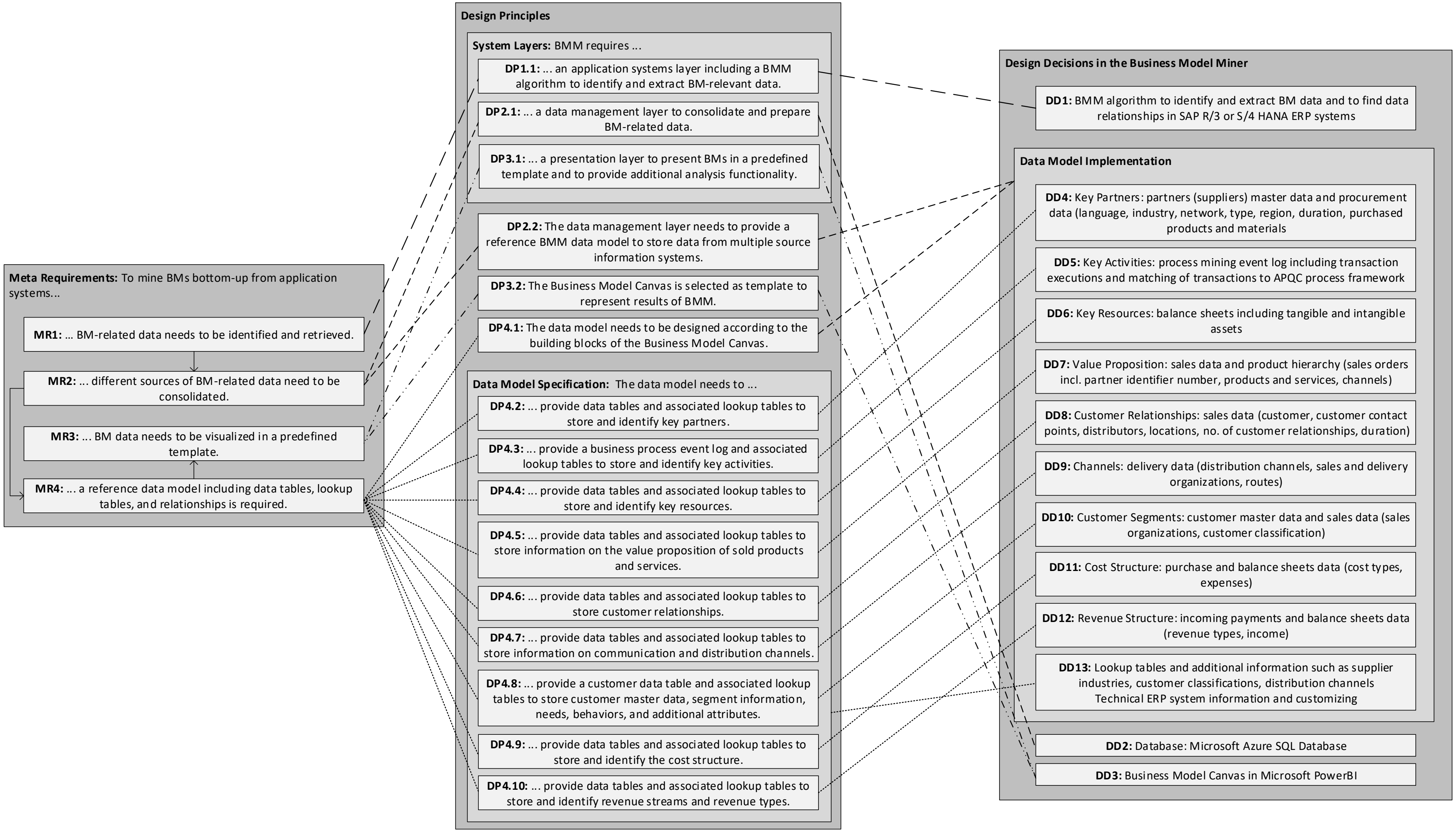
DP4.1: "The data model needs to be designed according to the building blocks of the BMC."

To realize DP4.1, a set of adjacent design principles were formulated to determine the content of the data model according to the contents of the BMC.

Table 7: Design principles for the data model in the second design cycle

BMC Building Bock	**Design Principle for the data model**	
	DP	The data model needs to provide…
Key Partners	DP4.2	…data tables and associated lookup tables to store and identify key partners.
Key Activities	DP4.3	…a BP event log and associated lookup tables to store and identify key activities.
Key Resources	DP4.4	… data tables and associated lookup tables to store and identify key resources.
Value Proposition	DP4.5	… data tables and associated lookup tables to store information on the value proposition of sold products and services.
Customer Relationships	DP4.6	… data tables and associated lookup tables to store customer relationships.
Channels	DP4.7	… data tables and associated lookup tables to store information on communication and distribution channels.
Customer Segments	DP4.8	… a customer data table and associated lookup tables to store customer master data, segment information, needs, behaviors, and additional attributes.
Cost Structure	DP4.9	… data tables and associated lookup tables to store and identify the cost structure.7
Revenue Structure	DP4.10	… data tables and associated lookup tables to store and identify revenue streams and revenue types.

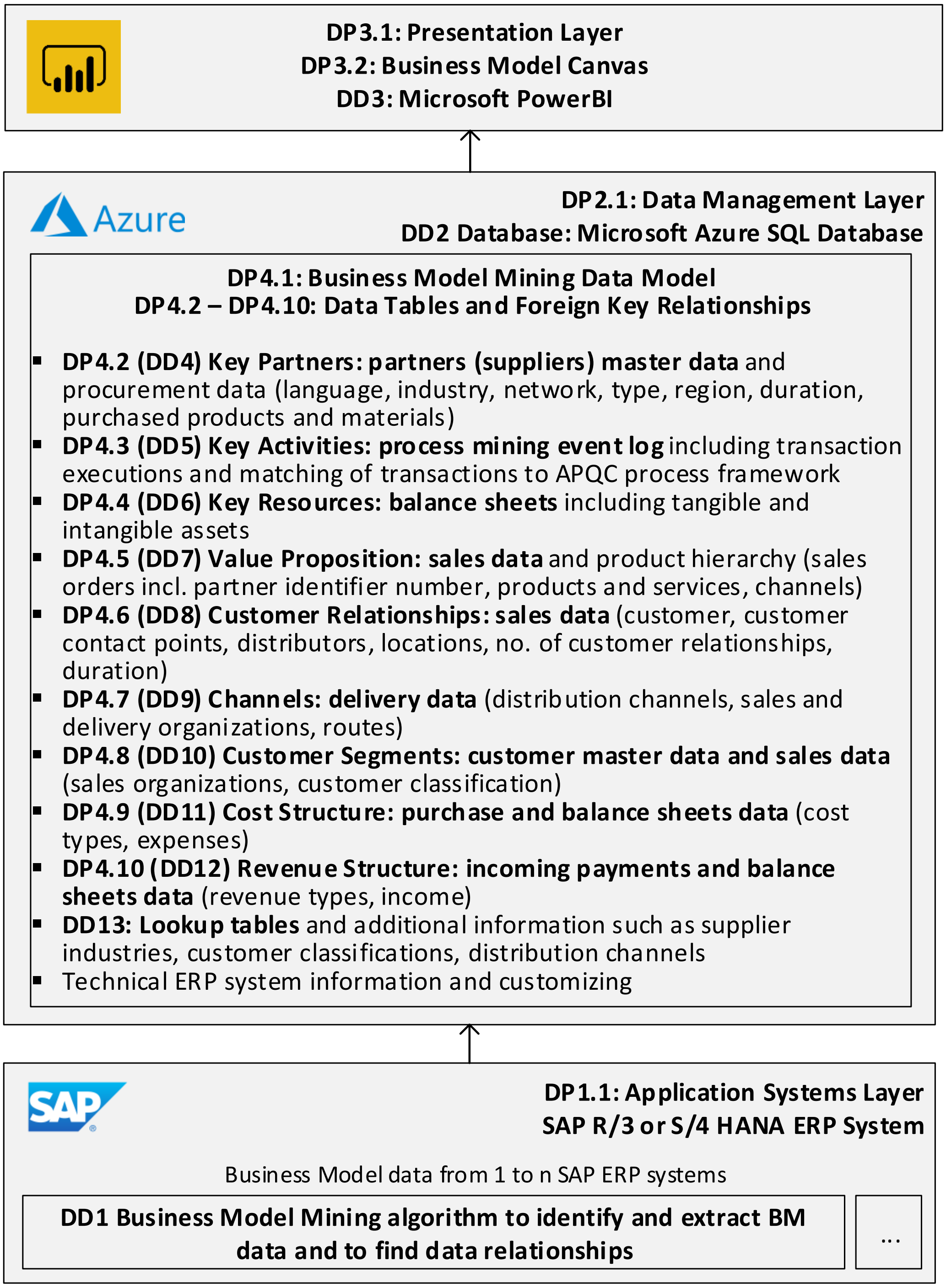
Figure 24: Overview over design requirements (meta requirements, design principles, and design decisions)



4.3.3 Development: Instantiation of the "Business Model Miner 2.0"

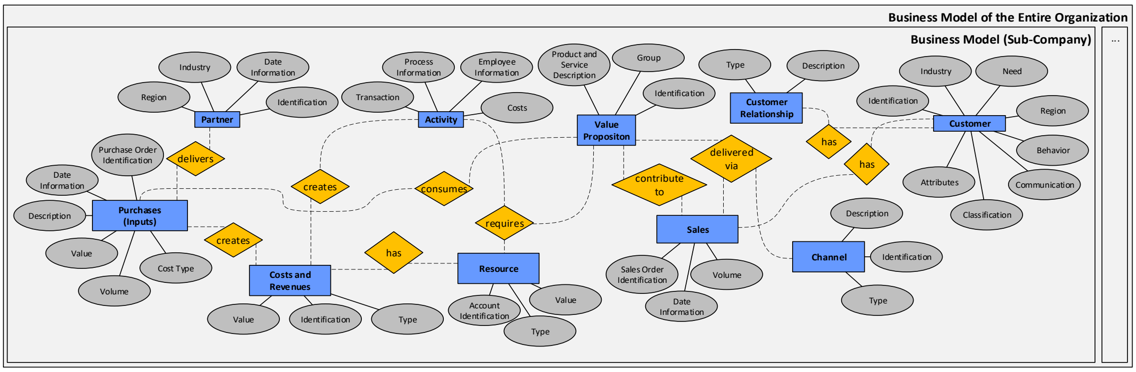
The final prototype after the changes and additional requirements in the second design cycle is conceptualized in figure 25.

Figure 25: Design requirements (conceptualization) of the final Business Model Miner



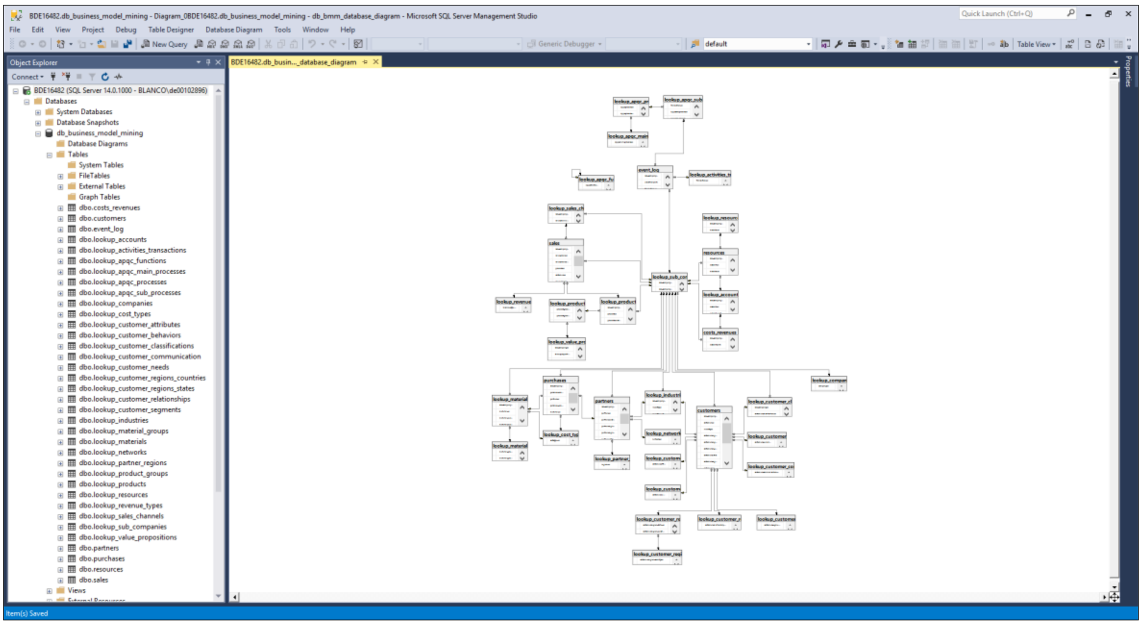
The implementation of the data model according to the design requirements consists of 10 fact tables and 39 lookup tables which are connected through foreign key relationships to the fact tables as outlined in the following entity-relationship diagram in figure 26.

Figure 26: Entity relationship diagram of the BMM data model



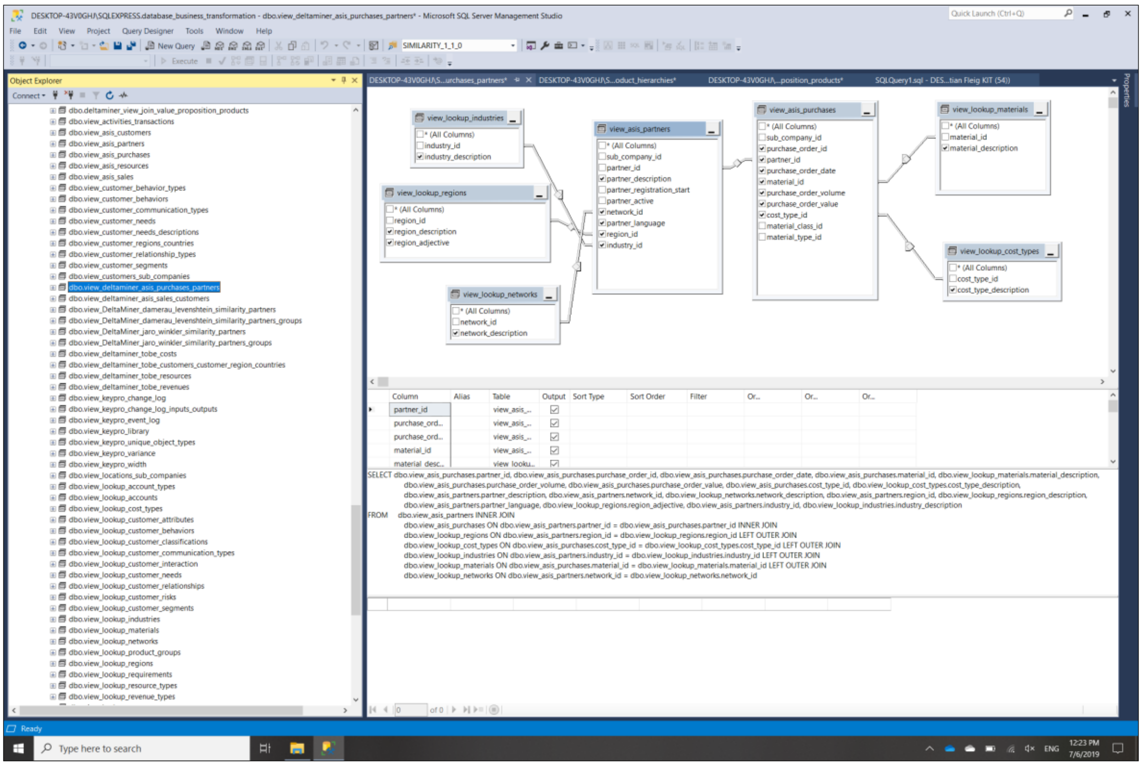
The data management layer (DP2.1) including the data model (DP4.1) with data tables and relationships (DPs 4.2-4.10) in the final BM-Miner instantiation is implemented in Microsoft Azure SQL in Microsoft Server Management Studio.

Figure 27: Database diagram in design cycle 2 (data model for BMM)



The data model further includes 144 views to relate and merge data across the different components of the BM to each other. For example, figure 28 contains a view which relates purchasing data from key partners and attaches additional information such as materials, cost types, industries, regions, and networks.

Figure 28: Exemplary view including data tables and relationships in the database



In the presentation layer (DP3.1), the interface of the BM-Miner in Microsoft PowerBI provides one summary dashboard which imitates the traditional BMC and 11 detailed dashboards for the individual analysis of each building block. Each dashboard element provides the ability to filter entries. For example, the BM-Miner thus allows selecting BMs by a company to analyze and compare BMCs and individual elements. Additionally, the tool can be used to explore the relationship between the elements through the connections in the data model. For example, by filtering out individual elements such as products, costs, revenues, customer segments, channels etc., the effect on the remaining BM can be analyzed for strategic "what-if" decision-making. Furthermore, each dashboard provides a time filter to analyze time developments for the individual building blocks. Figure 29 to figure 33 provide screenshots of the implementation for an education SAP R/3 system based on data of a fictitious bicycle company. Additional screenshots of the dashboards are attached in section 10.1 in the appendix.

Figure 29: Business Model Miner: BM Canvas summary dashboard

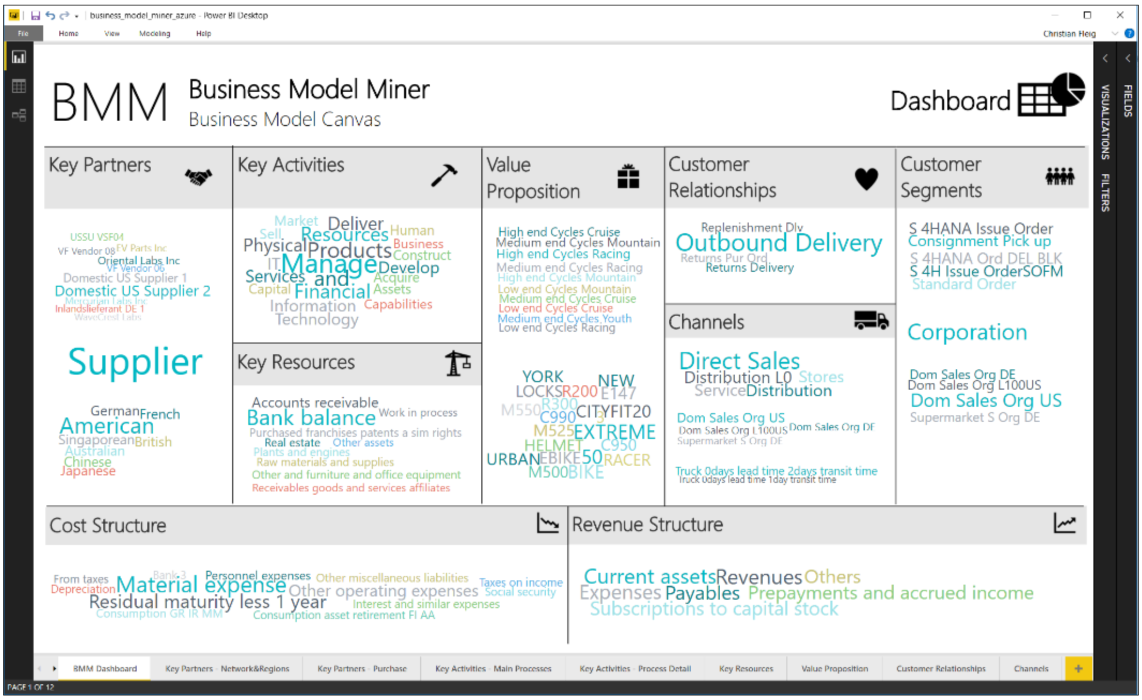


Figure 30: Business Model Miner dashboard: value proposition

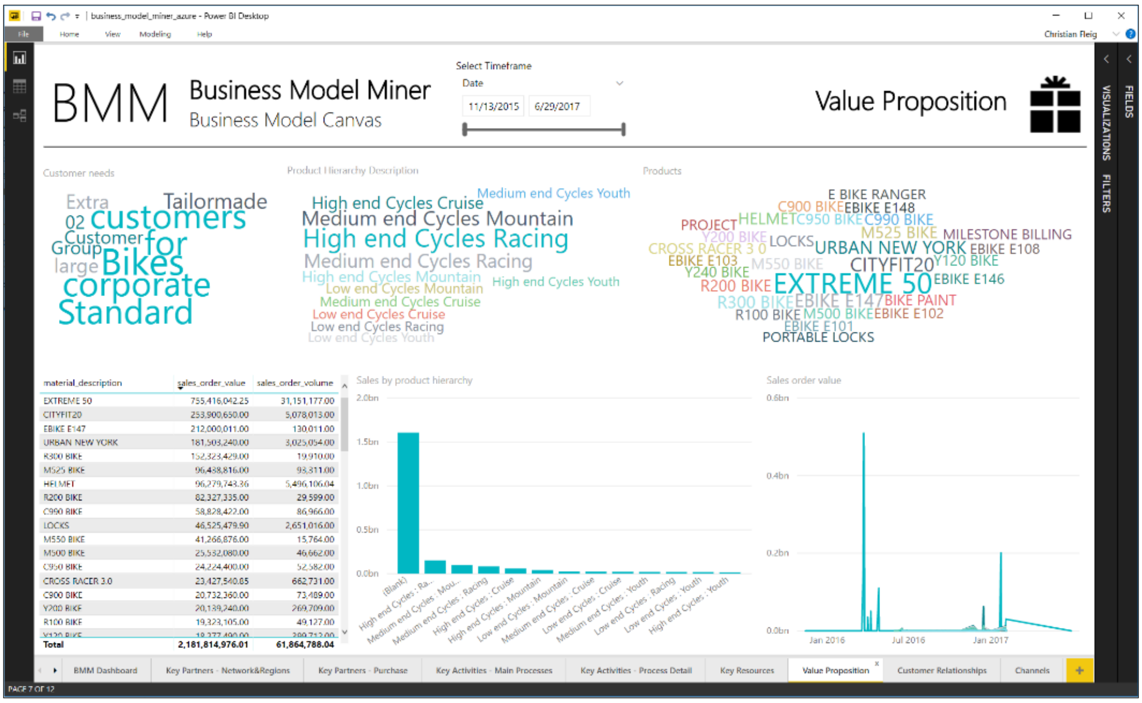


Figure 31: Business Model Miner dashboard: key partners (filtered for purchased brake sets)

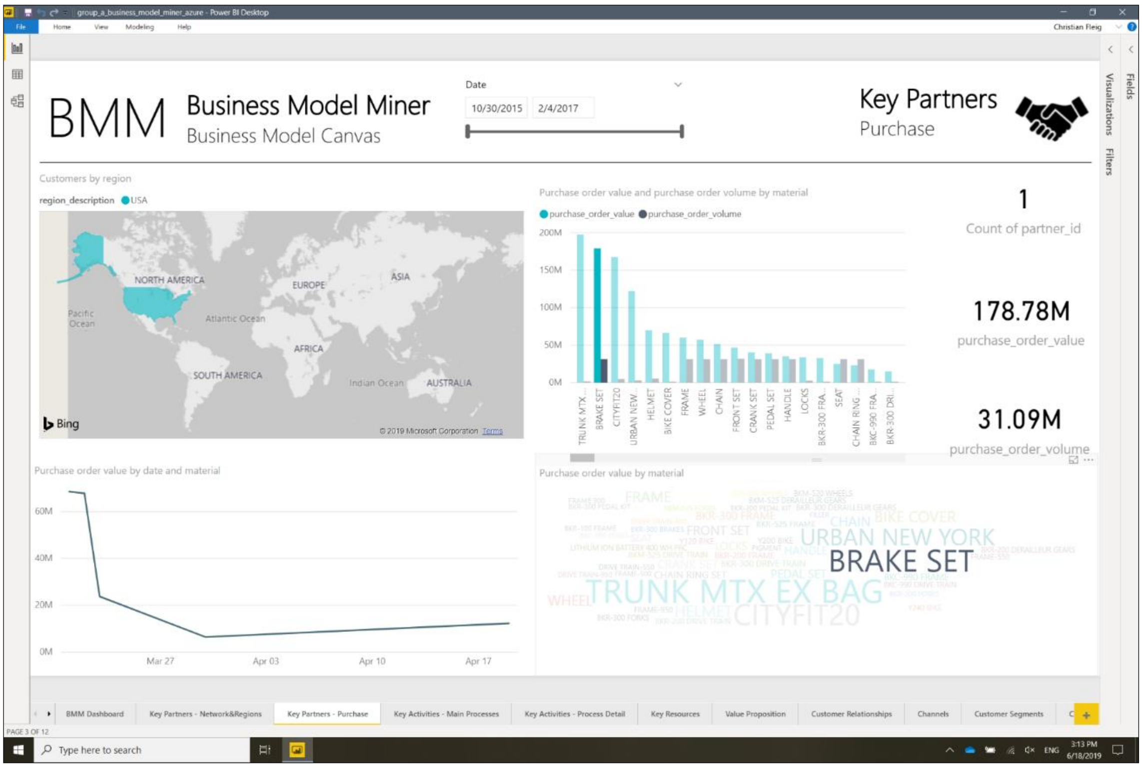


Figure 32: Business Model Miner dashboard: customer relationships

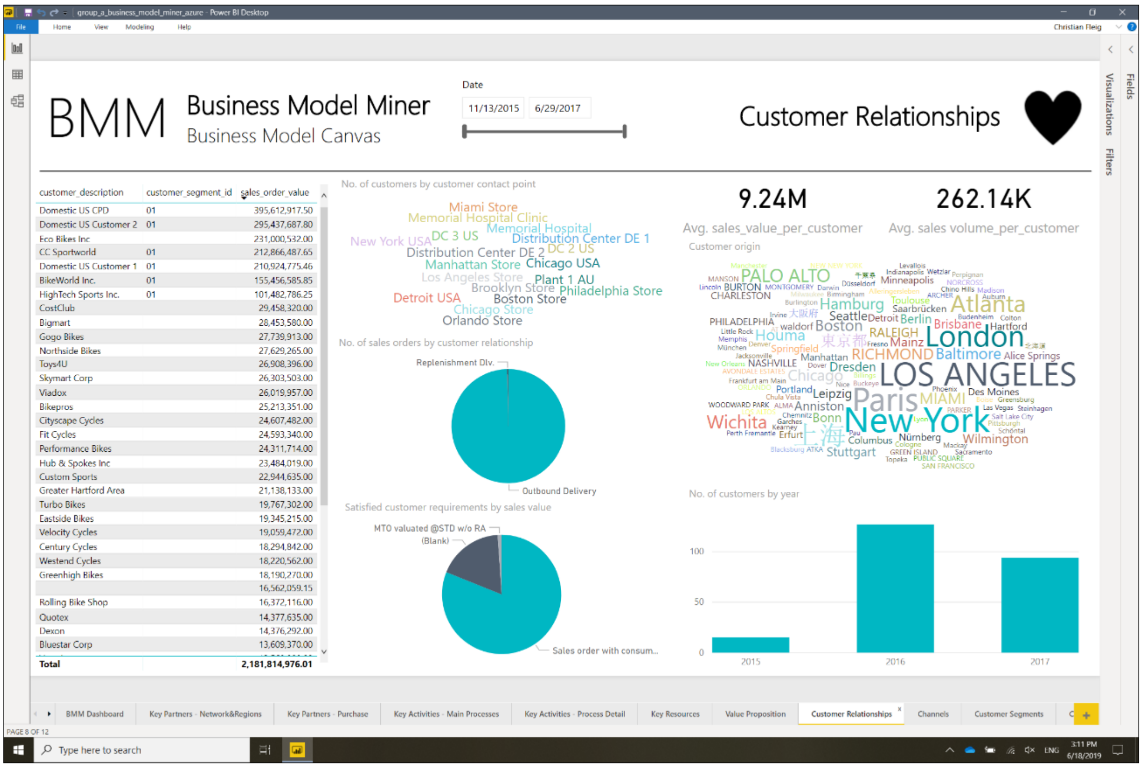
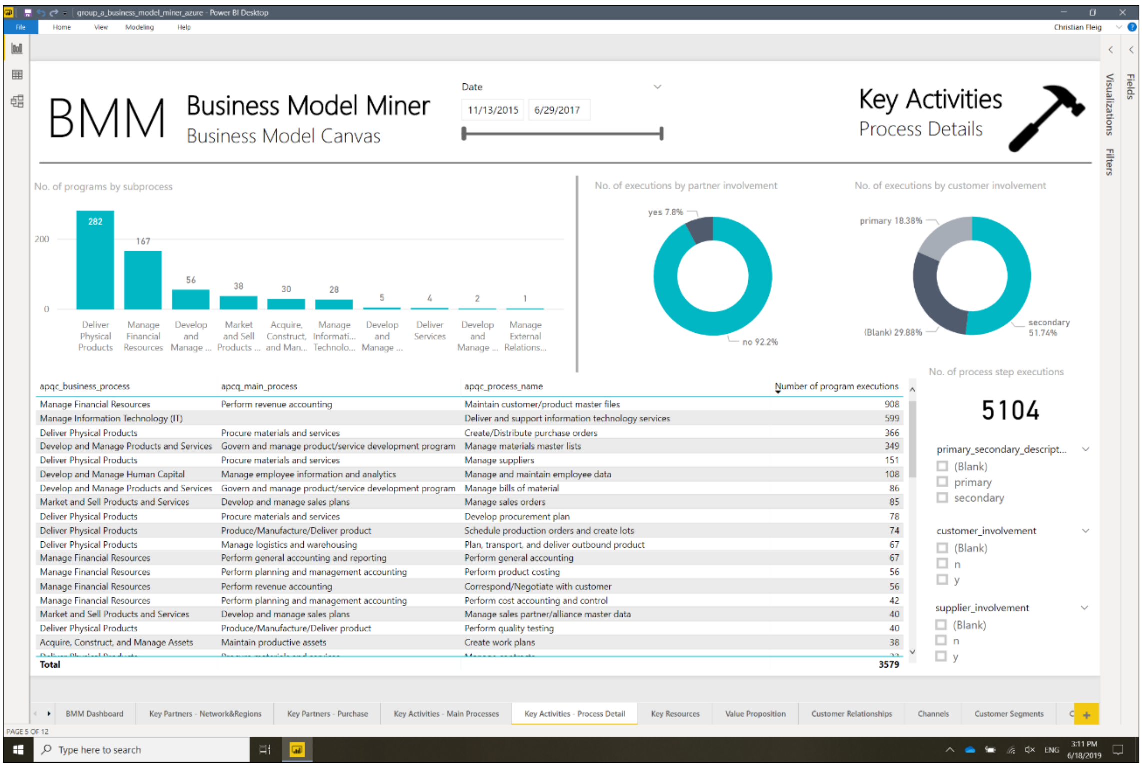


Figure 33: Business Model Miner dashboard: key activities



4.3.4 Laboratory Evaluation on Comprehension

The goal of the BMM system is to provide a software prototype for both experts as well as novices to understand the BM. Thus, a controlled between-subject laboratory experiment among students was conducted as a second evaluation within DSR project 1 to verify that BMM might contribute to the comprehension among novices in four groups. Due to their limited prior knowledge of BMs as well as experiment processes, students are generally acknowledged as an adequate sample in design-oriented experiments (Burton-Jones and Meso, 2008; Morana *et al.*, 2019).

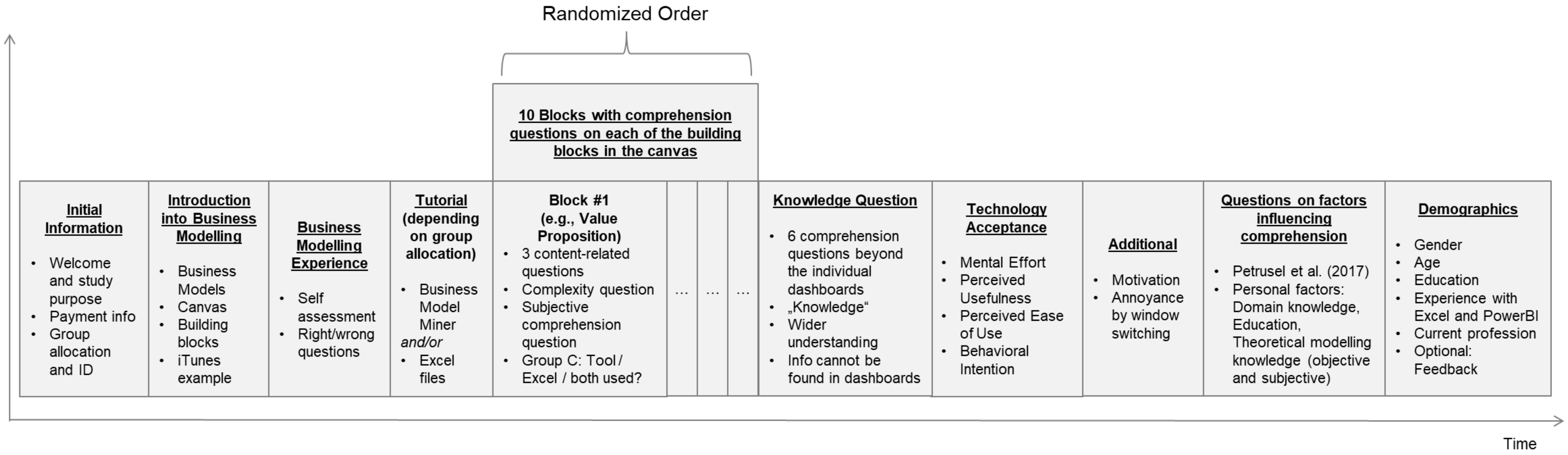
4.3.4.1 Experiment Setup

Group A (baseline group) received the BM-related data in Microsoft Excel spreadsheets without the support of a data-driven BM software. For comparison between spreadsheet tables in Group A and the functionality provided by the data model behind the BM-Miner, Group B received the same BM data as the other groups, but dashboards arranged in interactive tables with the BM mining data model. Further, group C received the complete functionality of the artifact including interactive dashboards. Finally, group D provides subjects with the choice between Microsoft Excel as in group A or the BM-Miner as in group C. Screenshots for each group specification are provided in section 10.2 in the appendix.

The sessions were conducted at an experimental lab at the university. The experiment was entirely survey-based. The survey was implemented in the open-source platform LimeSurvey[11] and is attached in the online appendix of this dissertation. Subjects were randomly assigned to one of the four groups. After receiving initial information, subjects were given an introduction into business modeling including BMs and the BMC with an Apple iTunes example taken from Osterwalder and Pigneur (2010). Afterward, subjects were asked questions concerning their subjective self-assessment of their Business modeling experience and asked objective right/wrong questions based on the introductory information. Further, subjects received a group-specific tutorial into the BM-Miner and/or the required functions of Microsoft Excel. In the following, subjects were presented ten blocks in randomized order with comprehension questions on each of the building blocks of the BMC plus the aggregated BMC dashboard to prevent position and carry-over effects due to the order of comprehension questions (cf. section 6.2.3.1) (Christensen, Johnson and Turner, 2011; Clark-Carter, 2004, 2009). Each block of the comprehension questions comprised three content-related questions plus a question on subjective comprehension and a question asking for the perceived complexity of the question. In group C, subjects were additionally asked which medium was used to answer the questions for the respective building block. In addition to the comprehension questions on the nine building blocks, subjects were asked six comprehension questions concerning a more comprehensive understanding of the BM which could not be answered with an individual dashboard. Subjects were further asked for the subjective comprehension of the entire medium in terms of constructs that impact comprehension (complexity, number of elements, usability, wording (Mendling, Strembeck and Recker, 2012; Petrusel, Mendling and Reijers, 2017)). Finally, subject demographics gathered attributes on gender, age, education, occupation, as well as experience with Microsoft Excel and PowerBI. Subjects were given the possibility to provide feedback at the end of the experiment.

[11] https://www.limesurvey.org/

Figure 34: Laboratory experiment structure outline



4.3.4.2 Hypotheses Formulation

Building on prior research investigating how to measure comprehension objectively (Dikici et al. 2018), the evaluation hypothesizes that the BM-Miner increases BM comprehension even among non-expert users compared to standard approaches that are used in this context today such as spreadsheet-based analyses. The following hypotheses in the hypotheses matrix are formulated for the objective comprehension constructs in the experiment:

Table 8. Hypotheses to the objective comprehension constructs

	Effectiveness	Efficiency	Relative Efficiency
Group A: Excel	*Hypothesis H(A): compared to all other groups, subjects in group A without the BM-Miner perform relatively worst*		
	$H^{A}_{Effect.}$	$H^{A}_{Effic.}$	$H^{A}_{Rel.Effic.}$
Group B: Data Model	*Hypothesis H(B): subjects in group B with the BMM data model perform better than the baseline group A*		
	$H^{B}_{Effect.}$	$H^{B}_{Effic.}$	$H^{B}_{Rel.Effic.}$
Group C: BM-Miner (Dashboard)	*Hypothesis H(C): subjects in group C with the BM-Miner including dashboards perform better than groups A and B*		
	$H^{C}_{Effect.}$	$H^{C}_{Effic.}$	$H^{C}_{Rel.Effic.}$
Group D: BM-Miner & Excel	*Hypothesis H(D): subjects in group D perform relatively better than the baseline group A and group B with the data model, but relatively worse than group C with the BM-Miner*		
	$H^{D}_{Effect.}$	$H^{D}_{Effic.}$	$H^{D}_{Rel.Effic.}$

4.3.4.3 Data Analysis and Interpretation

Results are based on a comparison of mean values between the four different groups for the dependent variables *effectiveness*, *efficiency*, and *relative efficiency*. As dependent variables are measured on a continuous scale, the independent variable consists of two or more categorical groups, and observations are independent, the assumptions for a one-way ANOVA and Bonferroni post-hoc tests are validated. and significant outliers according to Field, Miles and Field (2012) are removed.

4.3.4.4 Sample Descriptives

Before the outlier removal, the initial pool of subjects comprised of 156 subjects. Incomplete responses (n = 0) and responses from participants who experienced technical problems or who interrupted or did not complete the experiment (n = 3) were removed. Further, outlier responses in relative efficiency with a z-score higher than 3.29 were eliminated (n = 2). Finally, responses from subjects who clicked through the survey or who answered the control question incorrectly were further removed (n = 9). Following the removal of outliers, group A comprised =32, group B = 35, group C = 38 and group D = 37 subjects.

The final subject pool comprised n = 142 subjects (140 students, 1 out of work, 1 employed for wages). Among subjects, 52 are females (36.62%) and 90 (63.38%) males with 66.19% of subjects at the age of 18-24 years, 30.99% of subjects between 25-29 and the remainder of 2.82% being older than 30 years. Subjects indicated a mean experience of 3.19 with Microsoft Excel and 1.54 with Microsoft PowerBI on a 1-5 Likert scale. Further, 27.47% indicated they were only motivated extrinsically, 69.72% were also intrinsically motivated to participate in the experiment by non-monetary reasons.

4.3.4.5 Assumptions Tests

In the assumptions tests, a Shapiro-Francia W' tests for normality and Levene tests for homogeneity of variances were conducted. Results for the analysis of each dependent variable are presented in table 9.

Table 9: Overview of assumptions tests

	Normality							Equality of Variances	
	Shapiro-Francia Test				Skewness & Kurtosis Tests			Levene Test	
	W'	V'	z	Prob > z	Pr (Skewness)	Pr (Kurtosis)	Hypothesis of Normality	Pr > F (W0)	Hypothesis of Homogeneity of Variances
Effectiveness	0.98336	2.027	1.429	0.07648	0.0624	0.1577	Supported	0.09016383	Supported
Efficiency	0.96624	4.113	2.860	0.00212	0.0051	0.5918	Rejected	0.14749076	Supported
Relative Efficiency	0.97716	2.782	2.069	0.01926	0.0104	0.9924	Rejected	0.10426673	Supported

4.3.4.6 Results

4.3.4.6.1 Effectiveness

For effectiveness, data is normally distributed in the Shapiro-Francia test ($p > z = 0.07648$, pr(skewness) = 0.0624, pr(kurtosis) = 0.1577) and exhibits homogeneity of variances in the Levene test (pr > F = 0.09016). Thus, assumptions for a one-way ANOVA are satisfied.

Figure 35: Bonferroni post-hoc test for pairwise comparison for effectiveness

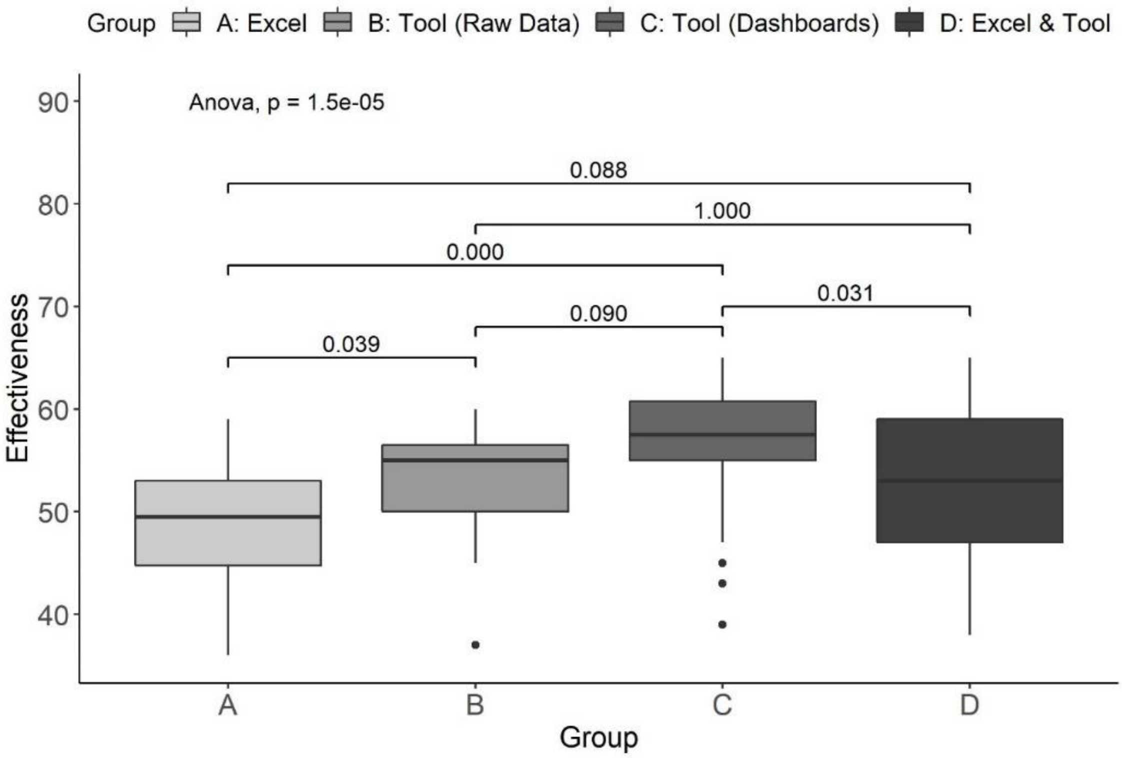


Table 10: Results of the one-way ANOVA for effectiveness

Source	Analysis of Variance				
	SS	**Df**	**MS**	**F**	**Prob > F**
Between Groups	1041.90001	3	347.300003	9.14	0.0000
Within Groups	5242.04365	138	37.9858236		
Total	6283.94366	141	44.5669763		
Bartlett's test for equal variances: chi2(3) = 4.7734 Prob>chi2 = 0.189					

In order to compare groups individually against each other, Dunn-Bonferroni post-hoc tests (Dunn, 1964) are conducted to locate where significant differences between the groups occur, while preventing family-wise type I error for multiple comparisons due to a Bonferroni correction (Field, Miles and Field, 2012).

Table 11: Bonferroni post-hoc test for pairwise comparisons in effectiveness

	Contrast	**Std. Error**	**t**	**P > | t |**	**[95% Confidence Interval]**	
Group B vs.A	4.161607 *	1.507437	2.76	0.039	.1264643	8.19675
Group C vs.A	7.71875 ***	1.478744	5.22	0.000	3.760413	11.67709
Group D vs.A	3.678209	1.487851	2.47	0.088	-.3045054	7.660924

	Contrast	Std. Error	t	P > | t |	[95% Confidence Inter-val]	
Group C vs.B	3.557143	1.443931	2.46	0.090	-.3080052	7.422291
Group D vs.B	-.4833977	1.453256	-0.33	1.000	-4.373508	3.406712
Group D vs.C	-4.040541 *	1.423471	-2.84	0.031	-7.850922	-.2301587

Subjects in the Excel baseline group A performed worst with a mean of 48.78 correct answers (Std.Dev = 5 .078), followed by group D (choice between Excel and software artifact) with a mean of 52.46 (Std.Dev = 7.35) correct answers. Group B (data model in BMMiner) achieved a mean of 52.94 (Std.Dev = 5.81) correct responses. Group C with the complete tool functionality performed best with a mean of 56.5 (Std.Dev = 6.04). Further, to determine whether the mean differences between the individual groups are significant, a Bonferroni post-hoc test for pairwise comparisons was employed. In particular, the mean difference between group C and the baseline group A is significant at the 1%-level, with the BMMiner group C achieving a higher mean of 7.72. The effect size for the one-way ANOVA is at Eta-squared of 16.58%. However, group B with mined BMs in tabular form is only weakly significant at the 5%-level when compared to the baseline group. In addition to the Bonferroni post-hoc test, a series of alternative post-hoc tests with similar results was performed. Additional post-hoc tests are reported in table 12.

Table 12: Overview of alternative post-hoc tests for pairwise comparisons for effectiveness

	Contrast	Std. Error	t	P > | t |					
				Sidak	Scheffe	Tukey	Student-Newman-Keuls	Duncan	Dunnett
Group B vs.A	4.161607	1.507437	2.76	0.039 *	0.059	0.033 *	0.018 *	0.009 **	0.018 *
Group C vs.A	7.71875	1.478744	5.22	0.000 ***	0.000 ***	0.000 ***	0.000 ***	0.000 ***	0.000 ***
Group D vs.A	3.678209	1.487851	2.47	0.085	0.112	0.069	0.015 *	0.015 *	0.039 *
Group C vs.B	3.557143	1.443931	2.46	0.087	0.114	0.070	0.015 *	0.015 *	-
Group D vs.B	-.4833977	1.453256	-0.33	1.000	0.990	0.987	0.740	0.740	-
Group D vs.C	-4.040541	1.423471	-2.84	0.031 *	0.049 *	0.027 *	0.014 *	0.007 **	-

4.3.4.6.2 Efficiency

Concerning efficiency, the Shapiro-Francia W' test rejected the assumption of normally distributed data ($p > z = 0.00212$, pr(skewness) = 0.0051, pr(kurtosis) = 0.5918). Thus, a nonparametric Kruskal-Wallis test and a Bonferroni post-hoc test were performed to determine the significance of pairwise mean comparisons.

Table 13: Kruskal-Wallis test on efficiency

	Kruskal-Wallis Test on Efficiency	
	Observations	**Rank Sum**
Group A: Excel	32	3377.00
Group B: Data Model	35	2424.00
Group C: BM Miner (Dashboard)	38	2014.00
Group D: BM Miner & Excel	37	2338
Chi-squared = 31.201 with 3 d.f. Probability = 0.0001 Chi-squared with ties = 31.201 with 3 d.f. Probability = 0.0001		

Figure 36: Bonferroni post-hoc test for pairwise comparison in efficiency

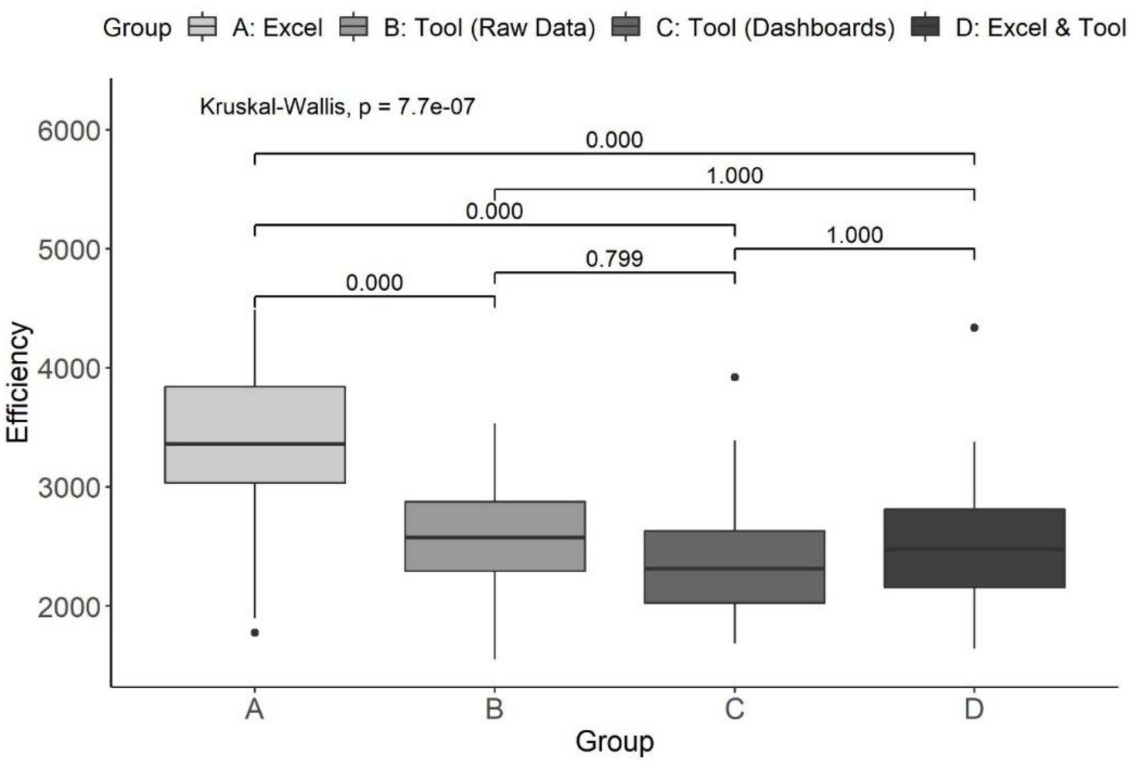


Table 14: Bonferroni post-hoc test for pairwise comparison in efficiency

	Bonferroni Pairwise Comparison of Efficiency					
	Contrast	Std. Error	t	P > | t |	[95% Confidence Interval]	
Group B vs.A	-11.76947 ***	2.35277	-5.00	0.000	-18.06742	-5.471517
Group C vs.A	-15.17365 ***	2.307987	-6.57	0.000	-21.35172	-8.995575
Group D vs.A	-12.83099 ***	2.322201	-5.53	0.000	-19.04711	-6.614871
Group C vs.B	-3.404181	2.253651	-1.51	0.799	-9.436807	2.628445
Group D vs.B	-1.061526	2.268206	-0.47	1.000	-7.133112	5.010061
Group D vs.C	2.342655	2.221718	1.05	1.000	-3.604494	8.289803

Subjects in the Excel baseline group required a mean of 55.16 minutes to answer comprehension questions (Std.Dev = 12.11), while subjects in group B required 43.38 minutes (Std.Dev = 8.07). Group C needed 39.99 minutes (Std.Dev = 8.82), while the choice group D required a mean of 42.33 minutes (Std.Dev = 9.32). Differences between the treatment groups with the BMMiner artifact are significant at the 1%-level, with the data model group B answering the questions 11.77 minutes faster than the baseline group. Group C takes 15.17 minutes less than the Excel group. Group D with a choice between Excel and the artifact further comprehends the BM 12.83 minutes faster than the baseline group. However, the difference between the data model group B and group C with graphical dashboards is not significant. Alternative post-hoc tests are reported in table 15.

Table 15. Overview over alternative post-hoc tests for pairwise comparisons

	Post-Hoc Tests for Pairwise Comparisons								
				P > | t |					
	Contrast	Std. Error	t	Sidak	Scheffe	Tukey	Student-Newman-Keuls	Duncan	Dunnett
Group B vs.A	-11.76947	2.35277	-5.00	0.000 ***	0.000 ***	0.000 ***	0.000 ***	0.000 ***	0.000 ***
Group C vs.A	-15.17365	2.307987	-6.57	0.000 ***	0.000 ***	0.000 ***	0.000 ***	0.000 ***	0.000 ***
Group D vs.A	-12.83099	2.322201	-5.53	0.000 ***	0.000 ***	0.000 ***	0.000 ***	0.000 ***	0.000 ***
Group C vs.B	-3.404181	2.253651	-1.51	0.576	0.518	0.434	0.289	0.157	-
Group D vs.B	-1.061526	2.268206	-0.47	0.998	0.974	0.966	0.641	0.641	-
Group D vs.C	2.342655	2.221718	1.05	0.876	0.774	0.718	0.294	0.294	-

4.3.4.6.3 Relative Efficiency

The final set of tests verifies whether the BM-Miner also improves the relative efficiency of users in comprehending the BM by relating the number of correct answers (effectiveness) to the time required (efficiency). As student data for *relative efficiency* is not normally distributed (p > z = 0.01 in the Shapiro-Francia W' test), a further Kruskal-Wallis test was performed.

Table 16: Kruskal-Wallis test in relative efficiency

	Kruskal-Wallis Test on Efficiency	
	Observations	**Rank Sum**
Group A: Excel	32	1031.00
Group B: Data Model	35	2631.00
Group C: BM Miner (Dashboard)	38	3661.00
Group D: BM Miner & Excel	37	2830.00
Chi-squared = 43.860 with 3 d.f. Probability = 0.0001 Chi-squared with ties = 43.860 with 3 d.f. Probability = 0.0001		

Figure 37: Bonferroni Post-Hoc test for pairwise comparison in relative efficiency

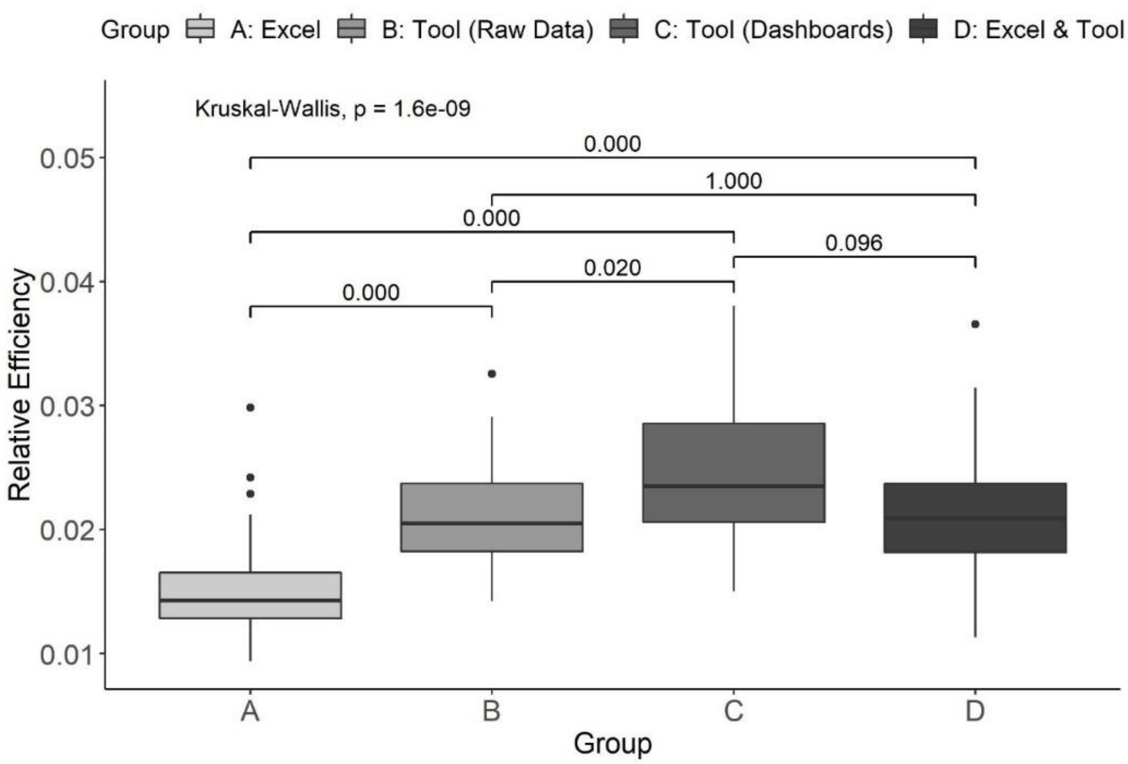


Table 17: Bonferroni Post-Hoc test for pairwise comparison in relative efficiency

	Bonferroni Pairwise Comparison of Efficiency					
	Contrast	Std. Error	t	P > | t |	[95% Confidence Interval]	
Group B vs.A	0.324315 ***	0.0751201	4.32	0.000	0.1232316	0.5253984
Group C vs.A	0.5392699 ***	0.0736903	7.32	0.000	0.342014	0.7365258
Group D vs.A	0.3662704 ***	0.0741441	4.94	0.000	0.1677996	0.5647411
Group C vs.B	0.2149549 *	0.0719554	2.99	0.020	0.0223429	0.4075669
Group D vs.B	0.0419554	0.0724201	0.58	1.000	-0.1519006	0.2358113
Group D vs.C	-0.1729995	0.0709359	-2.44	0.096	-0.3628824	0.0168833

As it is the case for efficiency, treatment groups with BMMiner support achieve higher values (higher values are better). Group A achieves a mean value of 0.02 (Std.Dev = 0.00091), group B of 0.21 (Std.Dev = 0.00087), group C of 0.03 (Std.Dev = 0.00083) and group D of 0.02 (Std.Dev = 0.00084). Concerning the pairwise comparison in the Bonferroni post-hoc test, differences between treatment groups and the baseline group are significant at the 1%-level.

Table 18: Overview of alternative post-hoc tests for pairwise comparisons

	Post-Hoc Tests for Pairwise Comparisons								
	Contrast	Std. Error	t	P > | t |					
				Sidak	Scheffe	Tukey	Student-Newman-Keuls	Duncan	Dunnett
Group B vs.A	0.0054052	0.001252	4.32	0.000 ***	0.001 **	0.000 ***	0.000 ***	0.000 ***	0.000 ***
Group C vs.A	0.0089878	0.0012282	7.32	0.000 ***	0.000 ***	0.000 ***	0.000 ***	0.000 ***	0.000 ***
Group D vs.A	0.0061045	0.0012357	4.94	0.000 ***	0.000 ***	0.000 ***	0.000 ***	0.000 ***	0.000 ***
Group C vs.B	0.0035826	0.0011993	2.99	0.020 *	0.034 *	0.017 *	0.009 **	0.005 **	-
Group D vs.B	0.0006993	0.001207	0.58	0.993	0.953	0.938	0.563	0.563	-
Group D vs.C	-0.0028833	0.0011823	-2.44	0.092	0.119	0.075	0.016 *	0.016 *	-

4.3.4.6.4 Subjective Comprehension

Besides objective comprehension in terms of effectiveness, efficiency and relative efficiency, subjective comprehension for the BM-Miner and the Excel baseline was evaluated by asking subjects in groups A, C and D for a self-estimate of their comprehension. As revealed by table 19, the artifact is found to be less complicated than the baseline condition. However, subjects perceive the number of elements in the dashboard configuration of the BM-Miner to be comparably high, while the tabular specification in group B is lowest. Further, usability in the baseline group is lowest, while it is higher for the group with the BM-Miner. Concerning the wording (higher values are better), subjects perceive the BM-Miner relatively more comprehensible. Concerning the overall subjective comprehension, the baseline group evaluates BM data in Excel worst, while subjects in group B perceive the BM-Miner to be relatively most comprehensible.

Table 19. Subjective comprehension (descriptive mean values)

	Subjective Comprehension				
	Complexity	**Number of elements**	**Usability**	**Wording**	**Subjective Comprehension**
Group A: Baseline (Excel)	4.0625	4.125	2.90625	2.6875	2.59375
Group C: BM Miner Dashboards	3.368421	4.289474	3.473684	2.947368	3.236842
Group D: Choice (Excel)	3.366667	3.966667	3.833333	3.533333	3.366667
Group D: Choice (BM Miner)	4.095238	4.47619	2.666667	2.809524	2.619048

4.3.4.6.5 Test Statistics

Table 20 and table 21 provide test statistics and effect sizes for the performed tests. For the one-way ANOVA on effectiveness, achieved test power is 99.00% based on average group size (at α error probability of 0.05)[12].

Table 20: Test statistics for the one-way ANOVA for effectiveness

	Effect size f	Effect size Cohen's d	Noncentrality parameter λ	Critical F	Power (1-β error probability)
Effectiveness	0.413	1.169	24.2207980	2.6702030	0.9900521

Table 21: Test statistics for the Kruskal-Wallis tests for efficiency and relative efficiency

	Effect size Cohen's d	Effect size Eta squared (η2)
Efficiency	1.014	0.204
Relative Efficiency	1.297	0.296

4.3.4.6.6 Hypotheses Support

Table 22 contains the remaining result interpretation concerning the hypotheses.

Table 22: Hypotheses support

	Effectiveness		Efficiency		Relative Efficiency	
Group A: Excel	*Hypothesis H(A): compared to all other groups, subjects in group A without the BM-Miner perform relatively worst*					
	$H^{A}_{Effect.}$	***Partially supported***	$H^{A}_{Effic.}$	***Supported (***)***	$H^{A}_{Rel.Effic.}$	***Supported (***)***
Group B: Data Model	*Hypothesis H(B): subjects in group B with the BMM data model perform better than the baseline group A*					
	$H^{B}_{Effect.}$	***Weakly supported (*)***	$H^{B}_{Effic.}$	***Supported (***)***	$H^{B}_{Rel.Effic.}$	***Supported (***)***
Group C: BM Miner (Dash-board)	*Hypothesis H(C): subjects in group C with the BM-Miner including dashboards perform better than groups A and B*					
	$H^{C}_{Effect.}$	***Partially supported***	$H^{C}_{Effic.}$	***Partially supported***	$H^{C}_{Rel.Effic.}$	***Partially supported***
Group D: BM Miner & Excel	*Hypothesis H(D): subjects in group D perform relatively better than the baseline group A and group B with the data model, but relatively worse than group C with the BM-Miner*					
	$H^{D}_{Effect.}$	***No support***	$H^{D}_{Effic.}$	***No support***	$H^{D}_{Rel.Effic.}$	***Partially supported***

[12] Test statistics are computed using the tool G*Power 3.1 by University of Duesseldorf (2019).

5 DSR Project 2: Design of a DSS to Discover Important Organizational BPs[13]

Companies nowadays primarily build their operations on application systems (Fischer *et al.*, 2017), and increasingly generate vast amounts of data (Hayashi, 2014; Kroker, 2017) in daily business activity. In particular, organizational application systems such as Enterprise Resource Planning (ERP), Workflow Management (WfM), Customer Relation Management (CRM) or Supply Chain Management (SCM) systems store large amounts of process-related data (van der Aalst *et al.*, 2007). This data might be used to extract process-related information (Schönig *et al.*, 2016) on process landscapes and process importance. For example, SAP ERP systems in practice store each executed transaction and associated information in large event log tables. An SAP transaction is a function or running program to perform specific actions in the ERP system (Orosz, 2011). Therefore, a transaction (TA) is comparable to a process step and can thus be assigned to one or more BPs. In addition, a change is defined as any change to a field in a data table that results from a transaction execution. These transaction programs reveal information about associated BPs. Transactions can be matched to BPs to determine the quantifiable importance metrics, and then decide whether a BP seems to be of primary or secondary importance for the organization.

Besides, as a finding of process discovery and prioritization workshops in the BPS and SAP S/4 HANA migration project at the industry partner, decision-makers stated that they frequently need to rely on non-data-driven intangible knowledge about BPs to determine which of the BPs exists and is of primary importance in the organization.

5.1 Outline of DSR Project 2: Design Cycles

To support BPS initiatives and to contribute to research on process importance, DSR project 2 designs the data-driven process mining DSS "KeyPro" (abbreviation for "Key Process Miner") to automatically discover the set of BPs ("process landscape") from log data in organizational application systems, and to objectively quantify the importance of

[13] This chapter contains content previously published in Fleig, Augenstein and Maedche (2018b).

discovered BPs based on importance metrics. To support decision-makers in determining "key" organizational BPs, the construct of "process importance" is proposed from BPM and BM literature. Thereby, DSR project 2 leverages existing literature and conceptualizes "process importance" as a multi-dimensional construct that can be "proxied" by objective importance metrics. Results of the process discovery and importance analysis are presented and visualized in interactive BI dashboards for decision-makers. Thereby, KeyPro is designed as an alternative data-driven way to discover and to explore important BPs besides the non-data-driven approaches relying on tacit managerial and human BP knowledge.

To design the artifact, DSR project 2 proceeds as follows in two design cycles. The goal of the first design cycle is to design an original prototype artifact to explore whether data-driven "key process mining" DSSs might improve the foundation for decision-making in BPM initiatives. The goal of the second design cycle is to further improve the artifact by incorporating additional literature findings, practical evidence, and requirements. In particular, the second design cycle identifies starting points for improvement of the artifact to improve the comprehension of users.

Therefore, the problem awareness phase in the first design cycle performs a series of workshops at the industry partner to find further practical evidence for the need for a data-driven DSS for process landscape discovery and importance prioritization besides the literature-based justification for the DSR project in the introduction. Afterward, the suggestion phase performs a literature review to identify process importance metrics which can be calculated objectively from data in application systems and derives design requirements for the artifact from literature and the expert workshops within the BPS and SAP S/4 HANA migration project.

The evaluation phase conducts a field study in four manufacturing companies to determine whether the proposed data-driven approach to discovering BPs yields significant differences compared to human, non-data-driven process landscape discovery. First, KeyPro is implemented based on real-life data from three different SAP R/3 ERP systems representing three different manufacturing companies of the industry partner to demonstrate technical feasibility. Throughout the field study, a process library ("global process list") of 279 processes occurring in the corporation is retrieved for process matching in KeyPro in workshops with 52 process experts. To identify processes in the process landscape from ERP transactions and to calculate the process importance metrics, 773 unique SAP R/3 ERP transactions are matched to BPs in the global process list. Besides, two focus group interviews in the Finance and Controlling departments of one of the companies are conducted to validate the hypothesis of deviations between non-data-driven process perceptions and data-driven results for process importance metrics by KeyPro.

The problem awareness phase of the second design cycle conducts a further workshop series with industry experts from five companies in the energy sector beyond manufacturing to receive feedback and additional design requirements. The suggestion phase further refines and extends the design requirements. Finally, the evaluation phase performs a controlled laboratory evaluation with novice students on artifact comprehension for KeyPro 2.0 based on data from an educational SAP S/4 HANA system of a fictitious bicycle company to determine which of the dashboards need improvements in the further development of the artifact. However, the laboratory experiment is only provided with descriptive results on comprehension, while the comparison of dashboard comprehension and technology acceptance with inductive statistical tests is not part of this dissertation. Figure 38 summarizes the outline of DSR project 2.

Figure 38: Overview of design cycle contents of DSR project 2

Process Iteration

	First Design Cycle	Second Design Cycle
Problem Awareness	• Workshop series in the context of the BPS and SAP S/4 HANA migration project	• Workshop series in the energy sector
Suggestion	• Literature review to identify process importance metrics • Design requirements	• Refinement of design requirements and validation • Further literature review on process importance metrics with focus on BMs
Development	• Instantiation of KeyPro 1.0 based on three real-life SAP R/3 systems	• Extended instantiation of KeyPro 2.0 on data from educational SAP S/4 HANA IDES system
Evaluation	• Field study evaluation and case studies on differences between top-down and bottom-up process landscape perceptions	• Controlled laboratory experiment on objective comprehension
Conclusion	• Results analysis	• Results analysis

5.2 Design Cycle 1: KeyPro 1.0

5.2.1 Suggestion: Design Requirements

The suggestion phase of the first design cycle derives design requirements in industry partner workshops to first derive meta requirements (MRs) (Hevner *et al.*, 2004) in section 5.2.1.1 The design principles (DPs) in section 5.2.1.2 concretize these generic meta requirements into a blueprint conceptualization which serves as guideline during development and system implementation.

5.2.1.1 Meta Requirements

Workshops were conducted with corporate-level managers of the project core team (cf. section 3.4) in the context of the BPS and SAP S/4 HANA migration project with the goal of creating a high-level roadmap for standardization and system migration. During the workshops, decision-makers discovered the need to prioritize BPs according to their importance for the organization to focus managerial attention and resources of the project to “key” BPs. These “key” BPs should be analyzed with a data-driven process mining application and be placed earlier on the roadmap for migration into the new ERP system. In more detail, managers highlighted the need for two BPM analyses for the creation of the roadmap. First, the non-data-driven “global process list” of the process landscape by human process owners needed to be validated by a data-driven analysis to ensure correctness and completeness. Second, due to a strictly limited budget in monetary, time, and human resources, the BPS project needed to be focused on the “important” BPs. Based on the outcomes of these expert workshops, two meta-requirements (MRs) for KeyPro were articulated by managers. First, the solution should discover the process landscape of the organization, and provide an objective measurement of process importance based on the data stored in application systems. Thus, MR1 is formulated as follows:

MR1: The DSS needs to extract data from organizational application systems to discover the BP landscape and to compute process importance objectively.

Furthermore, the artifact is required to present findings in an interactive user interface which provides decision-makers the possibility to explore important BPs as an input for decision-making. Thus, MR2 is formulated as follows:

MR2: The DSS needs to provide decision-makers with the possibility to interactively explore important BPs.

5.2.1.2 Design Principles

Based on the two meta-requirements, design principles (DPs) are articulated for the artifact from a conceptual point of view. Thereby, three layers are distinguished: First, the source application systems layer comprises the different underlying application systems which provide the data necessary for the data-driven determination of important BPs (DP1). Second, the data management layer consolidates and transforms data retrieved from the organizational application systems layer and calculates process importance (DP2). Third, the presentation layer presents the results to users and allows for interactive exploration (DP3).

MR1 requires the ability to integrate data sources such as organizational application systems to measure proxies of process importance. The layer comprises log data stored by the application system and requires each entry to possess a timestamp for the exact determination of when the process was executed. Further, a unique identifier is required to assign an action in the system to a particular BP. In addition, the involved process stakeholders dimension requires information about the person or user who executed the action. Furthermore, to determine customer and supplier involvement, for each execution the information is necessary whether the action has a direct customer or supplier interface. Furthermore, each action performed in the application system needs to be assigned to either a primary or secondary BP for the value creation dimension. Thus, DP1 requires:

DP1.1: The DSS needs to provide a source organizational application systems layer.

The data management layer is required to consolidate the data retrieved in the source organizational application systems layer and to merge data from different sources of process information. For example, organizations frequently implement more than one application system to manage BPs. Thus, process-relevant data might be distributed across multiple different systems. Thus, process mining and -related technologies usually require data acquisition and preprocessing steps (van der Aalst *et al.*, 2011). As process information is disseminated across various sources such as ERP, WfM, CRM, SCM or other systems, the layer needs to consolidate all data for a holistic overview of all related systems. Additionally, the data management layer is required to transform the data for the calculation of the metrics of process importance for all processes and sub-processes. Therefore, DP2 is formulated as follows:

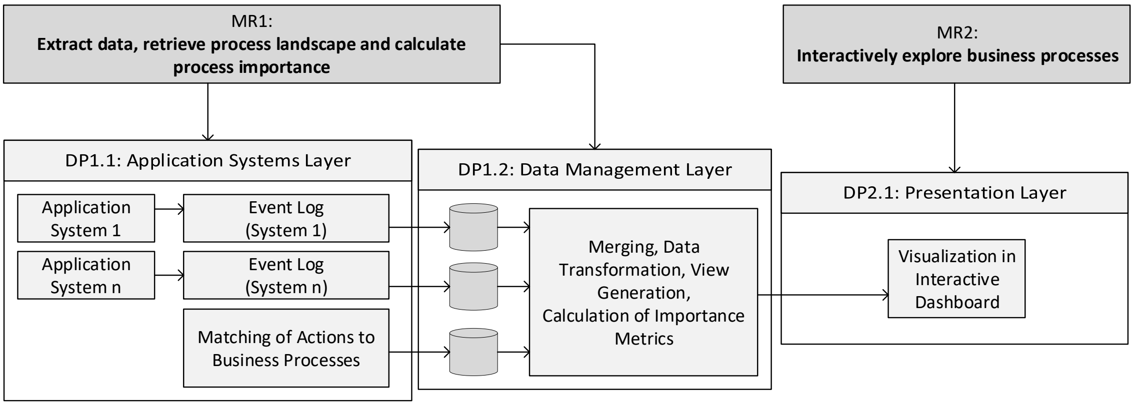
DP1.2: The DSS needs to provide a data management and a process importance calculation layer.

Finally, the presentation layer needs to provide the possibility to interactively explore BPs along the dimensions of process importance as articulated by MR2.

DP2.1: The DSS needs to provide interactive decision support with a presentation layer.

Figure 39 illustrates the blueprint conceptualization including meta-requirements and design principles, which serve as developmental guidelines during the instantiation.

Figure 39: Design requirements (Conceptualization)



5.2.1.3 Design Decisions: Operationalization of Process Importance Metrics in Design Cycle 1

As a conceptual foundation for KeyPro, the suggestion phase introduces several dimensions of process importance which can be objectively quantified by existing data stored in application systems. In total, four dimensions of process importance were identified in current research. As process importance is a multidimensional construct (Zelt *et al.*, 2018), each dimension reflects a different perception of process importance. First, the number of process executions reflects the assumption that more important BPs are executed more often in an organization. Second, the process stakeholders dimension builds on the idea that important BPs are characterized by a higher number of people involved in BPs. Third, the customer or supplier involvement dimension assumes that BPs with a direct interface to the external environment such as customers or suppliers are more important for organizational success. Fourth, value creation builds on the academic distinction into primary and secondary activities in the value chain as an objective classification into value and non-value generating activities. The following paragraph describes each of these dimensions in more detail and introduces quantifiable metrics for each dimension.

5.2.1.3.1 Process Executions (DD1)

Several contributions such as Tenhiälä (2011) or Zelt *et al.* (2018) introduce volume or frequency (Ingvaldsen *et al.*, 2005) as a measure of BPs. For example, process executions is a frequently applied metric in BP analysis (Bider and Perjons, 2017; Ingvaldsen *et al.*, 2005). In addition, the number of process executions might be related to organizational performance, strategy, and BMs. For example, in case of increasing demand, different BPs such as production, sales, or procurement are executed more often, which implies a higher significance of these BPs to satisfy demand and reach strategic goals. Products and services with higher demand and thus a higher performance impact require a higher number of process executions for production and demand satisfaction and different production systems (Kim and Lee, 1993; Schroeder, Congden and Gopinath, 1995). Therefore, the number of executions of a BP is introduced as the first indication of potential process importance. This dimension accounts for the number of process executions as a volume construct and assumes a higher volume to be associated with higher importance (Tenhiälä, 2011). For example, in Bider and Perjons (2017), processes are quantified in terms of the number of process executions in a time unit.

Thus, the metric of process executions is operationalized by the number of process executions over a certain period of time (DD1).

5.2.1.3.2 Process Stakeholders (DD2)

BPs further have a social perspective and are embedded in a social network (Puchovsky, Di Ciccio and Mendling, 2016), with actors participating in a BP (Koubarakis and Plexousakis, 2001; Malinova, Leopold and Mendling, 2015). As a second dimension of process importance, the number of people involved in the execution of a BPs serves as an indication of how important a process might be for the organization (Willaert *et al.*, 2007). Stakeholders include both natural persons and users such as employees, customers, suppliers, or partners, as well as non-human users such as system users in an ERP system. Besides, stakeholders might be internal or external to the organization (Gibb, Buchanan and Shah, 2006). People and people management are essential for process-oriented organizations and thus serve as another indication of process importance. For example, the contribution by Yoon et al. (Yoon, Guimaraes and Clevenson, 1998) defines the degree of labor intensity as "*the amount of people's time and effort necessary to solve the problem*" (Yoon, Guimaraes and Clevenson, 1998). In Andersson, Bergholtz and Gregoire

(2006) and Ingvaldsen *et al.* (2005), information on BPs is acquired in terms of involved user roles, departments, or customers, or accountabilities (Valiris and Glykas, 2004). Further, Bider and Perjons (2017) quantify stakeholders via the number of stakeholders.

The metric of process stakeholders is therefore operationalized by the number of different process stakeholders including employees, customers, suppliers, departments, and roles involved in a BP for a certain period of time (DD2).

5.2.1.3.3 Customer and Supplier Involvement (DD3)

Third and in addition to the number of process executions and involved process stakeholders, literature finds customer (Chase, 1981) and supplier influence (Yoo, Shin and Park, 2015) to be of high importance for BPs. For example, customer satisfaction potentially influences firm performance, and process failure becomes more damaging in the presence of customers as customers might switch to another provider (Hess Jr., Ganesan and Klein, 2003), which might negatively impact the lifetime value of customers (Kumar and Petersen, 2005). In addition, the seminal contribution by Champy (Champy, 2003) highlights the requirement to consider BPs spanning across organizational boundaries to customers and suppliers up- and downstream in the value chain. Consequently, customer and supplier involvement, therefore, captures whether a BP has a direct interface to customers and/or suppliers in either a binary or value-weighted way (DD3).

5.2.1.3.4 Process Primacy (DD4)

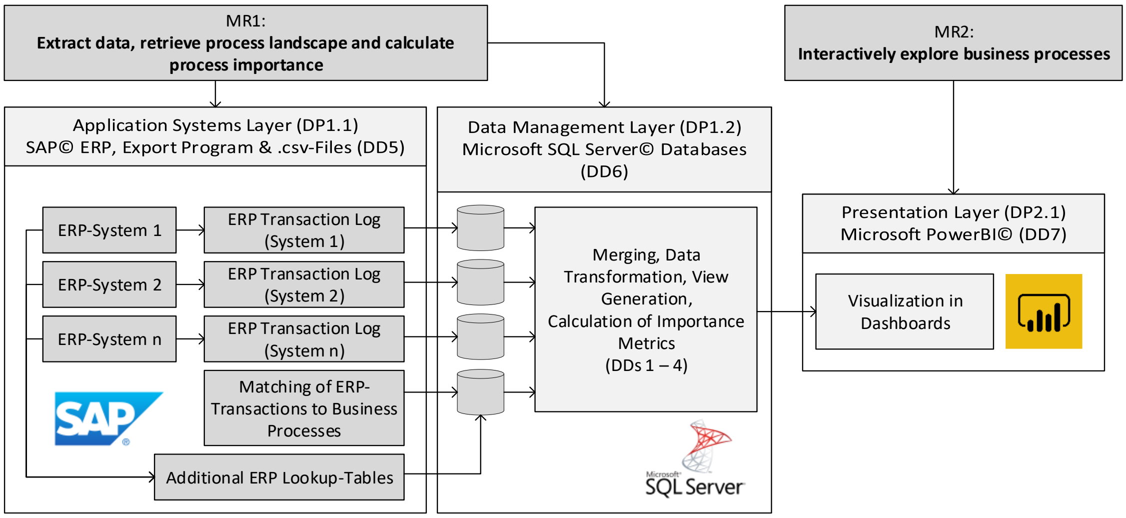
Processes in organizations are frequently organized in process maps (Malinova, Leopold and Mendling, 2015). Finally, primacy was identified as the fourth dimension of process importance to account for the type of BP and the strategic position in the value chain of an organization. As indicated in the workshops conducted at the industry partner in the problem awareness phase, decision-makers stated that managers tend to overestimate the significance of their own process of responsibility for the organizational value creation and tend to classify their own processes as primary activities.

Therefore, BPs are classified as primary or secondary activities along the widely accepted value chain by Porter (Porter, 1985) to gain an academic classification of whether a specific BP is directly or only indirectly related to the organizational value creation. The process primacy metric is operationalized by classifying processes as primary or secondary according to the value chain by Porter (1985) (cf. section 2.3.6) (DD4).

5.2.2 Development: Instantiation of "KeyPro 1.0"

Figure 40 illustrates the KeyPro prototype implementation for SAP R/3 source systems (DP1.1), a Microsoft SQL Server database (DP1.2), and Microsoft PowerBI (DP2.1).

Figure 40: Implementation of KeyPro 1.0 in the first design cycle



5.2.2.1 Application Systems Layer: SAP R/3 and S/4 HANA ERP Systems (DD5)

Regarding the research context of the SAP S/4 HANA migration project, KeyPro was instantiated for SAP R/3 ERP systems (DD5).

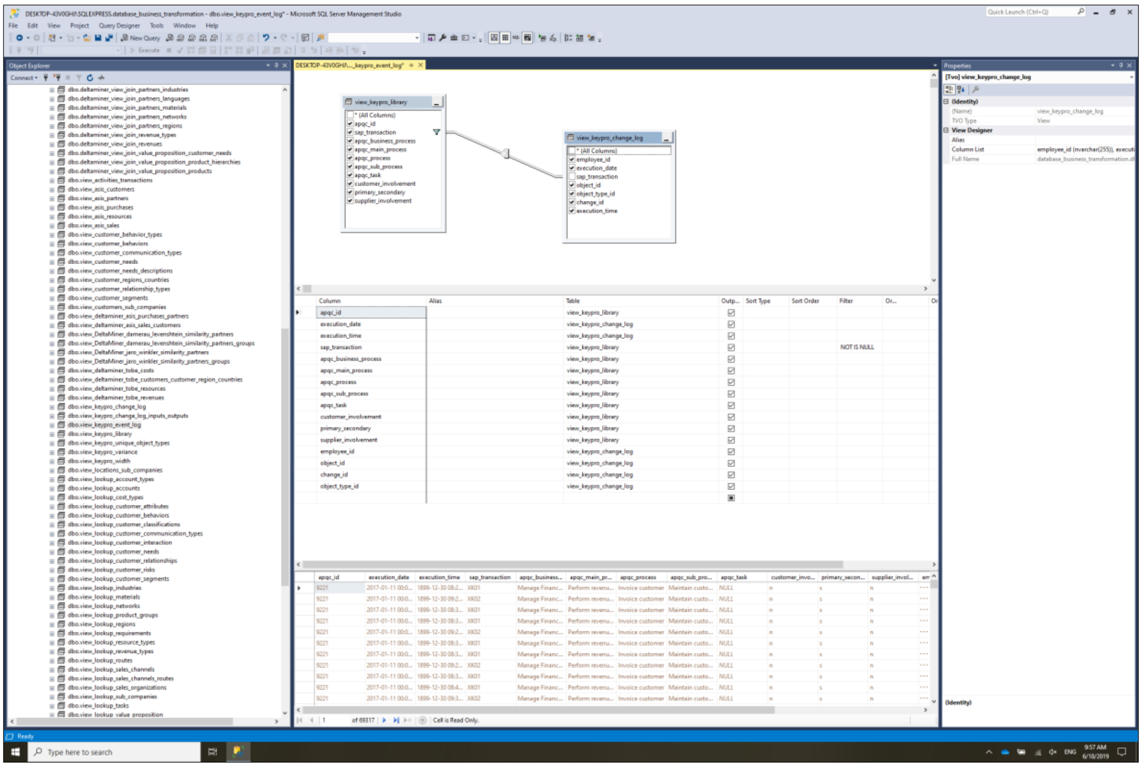
Within the SAP systems in the application systems layer the ABAP table extractor application "Z_DATA_DRIVEN_DSS_EXPORT" was developed for DSR projects 1 and 2 to export relevant log data plus additional lookup-tables as .csv file close to real-time. The program can be implemented in any SAP ERP system. Therefore, KeyPro is able to handle and combine data from multiple SAP ERP systems, and to display results in near real-time.

5.2.2.2 Data Management and Process Importance Calculation Layer: Microsoft SQL Server (DD6)

All event log files are imported into a central database in the data management layer. Due to the wide dissemination of application systems in organizations and the free availability in the Express Edition, the data management layer is implemented using a Microsoft SQL Database on Microsoft Azure and Microsoft SQL Server Management Studio (SSMS)

(DD6). However, KeyPro scripting can be run on any SQL-compliant relational database system.

Figure 41: Data management layer in Microsoft SQL Server and SQL Server Management Studio (SSIS) (DD6)



The data management layer further contains merging steps of the application system files into one central database including data transformation and process importance calculation steps. Additionally, the data management layer contains a lookup-table ("process matching library") which contains the matching of transactions to the BPs.

5.2.2.3 Visualization Layer: Microsoft PowerBI (DD7)

Finally, the presentation layer is implemented in Microsoft PowerBI due to the capability to handle large amounts of data and the rich pageant of different visualizations, the free availability of the solution and its ability to connect to many different database formats. The visualization layer in Microsoft PowerBI contains one dashboard page for each of the process importance metrics. Each dashboard provides the ability to filter by organizations to analyze and compare BPs across different companies. All dashboards such as the diagrams or word clouds in Microsoft PowerBI provide the ability to filter on the dashboard, page, and report level. Further, each dashboard page contains a time filter to analyze process importance and related metrics for a specific period of time and to analyze the evolution of process importance over time. For each level in the hierarchy of business functions, main- and sub-processes, a word cloud illustrates the most important processes (word size according to importance metrics). All fields contain the ability to select and filter for specific processes, and thus to drill-down into metrics for specific processes.

Figure 42: Dashboard for process executions (aggregated 2010-2017) for an SAP R/3 ERP system of the industry partner

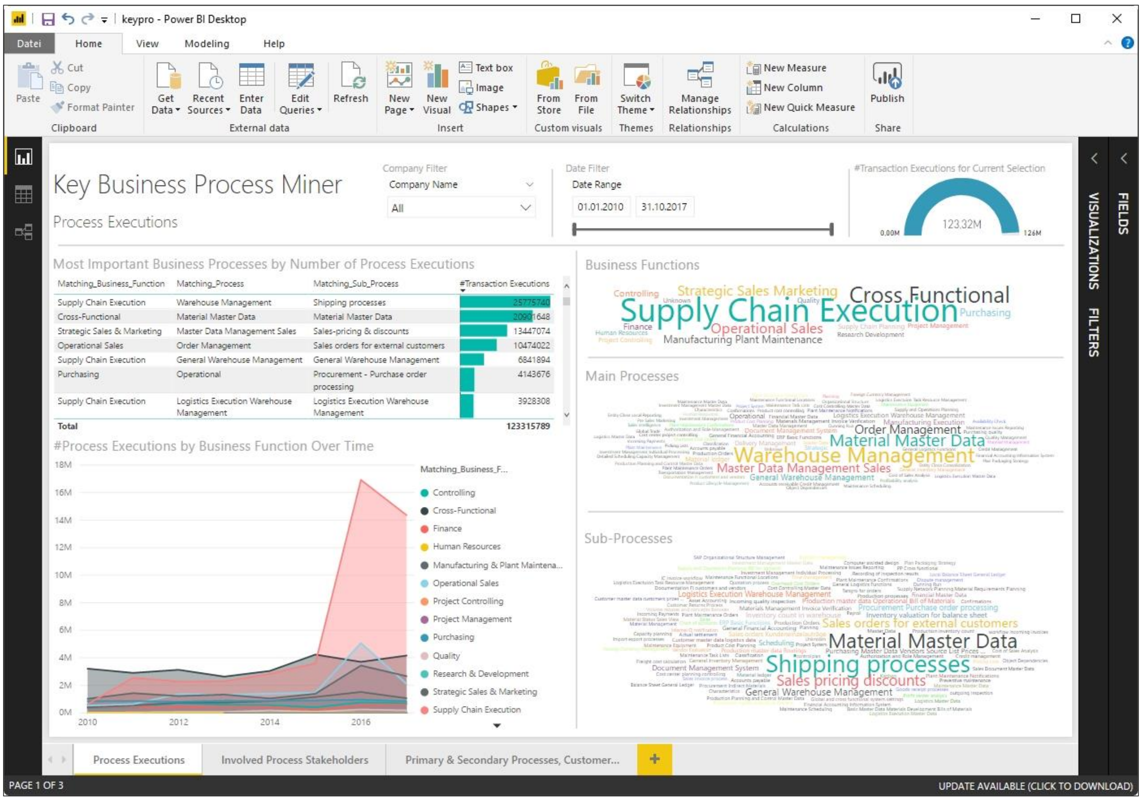
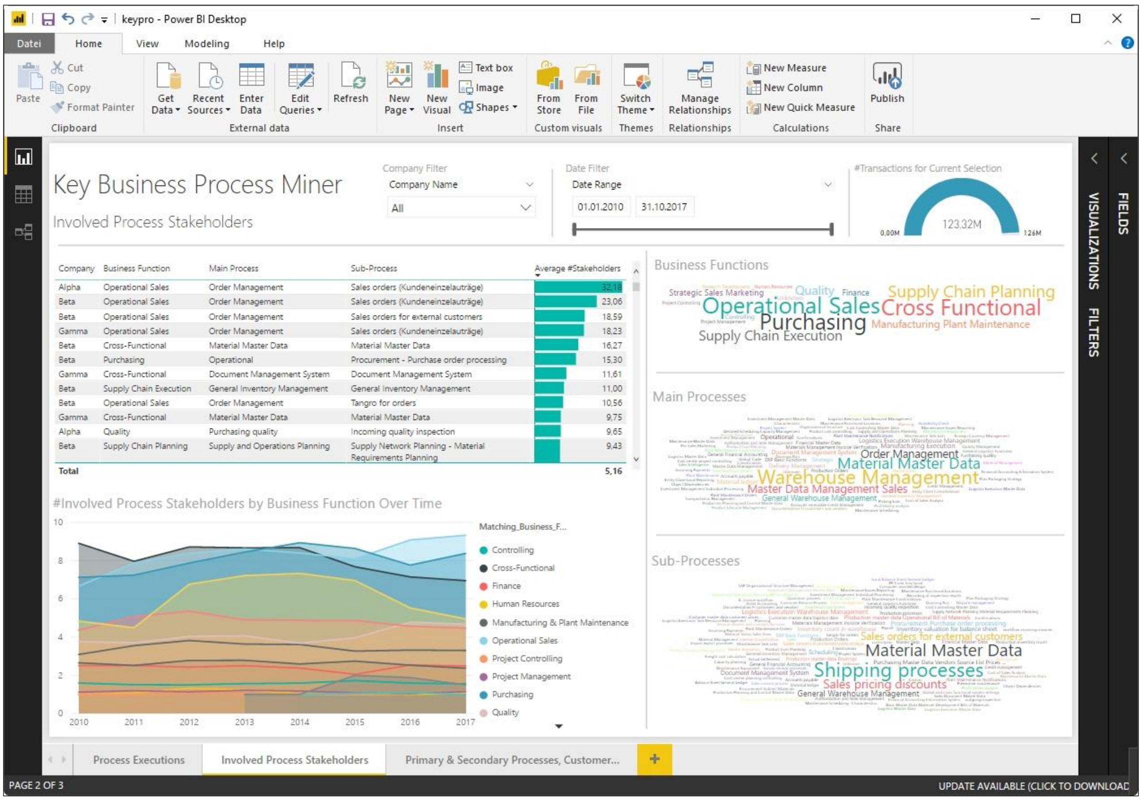


Figure 43: Dashboard for process stakeholders (aggregated 2010-2017) for an SAP R/3 ERP system



5.2.3 Evaluation: Field Study at the Industry Partner

The underlying dataset for the evaluation of the KeyPro DSS comprises an event log from three real-world SAP R/3 ERP systems of the at the industry partner (DD5). The event log file captures each transaction execution which results in a change to the underlying ERP database. In total, the event log file covers a period from 01/01/2010 to 31/10/2017 and includes 152.947.233 changes for all companies. Changes unrelated to transactions such as ERP-internal actions which are not due to the execution of BPs were removed, leaving a final sum of 125.504.530 changes (executed process steps). The following table 23 gives an overview of the ERP log files for KeyPro implementation.

Table 23: Overview over dataset from SAP R/3 ERP systems (TA = transaction)

ERP System of Company	Total number of changes	Changes in database unrelated to transaction (TA) (removed)		Number of changes remaining	Unique TAs
Alpha	42.666.436	10.206.791	23.92%	32.459.645	363
Beta	88.245.019	15.738.565	17.86%	72.506.454	582
Gamma	22.035.778	1.497.374	6.80%	20.538.431	433
Total	**152.947.233**	**27.442.730**	**17.94%**	**125.504.530**	**773**

5.2.3.1 Evaluation for Differences between Data-Driven and Non-Data-Driven Process Discovery

5.2.3.1.1 Study Overview and Hypotheses

In the first design cycle, a field study was conducted at the industry partner to validate the hypothesis that differences exist between human, non-data-driven perceptions of the process landscape and data-driven analyses delivered by KeyPro. The field study intended to validate that a data-driven process landscape discovery yields additional BPs which are not recognized by human decision-makers in a non-data-driven analysis. The research hypothesis thus states:

Hypothesis: The number of BPs discovered in non-data-driven analyses by human decision-makers differs significantly from the data-driven process landscape discovery.

Participants in the field study were "Global Business Function Responsibles" (GBFRs) who are organized in a matrix across different three different companies (Alpha, Beta, Gamma) within the corporation. Each person in the matrix is responsible for all BPs in the process hierarchy within one of the 14 business functions (Controlling, Cross-Functional, Finance, Human Resources, Manufacturing & Plant Maintenance, Operational Sales, Purchasing, Quality, Research & Development, Strategic Sales & Marketing, Supply Chain Execution, Supply Chain Planning, Project Controlling, Project Management). Each business function further comprises several main processes such as "Order Management" in Sales. Each main process is further split into several sub-processes such as "Sales Orders for External Customers" in Order Management, such that the process hierarchy contains three levels. In addition, each business function is supported by one IT consultant in the IT service provider of the corporation.

Table 24: "GBFR-Matrix" organization of process owners at the industry partner

Company	Business Functions			
	Finance	**Sales**	**HR**	**…**
Alpha	GBFR (Person 1) (Finance | Company A)	GBFR (Person 2) (Sales | Company A)	…	…
Beta	…	…	…	…
Gamma	…	…	…	…
IT Service Provider	…	…	…	…

The 52 different GBFRs in process management workshops first listed all BPs of the corporation. For each business function, process owners performed at least one monthly workshop session of about 3 hours to collect all main processes and adjacent sub-processes between January 2017 and October 2018. In the workshop series, GBFRs created a “global process list” including 49 main processes and 278 BPs across the 14 business functions. Second, GBFRs were asked to indicate for each of the BPs in the global process list whether the BP occurred in their company within the preceding 12 months (i.e., whether the BP exists within the process landscape of the particular company) or not to create a non-data-driven view on the process landscape. Third, 773 unique transactions of the SAP-ERP system were matched to the global process list of BPs retrieved from the process owners as process library in KeyPro. Fourth, KeyPro was applied to data for each of the SAP R/3 systems in each corporation for the previous year for the data-driven analysis.

5.2.3.1.2 Descriptive Results

Results from the comparison of the non-data-driven process list and the data-driven analysis reveal significant differences between both perspectives across the different companies.

Table 25: Summary statistics for field evaluation with a binary indication whether a BP occurs in the respective company (1 indicates a BP occurs, 0 otherwise)

	Non-Data-Driven			Data-Driven (KeyPro)		
	Alpha	Beta	Gamma	Alpha	Beta	Gamma
# of BPs Considered (N)	278	278	278	278	277*	278
Min	0	0	0	0	0	0
Max	1	1	1	1	1	1
Range	1	1	1	1	1	1
Mean	0.6726619	0.647482	0.5755396	0.1294964	0.3285199	0.3093525
Variance	0.2209828	0.2290731	0.2451757	0.113134	0.2213938	0.2144249
Std.Dev.	0.4700881	0.4786158	0.4951522	0.336354	0.470525	0.4630603

*For company Beta, one process had to be removed for SAP specific customizing.

In company Alpha, 200 BPs are recognized in total. 187 BPs are discovered non-data-driven, while KeyPro recognized 36 BPs. Out of the 187 BPs discovered by humans, 164 could not be discovered in data (82.00%) (non-data-driven only). KeyPro discovered 13 additional BPs which were not indicated in the non-data-driven analysis (6.50%) (data-driven only). The overlap of BPs which are discovered by both humans and the artifact includes 23 BPs (11.50%). Although the number and share of BPs which are yielded additionally by KeyPro are rather low, the discovery differs across the business functions. For example, while the artifact performs rather low in functions such as Operational Sales (35.29%), Quality (30.00%), Strategic Sales & Marketing (18.18%) or Supply Chain Execution, the artifact discovers 100.00% of BPs in functions such as Cross-Functional, Human Resources, Purchasing, and Research & Development which are “forgotten” by humans.

For company Beta, the set of discovered processes in the landscape includes 241 BPs in total. Again, the majority of BPs are discovered by human decision-makers (180; 74.69%), while KeyPro discovers 91 BPs (37.76%). The share of BPs which is discovered data-driven only is at 25.31% (61 BPs). Comparably to company Alpha, the artifact discovers BPs which are not recognized by humans. This finding covers BPs which span organizational boundaries such as Cross-Functional processes, Project Management, but also covers Human Resources, Project Controlling, and Purchasing. Again, the share of BPs which is discovered by humans only is particularly high in functions with a high degree of paper-based processes (e.g., Quality with 70.00%), and third-systems involved such as Excel in Controlling (38.89%), manufacturing execution systems (MES) in supply chain execution and planning (81.82% and 85.06%, respectively), or a CRM system in Operational Sales (64.71%). The overlap is at 12.45%.

In company Gamma, humans and the artifact together discovered 229 BPs. Comparably to the other companies, the major share of BPs in the company was discovered by human decision-makers (180 BPs; 69.87%). The artifact discovered 86 BPs (37.55%), but yielded 69 BPs (30.13%) of processes which were not recognized by humans. While 143 (62.45%) of all BPs in company Gamma were detected only non-data-driven, the overlap of BPs discovered by both is 17 (7.42%).

Figure 44: Process discovery results for company Alpha

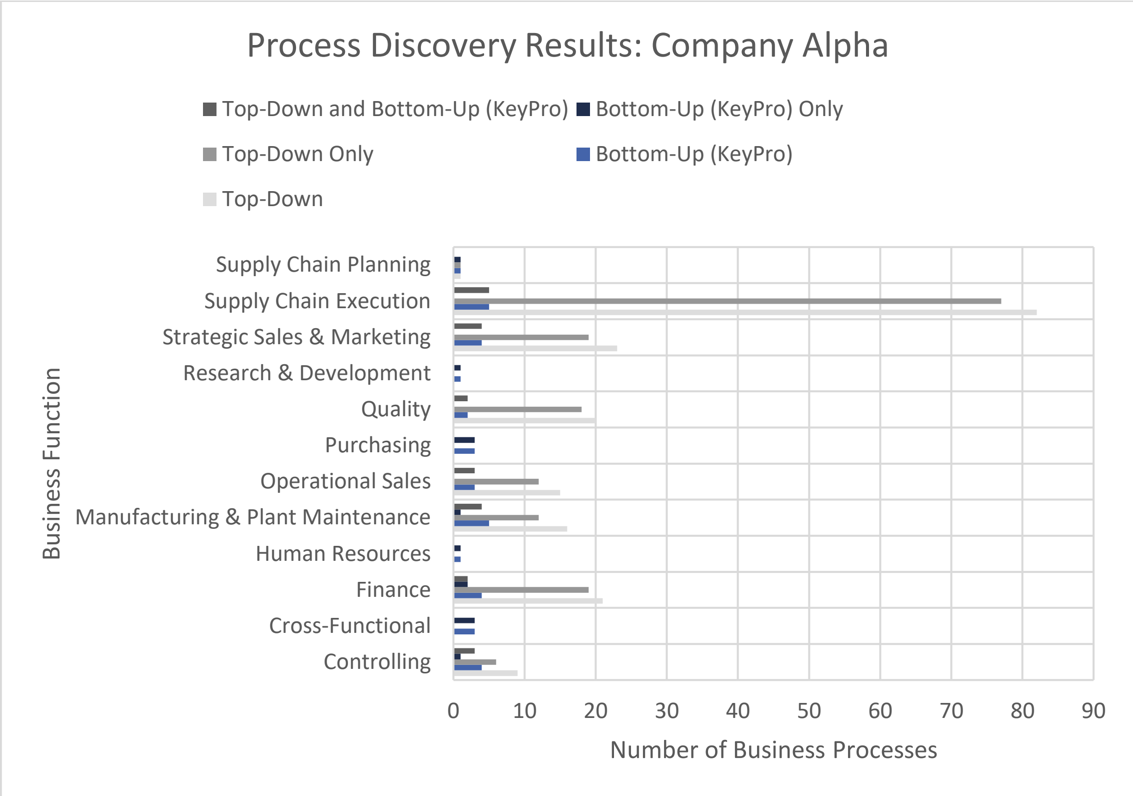


Figure 45: Process discovery results for company Beta

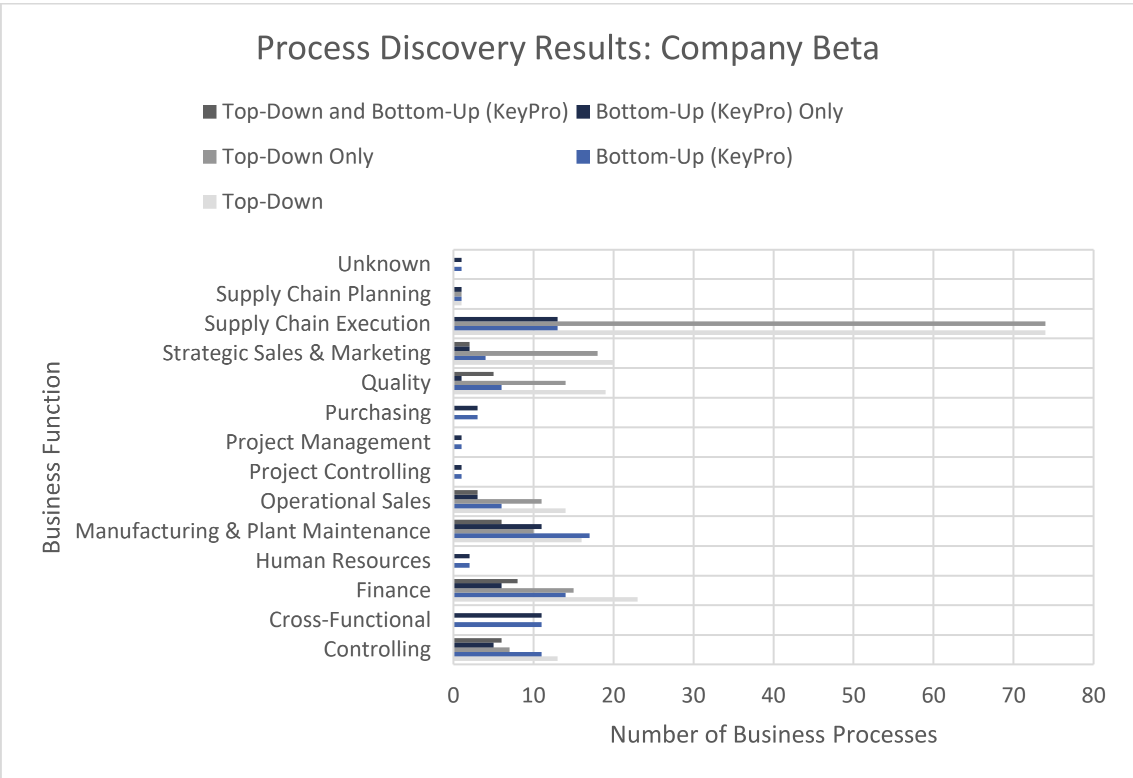


Figure 46: Process discovery results for company Gamma

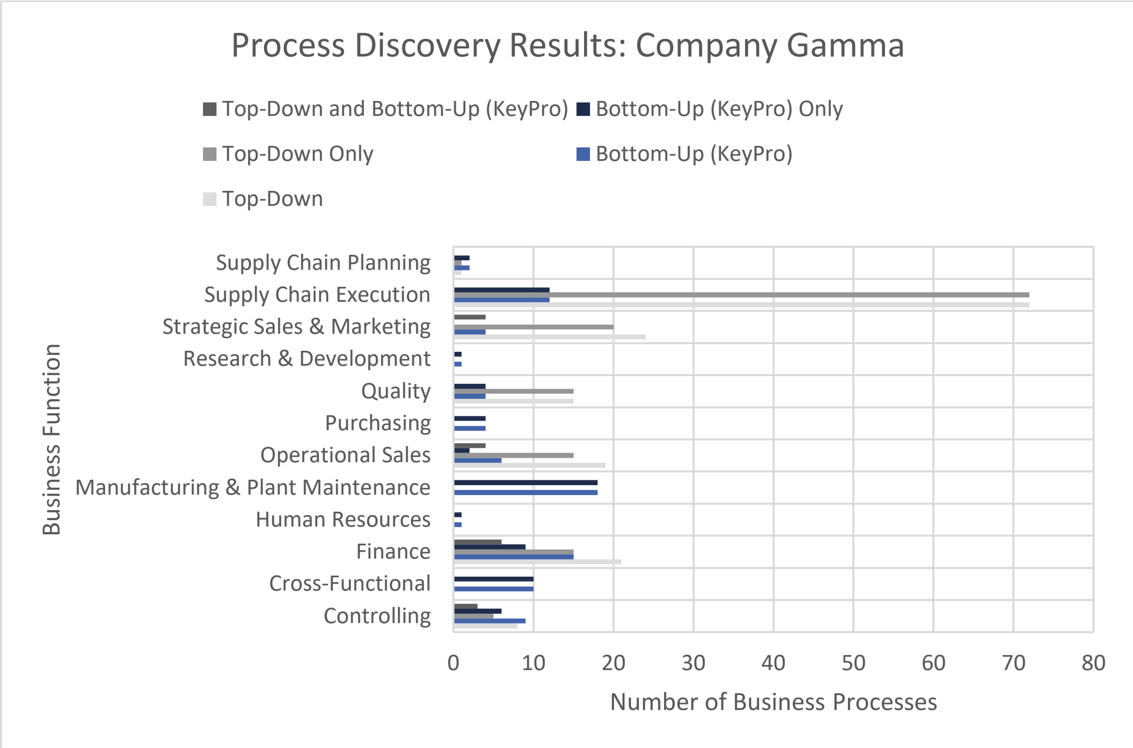


Table 26: Results of the field study comparison of non-data-driven and data-driven process discovery (aggregated on business functions) (Company Alpha)

Company Alpha											
		# Processes Discovered …									
		Non-Data-Driven		Data-Driven (KeyPro)		Non-Data-Driven Only		Data-Driven (Key-Pro) Only		Non-Data-Driven and Data-Driven (Overlap)	
Business Function	# Sub-Processes Discovered in BP Landscape	#	%	#	%	#	%	#	%	#	%
Controlling	10	9	90.00	4	40.00	6	60.00	1	10.00	3	30.00
Cross-Functional	3	0	0.00	3	100.00	0	0.00	3	100.00	0	0.00
Finance	23	21	91.30	4	17.39	19	82.61	2	8.70	2	8.70
Human Resources	1	0	0.00	1	100.00	0	0.00	1	100.00	0	0.00
Manufacturing & Plant Maintenance	17	16	94.12	5	29.41	12	70.59	1	5.88	4	23.53
Operational Sales	15	15	100.00	3	20.00	12	80.00	0	0.00	3	20.00
Purchasing	3	0	0.00	3	100.00	0	0.00	3	100.00	0	0.00
Quality	20	20	100.00	2	10.00	18	90.00	0	0.00	2	10.00
Research & Development	1	0	0.00	1	100.00	0	0.00	1	100.00	0	0.00
Strategic Sales & Marketing	23	23	100.00	4	17.39	19	82.61	0	0.00	4	17.39
Supply Chain Execution	82	82	100.00	5	6.10	77	93.90	0	0.00	5	6.10
Supply Chain Planning	2	1	50.00	1	50.00	1	50.00	1	50.00	0	0.00
Grand Total (Company Alpha)	**200**	**187**	**93.50**	**36**	**18.00**	**164**	**82.00**	**13**	**6.50**	**23**	**11.50**

Table 27: Results of the field study comparison of non-data-driven and data-driven process discovery (aggregated on business functions) (Company Beta)

Company Beta											
		# Processes Discovered …									
		Non-Data-Driven		Data-Driven (KeyPro)		Non-Data-Driven Only		Data-Driven (Key-Pro) Only		Non-Data-Driven and Data-Driven (Overlap)	
Business Function	**#Sub-Processes Discovered in BP Landscape**	**#**	**%**	**#**	**%**	**#**	**%**	**#**	**%**	**#**	**%**
Controlling	18	13	72.22	11	61.11	7	38.89	5	27.78	6	33.33
Cross-Functional	11	0	0.00	11	100.00	0	0.00	11	100.00	0	0.00
Finance	29	23	79.31	14	48.28	15	51.72	6	20.69	8	27.59
Human Resources	2	0	0.00	2	100.00	0	0.00	2	100.00	0	0.00
Manufacturing & Plant Maintenance	27	16	59.26	17	62.96	10	37.04	11	40.74	6	22.22
Operational Sales	17	14	82.35	6	35.29	11	64.71	3	17.65	3	17.65
Project Controlling	1	0	0.00	1	100.00	0	0.00	1	100.00	0	0.00
Project Management	1	0	0.00	1	100.00	0	0.00	1	100.00	0	0.00
Purchasing	3	0	0.00	3	100.00	0	0.00	3	100.00	0	0.00
Quality	20	19	95.00	6	30.00	14	70.00	1	5.00	5	25.00
Strategic Sales & Marketing	22	20	90.91	4	18.18	18	81.82	2	9.09	2	9.09
Supply Chain Execution	87	74	85.06	13	14.94	74	85.06	13	14.94	0	0.00
Supply Chain Planning	2	1	50.00	1	50.00	1	50.00	1	50.00	0	0.00
Unknown	1	0	0.00	1	100.00	0	0.00	1	100.00	0	0.00
Grand Total (Company Beta)	**241**	**180**	**74.69**	**91**	**37.76**	**150**	**62.24**	**61**	**25.31**	**30**	**12.45**

Table 28: Results of the field study comparison of non-data-driven and data-driven process discovery (aggregated on business functions) (Company Gamma)

Company Gamma											
		# Processes Discovered …									
		Non-Data-Driven		Data-Driven (KeyPro)		Non-Data-Driven Only		Data-Driven (Key-Pro) Only		Non-Data-Driven and Data-Driven (Overlap)	
Business Function	**#Sub-Processes Discovered in BP Landscape**	**#**	**%**	**#**	**%**	**#**	**%**	**#**	**%**	**#**	**%**
Controlling	14	8	57.14	9	64.29	5	35.71	6	42.86	3	21.43
Cross-Functional	10	0	0.00	10	100.00	0	0.00	10	100.00	0	0.00
Finance	30	21	70.00	15	50.00	15	50.00	9	30.00	6	20.00
Human Resources	1	0	0.00	1	100.00	0	0.00	1	100.00	0	0.00
Manufacturing & Plant Maintenance	18	0	0.00	18	100.00	0	0.00	18	100.00	0	0.00
Operational Sales	21	19	90.48	6	28.57	15	71.43	2	9.52	4	19.05
Purchasing	4	0	0.00	4	100.00	0	0.00	4	100.00	0	0.00
Quality	19	15	78.95	4	21.05	15	78.95	4	21.05	0	0.00
Research & Development	1	0	0.00	1	100.00	0	0.00	1	100.00	0	0.00
Strategic Sales & Marketing	24	24	100.00	4	16.67	20	83.33	0	0.00	4	16.67
Supply Chain Execution	84	72	85.71	12	14.29	72	85.71	12	14.29	0	0.00
Supply Chain Planning	3	1	33.33	2	66.67	1	33.33	2	66.67	0	0.00
Grand Total (Company Gamma)	**229**	**160**	**69.87**	**86**	**37.55**	**143**	**62.45**	**69**	**30.13**	**17**	**7.42**

5.2.3.1.3 t-Tests for Significance of Differences Between Data-Driven and Non-Data-Driven Process Landscape Discovery

In addition to the descriptive analysis, a series of t-tests validates the hypothesis and tests whether the observed differences between non-data-driven and data-driven process discovery are statistically significant. Thus, two-sample t-tests are conducted for each company. In assumption testing, Shapiro-Wilk tests for normality are conducted for each company. As revealed by table 29, all null hypotheses (except for the data-driven KeyPro results for company Alpha) for normal distribution of the variables cannot be rejected. Thus, the assumption is that data is normally distributed.

Table 29: Shapiro-Wilk test for normality

Company	Variable	Obs.	W	V	z	Prob > z
Alpha	Manual	278	0.99597	0.803	-0.513	**0.69613**
	Data-Driven (KeyPro)	278	0.95699	8.565	5.023	**0.00000 *** **
Beta	Manual	278	0.99724	0.551	-1.396	**0.91863**
	Data-Driven (KeyPro)	277	0.99336	1.318	0.646	**0.25904**
Gamma	Manual	278	0.99937	0.125	-4.857	**1.00000**
	Data-Driven (KeyPro)	278	0.99190	1.614	1.119	**0.13155**

To validate the assumption that non-data-driven results by humans and data-driven results by KeyPro exhibit homogeneous variances, Levene tests for equality of variances are conducted. As revealed by Levene test results in table 30, for companies Beta and Gamma assumptions are fulfilled (null hypothesis of homogeneity of variances not rejected). For company Alpha, t-tests need to be adjusted for variance inequality.

Table 30: Levene test Results for equality of variances

<table>
<tr><th>Comp.</th><th>Variable</th><th>Obs.</th><th>Mean</th><th>Std.Err.</th><th>Std. Dev.</th><th colspan="2">[95% Conf. Interval]</th></tr>
<tr><td rowspan="4">Alpha</td><td>Manual</td><td>278</td><td>0.6726619</td><td>0.028194</td><td>0.4700881</td><td>0.6171601</td><td>0.7281636</td></tr>
<tr><td>Data-Driven (KeyPro)</td><td>278</td><td>0.1294964</td><td>0.0201732</td><td>0.336354</td><td>0.0897842</td><td>0.1692086</td></tr>
<tr><td>Combined</td><td>556</td><td>0.4010791</td><td>0.0208043</td><td>0.4905583</td><td>0.3602143</td><td>0.4419439</td></tr>
<tr><td colspan="7">Ratio = sd(manual_alpha) / sd(tool_alpha)
H(0): ratio = 1
f = 1.9533
Degrees of freedom = 277 . 277
H(a): ratio < 1: Pr(F < f) = 1.0000
H(a): ratio != 1: 2 * Pr(F > f) = 0.0000
H(a): ratio > 1: Pr(F > f) = 0.0000</td></tr>
<tr><td rowspan="2">Beta</td><td>Manual</td><td>278</td><td>0.647482</td><td>0.0287055</td><td>0.4786158</td><td>0.5909734</td><td>0.7039906</td></tr>
<tr><td>Data-Driven (KeyPro)</td><td>277</td><td>0.3285199</td><td>0.0282711</td><td>0.470525</td><td>0.2728655</td><td>0.3841743</td></tr>
</table>

Comp.	Variable	Obs.	Mean	Std.Err.	Std. Dev.	[95% Conf. Interval]	
	Combined	555	0.4882883	0.0212371	0.5003138	0.4465731	0.5300034
	Ratio = sd(manual_beta) / sd(tool_beta) H(0): ratio = 1 f = 1.0347 Degrees of freedom = 277 . 276 H(a): ratio < 1: Pr(F < f) = 0.6115 **H(a): ratio != 1: 2 * Pr(F > f) = 0.7771** H(a): ratio > 1: Pr(F > f) = 0.3885						
Beta	Manual	278	0.5755396	0.0296973	0.4951522	0.5170786	0.6340005
	Data-Driven (KeyPro)	278	0.30093525	0.0277725	0.4630603	0.2546805	0.3640245
	Combined	556	0.442446	0.0210827	0.4971238	0.4010343	0.4838578
	Ratio = sd(manual_gamma) / sd(tool_gamma) H(0): ratio = 1 f = 1.1434 Degrees of freedom = 277 . 277 H(a): ratio < 1: Pr(F < f) = 0.8673 **H(a): ratio != 1: 2 * Pr(F > f) = 0.2654** H(a): ratio > 1: Pr(F > f) = 0.1327						

Differences between non-data-driven and data-driven process discovery are significant for all companies. In particular, the hypothesis H(a): diff != 0 that both mean values are different from each other is strongly significant at Pr(|T| > |t|) = 0.0000 for all companies. In addition, the t-tests further reveal strong statistical support for H(a): diff > 0, which tests for the difference between the mean number of processes being recognized by human process owners compared to KeyPro results. The significance at Pr(T > t) = 0.0000 for all companies implies that human process owners recognize more BPs than the tool as relevant to their company, while KeyPro discovers less BPs than humans.

Table 31: t-test results for the comparison of mean values between non-data-driven and data-driven (KeyPro) results (Company Alpha)

Variable	Obs.	Mean	Std.Err.	Std. Dev.	[95% Conf. Interval]	
Two-sample t-test with unequal variances						
Manual	278	0.6726619	0.028194	0.4700881	0.6171601	0.7281636
Data-Driven (KeyPro)	278	0.1294964	0.0201732	0.336354	0.0897842	0.1692086
Combined	556	0.4010791	0.0208043	0.4905583	0.3602143	0.4419439
Diff		0.5431655	0.0346678		0.4750534	0.6112775
Diff = mean(manual_alpha) – mean(tool_alpha) t = 15.6677 Satterthwaite's degrees of freedom = 501 . 724 H(a): diff < 0: Pr(T < t) = 1.0000 **H(a): diff != 0: Pr(|T| > |t|) = 0.0000** **H(a): diff > 0: Pr(T > t) = 0.0000**						

Table 32: t-test results for the comparison of mean values between non-data-driven and data-driven (KeyPro) results (Company Beta)

Variable	Obs.	Mean	Std.Err.	Std. Dev.	[95% Conf. Interval]	
Two-sample t-test with equal variances						
Manual	278	0.647482	0.0287055	0.4786158	0.5909734	0.7039906
Data-Driven (KeyPro)	277	0.3285199	0.0282711	0.470525	0.2728655	0.3841743
Combined	555	0.4882883	0.0212371	0.5003138	0.4465731	0.5300034
Diff		0.3189622	0.0402909		0.2398202	0.3981042
Diff = mean(manual_beta) – mean(tool_beta) t = 7.9165 Degrees of freedom = 553 H(a): diff < 0: Pr(T < t) = 1.0000 **H(a): diff != 0: Pr(|T| > |t|) = 0.0000** **H(a): diff > 0: Pr(T > t) = 0.0000**						

Table 33: t-test results for the comparison of mean values between non-data-driven and data-driven (KeyPro) results (Company Gamma)

Variable	Obs.	Mean	Std.Err.	Std. Dev.	[95% Conf. Interval]	
Two-sample t-test with equal variances						
Manual	278	0.5755396	0.0296973	0.4951522	0.5170786	0.6340005
Data-Driven (KeyPro)	278	0.30093525	0.0277725	0.4630603	0.2546805	0.3640245
Combined	556	0.442446	0.0210827	0.4971238	0.4010343	0.4838578
Diff		0.2661871	0.04066		0.1863203	0.3460538
Diff = mean(manual_gamma) – mean(tool_gamma) t = 6.5466 Degrees of freedom = 554 H(a): diff < 0: Pr(T < t) = 1.0000 **H(a): diff != 0: Pr(|T| > |t|) = 0.0000** **H(a): diff > 0: Pr(T > t) = 0.0000**						

Table 34 reports test statistics for the t-tests. Cohen's d is calculated as $d = (M_2 - M_1) / SD_{pooled}$. Test statistics for two-tailed t-tests are calculated by the tool G*Power (University of Duesseldorf, 2019) under the standard assumption for the α error probability of 0.05.

Table 34: Test statistics and effect sizes for t-tests

	Cohen's d	Gates' delta	Hedges d	Critical t	Noncentrality parameter δ	Power (1-β err prob)
Alpha	1.316486	1.148936	1.316486	1.9642553	15.5211410	1.0000000
Beta	0.673647	0.666667	0.673634	1.9642631	7.9350227	1.0000000
Gamma	0.562012	0.54	0.562012	1.9642553	6.6260238	0.9999984

5.2.3.2 Hypotheses Support

In sum, these findings yield evidence for a complementary role of the data-driven DSS to "enrich" the discovery of humans with a data-driven perspective. While the artifact does not perform “better” in terms of the number of processes discovered, the artifact has the potential to “complete the picture” for decision-makers. First, in all companies, the artifact contributed a share of 6.50% to 30.13% of BPs which were forgotten by human decision-makers, even though several major systems responsible for BPs were not integrated into the analysis. Thus, the approach relies on the holistic integration of all associated systems in the organization to yield complete analysis and is particularly suited for organizations with a low number of different application systems. Second, discovery rates are highly dependent upon the respective area and business function. The artifact performs comparably better in areas with a low degree of “shadow” applications and paper-based process steps or in BPs which span organizational units without clear responsibilities. Nevertheless, even in an unfinished state in design cycle 1 with not all application systems integrated, the artifact discovers additional BPs and thus complements the foundations for decision-making in BPM initiatives by providing the additional information from a data-driven perspective. The t-tests further showed that differences between a data-driven and a human non-data-driven view on the process landscape are statistically significant across all companies. Thus, findings are interpreted as support for the research hypothesis that there are differences in the number of processes discovered.

5.2.3.3 Focus Group Interviews on Process Importance Metrics

Besides the tests for differences between the number of BPs recognized as occurring in a company, the field evaluation closed with two focus group interviews to validate and scrutinize the potential of KeyPro to enrich the process understanding of organizational decision-makers. The evaluation of KeyPro was performed in two focus groups for two business functions in company Gamma, namely “Controlling” and “Finance”. Process owners from the GBFR-matrix in the Finance and Controlling departments were asked to determine the following metrics in table 35 for the dimensions of process importance for each BP in their area of responsibility. As several metrics such as the number of process executions, or the number of stakeholders related to a BP are time-dependent and potentially changing over time, process owners were asked to provide an average over the last 12 months. Process owners were further asked to also include system-performed actions in their indication to account for processes not triggered explicitly by stakeholders themselves.

Table 35: Manual evaluation by process owners (exemplary excerpt)

Processes			Process Importance Metrics				
Business Function	**Main Process**	**Sub-Process**	**Avg. Executions**	**Avg. Distinct Users**	**Customer**	**Supplier**	**Value creation**
Controlling	Investment Management	Planning & Administration	33	1	No	No	Secondary
Finance	Accounts Payable	Accounts Payable Management	2000	2	No	Yes	Secondary

5.2.3.3.1 Focus Group 1: Evaluation for Business Function "Controlling"

For the business function "Controlling", process owners indicated a mean number of 80.03 BP executions per month (min = 0, max = 400, SD = 134.61). According to the non-data-driven evaluation by process owners, the two most important main processes for Controlling in the number of process executions metric are "Product Cost Controlling" (n = 460 mean monthly executions) and "Profitability Analysis" (n = 326 mean monthly executions), while "Material Ledger" and "Financial Details" constitute the least important main processes (with n = 0.17 and n = 0.25 mean monthly executions, respectively). Within the most important main process "Product Cost Controlling", the sub-processes "Product Cost Planning" was indicated at n = 400 executions, "Calculation of Intercompany Prices" at n = 30 executions, and "Update Transfer Price Data" at n = 30 executions. In the involved process stakeholder metrics, process owners indicated a mean of 1.82 distinct persons involved in the execution of a sub-process (min = 0, max = 5, SD = 1.64). Regarding stakeholders, "Profitability Analysis" constitutes the most important main process with a mean number of 10 different people being involved per month, while "Product Cost Controlling" constitutes the second most important main process with n = 7 stakeholders. Further, as expected for the internal Controlling business function, none of the sub-processes was indicated to have any direct interface to customers or suppliers in the supplier or customer involvement metrics. Finally, in accordance with the scientific allocation of "Controlling" to the secondary activities in the value chain by Porter (Porter, 1985), process owners perceived all main and sub-processes as secondary to the value creation.

Compared to results delivered by KeyPro, significant differences are revealed for the preceding 12 months prior to the evaluation. In the number of process executions, the most important main process is "Material Ledger" with n = 32150.25 monthly executions (due to the automatic inventory valuation for balance sheets performed by the ERP). The second-most important main process is "Cost Center & Project Controlling" with a mean of 505.92 monthly executions. This strongly contrasts non-data-driven perceptions. For example, the "system reality" for "Product Cost Controlling" reveals only n = 36.5 monthly executions of the associated ERP transaction, such that process owners significantly overestimate the importance of this process. In terms of involved process stakeholders, KeyPro revealed the main processes "Product Cost Planning" (n = 1.20 stakeholders) and "Cost Center & Project Controlling" (n = 1.11 stakeholders) to be most important.

5.2.3.3.2 Focus Group 2: Evaluation for Business Function "Finance"

In addition to "Controlling", a second focus group interview was conducted for the business function "Finance". Process owners reported a mean of 1019.06 sub-process executions per month (min = 0, max = 5500, SD = 1716.61). In the perception of process owners, the two most important main processes in the number of process executions are "Accounts Payable" (n = 9500 mean monthly executions) and "Accounts Receivable and Credit Management" (n = 5750 mean monthly executions). This perception strongly contrasts data-driven findings by KeyPro, with the main process "Financial Master Data" and "Documentation FI Customers" being the most executed process (n = 2221.92 and n = 426 mean monthly executions, respectively). The main processes "Accounts Payable" and "Accounts Receivable and Credit Management" were executed much more infrequently than stated by process owners (n = 344.42 and n = 426 mean monthly executions, respectively). Furthermore, process owners stated that the main processes "Incoming Payments" and "Foreign Currency Management" were not executed by the department at all. However, still the associated ERP transactions were executed several times during the year preceding the evaluation at n = 0.08 and n = 1.33 times a month on average, which indicates the processes were "forgotten" by process owners in workshops due to their infrequency.

In terms of the process stakeholder metric, process owners stated the main processes with the highest number of distinct stakeholders likewise being "Accounts Payable" and "Entity Close and Consolidation" with n = 9 and n = 8.17 different stakeholders, respectively. This perception is partly revoked by findings from ERP data in KeyPro. Although "Accounts Payable" is executed by the highest number of distinct users and thus can be termed the most important main process in accordance with non-data-driven perceptions, the absolute number of different stakeholders executing the process strongly contrasts managerial perceptions. While managers believe the number of different process executors related to “Accounts Payable” is at an average of n = 9, the corresponding ERP transactions are executed by only 1.89 stakeholders per month. The same finding holds true for “Entity Close and Consolidation”, with only 1.07 different stakeholders being involved in transaction executions. Furthermore, KeyPro ranks the main process “Accounts Receivable and Credit Management” as the most important process in the department in terms of different stakeholders with a monthly average of 1.92 different users. Regarding customer or supplier involvement, managers stated the sub-processes “Credit Management”, “Dispute Management”, and “Accounts Payable Invoice Management” to have a direct interface to customers. These perceptions are supported by KeyPro, however, KeyPro in addition highlights the sub-process “Dunning Run” to have a customer interface, which was not considered by process owners. Regarding supplier involvement, both human managers and KeyPro in accordance find “Accounts Payable” to be the only process having a supplier interface. However, for the sub-process of incoming paper-based invoices, KeyPro was unable to detect the process in the log data, and thus was outperformed by human managers. Finally, in terms of value creation, all process owners perceived their processes as secondary to the organizational value creation in accordance with the value chain by Porter (1985).

5.2.3.4 Field Study Limitations

The field study was performed to explore the existence and the potential of a data-driven DSS for process landscape discovery and importance calculation with external validity. However, the field study suffers from several limitations. First, for comparing the non-data-driven process list with the data-driven analysis, transactions from the application system had to be matched to the “global process list”. Thus, results from the data-driven process discovery highly depend on the correctness and completeness of the matching. Although the matching was conducted by two persons individually and validated with IT consultants at the IT service provider of the industry partner, results might be biased by an incorrect or incomplete matching. Besides, the matching was conducted in a 1:1 cardinality, i.e., one transaction within the SAP system was assigned to one single BP. However, some transactions within the ERP system are used for multiple different BPs. Second, although all three companies in the field study rely on the SAP R/3 ERP suite to a large degree, log data from other satellite systems that are further responsible for several BPs could not be retrieved. Thus, the data-driven perspective yields only BPs within the SAP systems, which possibly understates the potential of the data-driven approach to discover BPs. For example, the finding of low discovery rates of the artifact in functions such as Strategic Sales & Marketing or Supply Chain Execution is due to the involvement of third systems such as the CRM or the Advanced Planning and Optimization (APO) systems.

5.3 Design Cycle 2 – KeyPro 2.0

5.3.1 Problem Awareness

The field evaluation in design cycle 1 revealed a complementary role of "key process mining" to enrich the organizational non-data-driven understanding of the process landscape with an additional data-driven, data-driven view on BPs. To receive further feedback and directions for further development the artifact was demonstrated in workshops in the energy sector in the problem awareness phase of design cycle 2. A key question in the workshops was how the artifact could be utilized to identify key processes for prioritizing "lighthouse" BPs in usability improvement projects, and how the artifact might be enhanced to suit to other contexts and industries. Workshops were conducted with industry experts and managers from organizations in the energy sector, including a large German energy provider and the associated IT / invoicing provider, an umbrella organization for networking German energy companies, another invoicing service provider, and three energy consultancies. During the workshops, requirements for the artifact were formulated to validate and extend the existing design requirements.

Table 36: Design requirements formulated during the energy sector workshops in the problem awareness phase of design cycle 2

	Design Requirement	Status in Design Cycle 1
✓	Initial key figure catalog	Implemented (DDs1-4)
✓	A standardized data model for the inclusion of data from non-SAP systems and company-specific developments / processes	Implemented (DP 1.2 and DD6)
✓	Scalable software architecture for large amounts of data	Implemented (DP 1.2 and DD6)
✓	Database layer for cloud or local data storage	Implemented (DP 1.2 and DD6)
✓	Data management layer for preprocessing the data	Implemented (DP 1.2 and DD6)
✓	Visualization of data in standard templates ("dashboards")	Implemented (DP 2.1 and DD7)

	Design Requirement	Status in Design Cycle 1
✓	Standard solution for table export of large amounts of data from SAP R/3 systems (e.g. via ABAP application)	Implemented (DP1.1 and DD5)
⚙	More generic matching to BPs "beyond manufacturing", e.g., energy industry process library / matching of ERP-transactions (SAP) to energy reference processes	Not implemented (→DS2)
⚙	Customizable Process Importance Index	Not implemented (→DS2)
⚙	Extended key figure catalog (e.g., value creation, input & output, and others)	Not implemented (→DS2)
⚙	Anonymization of data	Not implemented (→DS2)
⚙	Authorization concept for multiple user groups	Not implemented (→DS2)

5.3.2 Suggestion: Design Requirements

The workshop results in table 36 yield additional requirements. First, as KeyPro was developed in the context of the BPS and SAP S/4 HANA migration project in manufacturing, the artifact is required to "learn" BPs and reference processes "beyond manufacturing" from other industries such as the "APQC process classification framework" (APQC, 2017) or the energy sector reference process list. Thus, an additional design principle DP1.3 is formulated to require matching of system transactions to a generic, industry-independent process library:

DP1.3: The DSS needs to provide an industry-independent process library and associated matchings of system transactions.

In addition to the individual process importance metrics discovered, calculated and presented in the literature in the first design cycle, workshop participants highlighted the requirement to aggregate findings into a single process importance value ("KPI"). As BPM initiatives and process activities are however undertaken for different purposes and goals, the different metrics might differ in their relative weight for the process importance. For example, while in a BPS project the number of process variant executions might be relatively more important than the involvement of customers and suppliers, a usability project might consider processes with a high number of users relatively more important. Therefore, the so-called "process importance index" (PPI) was proposed as a normalized, individually configurable ("modular") metric which allows assigning individual weights to the constituent importance metrics. These insights are incorporated by DP1.4 into the artifact:

DP1.4: The DSS needs to provide a configurable and modular aggregation ("process importance index") of the importance metrics including individual metric weights.

Besides the necessity to aggregate importance metrics into a single “PPI”, workshop participants further expressed concerns concerning the completeness and exhaustiveness of the identified metrics in design cycle 1. Participants noted that the existing metrics such were highly focused on a particular BP, while metrics that focus on the BM layer of the organizational “pyramid” or a more project-oriented focus were missing. Therefore, design cycle 2 additionally reviews existing literature on performance metrics with a more particular focus on organizational BMs and BPM literature.

Finally, practitioners in the workshops provided feedback concerning the use of the tool in the daily operations of organizations. In particular, practitioners required two minor requirements regarding the implementation, which included the anonymization of user-related data for privacy and data protection, as well as the necessity to restrict access to process data based on user groups. Both requirements are merged in DP1.5.

DP1.5: The DSS needs to make data anonymous and ensure access control via an authorization concept for user groups.

5.3.2.1 Design Decisions: Operationalization of Additional Process Importance Metrics in Design Cycle 2[14]

5.3.2.1.1 Value Creation (DD8)

The value creation of a BP is related to BP importance (Zelt, Schmiedel and vom Brocke, 2018). BPs impact the value creation through the costs incurred and revenues created for the organization when executing the BP (Bessai *et al.*, 2008; Valiris and Glykas, 2004). For instance, more important BPs might consume more or other types of resources (e.g., more expensive inputs, more skilled employees) and produce a different output (e.g., products of a higher value). Value creation captures both the actual monetary as well as the temporal value of a BP, including duration and speed as performance measures in analyzing or redesigning BPs (Bessai *et al.*, 2008; Ingvaldsen *et al.*, 2005; Puchovsky, Di Ciccio and Mendling, 2016; Valiris and Glykas, 2004). To capture the temporal dimension, Andersson, Bergholtz and Gregoire (2006) measure process duration. Likewise,

[14] The literature review in design cycle 2 was conducted in collaboration with a supervised master thesis and is based on Hummel (2019).

Ingvaldsen *et al.* (2005) visualize process improvement potential and variations in value in the process execution time (i.e., longer execution times bind more organizational resources).

The value creation is closely related to the BM concept, which was introduced in section 2.2.1 as "*the rationale of how an organization creates, delivers, and captures value*" (Osterwalder and Pigneur, 2010). Therefore, the identified components of BMs in the literature review in section 2.3.3.4 are further metrics of the importance of BP for the organizational value creation. The identified BM components include customers, networks and partnerships (which are already included in an own importance metrics), governance, resources and skills, costs and revenues, products and services, the value proposition, and the organizational structure (cf. table 3 in section 2.3.3.4). While the determination of BMs and BM components was covered within DSR project 1 on BMM, linking these components to an individual transaction within the application system requires an intense effort. Therefore, KeyPro employs an approach that relies on estimates for the average durations, costs and revenues linked to a transaction.

In KeyPro, the average duration of a transaction serves to estimate the temporal dimension of process costs. The monetary dimension is captured by multiplying the duration of a process activity (transaction) with the costs and revenues incurred (e.g., the hourly rate of an employee, revenues generated from product sales) (DD8).

5.3.2.1.2 Process Size (DD9)

BPs differ in terms of the number of associated elements such as process activities. For BPM initiatives, the knowledge on how many elements are related to a BP is crucial to determine the effort required to analyze, plan, change, renew, outsource and implement a BP in an organization. The assessment of the process extent is thus an essential prerequisite for process projects (Krause, Bewernik and Fridgen, 2013). For example, Krause, Bewernik and Fridgen (2013) recommend prioritizing projects descending according to the ratio of expected project return and project size, which depends on the size of the BP to be redesigned.

Process size is operationalized by the sum of the number of process activities and nodes within the BP (DD9).

5.3.2.1.3 Process Inputs and Outputs (DD10)

BPs consume inputs to produce outputs and to achieve one or more process- and organizational goal (cf. section 2.3.1). While the monetary dimension of inputs and outputs is captured in “value creation”, the inputs and outputs dimension employs a systems-oriented perspective. Repa (2014) highlights the importance of the inputs and outputs of BPs for subsequent process behavior and achievement of process goals. A change in the input of a BP might change the output of the BP and thus influence the following dependent BP. For example, more important BPs might consume more system resources and data within the ERP system, and the execution of the process might trigger more activity such as changes (Puchovsky, Di Ciccio and Mendling, 2016) in the database. Likewise, Andersson, Bergholtz and Gregoire (2006) analyze the technical and administrative complexity of process inputs and outputs. Similarly, Ingvaldsen *et al.* (2005) capture business documents involved in the process.

In KeyPro, process inputs and outputs are realized by counting the number of unique data inputs and outputs for a particular process (DD10).

5.3.2.2 Summary: Final Data-Driven Process Importance Metrics

Table 37 contains an overview of the final process importance metrics, references, operationalizations in the artifact implementation, and associated design decisions.

Table 37: Final Importance Metrics and Design Decisions (based on (Hummel, 2019))

Importance Metric	Selected References	Implementation in KeyPro (SAP Systems)	DDs
Executions	(Bessai *et al.*, 2008; Bider and Perjons, 2017; Gebauer and Lee, 2008; Gebauer and Schober, 2006; Ingvaldsen *et al.*, 2005; Kim and Lee, 1993; Schroeder, Congden and Gopinath, 1995; Tenhiälä, 2011; Zelt *et al.*, 2018; Zelt, Schmiedel and vom Brocke, 2018)	KeyPro analyzes the event log for the number of executions of a particular transaction within a particular time range and by linking the transaction to the process library.	DD1 (Cycle 1)

Importance Metric	Selected References	Implementation in KeyPro (SAP Systems)	DDs
Stakeholders	(Andersson, Bergholtz and Gregoire, 2006; Bessai *et al.*, 2008; Bider and Perjons, 2017; Gibb, Buchanan and Shah, 2006; Ingvaldsen *et al.*, 2005; Koubarakis and Plexousakis, 2001; Puchovsky, Di Ciccio and Mendling, 2016; Rosemann and vom Brocke, 2015; Valiris and Glykas, 2004; Willaert *et al.*, 2007; Yoon, Guimaraes and Clevenson, 1998; Zelt, Schmiedel and vom Brocke, 2018)	KeyPro counts the unique user IDs within the event log. In order to retrieve customers and suppliers, transactions in the event log are linked to the execution tables containing sales and purchase orders and looking up the unique customer and supplier IDs. Departments and user roles are retrieved by linking the user to data tables in user management.	DD2 (Cycle 1)
Customer and Supplier Involvement	(Anning-Dorson, 2018; Champy, 2003; Chase, 1981; Hess Jr., Ganesan and Klein, 2003; Kumar and Petersen, 2005; Yoo, Shin and Park, 2015)	In KeyPro, the information on whether or not the transaction in the SAP system has an interface to a customer or supplier was manually added to the process library.	DD3 (Cycle 1)
Primacy	(Duan, Grover and Balakrishnan, 2009; Malinova, Leopold and Mendling, 2015; Ould, 1995; Porter, 1985)	In KeyPro, the 278 processes in the manufacturing library and the APQC classification framework were classified manually.	DD4 (Cycle 1)
Value Creation	(Bessai *et al.*, 2008; Duan, Grover and Balakrishnan, 2009; Ingvaldsen *et al.*, 2005; Kerremanns, 2013; Porter, 1985; Puchovsky, Di Ciccio and Mendling, 2016; Valiris and Glykas, 2004; vom Brocke and Rosemann, 2015; Wirtz, 2018; Zelt, Schmiedel and vom Brocke, 2018)	The duration of a process is calculated from the event log by subtracting the timestamp of the first process activity from the last process step. Alternatively, KeyPro provides an estimate with an average duration of a transaction from the system performance logs. Monetary costs are calculated by multiplying the duration with the hourly rate of the respective employee executing the process. Customer and supplier costs can be provided by a manually maintained cost table.	DD8 (Cycle 2)
Size	(Krause, Bewernik and Fridgen, 2013)	In KeyPro, process size is calculated by creating a tree structure of the process hierarchy in the process library (e.g., the APQC classification framework) and adding up the number of elements (main processes, sub-processes and tasks) belonging to a BP.	DD9 (Cycle 2)

Importance Metric	Selected References	Implementation in KeyPro (SAP Systems)	DDs
Process Inputs & Outputs	(Andersson, Bergholtz and Gregoire, 2006; Gibb, Buchanan and Shah, 2006; Ingvaldsen *et al.*, 2005; Puchovsky, Di Ciccio and Mendling, 2016; Repa, 2014; Rosemann and vom Brocke, 2015; Zelt, Schmiedel and vom Brocke, 2018)	When a process activity (transaction) is executed in the SAP system, a change document is created in the event log table including a change ID. In addition to counting the number of change IDs, the change ID is further applied to count the number of changed objects, table IDs and field IDs in the system in process execution.	DD10 (Cycle 2)

5.3.2.3 Process Importance Index Calculation (DD11)

According to DP1.4, the DSS artifact needs to provide a single aggregated measure of process importance within one metric. Therefore, DD11 implements a formula for the aggregation of the individual metrics in table 37 including a normalization. The idea to aggregate and normalize the metrics was derived in the initial workshops in the problem awareness phase. Normalized values for each of the importance metrics are between 0 ("unimportant") and 1 ("important"). The formula sets the difference between the observed value of the importance metric (M) to the minimum value (M_{min}) in relation to the difference between the maximum and the minimum value of the respective metric ($M_{max} - M_{min}$).

Equation 1: Formula for the normalization of individual process importance metrics

$$I_{norm(m)} = \frac{M - M_{min}}{M_{max} - M_{min}}$$

For calculating the overall PPI, each individual normalized process importance metric is multiplied by the relative weight of the metric (w_m) in decision-making. The relative weight can be adjusted by decision-makers depending on the project at hand. By standard, the KeyPro implementation weighs all metrics equally. Each importance metric receives a relative weight, such that the sum of all weights is 1.

Equation 2: Individual weights for each process importance metric in decision-making

$$w = (1/\sum_{i=1}^{I} w_{m(i)})$$

Thus, the importance index for a BP PPI_P is a value between 0 and 1 and calculated as the sum of all decision-relevant metrics (m to M)

Equation 3: Formula for the process importance index (PPI)

$$PPI_P = \sum_{m=1}^{M} w_m \cdot I_{norm(m)}$$

5.3.3 Development: Instantiation of "KeyPro 2.0"

The additional design requirements identified in the second design cycle of DSR project 2 were implemented accordingly into the final conceptualization and instantiation "KeyPro 2.0". Figure 47 summarizes design decisions which served as guidelines for the technical implementation.

Figure 47: Overview over design requirements (meta requirements, design principles, and design decisions)

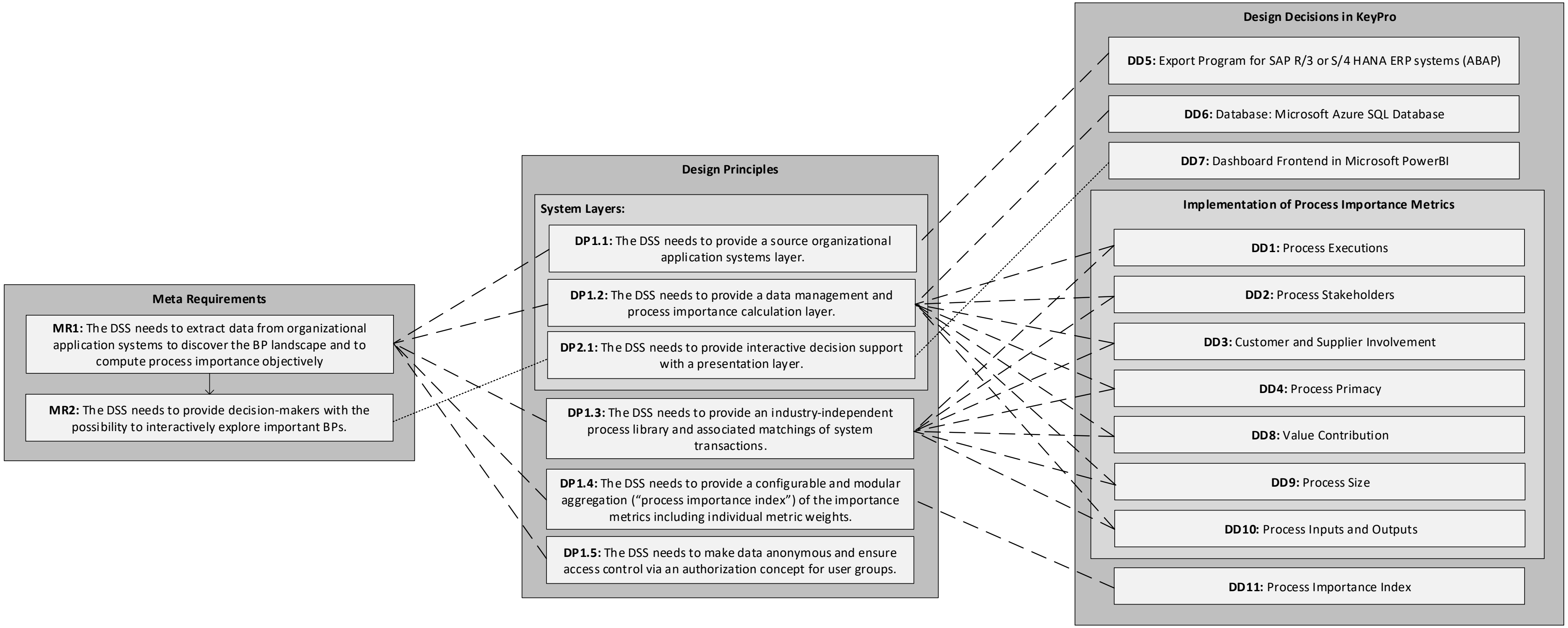
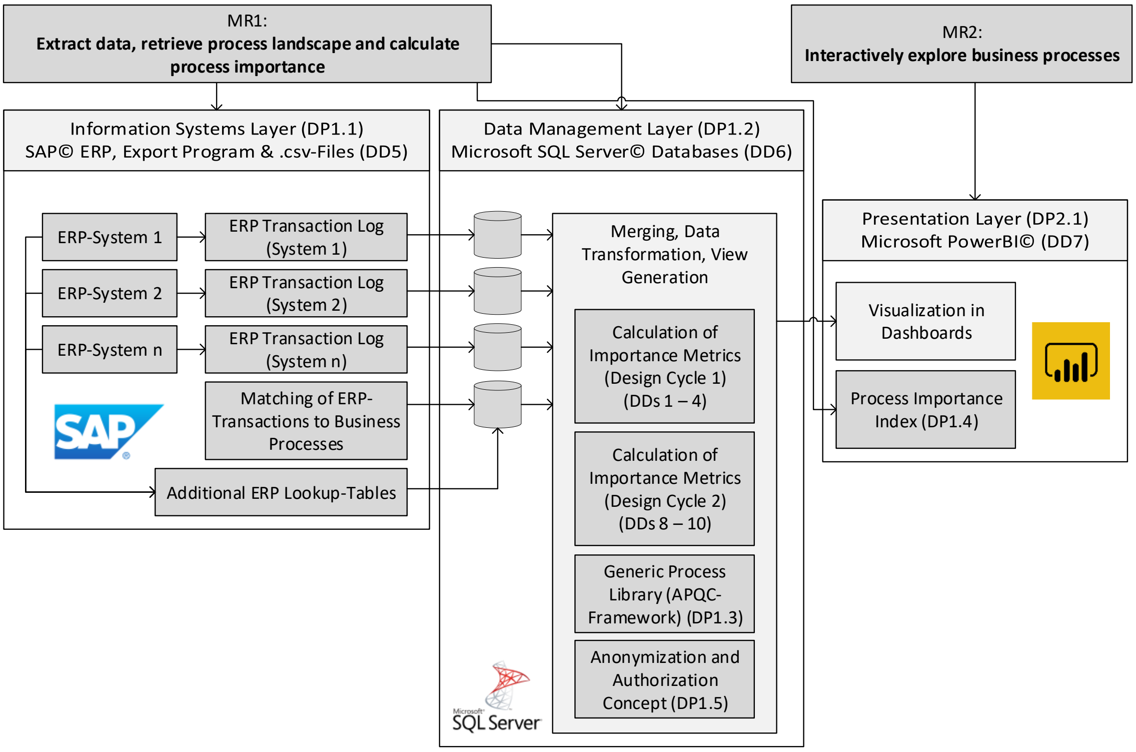


Figure 48 illustrates the final implementation in design cycle 2 with extensions in the data management layer with the additional importance metrics (DDs 8-10), the additional matching of the ERP transactions to the generic process library of the APQC framework (APQC, 2017), the practical requirements of the anonymization and authorization concept (DP1.5), and the PPI which is calculated in the BI application in the presentation layer (DP1.4 and DD11).

Figure 48: Final KeyPro 2.0 implementation according to design requirements



The final artifact implementation contains 7 detail dashboards for each metric and a summary dashboard on process importance and the PPI. Few (2013) perceives a dashboard as "*a visual display of the most important information needed to achieve one or more objectives that have been consolidated on a single computer screen so it can be monitored and understood at a glance*". Figure 49 illustrates an exemplary detail dashboard for the importance metric "inputs and outputs" based on data from an SAP S/4 HANA IDES system of a fictitious bicycle company.

Figure 49: Exemplary dashboard for process inputs & outputs (based on (Hummel, 2019))

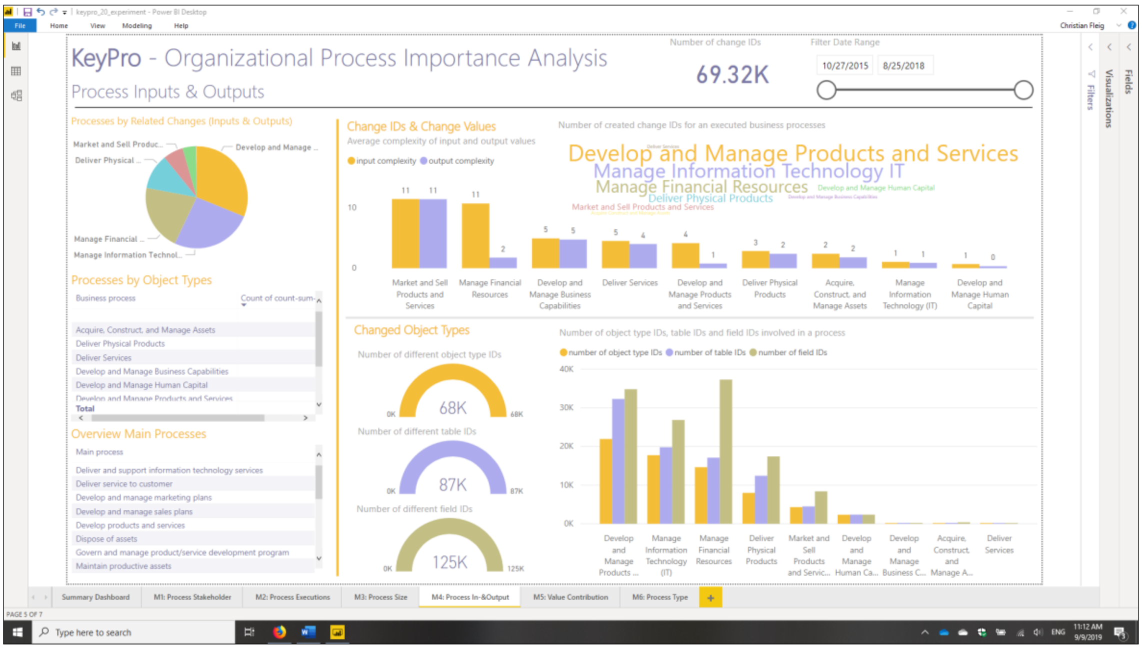


Figure 50: Summary dashboard with global process list sorted by PPI and detail dashboards in KeyPro (based on (Hummel, 2019))

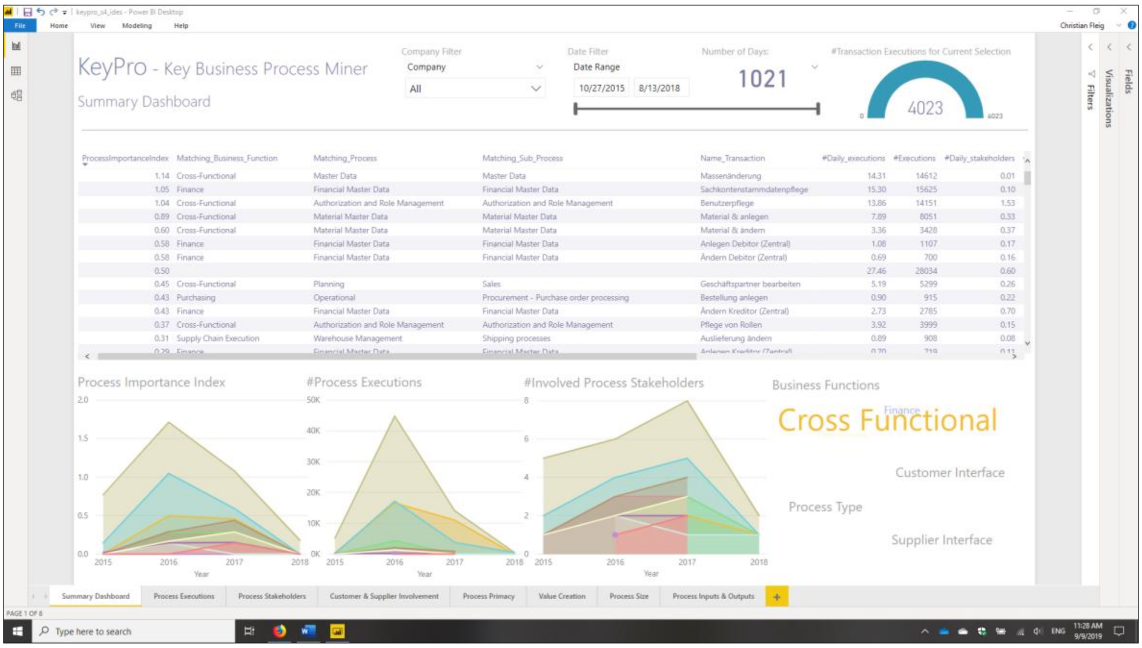
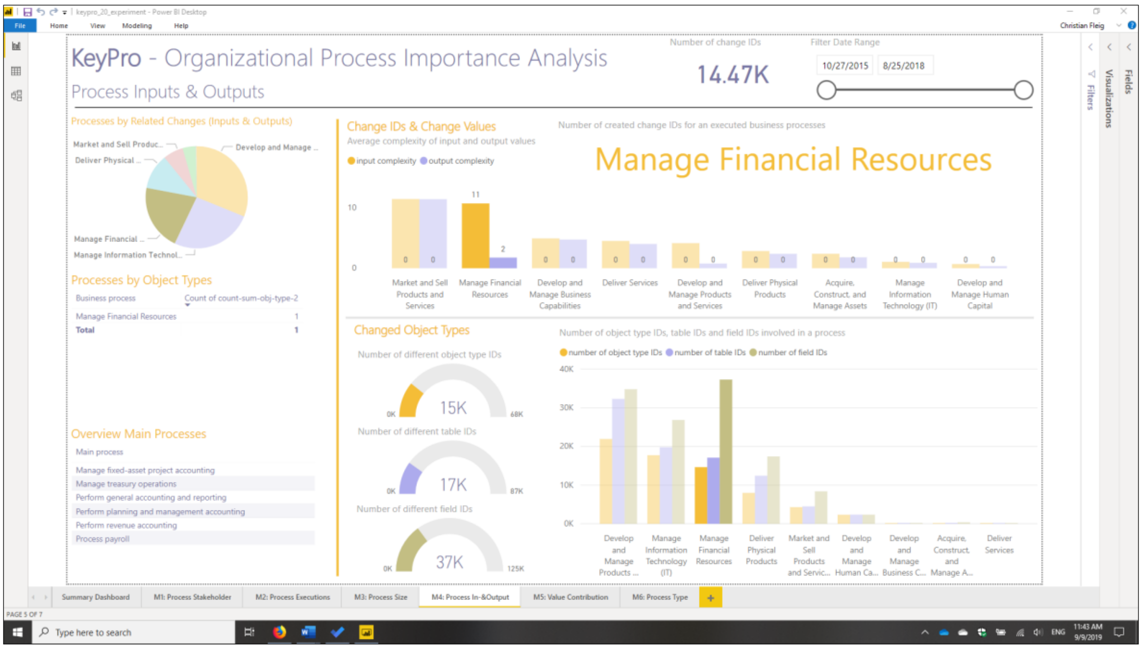


Figure 51: Exemplary dashboard for process inputs & outputs (filtered for the main process "Manage Financial Resources") (based on (Hummel, 2019))



All metrics dashboards are created with the same template in size, colors, and basic structure. Each dashboard contains a header bar with a company filter (e.g., the company code in an SAP system), a filter for the date range, as well as a text search bar to search for a BP. On the left-hand side of the dashboards, KeyPro provides the process hierarchy in tabular form to select among the business functions, main-, and sub-processes. However, dashboards differ in terms of the elements used to represent the differing content of the individual metrics.

Table 38: Overview of the design of the individual dashboards to represent importance metrics

Dashboard / Metric	**Dashboard elements (In Addition to Basic Layout)**
Stakeholders	2 semi-circle diagrams to visualize the number of involved employees and departments; 1 word cloud on involved departments; 1 area diagram including the number of involved employees by the department over time; 2 bar charts to represent the share of processes with/without customer and stakeholder involvement
Executions	1 semi-circle diagram including the number of process executions; 1 table including scattering parameters; 1 line diagram to represent process executions over time
Size	1 tree diagram with process hierarchy; 5 semi-circles to represent the numbers of nodes in the hierarchy (business processes, main processes, processes, sub-processes) and the overall process size
In- & Outputs	3 bar charts on change IDs / change values, the number of change IDs, and the number of changes / tables / fields; 1 text box with the number of changes ("KPI"); 3 semi-circle diagrams

Dashboard / Metric	Dashboard elements (In Addition to Basic Layout)
Value Creation	2 bar charts to represent the average and sum of process durations; 2 semi-circle diagrams on average process duration and costs; 2 text boxes to represent total durations and costs
Primacy	2 pie charts to represent the share of primary / secondary processes regarding executions / process hierarchy; 4 text boxes on numbers of primary / secondary processes regarding executions / hierarchy; 2 stacked bar charts including the number of processes by executions and process hierarchy
Summary Dashboard	1 semi-circle diagram on the overall PPI; 6 semi-circle diagrams on the individual importance metrics; 1 bar chart on the 5 most important processes;

In the summary dashboard including the PPI, each process importance metric is provided in a semi-circle diagram, with one PPI diagram combining all the metrics according to the equation in Equation 3in section 5.3.2.3. The metrics which are included in the calculation of the overall PPI can be adjusted with filters.

Figure 52: Process Performance Index (PPI) in KeyPro on the summary dashboard (based on (Hummel, 2019))

5.3.4 Evaluation: Laboratory Experiment on Comprehension[15]

In line with the other DSR projects in this thesis, KeyPro was evaluated for the ability to contribute to the comprehension of users when interacting with the artifact to better understand the process landscape of the organization as a prerequisite for decision-making in BPM projects such as BPS. The evaluation in design cycle 2 conducts a controlled laboratory experiment on comprehension with students to demonstrate that novice users are able to comprehend process information presented by the tool, and provides descriptive results of the comprehension of the individual dashboards. Second, the evaluation tries to identify dashboards with potential for improvement in comprehension in future development. Due to scope limitations of this thesis, the analysis is limited to presenting descriptive results. The statistical analysis compare dashboards against each other in order to identify dashboards with improvement potential is attached in section 10.4 in the appendix.

In the experiment, objective comprehension is operationalized as in the laboratory experiment in DSR project 1 in section 4.3.4 by measuring the *effectiveness* (the number of correctly answered questions), *efficiency* (the time required to answer the questions) and *relative efficiency* (the number of correctly answered questions divided by the time required) to measure comprehension (Mendling, Strembeck and Recker, 2012; Sharda, Barr and McDonnell, 1988; Venable, Pries-Heje and Baskerville, 2014).

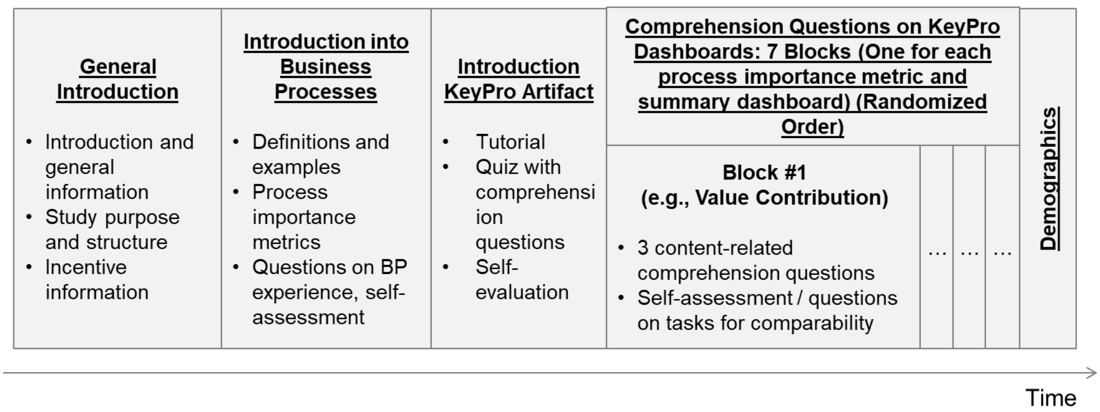
5.3.4.1 Experiment Structure and Content

The experiment structure contains an online survey of five sections. First, the introduction presents initial information on the experiment and the KeyPro research project background. Subjects receive information on the experiment structure, a privacy note, and the expected duration. The second part of the survey introduces the notion of BPs in general and the importance metrics by providing generic definitions, illustrations, and examples. Subjects are asked conclusive comprehension questions on the presented process theory part. Besides, the second part contains a self-evaluation, and a self-estimate of experience with BPs. Afterward, the third section introduces the KeyPro evaluand to subjects. The

[15] The experiment was conducted within the context of a supervised master thesis by Hummel (2019).

section presents screenshots and introductions into tool usage and background information on the information in the tool. Subjects are asked whether the information on KeyPro was understood. In the fourth part, subjects are asked to answer content-related comprehension questions by using the KeyPro artifact based on data from an educational SAP S/4 HANA system of a fictitious bicycle manufacturing corporation. Comprehension questions require subjects to find and understand the information by using the interactive dashboard functions such as filtering or drilling down into the dashboards. The order of the comprehension question blocks on the individual dashboards is randomized. Question blocks contain three multiple-choice questions, plus three questions on perceived complexity, required thinking and problem-solving skills, and on how challenging subjects perceived the questions. The fifth part asks demographic questions including gender, age, education, profession, and experience with Microsoft PowerBI.

Figure 53: Experiment structure



5.3.4.2 Experiment Execution and Sample Description

The experiment sessions were conducted in March / April 2019 in a computer pool at the "Institute of Information Systems & Service Design" (ISSD) at Karlsruhe Institute of Technology (KIT). On average, sessions lasted 54.65 minutes (Std. Dev = 13.97 minutes, min = 35.44 minutes, max = 89.44 minutes). Each subject received the survey implemented online and the KeyPro artifact on screen as well as a printout of the theory section of the survey. As an incentive, subjects received gifts and had the chance to win a voucher. In total 30 subjects participated during the experiment (18 females and 12 males). On average, participants were 27.2 years old (Std.Dev = 7.5 years). 63.3% of participants pursue a Bachelor's degree, while 26.7% are Master students. The remaining subjects are either high school graduates or others. In profession, 76.7% of subjects indicated "student", while 16.7% of the sample is employed for wages. The remaining part is either self-employed or out of work. Besides, subjects were asked for a self-estimate on experience with theoretical and practical BPs and their proficiency in Microsoft PowerBI on a 1-5 Likert scale (1 indicates "very low" and 5 indicates "very high"). The results are indicated in table 39.

Table 39: Descriptives on experience with BPs and Microsoft PowerBI

	Descriptives				
	Mean	**Variance**	**Std.Dev.**	**Min**	**Max**
Theoretical Experience	2.63	0.8322	0.9123	1	4
Practical Experience	2.37	0.9656	0.9826	1	4
Microsoft PowerBI	1.60	0.7733	0.8794	1	4

5.3.4.3 Results Analysis

The analysis of the experiment contains three parts. Results on effectiveness, efficiency, and relative efficiency are analyzed descriptively. On average, subjects achieved a mean value of 2.62 correct responses (max = 3) for effectiveness. The dashboard on the value creation metric performs worst with a mean value of 2.37, while the dashboard on size achieves the best result with a mean of 2.93.

Table 40: Results for effectiveness

	Effectiveness				
	Mean	**Variance**	**Std.Dev**	**Min**	**Max**
Stakeholders	2.433333	0.5298851	0.727932	1	3
Executions	2.8	0.1655172	0.4068381	2	3
Size	2.933333	0.0643678	0.2537081	2	3
Inputs & Outputs	2.866667	0.1195402	0.3457459	2	3
Value Creation	2.366667	0.3781609	0.6149479	1	3
Process Primacy	2.7	0.2172414	0.4660916	2	3
Summary Dashboard	2.466667	0.4643678	0.6814454	1	3
Total	**2.618333**	**0.0360316**	**0.1898199**	**2.175**	**3**

In terms of efficiency, subjects required an average of 245.12 seconds to understand the contents of a metrics dashboard and to answer the comprehension questions. Although the value creation dashboard achieved the lowest effectiveness, the dashboard performed best regarding the time required with a mean of 195.30 seconds. The dashboard on process size required the highest amount of time with a mean value of 340.30 seconds. These results are further confirmed by evidence from relative efficiency, with the size dashboard exhibiting the worst comprehension (mean value of 0.11), while the value creation and the executions dashboards perform best (mean values of .0164 and .01641, respectively). Detailed statistical tests are provided in section 10.4 in the appendix.

Table 41: Results for efficiency

	Efficiency				
	Mean	**Variance**	**Std.Dev**	**Min**	**Max**
Stakeholders	197.34	6764.74	82.25	68.10	410.05
Executions	214.75	12651.42	112.48	93.67	478.77
Size	340.30	29677.61	172.27	132.35	928.98
Inputs & Outputs	274.35	9438.72	97.15	159.38	588.66
Value Creation	195.30	9967.92	99.84	59.08	433.54
Process Primacy	271.70	26994.35	164.30	82.93	712.82
Summary Dashboard	222.12	7928.35	89.04	77.67	441.84
Total	**245.12**	**14774.73**	**116.76**	**96.17**	**570.67**

Table 42: Results for relative efficiency

	Relative Efficiency				
	Mean	**Variance**	**Std.Dev**	**Min**	**Max**
Stakeholders	0.0148365	0.0000627	0.0079175	0.0029113	0.0301023
Executions	0.0164067	0.0000576	0.0075911	0.0041774	0.0320273
Size	0.0106353	0.000023	0.0047944	0.0021529	0.0226672
Inputs & Outputs	0.0116086	0.0000143	0.0037867	0.0033975	0.0188229
Value Creation	0.0164572	0.0001453	0.0120554	0.0035435	0.0507786
Process Primacy	0.0138229	0.0000696	0.0083447	0.0028058	0.0361751
Summary Dashboard	0.0131197	0.0000507	0.0071238	0.0025893	0.038625

6 DSR Project 3: Design of a Process Mining DSS for Data-Driven BPS[16]

Rapidly evolving competitive environments and emerging business opportunities require the standardization of BPs in the organization in response to new conditions (Teece, 2010). Traditional non-data-driven approaches to BPS rely on "de-jure" process analyses instead of "de-facto" data-driven approaches (Fleig, Augenstein and Maedche, 2018c). These “de-jure” approaches suffer from a number of insufficiencies as they are based on handmade process models which are often biased compared to process reality (van der Aalst, 2011). However, the standardization of a BP requires organizations to precisely understand the real-world execution of the as-is process to select an appropriate standard process design (Tiwari, Turner and Majeed, 2008) which matches BPS contingencies as required by the OCT kernel theory (cf. section 2.1.1 and section 2.3.3). Therefore and as motivated in section 1.1.3, DSR project 3 suggests and develops a process mining-enabled DSS to recommend a standard process design for an as-is process from a repository of possible alternative standard process designs by taking into account the BPS contingency factors. Thus, the DSS in DSR project 3 aims to reduce the overall costs of BPS, to optimize the degree of fit between the organization and the implemented processes as required by OCT, and to minimize the degree of organizational change required in BPS and ERP implementation projects.

6.1 Outline of DSR Project 3: Design Cycles

DSR project 3 consists of two design cycles. The problem awareness phase first discovers the need to design BPMN process models with additional contingency factors on BPS which increase the comprehension of decision-makers for selecting standard BPs. Therefore, the goal of the first design cycle is to derive, implement, and evaluate process model variants for representing BPS contingency factors. Figure 54 provides an overview of the design cycle contents in DSR project 3.

[16] This chapter contains content previously published in Fleig, Augenstein and Maedche (2018a, 2018c), Fleig (2017); Fleig, Augenstein and Maedche (2019).

Figure 54: Overview of design cycle contents of DSR project 3

Process Iteration	First Design Cycle	Second Design Cycle
Problem Awareness	• Expert workshops in the SAP S/4 HANA and BPS project at the industry partner • Literature-based motivation of the need for data-driven selection of standard process designs based on BPS contingency factors	
Suggestion	• Literature review on influence factors on process model comprehension	• Design requirements for process mining-enabled DSS to recommend standard process designs from a process repository based on similarity of BPS contingency factors
Development	• Implementation of alternative process model variants for representing BPS contingency factors based on literature findings	• Implementation of DSS in Apromore for SAP R/3 systems
Evaluation	• Controlled laboratory experiment on comprehension of process model alternatives	• Field application of the DSS at the industry partner for SAP R/3 purchase-to-pay and order-to-cash processes with SAP Best Practices Explorer
Conclusion	• Results analysis • Selection of one process model design alternative for implementation in DSS	• Results analysis

Thus, the adjacent suggestion phase first reviews existing research on comprehension and derives determinants on process model comprehension (PMC) from literature to propose different alternative process model variants. As opposed to the suggestion phases of the other design cycles and regarding the research goal of designing a data-driven DSS for the selection of standard BPs, the suggestion phase of DSR project 3 does not derive a specific and self-contained set of DRs for the process model variants. Nevertheless, DRs for the DSS are derived in the second design cycle, including the need for process models to increase comprehension. The development phase implements four different process model variants. Finally, the evaluation phase conducts a controlled laboratory experiment on PMC of the alternatives to select the one process model variant with the highest PMC.

However, selecting standard BPs based on BPS contingency factors requires data-driven inputs from process mining, a high degree of manual effort, and involves substantial complexity due to a high number of process variants and contingency factors. Therefore, the problem awareness phase reveals the need for a data-driven DSS to support the selection of standard BPs from literature and the industry partner BPS and S/4 HANA migration project. The suggestion phase thus derives design requirements for a process mining DSS including a similarity-based process matching algorithm to select process models from a repository of different alternative standard processes based on the similarity of contingency factors. The development phase subsequently implements a prototype instantiation of the DSS in the open-source process analytics platform “Apromore” (The Apromore Initiative, 2018) including the process models for BPS contingency factors from the first design cycle. For an evaluation of the prototype in the second design cycle, the technical feasibility of the DSS is demonstrated in a field showcase in the context of the BPS and SAP S/4 HANA migration project at the industry partner. In particular, the DSS is applied for the SAP R/3 ERP purchase-to-pay and the order-to-cash processes which were selected as “important” BPs by the KeyPro artifact in DSR project 2 to recommend a standard BP design for the future SAP S/4 HANA processes from the SAP Best Practices Explorer database.

6.2 Design Cycle 1: Process Model Variants for BPS Contingency Factors[17]

6.2.1 Suggestion: Process Model Variants for BPS Contingency Factors

Previous research on process model comprehension has identified numerous impact factors (Figl, 2017) on the part of the model and on the part of the user which need to be taken into account for designing comprehensible process models for BPS contingency factors (Dikici, Turetken and Demirors, 2018). The following section reviews existing research on determinant factors on PMC to propose different alternative process model variants that are to be evaluated in terms of their ability to contribute to user comprehension to select the process model variant with the highest PMC for implementation in the DSS.

To summarize the state of research on impact factors of PMC, a literature review on PMC and (understandability as a synonym) was conducted in academic databases such as Scopus, Web of Science and EBSCOHost. Contributions in the literature review include English and German journal contributions as well as books and conference proceedings which

[17] Parts of this chapter build on the results of a supervised master thesis by Beck (2018).

were published in a period between 1997 and 2017. Contributions in the literature pool focus on empirical studies that examine the impact factors on PMC. To structure the contributions into dimensions according to which different process model variants are developed in the next phase, the contribution by Gemino and Wand (2003) is taken as a reference. In Gemino and Wand (2003), the authors distinguish the categories according to content as the information on the domain which is contained in models, presentation method as the way the information is presented to users, and user-related characteristics (Gemino and Wand, 2003). Therefore, findings in table 43 are categorized into process model-related and user-related factors and described in the following. For process model-related factors, the literature review identified "primary notation", "secondary notation", "complexity", "labeling" and "others". Concerning user-related factors, "objective experience", "subjective experience" and "personal characteristics" were identified as determinants of PMC.

6.2.1.1 Process Model-Related Factors

6.2.1.1.1 Primary Notation

"Primary notation" comprises the syntax or language to depict a process model (Figl and Strembeck, 2015), such as Petri nets, event-driven process chains (EPCs), or BPMN which differ regarding their comprehension (Sarshar and Loos, 2005). Besides, further research finds differences in PMC between EPCs vs. Unified Modeling Language (UML) (Jošt *et al.*, 2016), process- vs. object-based notations (Agrawal, De and Sinha, 1999), high- vs. low communication flow diagrams (Kock *et al.*, 2009) and imperative vs. declarative process models (Pichler *et al.*, 2012). In particular, the primary notation "Business Process Model and Notation" (BPMN) has received a high degree of attention in PMC research. Although some studies find no significant effect compared to EPCs (Recker and Dreiling, 2007, 2011), a high number of studies finds BPMN to be superior in terms of comprehension compared to C-Yawl (Döhring, Reijers and Smirnov, 2014), text-based models (Figl and Recker, 2016a), EPCs (Gabryelczyk and Jurczuk, 2017; Weitlaner, Guettinger and Kohlbacher, 2013), written use cases (Ottensooser *et al.*, 2012) or text-based instructions (Rodrigues *et al.*, 2015). However, contrasting contributions find BPMN to be less comprehensible than BPMS (Gabryelczyk and Jurczuk, 2017), UML AD and EPCs (Jošt *et al.*, 2016), deontic BPMN (Natschläger, 2011), HPN (Stitzlein, Sanderson and Indulska, 2013), SBD (Weitlaner, Guettinger and Kohlbacher, 2013) or eEPCs (Wiebring and Sandkuhl, 2015). In addition, research further identified notational characteristics as precedents of comprehension (Figl, 2017) as well as the aesthetics (Figl, Mendling and Strembeck, 2013) of visual elements such as symbols or the gateways (Figl, Recker and Mendling, 2013; Gabryelczyk and Jurczuk, 2017; Recker, 2013).

6.2.1.1.2 Secondary Notation

Besides the primary notation, "secondary notation" captures elements of process models that convey information for the interpretation such as modeling conventions (Petre, 2006) and possibly influences PMC. From PMC literature, the major streams in secondary notation include the integrated visualization of the process model, visual guidance of the user when interacting with the model, the decomposition of the model into structural elements, and the model layout.

Integrated visualization has been discovered as a determinant of PMC with a positive impact (Radloff, Schultz and Nüttgens, 2015; Reggio *et al.*, 2015; Schultz and Radloff, 2014; Trkman, Mendling and Krisper, 2016; Wang, Indulska and Sadiq, 2016). In integrated visualization, information such as BPS contingency factors is integrated into the process model (Wang, 2017). Examples include objects or (linked) rules (Koschmider, Kriglstein and Ullrich, 2013; Wang *et al.*, 2017), constraints (Reggio *et al.*, 2015), perspectives (Mturi and Johannesson, 2013), controls (Radloff, Schultz and Nüttgens, 2015; Schultz and Radloff, 2014) or even user stories (Trkman, Mendling and Krisper, 2016).

Besides, visual guidance exerts a positive impact on PMC in secondary notation (Johannsen, Leist and Braunnagel, 2014; Johannsen, Leist and Tausch, 2014; Reijers, Mendling and Dijkman, 2011; Turetken *et al.*, 2016) and comprises visual elements of the process model to guide users including colors (Kummer, Recker and Mendling, 2016; Petrusel, Mendling and Reijers, 2016), symbols, syntax highlighting (Reijers *et al.*, 2011), graphical annotations (Figl and Recker, 2016a) or perceptual discrimination (Stark, Braun and Esswein, 2016).

In addition, the model layout constitutes another factor of PMC, which has been found to positively impact PMC (Mendling *et al.*, 2018; Petrusel, Mendling and Reijers, 2016).

6.2.1.1.3 Complexity

Model complexity is determined by process model elements including size, the number of gateways, structuredness or connectivity. Process model size comprises the number of process nodes, arcs or diameters and numerous publications find a significant inverse impact of model size on PMC (Döhring, Reijers and Smirnov, 2014; Mendling and Strembeck, 2008; Recker, 2013; Sánchez-González *et al.*, 2010; Zimoch *et al.*, 2017). Besides, an increasing number of gateways (Reijers and Mendling, 2011; Sánchez-González *et al.*, 2012), gateway interplay (Figl and Laue, 2011, 2015; Laue and Gadatsch, 2011; Melcher *et al.*, 2010; Mendling and Strembeck, 2008; Sarshar and Loos, 2005; Weitlaner, Guettinger and Kohlbacher, 2013) and heterogeneity of gateways (Mendling and Strembeck, 2008; Reijers and Mendling, 2011; Sánchez-González *et al.*, 2010; Sánchez-González *et al.*, 2012) negatively affects PMC. Furthermore, the degree of gateways (Reijers and Mendling, 2011; Sánchez-González *et al.*, 2012), mismatch (Reijers and Mendling, 2011; Sánchez-González *et al.*, 2012) or complexity negatively impacts PMC (Rolón *et al.*, 2009; Sánchez-González *et al.*, 2012).

The complexity of process models further entails the structuredness of the model (Dumas *et al.*, 2012; Figl and Laue, 2011, 2015; Mendling and Strembeck, 2008; Sánchez-González *et al.*, 2010) and connectivity of model elements (Reijers and Mendling, 2011; Sánchez-González *et al.*, 2010).

6.2.1.1.4 Labeling

Labelling includes factors that are related to the naming of elements in the process model. In labeling, PMC literature identified abstraction of labels (Figl and Strembeck, 2015; Mendling and Strembeck, 2008; Mendling, Strembeck and Recker, 2012), revisions (Koschmider *et al.*, 2015), styles of wording (Mendling, Reijers and Recker, 2010) and the length of textual elements (Mendling and Strembeck, 2008) as determinants of PMC.

6.2.1.1.5 Others

“Others” is a collection of different factors unrelated to the previous categories and comprises the application of modeling guidelines (Heggset, Krogstie and Wesenberg, 2015; Sánchez-González *et al.*, 2017), the ease of generating the process model (Kock *et al.*, 2009) or model soundness (Mendling and Strembeck, 2008). However, while some studies find guidelines and the ease of generating the process model generation to contribute to PMC (Heggset, Krogstie and Wesenberg, 2015; Kock *et al.*, 2009; Sánchez-González *et al.*, 2017), soundness is not found to foster PMC (Mendling and Strembeck, 2008).

6.2.1.2 User-Related Factors

Numerous studies find a significant impact of objectively measurable experience (for example in process modeling knowledge tests such as by Mendling, Strembeck and Recker (2012), conceptual familiarity tests as in Figl and Recker (2016a) or educational backgrounds (Reggio *et al.*, 2015)) by users on PMC (Figl and Laue, 2015; Figl, Mendling and Strembeck, 2013; Figl, Recker and Mendling, 2013; Figl and Strembeck, 2015; Kummer, Recker and Mendling, 2016; Mendling *et al.*, 2018; Mendling and Strembeck, 2008; Mendling, Strembeck and Recker, 2012; Recker, 2013; Turetken, Vanderfeesten and Claes, 2017).

Besides objective experience in process models, subjective self-assessments concerning experience including theoretical or practical knowledge (Figl, Mendling and Strembeck, 2013; Johannsen, Leist and Braunnagel, 2014; Recker and Dreiling, 2007, 2011; Reijers and Mendling, 2011; Weitlaner, Guettinger and Kohlbacher, 2013) or familiarity (Kummer, Recker and Mendling, 2016; Mendling *et al.*, 2018; Recker, 2010, 2013) are determined by literature as influencing variables of PMC. In addition, other subjectively measurable user-related factors include intensity of modeling or modeling duration (Johannsen, Leist and Tausch, 2014; Mendling *et al.*, 2018; Mendling and Strembeck, 2008; Mendling, Strembeck and Recker, 2012; Ottensooser *et al.*, 2012; Recker and Dreiling, 2011; Reijers and Mendling, 2011; Reijers, Mendling and Dijkman, 2011).

Finally, personal characteristics were discovered to influence PMC with constructs such as education (Döhring, Reijers and Smirnov, 2014; Mendling *et al.*, 2018; Reijers and Mendling, 2011; Reijers, Mendling and Dijkman, 2011; Weitlaner, Guettinger and Kohlbacher, 2013), cognition (Figl and Recker, 2016a; Ottensooser *et al.*, 2012; Petrusel, Mendling and Reijers, 2017; Recker, Reijers and van de Wouw, 2014; Turetken, Vanderfeesten and Claes, 2017), domain knowledge (Johannsen, Leist and Braunnagel, 2014; Recker and Dreiling, 2007; Recker, Reijers and van de Wouw, 2014; Reijers, Mendling and Dijkman, 2011; Stitzlein, Sanderson and Indulska, 2013; Turdasan and Petrusel, 2016; Turetken *et al.*, 2016) or others such as sex (Radloff, Schultz and Nüttgens, 2015; Schultz and Radloff, 2014), culture (Kummer and Schmiedel, 2016) and second language (Recker and Dreiling, 2011).

6.2.1.3 Selection of Impact Factors for Development of Process Model Variants

Resulting from the literature review on process model-related impact factors on PMC in section 6.2.1, the development of the process model variants for BPS contingency factors focuses on the process model-related factors. Personal factors cannot be changed in the development of process models and are therefore not regarded. The most promising constructs in the secondary notation for developing process models are integrated visualization, model decomposition and visual guidance, which are selected for the representation of contingency factors in different variants. To isolate the effects of the chosen independent variables from the other impact factors on PMC from the process model, the other factors from “primary notation”; “secondary notation”, “complexity”; “model labeling” and “quality” need to be controlled and kept constant during the development of the attribute-enriched process model variants. First, to control for the impact of primary notation, all process model variants are created in BPMN due to the wide acceptance of the notation in academia and practice (Figl and Laue, 2015). Second, model complexity is controlled by creating process model variants with the same complexity. All process model variants in the development and evaluation phase are therefore created as norm-complexity based on Recker (2013) and Kunze *et al.* (2011). All process model variants include twelve nodes (with eight tasks and four gateways), 15 arcs and a connector degree of three. Third, label design is held constant by writing all labels in non-abstract verb-object style and by naming all BPS contingency factors identically. Fourth, all process model variants are designed according to the “7PMG” modeling guidelines provided by Mendling, Reijers and van der Aalst (2010).

Table 43: Contributions on process model comprehension (based on (Beck, 2018))

Contribution	PM-related factors					User-related factors		
	Notation (Primary)	**Notation (Secondary)**	**Complexity**	**Labeling**	**Others**	**Objective Experience**	**Subjective Experience**	**Personal**
(Agrawal, De and Sinha, 1999)	±							
(Döhring, Reijers and Smirnov, 2014)	+		+					○
(Dumas *et al.*, 2012)			+			±		
(Figl and Laue, 2011)			+					
(Figl and Laue, 2015)			+			+		
(Figl, Mendling and Strembeck, 2013)	+					±	+	
(Figl and Recker, 2016b)	±	±				±		±
(Figl, Recker and Mendling, 2013)	+					+		
(Figl and Strembeck, 2015)		○		+		+		
(Gabryelczyk and Jurczuk, 2017)	+							
(Gross and Doerr, 2009)	○							
(Heggset, Krogstie and Wesenberg, 2015)					±			
(Hipp *et al.*, 2015)	+							
(Johannsen, Leist and Braunnagel, 2014)		+				○	○	○
(Johannsen, Leist and Tausch, 2014)		±						
(Jošt *et al.*, 2016)	±							
(Kock, Danesh-Pajou and Komiak, 2008)	○							
(Kock *et al.*, 2009)	+				+			
(Koschmider, Kriglstein and Ullrich, 2013)		+						
(Koschmider *et al.*, 2015)				+				
(Kummer, Recker and Mendling, 2016)		±				±	○	+
(Laue and Gadatsch, 2011)			±					

Contribution	PM-related factors					User-related factors		
	Notation (Primary)	Notation (Secondary)	Complexity	Labeling	Others	Objective Experience	Subjective Experience	Personal
(Melcher *et al.*, 2010)			±					
(Mendling *et al.*, 2018)		+				+	+	+
(Mendling, Reijers and Recker, 2010)				+				
(Mendling and Strembeck, 2008)			+	+	○	+	○	
(Mendling, Strembeck and Recker, 2012)				+		+	+	
(Mturi and Johannesson, 2013)		±						
(Natschläger, 2011)	±							
(Ottensooser *et al.*, 2012)	±						±	±
(Petrusel, Mendling and Reijers, 2016)		+						
(Petrusel, Mendling and Reijers, 2017)								+
(Radloff, Schultz and Nüttgens, 2015)		+						○
(Recker, 2013)	+		+			+	○	
(Recker and Dreiling, 2007)	○						○	○
(Recker and Dreiling, 2011)	○						+	+
(Recker, Reijers and van de Wouw, 2014)						○		+
(Reggio *et al.*, 2015)		+				+		
(Reijers *et al.*, 2011)		±						
(Reijers and Mendling, 2011)			+				○	±
(Reijers, Mendling and Dijkman, 2011)		±					○	○
(Rodrigues *et al.*, 2015)	±							
(Rolón *et al.*, 2009)			+					
(Sánchez-González *et al.*, 2012)			+					
(Sánchez-González *et al.*, 2017)					±			
(Sánchez-González *et al.*, 2010)			+					
(Sarshar and Loos, 2005)	±		±					
(Schultz and Radloff, 2014)		+						○

Contribution	PM-related factors					User-related factors		
	Notation (Primary)	Notation (Secondary)	Complexity	Labeling	Others	Objective Experience	Subjective Experience	Personal
(Soffer, Wand and Kaner, 2015)								
(Stark, Braun and Esswein, 2016)		+						
(Stitzlein, Sanderson and Indulska, 2013)	±							○
(Trkman, Mendling and Krisper, 2016)		+						
(Turdasan and Petrusel, 2016)								○
(Turetken *et al.*, 2016)		+					○	○
(Turetken, Vanderfeesten and Claes, 2017)						+		+
(Wang, 2017)		+						
(Weitlaner, Guettinger and Kohlbacher, 2013)	±		±				○	+
(Wiebring and Sandkuhl, 2015)	±							
(Zimoch *et al.*, 2017)			±					
Number of studies	**21**	**18**	**15**	**5**	**4**	**15**	**14**	**19**

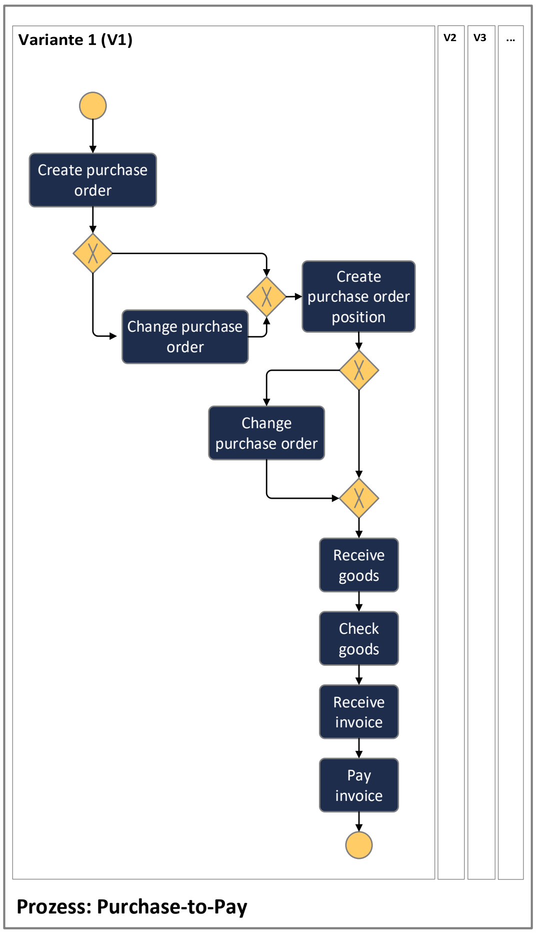
6.2.2 Development: Instantiation of BPMN Process Model Variants for BPS Contingency Factors[18]

Based on the findings from the literature review in the previous section 6.2.1, this section implements four different alternative process model variants that focus on “integrated modeling”, “decomposition”, and “visual guidance” for later evaluation and the implementation into the DSS. Process model variants are instantiated as prototypes in Microsoft Visio 2017 Professional and Java. For prototype development and evaluation of the process models, the industry partner provided process models for an SAP standard purchase-to-pay (“procurement”), returned shipments, order-to-cash (“sales”) and a production process.

In the first design variant, BPS contingency factors are presented in a tabular format next to the BPMN process model which is intended to mirror the current situation with process models being supplemented by additional process information such as Excel spreadsheets. The tabular process model variant is illustrated in figure 55.

[18] Process models were developed and implemented in collaboration with a supervised master thesis by Beck (2018).

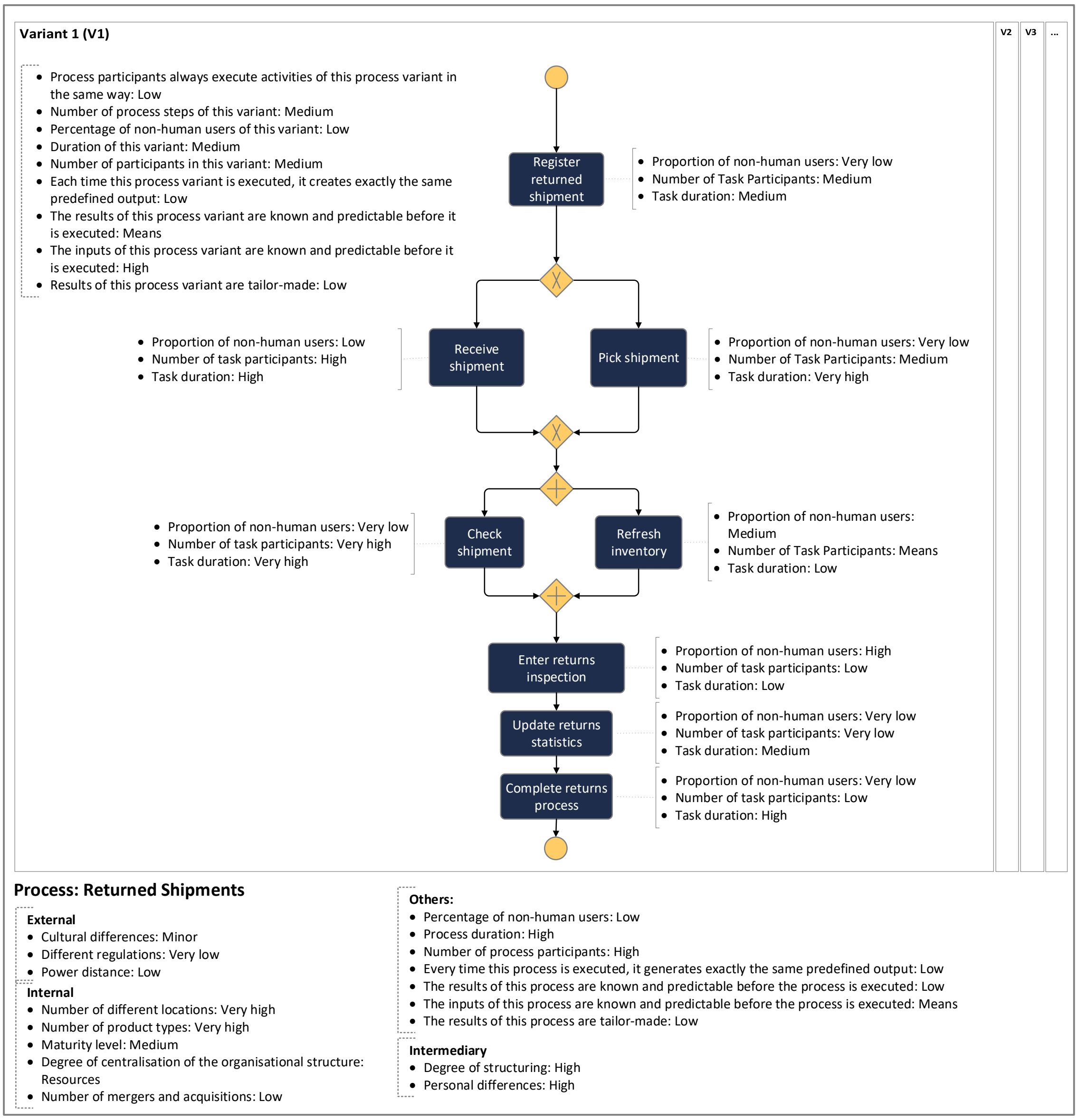
Figure 55: Process model variant 1 - tabular representation of contingency factors (based on (Beck, 2018))



Contingency Factor	Description	Value
Process-Level		
Process Execution	Degree of structure of process activities and process sequence	High
Inputs & Outputs	Stability of input and output factors of the business process	Medium
Documentation	Rigor and completeness of documentation materials and trainings	High
Data	Extent to which process data is consistent across the business process and IT systems employed	Low
Information Technology	Availability of a common technological platform to support the business process	Medium
Governance	Embedding of rules and formal control mechanisms in the business process	Medium
People & Knowledge	Knowledge and skill intensity, which the business process requires	High
Culture	Degree to which corporate and national culture is supportive of standardization	Low
Legal	Differences and commonalities in governmental regulations across countries	High
Collaboration & Communication	Common patterns of collaboration within and among work teams	High
Strategy	Strategic focus of the process with regards to standardization	Low
Variant-Level		
...		

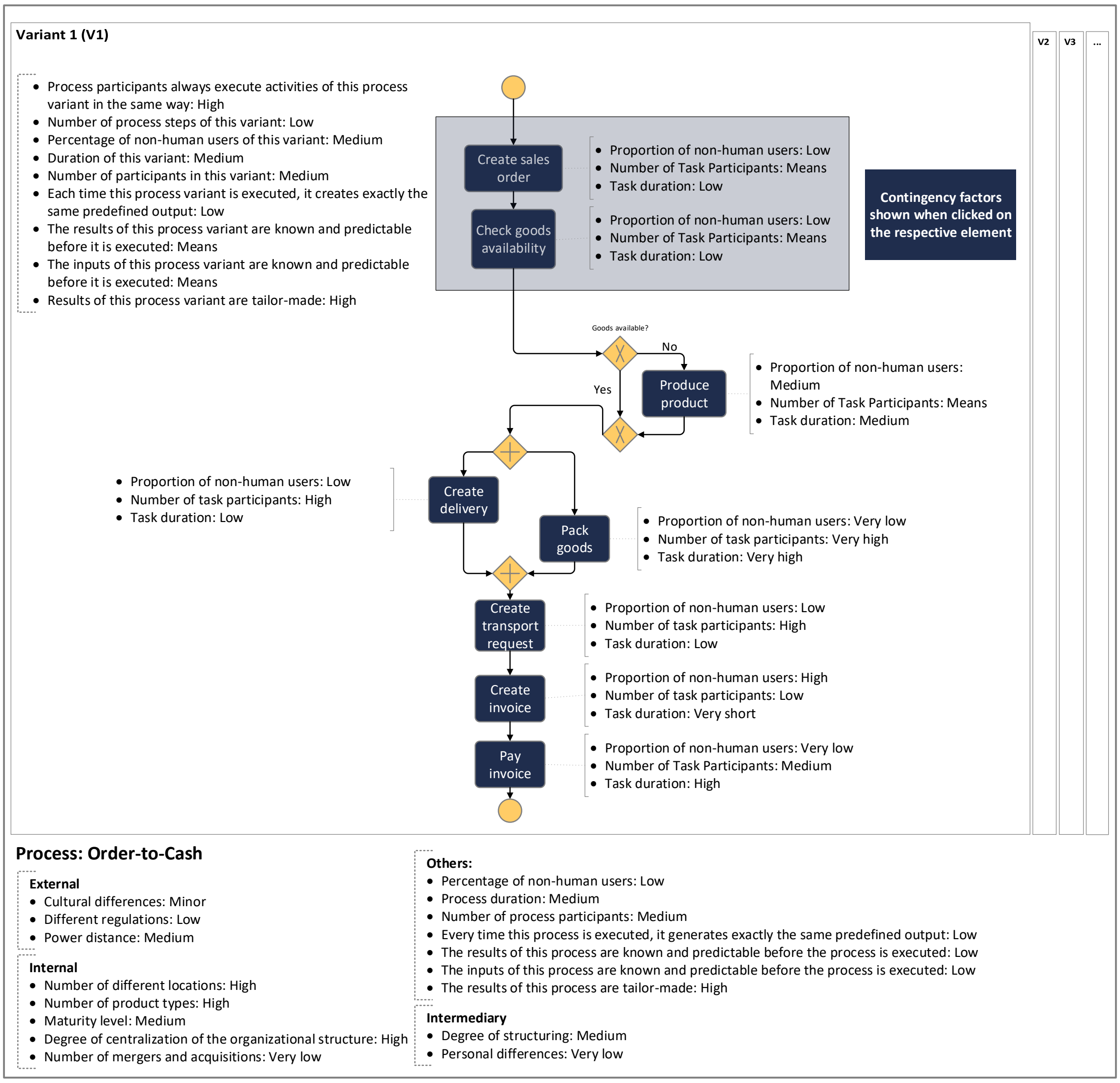
In the second and third design alternatives, the factors “integrated modeling” and “de-composition” are implemented by displaying contingency factors directly within the BPMN process model as either static (design 2, integrated modeling) or dynamic branches (design 3, decomposition). In the static, integrated modeling variant in figure 56, all BPS contingency factors and process information are visible without the need for interaction with the process model.

Figure 56: Process model variant 2 - static representation of contingency factors in branches (Integrated modeling) (based on (Beck, 2018))



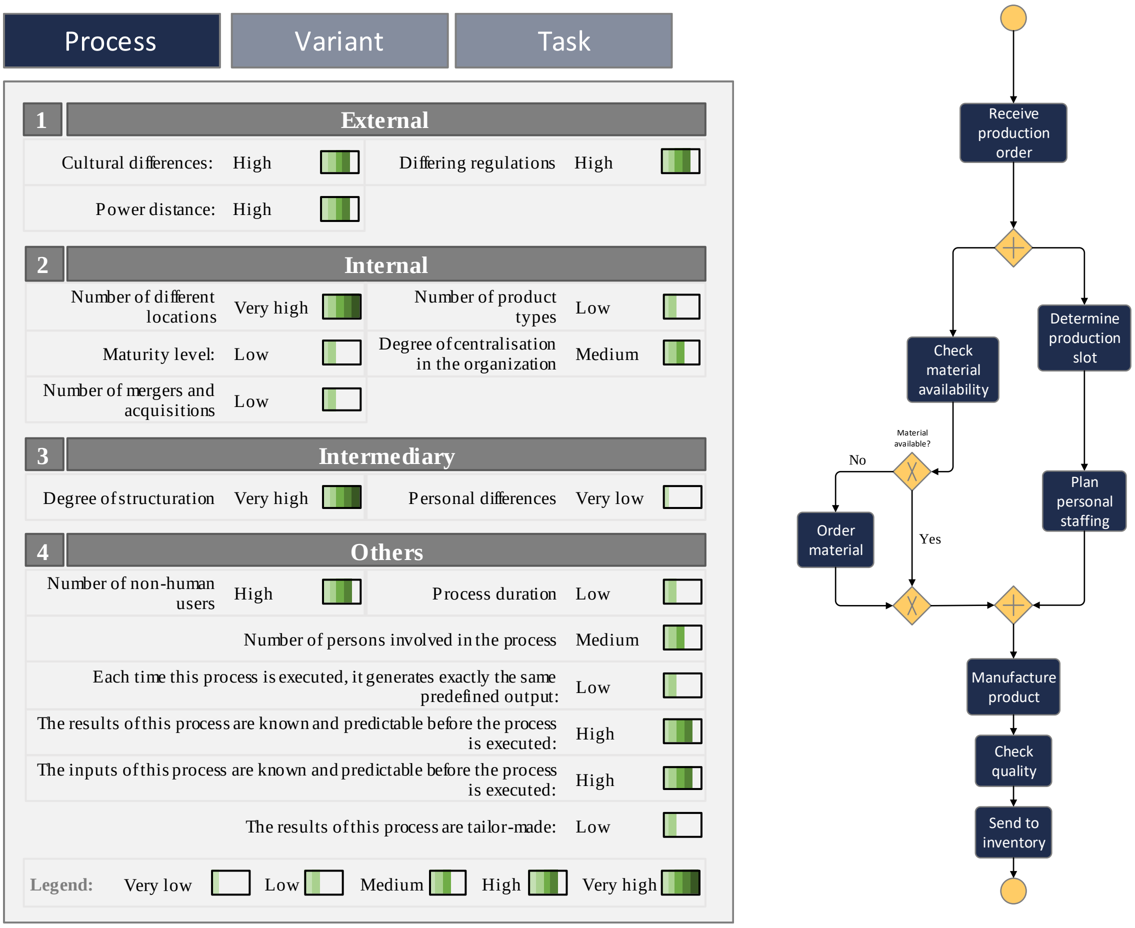
In contrast, the third decomposition variant in figure 57 tries to reduce the amount of information and BPS contingency factors displayed by providing users with the possibility to interactively hide or unhide process information. For example, when clicking on a task in the process model, associated BPS contingency factors are displayed.

Figure 57: Process model variant 3 – dynamic representation of contingency factors in branches (decomposition) (based on (Beck, 2018))



In the fourth alternative, a variant for "visual guidance" is implemented. Users are visually guided by graphical annotations such as icons that indicate the value for the respective BPS contingency factor and by providing "tabs" for the process-, variant-, and task-level contingency factors as illustrated in figure 58.

Figure 58: Process model variant 4 - guided representation of contingency factors in branches (visual guidance) (based on (Beck, 2018))



6.2.3 Evaluation: Laboratory Experiment on Process Model Comprehension[19]

Experiments are widely used in research on PMC (Mendling *et al.*, 2018). The aim of the evaluation in the first design cycle is to identify the process model variant with the highest comprehension for the implementation in the process mining DSS in the second design cycle. In order to select one of the four different design alternatives derived from literature

[19] The survey questionnaire was created in collaboration with a supervised mater thesis and is also contained in Beck (2018). Experiment data in Beck (2018) relies on a convenience sample from different experiment executions (not the laboratory sessions used as data in this thesis). Data analysis is conducted independently from Beck (2018).

and research on PMC, the first design cycle conducts a controlled laboratory experiment to evaluate and compare the model variants according to their comprehension.

6.2.3.1 Experiment Setup

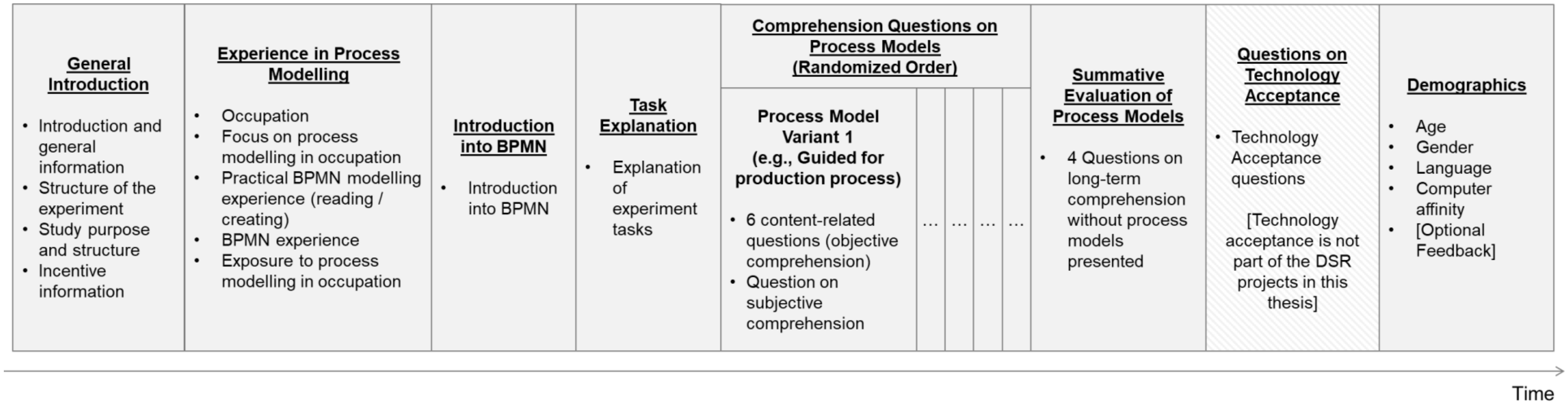
The experiment is conducted as a controlled laboratory experiment in an online survey in LimeSurvey[20] (open-source survey tool). The experiment is designed as a within-subject design (repeated measures) (Clark-Carter, 2004; Patig, 2008) such that all participants receive and evaluate all four process model variants implemented in the previous development phase in a randomized order. Within-subject designs allow controlling for participant-related, extraneous variables such as user-related factors (cf. table 43) which might impact the dependent variable of PMC (Patig, 2008). At the same time, within-subject designs increase statistical power due to a higher number of measurements per participant (Clark-Carter, 2004). However, within-subject designs possibly suffer from position or carry-over effects (Clark-Carter, 2009). Position effects impact the results from the position of the observation in the experiment (Hussy, Schreier and Echterhoff, 2013) due to fatigue, boredom, or learning effects and practice (Clark-Carter, 2009). In contrast, carry-over effects refer to the content (Hussy, Schreier and Echterhoff, 2013) and distortions of results related to prior measurements. For example, carry-over effects imply that one process model variant might be comprehended differently depending on the previous process model(s). The experiment uses randomized counterbalancing such that the sequence of process models is randomized to account for the challenges in within-subject designs (Christensen, Johnson and Turner, 2011).

The experiment consists of eight blocks as illustrated in figure 59. The survey is attached in the digital appendix of this dissertation. In the introduction, participants are welcomed and introduced into the study purpose, context and the structure of the experiment. Afterward, the practical and theoretical experience of participants in relation to process modeling knowledge is assessed. Practical experience is measured by self-evaluation and asks participants for their exposure (reading/writing) and the intensity of exposure to process models in their professional occupation and their overall BPMN and process modeling

[20] https://www.limesurvey.org/

experience. Questions are derived from Mendling *et al.* (2018) , Mendling, Reijers and Recker (2010) and Reijers and Mendling (2011). Theoretical knowledge on BPMN modeling is evaluated in an objective test of six right/wrong questions based on Mendling, Strembeck and Recker (2012). Afterward, the survey provides a tutorial into BPMN based on Pichler *et al.* (2012) and an explanation of the tasks during the comprehension questions to ensure that subjects have the required knowledge to answer the later comprehension questions. In the comprehension part, participants are asked content questions on the BPS contingency factors attached to the process models as well as to the overall process model. As in the previous laboratory experiment on comprehension in DSR projects 1 (BMM) and project 2 (KeyPro), comprehension is operationalized by *effectiveness* (the number of correctly answered comprehension questions), *efficiency* (the time required to answer comprehension questions), and *relative efficiency* (effectiveness divided by time) (cf. sections 4.3.4 and 5.3.4). The PMC section asks seven questions per process model variant. Four questions refer to the BPS contingency factors. Two further questions based on Reijers and Mendling (2011) refer to the general sequence of process activities and the execution order and logics such as process gateways. Each correct answer in the comprehension questions is rated at one point, while correct long-term comprehension questions are rated at two points. Wrong answers yield zero points. The final question asks participants for self-estimation in terms of perceived ease of comprehension as suggested by Recker and Dreiling (2011). Questions are designed comparably in terms of task difficulty and the wording to ensure comparability. To however prevent learning effects, different contingency factors and process elements are targeted by the questions (Patig, 2008). Further, subjects are allowed to look up information in the process model while answering the questions as in Mendling *et al.* (2018). In addition, subjects are asked comprehension questions that have to be answered without the process model visible on the screen to evaluate long-term comprehension. Subjects are further asked to directly compare the process model variants against each other by preference rankings (Figl and Recker, 2016a) according to perceived subjective comprehension. Finally, the last section captures demographic information based on Figl and Recker (2016a) and provides the option to give feedback. The survey is attached to the digital appendix of this dissertation.

Figure 59: Laboratory experiment structure outline



6.2.3.2 Results

Sessions were conducted between June 20, 2018 and July 13, 2018 in the "KD2Lab" at Karlsruhe Institute of Technology. The analysis of results follows seven steps based on Wohlin *et al.* (2012) and includes data validation, sample descriptives, descriptive results on comprehension, hypotheses formulation, appropriate tests for normal distribution and variance homogeneity, hypotheses testing, as well as the determination of effect sizes.

6.2.3.2.1 Data Validation

Before the analysis, data correctness was validated (Wohlin, Höst and Henningsson, 2003). As suggested by Field, Miles and Field (2012), outliers were eliminated based on the respective z-score, which is a metric for the distance of a data point to the mean in standard deviation units (Brown, 1988). Responses were verified according to completeness (n = 0 responses removed) and the number of wrongly answered control questions (n = 0). Besides, responses of participants who experienced technical problems were eliminated from the dataset (n = 0). Before outlier removal, the initial pool of subjects comprised n = 156 participants. Concerning effectiveness, four observations were identified as outliers and removed as the z-score exceeded ±3.29 (cf. section 4.3.4.4). Further, two observations were eliminated based on their efficiency result to account for implausible durations, as the time required to answer the questions exceeded a z-score of ±3.29. After the validation steps, the final pool of subjects comprised of 150 participants.

6.2.3.2.2 Sample Descriptives

The following sections provide numerical and graphical descriptions of the experiment sample and results (Wohlin *et al.*, 2012). Concerning gender, 38.67% (n = 58) of subjects were female, while the majority of 61.33% were male (n = 92). 79.33% of subjects were at the age of 21-30 years, while 19.33% (n = 29) were younger than 21 years. The remainder of 1.33% (n = 2) was at the age group of 31-40 years. Concerning their mother tongue, 85.33% (n = 128) were native German speakers, while 14.67% (n = 22) indicated their first language was not German.

In occupation, the final sample comprised 60.76% (n = 91) Bachelor students and 34.00% (n = 51) Master students. 1.33% of subjects were apprentices (n = 2), while 0.67% were occupied for wages (n = 1) and 3.33% (n= 5) indicated otherwise.

Concerning experience in process modeling, 52.00% (n = 78) indicated their current occupation was unrelated to process modeling, while the remainder replied their profession was weakly (44.00% (n = 66)) or strongly related (4.00% (n = 6)). Subjects stated their IT affinity at a mean of 3.92 (min = 1, max = 5, Std.Dev = 0.90).

Subjects were rather inexperienced in BP modeling, with only 28.67% of theory questions answered correctly. 53.33% of questions were answered with “unsure”, while 18.00% of responses to BP theory questions were wrong. These descriptives are reflected in practical experience, with 52.00% (n = 78) of subjects indicating their profession was unrelated to BP modeling. 44.00% (n = 66) indicated at least a weak relationship, while only 4.00% (n = 6) indicated a strong relationship. Participants stated a mean value of 0.37 hours per week spent with process models (min = 0, max = 5 hours). Table 44 reports an additional overview of the process modeling experience of experiment participants.

Table 44: Additional process modeling experience and self-reports

	Frequency	Percentage
Have you ever read a process model?		
Yes	54	36.00%
No	96	64.00%
Have you ever created a process model?		
Yes	38	25.33%
No	112	74.67%
Have you ever read a BPMN process model?		
Yes	38	25.33%
No	112	74.67%
Have you ever created a BPMN process model?		
Yes	13	8.67%
No	137	91.33%
Please indicate a self-estimation of your proficiency in BPMN.		
Very low	90	60.00%
Low	34	22.67%
Medium	24	16.00%
High	2	1.33%
How often do you encounter process models a week?		
Never	75	50.00%
Rarely	48	32.00%
Sometimes	25	16.67%
Often	2	1.33%

6.2.3.2.3 Descriptive Results

Table 45 provides descriptive results, which are graphically illustrated by box plot diagrams in figure 60. Subjects answered 88.89% of questions correctly in the table variant (baseline). In the static (integrated modeling) variant, 95.33% of questions were answered correctly, while the dynamic (decomposition) variant achieved 88.67% of correctly answered questions. In the guided (visual guidance) variant, 94.89% of questions were answered correctly. In absolute values, the mean value for effectiveness was highest for the guided variant at 5.59 (Std. Dev = 0.79, min = 2, max = 6) and lowest for the dynamic representation of BPS contingency factors at 4.99 (Std. Dev = 1.39, min = 0, max = 6). The table variant achieved 5.39 (Std. Dev = 1.13, min = 1, max = 6), while the static representation of contingency factors achieved a mean of 5.38 (Std. Dev = 0.80, min = 3, max = 6).

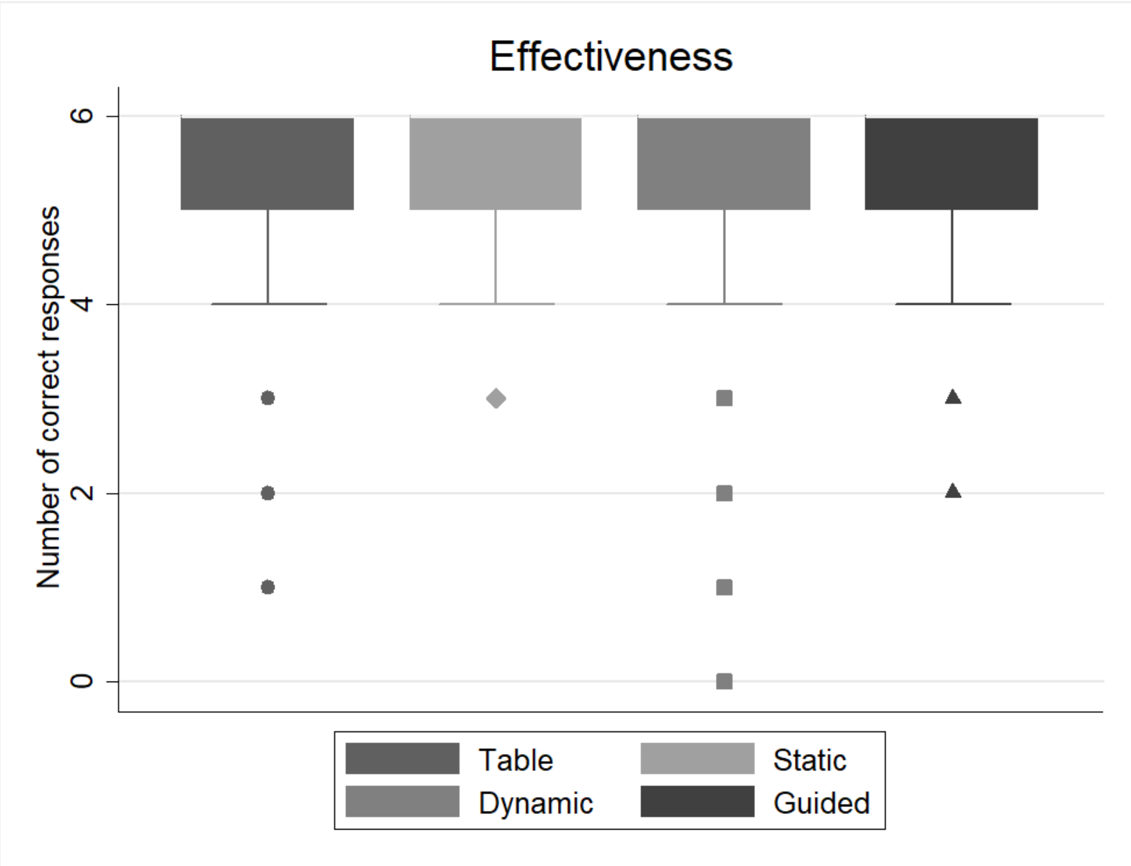
For efficiency, the static variant allowed participants to answer comprehension questions fastest in 202.68 seconds (Std. Dev = 92.56, min = 91.35, max = 611.37), while subjects required the longest time to retrieve the information from the tabular variant in 280.71 seconds (Std. Dev = 87.93, min = 142.33, max = 672.26). Further, participants required a mean of 236.34 seconds (Std. Dev = 82.26, min = 99.55, max = 513.25) in the dynamic variant and 246.63 seconds (Std. Dev = 95.27, min = 113.57, max = 662.34) in the guided variant, respectively.

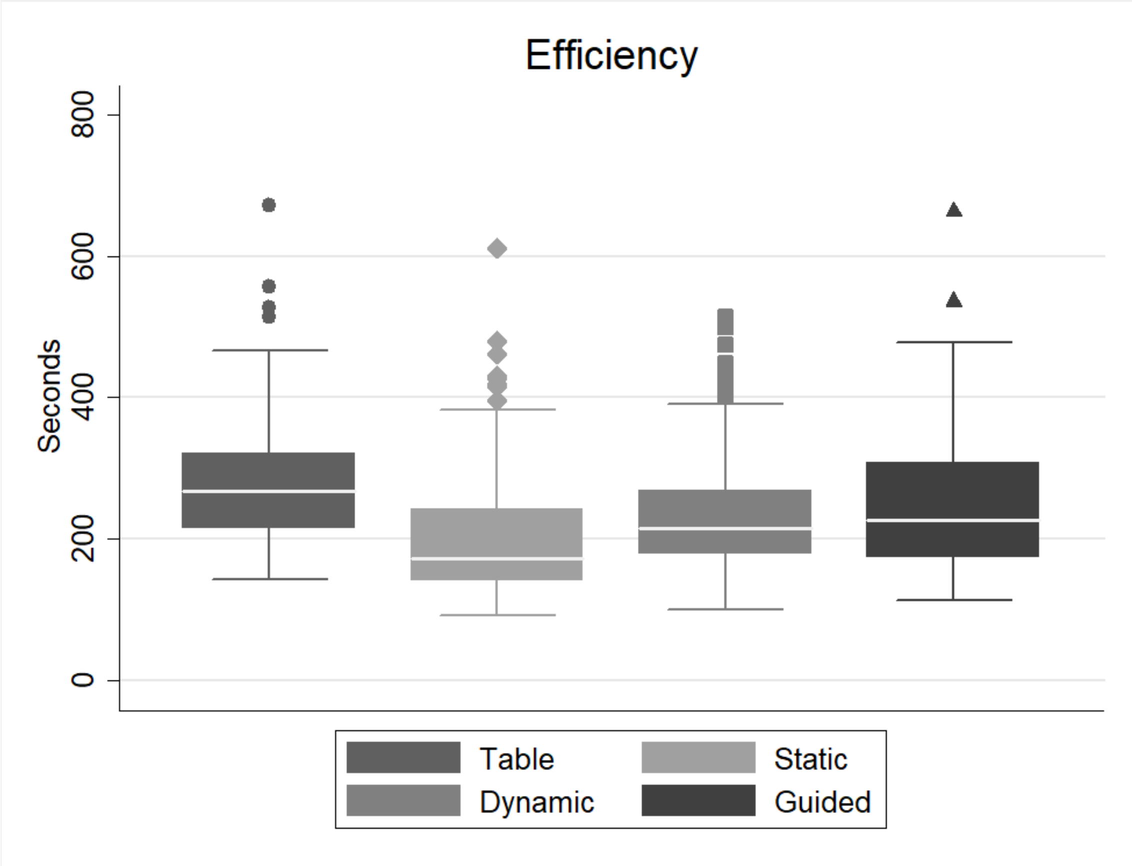
In relative efficiency, the highest mean value was however achieved for the static variant at 0.031 (Std. Dev = 0.0128063, min = 0.0081784, max = 0.0633647). The second-best variant in terms of relative efficiency was the guided variant with a mean value of 0.026 (Std. Dev = 0.0102976, min = 0.007549, max = 0.0528309), while the dynamic variant achieved a slightly lower relative efficiency of 0.0236962 (Std. Dev = 0.0106436, min = 0, max = 0.0529427). The lowest relative efficiency was realized by the tabular variant at a mean value of 0.021 (Std. Dev = 0.0073166, min = 0.0036611, max = 0.0405077).

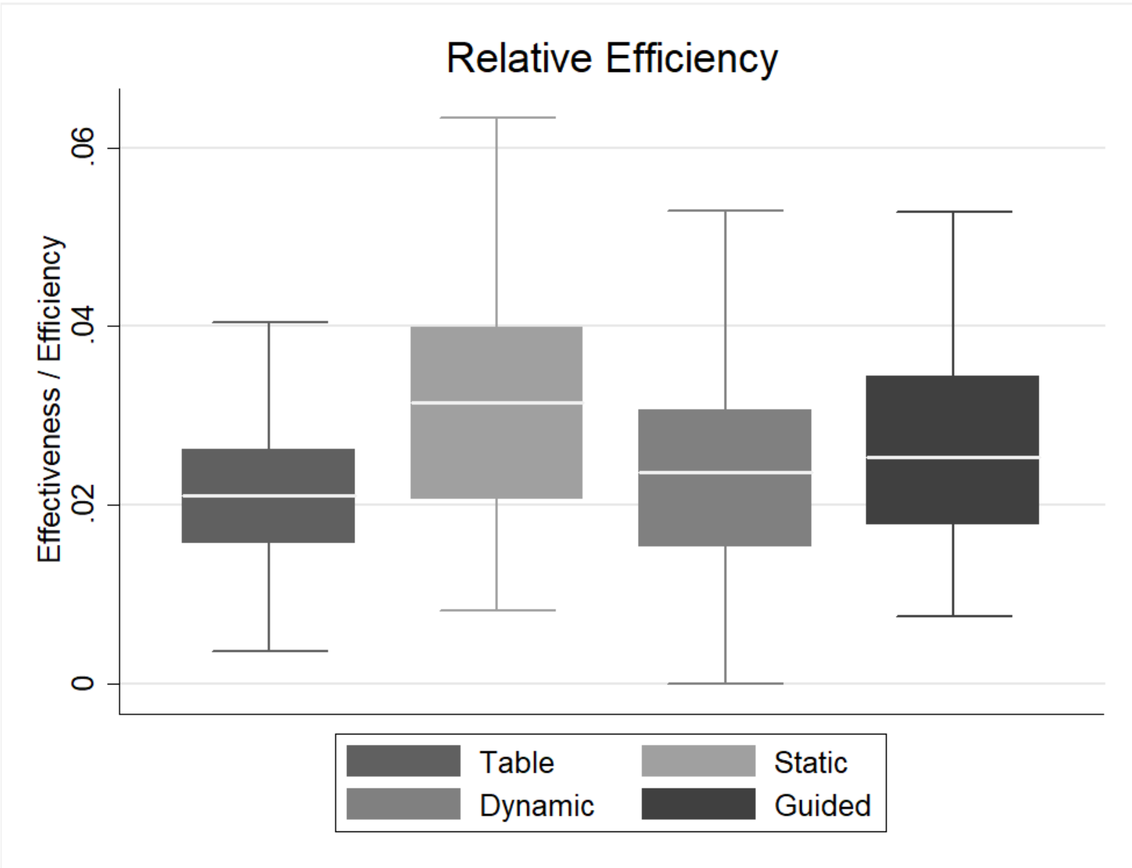
Table 45: Descriptive results

	Mean	Variance	Std.Dev.	Min	Max	Skewness	Kurtosis
Effectiveness [number of correctly answered questions]							
Table	5.393333	1.273781	1.128619	1	6	-2.304961	8.209441
Static	5.38	.6398658	.7999161	3	6	-1.182991	3.761598
Dynamic	4.993333	1.92613	1.387851	0	6	-1.529723	4.732698
Guided	5.593333	.6187472	.7866049	2	6	-2.219721	7.843438
Efficiency [seconds]							
Table	280.7118	7731.956	87.93154	142.33	672.26	1.255779	5.326755
Static	202.6799	8568.176	92.56444	91.35	611.37	1.497362	5.38079
Dynamic	236.3417	6766.107	82.25635	99.55	513.25	1.121516	4.007234
Guided	246.6321	9077.168	95.27417	113.57	662.34	1.196544	4.802377
Relative efficiency							
Table	.0207879	.0000535	.0073166	.0036611	.0405077	.0709241	2.675827
Static	.0313519	.000164	.0128063	.0081784	.0633647	.3367846	2.510041
Dynamic	.0236962	.0001133	.0106436	0	.0529427	.232966	2.637767
Guided	.0260979	.000106	.0102976	.007549	.0528309	.2640479	2.334422

Figure 60: Box plots for efficiency, effectiveness, and relative efficiency

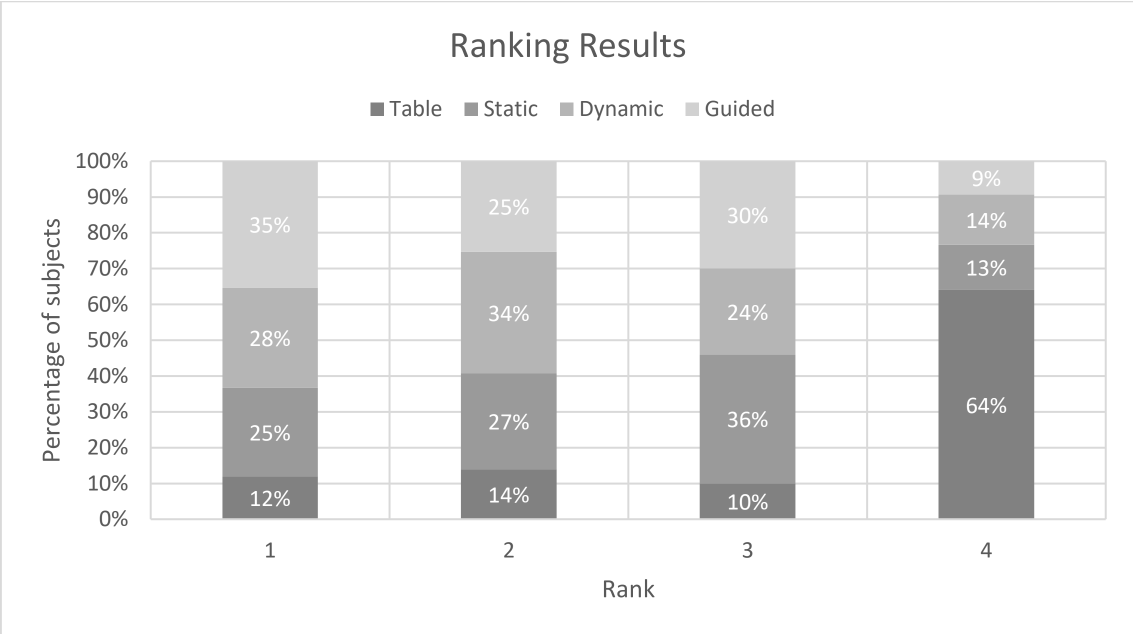



Efficiency
Seconds
0
200
400
600
800
Table
Static
Dynamic
Guided


Relative Efficiency
Effectiveness / Efficiency
0
.02
.04
.06
Table
Static
Dynamic
Guided

Participants were further asked to rank the process model variants according to their subjective comprehensibility from 1 (highest) to 4 (lowest). As illustrated in figure 61, 35.33% of subjects favored the guided variant at their highest comprehensibility, and 64% located the tabular variant at their lowest comprehensibility.

Figure 61: Comprehensibility: ranking results for the process model variants



6.2.3.2.4 Hypotheses Formulation

As the process model variants for the representation of the BPS contingency factors were derived based on PMC research and each variant focuses on one of the process model-related impact factors on PMC in section 6.2.1.1, the comprehension between the variants is expected to differ. Table 46 formulates hypotheses for each of the variants in terms of effectiveness, efficiency, and relative efficiency. Hypotheses in table 46 will be statistically tested in the following sections by testing for significance in the differences between the mean values of the process model variants.

Table 46. Hypotheses to the comprehension constructs

<table>
<tr><th></th><th>Effectiveness</th><th>Efficiency</th><th>Relative Efficiency</th></tr>
<tr><td rowspan="2">Table</td><td colspan="3">Hypothesis H(Table): The table variant performs worse than all the other process models in all comprehension constructs.</td></tr>
<tr><td>$H^{A}_{Effect.}$</td><td>$H^{A}_{Effic.}$</td><td>$H^{A}_{Rel.Effic.}$</td></tr>
<tr><td rowspan="2">Static</td><td colspan="3">Hypothesis H(Static): The static variant achieves the highest comprehension in terms of efficiency ($H^{B}_{Effic.}$) but not concerning effectiveness ($H^{B}_{Effect.}$) and relative efficiency ($H^{B}_{Rel.Effic.}$).</td></tr>
<tr><td>$H^{B}_{Effect.}$</td><td>$H^{B}_{Effic.}$</td><td>$H^{B}_{Rel.Effic.}$</td></tr>
</table>

	Effectiveness	Efficiency	Relative Efficiency
Dynamic	*Hypothesis H(Dynamic): The dynamic variant achieves higher comprehension in terms of effectiveness ($H^{B}_{Effect.}$) than the table and static variant, but not concerning efficiency ($H^{B}_{Effect.}$) and relative efficiency ($H^{B}_{Rel.Effic.}$).*		
	$H^{C}_{Effect.}$	$H^{C}_{Effic.}$	$H^{C}_{Rel.Effic.}$
Guided	*Hypothesis H(Guided):The guided variant achieves the highest relative efficiency ($H^{D}_{Rel.Effic.}$) and the highest effectiveness ($H^{D}_{Effect.}$), but not the highest efficiency ($H^{D}_{Effic.}$).*		
	$H^{D}_{Effect.}$	$H^{D}_{Effic.}$	$H^{D}_{Rel.Effic.}$

6.2.3.2.5 Assumptions Testing and Test Selection

To statistically validate the existence and the significance in the differences between the process model variants observed descriptively in section 6.2.3.2.3, a repeated-measures ANOVA is chosen to compare more than two means (process models) for normally distributed data with homogeneous variances on a metric scale. The assumptions testing conducts Shapiro-Wilk tests for normality, skewness/kurtosis tests, and Levene tests for homogeneity of variances. The Shapiro Wilk tests are conducted under the null hypothesis that data is normally distributed. As revealed in table 47, data on effectiveness and efficiency in most cases do not satisfy the assumption of normal distributions.

Table 47: Overview of assumptions tests

	Shapiro-Wilk				Skewness & Kurtosis		Hypothesis of Normality
	W’	V’	z	Prob > z	Pr (Skewness)	Pr (Kurtosis)	
Effectiveness							
Table	0.76903	26.874	7.461	0.00000	0.0000	0.0000	Rejected
Static	0.92530	8.692	4.902	0.00000	0.0000	0.0717	Rejected
Dynamic	0.84228	18.352	6.596	0.00000	0.0000	0.0029	Rejected
Guided	0.79354	24.023	7.207	0.00000	0.0000	0.0000	Rejected
Efficiency							
Table	0.91913	9.410	5.082	0.00000	0.0000	0.0005	Rejected
Static	0.85900	16.406	6.342	0.00000	0.0000	0.0004	Rejected
Dynamic	0.91408	9.998	5.220	0.00000	0.0000	0.0311	Rejected
Guided	0.90852	10.645	5.362	0.00000	0.0000	0.0023	Rejected

Relative Efficiency							
Table	0.99338	0.770	-0.593	0.72341	0.7113	0.4649	Supported
Static	0.97755	2.612	2.176	0.01476	0.0856	0.1632	Rejected
Dynamic	0.98996	1.169	0.353	0.36201	0.2289	0.3833	Supported
Guided	0.97752	2.616	2.180	0.01463	0.1740	0.0231	Supported

However, simulation studies revealed robustness of repeated measures ANOVAs against violations of the assumptions of normality (Vasey and Thayer, 1987) if this is the only violation (Berkovits, Hancock and Nevitt, 2000). Thus, the assumption of sphericity (the variances of the differences in all possible combinations of the related groups are equal) is tested in table 48 in Levene tests. The Levene tests are conducted under the null hypothesis of homogeneous variances. Thus, a value smaller than 0.05 implies that the hypothesis of variance homogeneity is to be rejected. As revealed by Levene tests, data for effectiveness, efficiency, and relative efficiency does not support the assumption of variance homogeneity.

Table 48: Levene test matrix for homoskedasticity of variances (p-values H0: ratio = 1)

Effectiveness				
	Table	Static	Dynamic	Guided
Table		0.00003257***	0.01204783*	0.00001342***
Static			0.0000***	0.83797236
Dynamic				0.0000***
Guided				
Efficiency				
	Table	Static	Dynamic	Guided
Table		0.53159262	0.4163727	0.32866565
Static			0.15069477	0.72514645
Dynamic				0.0739118
Guided				
Relative Efficiency				
	Table	Static	Dynamic	Guided
Table		0.0000***	0.0000***	0.0000***
Static			0.0246*	0.0081***
Dynamic				0.6872
Guided				

In order to account for violations in the assumptions, two different strategies exist. First, a repeated measures one-way ANOVA can be adapted with correction factors to account for sphericity violations. Second and in addition to the correction factors, a non-parametric test might be conducted. Compared to non-parametric statistical tests, parametric tests are associated with higher statistical power. However, parametric tests require the data sample to adhere to distributional assumptions such as normal distributions or homogeneity in variances (Bortz and Schuster, 2010). If data does not satisfy these assumptions, "assumption-free" (Field, Miles and Field, 2012) or "distribution-free" non-parametric tests provide an alternative. For the selection of a non-parametric test alternative, different possibilities such as the "Wilcoxon test" (Wilcoxon, 1945), the "Mann-Whitney test" (Mann and Whitney, 1947), the "Kruskal-Wallis test" (Kruskal and Wallis, 1952) as well as "Friedman's Analysis of Variance test" (Friedman's ANOVA) which applies ranks to determine differences between sample means (Friedman, 1937) exist. These non-parametric tests do not rely on actual values of the data, but on data ranks (Bühl, 2016).

For comparing two or more different conditions or groups, a Kruskal-Wallis test or a Friedman's ANOVA can be conducted (Field, Miles and Field, 2012). While the Kruskal-Wallis test compares two or more conditions from independent subjects, Friedman's ANOVA takes into account repeated measures by the same subjects (as in the within-subjects design of the experiment) (Field, Miles and Field, 2012). Therefore, the following analysis conducts both a repeated-measures ANOVA with correction factors for the violations of homogeneity of variances and sphericity as well as a Friedman's ANOVA.

6.2.3.2.6 Hypotheses Testing: Repeated Measures ANOVA with Correction Factors

Table 49 reports the results for effectiveness from the repeated measures one-way ANOVA with correction factors according to Huynh-Feldt, Greenhouse-Geisser, and Box's conservative correction. Each of the 150 participants received all four process model variants. Thus, the number of observations is 600. The adjusted R-squared is 33.51%. After application of the correction factors, p-values for effectiveness indicate strongly significant differences in the number of correctly answered questions between the process models at $p = 0.0000$ *** (Huynh-Feldt), $p = 0.0000$ *** (Greenhouse-Geisser), and $p = 0.0006$ *** (Box's Conservative). This finding provides evidence that at least one of the process models significantly differs from the others for effectiveness.

Table 49: Repeated measures one-way ANOVA: effectiveness

<table>
<tr><th colspan="7">Repeated Measures One-Way ANOVA: Effectiveness</th></tr>
<tr><td colspan="7">Number of obs = 600
R-squared = 0.5038
Root MSE = 0.876846
Adj R-squared = 0.3351</td></tr>
<tr><th>Source</th><th>Partial SS</th><th>df</th><th>MS</th><th>F</th><th colspan="2">Prob > F</th></tr>
<tr><td>Model</td><td>348.96</td><td>152</td><td>2.29578947</td><td>2.99</td><td colspan="2">0.0000</td></tr>
<tr><td>model</td><td>28.32</td><td>3</td><td>9.44</td><td>12.28</td><td colspan="2">0.0000</td></tr>
<tr><td>id</td><td>320.64</td><td>149</td><td>2.15194631</td><td>2.80</td><td colspan="2">0.0000</td></tr>
<tr><td>Residual</td><td>343.68</td><td>447</td><td>.76885906</td><td></td><td colspan="2"></td></tr>
<tr><td>Total</td><td>692.64</td><td>599</td><td>1.15632721</td><td></td><td colspan="2"></td></tr>
<tr><th colspan="7">Correction Factors to Account for Violation of Sphericity</th></tr>
<tr><td colspan="4">Between-subjects error term: id
Levels: 150 (149 df)
Lowest b.s.e. variable: id</td><td colspan="3">Huynh-Feldt epsilon = 0.9095
Greenhouse-Geisser epsilon = 0.8917
Box's conservative epsilon = 0.3333</td></tr>
<tr><th colspan="3"></th><th colspan="4">Prob > F</th></tr>
<tr><th>Source</th><th>df</th><th>F</th><th>Regular</th><th>Huynh-Feldt</th><th>Greenhouse-Geisser</th><th>Box's Conservative</th></tr>
<tr><td>Model</td><td>3</td><td>12.28</td><td>0.0000</td><td>0.0000</td><td>0.0000</td><td>0.0006</td></tr>
<tr><td>Residual</td><td>447</td><td colspan="5"></td></tr>
</table>

However, as an omnibus test, the repeated measures ANOVA only reveals that conditions are significantly different, but does not reveal between which conditions (process model variants) the differences occur (Field, Miles and Field, 2012). Therefore, post-hoc tests such as Dunn-Bonferroni tests (Dunn, 1964) to locate the differences between the models are conducted as proposed by Bühl (2016). Since such post-hoc tests are multiple testing, resulting p-values need to be corrected to avoid the possible inflation of the α-error (Field, Miles and Field, 2012).

In table 50, all model variants are compared against each other in terms of effectiveness. First, the slightly lower effectiveness of -0.01 of the static compared to the tabular variant is insignificant at $p = 1.0000$. Second, compared to the tabular variant, the dynamic variant performs significantly worse at a contrast of -0.4 at $p = 0.007$***. Third, the difference between the guided and the tabular variant is positive at 0.2, however, statistically insignificant. Fourth, compared to the static variant, the dynamic variant achieves a lower mean value for effectiveness by -0.39 at $p = 0.010$**. Fifth, the guided variant is significantly superior to the dynamic variant with a mean value which contrasts by 0.6 at $p = 0.0000$*** to the dynamic variant. Therefore, the guided variant is preferred for implementation from an effectiveness perspective, as it achieves the highest mean value and significantly outperforms the dynamic variant, while the mean value is higher compared to the tabular and static variants, although insignificant. Further, the guided variant seems to be suited for contexts that require users to deeply and correctly understand the content of process models for decision-making.

Table 50: Bonferroni post-hoc test for pairwise comparison in effectiveness

	Bonferroni Pairwise Comparison of Effectiveness					
	Contrast	**Std. Error**	**t**	**P > | t |**	**[95% Confidence Interval]**	
Static vs. table	-0.0133333	0.1219088	-0.11	1.000	-0.3360373	0.3093706
Dynamic vs. table	-0.4	0.1219088	-3.28	0.007 ***	-0.722704	-0.077296
Guided vs. table	0.2	0.1219088	1.64	0.608	-0.122704	0.522704
Dynamic vs. static	-0.3866667	0.1219088	-3.17	0.010 **	-0.7093706	-0.0639627
Guided vs. static	0.2133333	0.1219088	1.75	0.484	-0.1093706	0.5360373
Guided vs. dynamic	0.6	0.1219088	4.92	0.0000 ***	0.277296	0.922704

Table 51 reports ANOVA results for efficiency and further reveals significant differences in at least one of the variants when corrected for assumptions violations at p = 0.0000*** in any of the correction factors. The adjusted R-squared is 21.16%.

Table 51: Repeated measures one-way ANOVA: efficiency

<table>
<tr><th colspan="8">Repeated Measures One-Way ANOVA: Efficiency</th></tr>
<tr><td colspan="8">Number of obs = 600
R-squared = 0.4116
Root MSE = 83.1606
Adj R-squared = 0.2116</td></tr>
<tr><th>Source</th><th colspan="2">Partial SS</th><th colspan="2">df</th><th>MS</th><th>F</th><th>Prob > F</th></tr>
<tr><td>Model</td><td colspan="2">2162680.25</td><td colspan="2">152</td><td>14228.1595</td><td>2.06</td><td>0.0000</td></tr>
<tr><td>model</td><td colspan="2">464622.064</td><td colspan="2">3</td><td>154874.021</td><td>22.39</td><td>0.0000</td></tr>
<tr><td>id</td><td colspan="2">1698058.18</td><td colspan="2">149</td><td>11396.3636</td><td>1.65</td><td>0.0000</td></tr>
<tr><td>Residual</td><td colspan="2">3091309.5</td><td colspan="2">447</td><td>6915.68122</td><td colspan="2"></td></tr>
<tr><td>Total</td><td colspan="2">5253989.75</td><td colspan="2">599</td><td>8771.26836</td><td colspan="2"></td></tr>
<tr><th colspan="8">Correction Factors to Account for Violation of Sphericity</th></tr>
<tr><td colspan="4">Between-subjects error term: id
Levels: 150 (149 df)
Lowest b.s.e. variable: id</td><td colspan="4">Huynh-Feldt epsilon = 1.0062
*Huynh-Feldt epsilon reset to 1.0000
Greenhouse-Geisser epsilon = 0.9842
Box's conservative epsilon = 0.3333</td></tr>
<tr><th colspan="3"></th><th colspan="5">Prob > F</th></tr>
<tr><th>Source</th><th>Df</th><th>F</th><th>Regular</th><th>Huynh-Feldt</th><th>Greenhouse-Geisser</th><th colspan="2">Box's Conservative</th></tr>
<tr><td>Model</td><td>3</td><td>22.39</td><td>0.0000</td><td>0.0000</td><td>0.0000</td><td colspan="2">0.0000</td></tr>
<tr><td>Residual</td><td>447</td><td colspan="6"></td></tr>
</table>

Bonferroni post-hoc tests for efficiency further reveal strongly significant differences between all process model combinations except the guided and the dynamic variant. First, all variants require significantly less time compared to the tabular baseline variant. The difference between the tabular representation of BPS contingency factors compared to the static variant is highest at 78.03 seconds (p = 0.000***), while the dynamic variant required subjects 44.37 seconds less to answer comprehension questions (p = 0.000***). For the guided variant, the difference is 34.08 seconds (p = 0.006 ***). Second, compared to the static variant, the additional functionality to hide and unhide BPS contingency factors in the process model variant required participants an additional 33.66 seconds to answer comprehension questions (p = 0.007***). Third, the difference in the slower interaction with the process model for the guided variant is at 43.95 seconds (p = 0.000***) compared to the static and 10.29 (p = 1.000) compared to the dynamic variant. Therefore, the static process model variant is preferable for implementation from an efficiency point-of-view and suited for quickly retrieving information from process models.

Table 52: Bonferroni post-hoc test for pairwise comparison in efficiency

	Bonferroni Pairwise Comparison of Efficiency					
	Contrast	**Std. Error**	**t**	**P > | t |**	**[95% Confidence Interval]**	
Static vs. table	-78.03193	10.35107	-7.54	0.000 ***	-105.4322	-50.63167
Dynamic vs. table	-44.37007	10.35107	-4.29	0.000 ***	-71.77033	-16.9698
Guided vs. table	-34.07973	10.35107	-3.29	0.006 ***	-61.48	-6.679469
Dynamic vs. static	33.66187	10.35107	3.25	0.007 ***	6.261602	61.06213
Guided vs. static	43.9522	10.35107	4.25	0.000 ***	16.55194	71.35246
Guided vs. dynamic	10.29033	10.35107	0.99	1.000	-17.10993	37.6906

In line with the findings for effectiveness and efficiency, table 53 reveals significant differences at the 1%-level, in the ANOVA tests for relative efficiency at p = 0.0000*** for any of the applied correction factors.

Table 53: Repeated measures one-way ANOVA: relative efficiency

Repeated Measures One-Way ANOVA: Relative Efficiency					
Number of obs = 600 R-squared = 0.4674 Root MSE = 0.009397 Adj R-squared = 0.2862					
Source	**Partial SS**	**df**	**MS**	**F**	**Prob > F**
Model	.034631405	152	.000227838	2.58	0.0000
model	.009008885	3	.003002962	34.01	0.0000
id	.02562252	149	.000171963	1.95	0.0000
Residual	.039469769	447	.000088299		
Total	.074101174	599	.000123708		

Correction Factors to Account for Violation of Sphericity						
Between-subjects error term: id Levels: 150 (149 df) Lowest b.s.e. variable: id				Huynh-Feldt epsilon = 0.9463 Greenhouse-Geisser epsilon = 0.9269 Box's conservative epsilon = 0.3333		
			Prob > F			
Source	**df**	**F**	**Regular**	**Huynh-Feldt**	**Greenhouse-Geisser**	**Box's Conservative**
Model	3	34.01	0.0000	0.0000	0.0000	0.0000
Residual	447					

First, comparable to the previous findings, the superiority of the developed process models to the tabular representation of BPS contingency factors also applies in relative efficiency, with the static variant being relatively better by a ratio of 0.0106 at p = 0.0000***, and the guided variant by 0.0053 at p = 0.0000***. The difference between the dynamic and the tabular variant is however insignificant. Second, the additional functionality in the dynamic variant led to participants being by -0.008 less relatively efficient at p = 0.0000*** compared to the static variant. The same applies to the guided variant, which achieves a lower mean value by -0.0053 at p = 0.0000***. Therefore, the static variant performs also best from a relative efficiency perspective, as it achieves the highest mean value and the difference to the other variants is also statistically strongly significant in any combination.

Table 54: Bonferroni post-hoc test for pairwise comparison in relative efficiency

	Bonferroni Pairwise Comparison of Relative Efficiency					
	Contrast	**Std. Error**	**t**	**P > | t |**	**[95% Confidence Interval]**	
Static vs. table	0.010564	0.0012067	8.75	0.000 ***	0.0073697	0.0137584
Dynamic vs. table	0.0029083	0.0012067	2.41	0.098	-0.0002861	0.0061026
Guided vs. table	0.00531	0.0012067	4.40	0.000 ***	0.0021156	0.0085043
Dynamic vs. static	-0.0076558	0.0012067	-6.34	0.000 ***	-0.0108501	-0.0044614
Guided vs. static	-0.005254	0.0012067	-4.35	0.000 ***	-0.0084484	-0.0020597
Guided vs. dynamic	0.0024017	0.0012067	1.99	0.282	-0.0007926	0.0055961

6.2.3.2.7 Hypotheses Testing: Friedman's ANOVA

As an alternative to the corrections for violations in normality and sphericity in the repeated measures ANOVA in section 6.2.3.2.6, Friedman's ANOVA is conducted under the hypothesis that the treatments are equal. Thus, a p-value below 0.05 is interpreted as an indication that the process model variants are not equally comprehensible and that differences exist in at least one of the models. Thus, the findings in table 55 on effectiveness (p = 0.0004 ***), efficiency (p = 0.0011***) and relative efficiency (p = 0.0001***) approves the findings from the corrected ANOVA above.

Table 55: Effectiveness: Friedman test

Effectiveness	Efficiency	Relative Efficiency
Friedman = 213.4993 Kendall = 0.3582 P-value = 0.0004 ***	Friedman = 207.6705 Kendall = 0.3484 P-value = 0.0011***	Friedman = 221.3189 Kendall = 0.3713 P-value = 0.0001***

However, even though the Friedman tests are significant, the interpretation only allows drawing the conclusion that differences between the process model variants exist (Field, Miles and Field, 2012). However, to locate the differences at the level of each possible pair of process model combinations, appropriate post-hoc tests to compare the mean values of each possible combination against each other to determine which of the variant pairs differ significantly (Bühl, 2016). In table 56, Wilcoxon signed-rank post-hoc tests are conducted to compare all variants against each other and mostly confirm findings in the previous section.

Table 56: Results from Wilcoxon signed-rank post-hoc tests (p-vales for Ho: row = column)

Effectiveness				
	Table	Static	Dynamic	Guided
Table		0.3172	0.0063***	0.0700
Static			0.0074***	0.0024***
Dynamic				0.0000***
Guided				
Efficiency				
	Table	Static	Dynamic	Guided
Table		0.0000***	0.0000***	0.0009***
Static			0.0006***	0.0000***
Dynamic				0.5036
Guided				
Relative Efficiency				
	Table	Static	Dynamic	Guided
Table		0.0000***	0.0021***	0.0000***
Static			0.0000***	0.0000***
Dynamic				0.0304*
Guided				

6.2.3.2.8 Effect Sizes and Test Statistics

Effect sizes are provided in table 57 to quantify the discovered differences between the process model variants. Effect sizes are “an objective and (usually) standardized measure of the magnitude of the observed effect” (Field, Miles and Field, 2012). According to

Field, Miles and Field (2012), effect sizes should be determined for the pair-wise post-hoc tests, instead of the general Friedman's ANOVA: In terms of interpretation, research generally categorizes effect sizes below 0.3 as low, between 0.3 and 0.5 as medium, and above 0.5 as large (Cohen, 1992). Effect sizes r in table 57 are calculated as indicated by equation 4.

Equation 4: Formula to calculate effect size r

$$r = \frac{z}{\sqrt{N}}$$

For effectiveness, all measured effects can be categorized as low, with the highest effect occurring between the guided vs. the dynamic variant at 0.2945 and the tabular vs. dynamic variant at 15.77. For efficiency, the most substantial effect is observable in the table vs. static comparison at a medium effect of 0.4186. For relative efficiency, the effect is further most substantial for the table vs. static variant at 0.4548.

Table 57: Effect sizes

Effectiveness				
Mean value comparison		**Z**	**N**	**Effect Size**
Table	Static	1	300	0.057735027
Table	Dynamic	2.731	300	0.157674359
Table	Guided	-1.812	300	-0.10461587
Static	Dynamic	2.677	300	0.154556667
Static	Guided	-3.035	300	-0.17522581
Guided	Dynamic	5.101	300	0.294506372
Efficiency				
Table	Static	7.251	300	0.418637
Table	Dynamic	3.331	300	0.192315
Table	Guided	3.331	300	0.192315
Static	Dynamic	-3.425	300	-0.19774
Static	Guided	-4.5	300	-0.25981
Guided	Dynamic	0.669	300	0.038625
Relative Efficiency				
Table	Static	-7.877	300	-0.454778807
Table	Dynamic	-3.074	300	-0.177477473
Table	Guided	-4.96	300	-0.286365734
Static	Dynamic	5.692	300	0.328627773
Static	Guided	4.142	300	0.239138481
Guided	Dynamic	2.164	300	0.124938598

In table 58 test statistics and effect sizes for the performed ANOVA are provided under the standard assumptions of an α error probability of 0.05, a correlation among rep. measures of 0.5 and a non-sphericity correction ε of 1[21].

Table 58: Test statistics for the one-way ANOVAs

	η^2	Effect size f	Noncentrality parameter λ	Critical F	Power (1-β error probability)
Effectiveness	0.503811504	1.0076523	1218.436	2.6248581	1.0000000
Efficiency	0.411626279	0.8364210	839.5201	2.6248581	1.0000000
Relative efficiency	0.467352987	0.9367048	1052.899	2.6248581	1.0000000

6.2.3.2.9 Hypotheses Support and Variant Selection for Implementation

Table 59 contains the remaining result interpretation concerning the hypotheses. Contrary to the expectation that the tabular variant achieves the lowest comprehension, the tabular representation of BPS contingency factors achieved comparably high effectiveness, which leads to the rejection of $H^{A}_{Effect.}$. However, the variant performed worst for efficiency and was the least relatively efficient variant, which is interpreted as support for hypotheses $H^{A}_{Effic.}$ and $H^{A}_{Rel.Effic.}$. Besides, the static variant proved to be the most efficient process model variant, which yields support for $H^{B}_{Effect.}$. Contrary to the expectation in $H^{B}_{Rel.Effic.}$, the ratio of effectiveness to efficiency (relative efficiency) was found to be the highest for the static variant without visual guidance or decomposition features. For the dynamic variant, no support for the hypothesis $H^{C}_{Effect.}$ that the interactive decomposition features could be found. In contrast to the expectation, the variant performed worst in terms of effectiveness. Finally, the hypothesis for the guided variant of the best performance in relative efficiency was rejected by the findings for the static variant. Nevertheless, $H^{D}_{Effect.}$ is supported with the guided variant achieving the highest effectiveness.

[21] Test statistics are computed using the tool G*Power 3.1 University of Duesseldorf (2019).

Table 59: Hypotheses support

	Effectiveness		Efficiency		Relative Efficiency	
Table	*Hypothesis H(Table): The table variant performs worse than all the other process models in all comprehension constructs.*					
	$H^A_{Effect.}$	***Not supported***	$H^A_{Effic.}$	***Supported***	$H^A_{Rel.Effic.}$	***Supported***
Static	*Hypothesis H(Static): The static variant achieves the highest comprehension in terms of efficiency ($H^B_{Effic.}$) but not concerning effectiveness ($H^B_{Effect.}$) and relative efficiency ($H^B_{Rel.Effic.}$).*					
	$H^B_{Effect.}$	***Supported***	$H^B_{Effic.}$	***Supported***	$H^B_{Rel.Effic.}$	***Not supported (contrary)***
Dynamic	*Hypothesis H(Dynamic): The dynamic variant achieves higher comprehension in terms of effectiveness ($H^B_{Effect.}$) than the table and static variant, but not concerning efficiency ($H^B_{Effect.}$) and relative efficiency ($H^B_{Rel.Effic.}$).*					
	$H^C_{Effect.}$	***Not supported (contrary)***	$H^C_{Effic.}$	***Supported***	$H^C_{Rel.Effic.}$	***Supported***
Guided	*Hypothesis H(Guided):The guided variant achieves the highest relative efficiency ($H^D_{Rel.Effic.}$) and the highest effectiveness ($H^D_{Effect.}$), but not the highest efficiency ($H^D_{Effic.}$).*					
	$H^D_{Effect.}$	***Not supported***	$H^D_{Effic.}$	***Supported***	$H^D_{Rel.Effic.}$	***Supported***

Therefore, the static variant will be taken as the process model for implementation in the DSS in the second design cycle. However, to incorporate the findings in the laboratory experiment on the positive impact of visual guidance on the effectiveness of users when interacting with the process model and to the preference ranking which favored the guided variant (cf. figure 61), the static process models will be enhanced with user guidance features such as tabs.

6.3 Design Cycle 2: Process Mining DSS for Data-Driven BPS

6.3.1 Problem Awareness

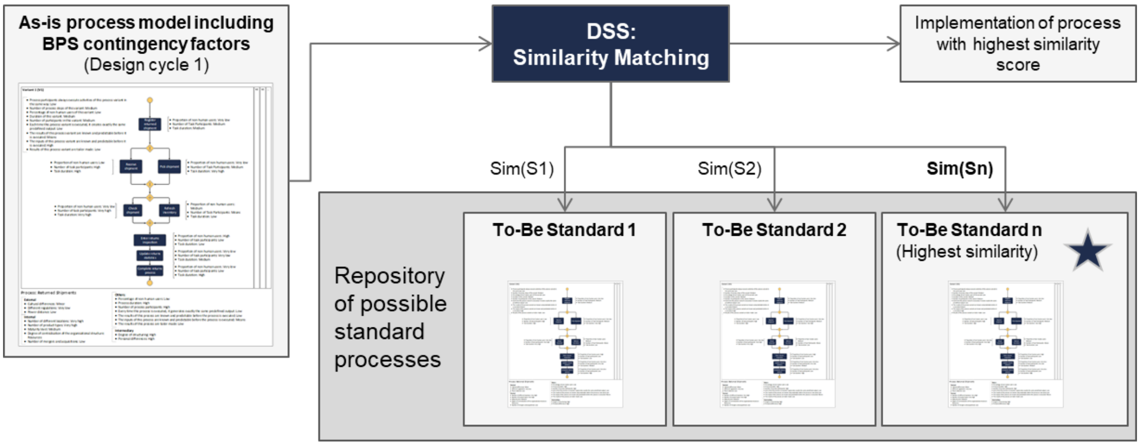
DSR project 3 is theoretically motivated by OCT by Donaldson (2001) and Sousa and Voss (2008). According to OCT in BPM, BPs interact with the environment (Melão and Pidd, 2000) and are highly context-dependent and contingent on the organizational environment (Škrinjar and Trkman, 2013; van der Aalst and Dustdar, 2012). Therefore, extant research such as the contribution by vom Brocke, Zelt and Schmiedel (2016) finds the effects of BPM to be contingent upon contextual factors including organizational factors such as the BM (cf. section 2.3.3.4) and process characteristics (cf. section 2.3.3.3). As a consequence, OCT requires the DSS to select and implement standard BPs which "fit" to the BPS contingency factors.

At the same time and according to Tanenbaum (2007) "*the good thing about standards is that there are so many to choose from*". Therefore, the purpose of the DSS is to provide decision support for the selection of a standard BP between different alternatives.

To realize the DSS, one method to select standard BPs among different decision alternatives is the application of BP similarity and process matching (Becker and Laue, 2012; Dijkman *et al.*, 2011; Fischer *et al.*, 2017; Ivanov, Kalenkova and van der Aalst, 2015; Li, Reichert and Wombacher, 2008; Martens, Fettke and Loos, 2014; Thaler *et al.*, 2016) to decide on which standard BP fits best to the BPS contingency factors. The application of similarity for process matching and selection is motivated by the minimization of disruptiveness of the new standard process design and thus the avoidance of misfits (Markus, 2004) as required by OCT (cf. section 2.1.1) when selecting a standard BP with a high degree of similarity between BPS contingency factors. Misfits are the result of a low similarity between the current BP and the future standard BP. When choosing a standard BP with a low degree of similarity, adverse misfit situations and risks might arise for the organization such as high costs and transformative efforts for restoring the fit in contingencies, a reduction of organizational performance, overhauled routines and the modification of well-accustomed workflows. Further, in the context of ERP implementations such as the BPS and SAP S/4 HANA migration project at the industry partner, adverse "technochange" situations and risks might arise for the organization. For instance, ERP implementation projects simultaneously impact technological as well as organizational structures and thus require significant efforts in terms of costs, IT project management and change management (Fischer *et al.*, 2017), or might lead to a reduction in organizational performance or incompliance with BPs and the ERP system (Fleig, Augenstein and Maedche, 2018a).

Therefore, Fischer *et al.* (2017) propose to use concepts of BP similarity to assess the process fit within the context of ERP implementation projects by comparing process models to reference models of ERP systems. By implementing BPs with a high degree of similarity between the as-is and the to-be process, process misfits as well as the time and costs of implementation for the standard BP can be reduced (Fischer *et al.*, 2017). The concept is illustrated in figure 62.

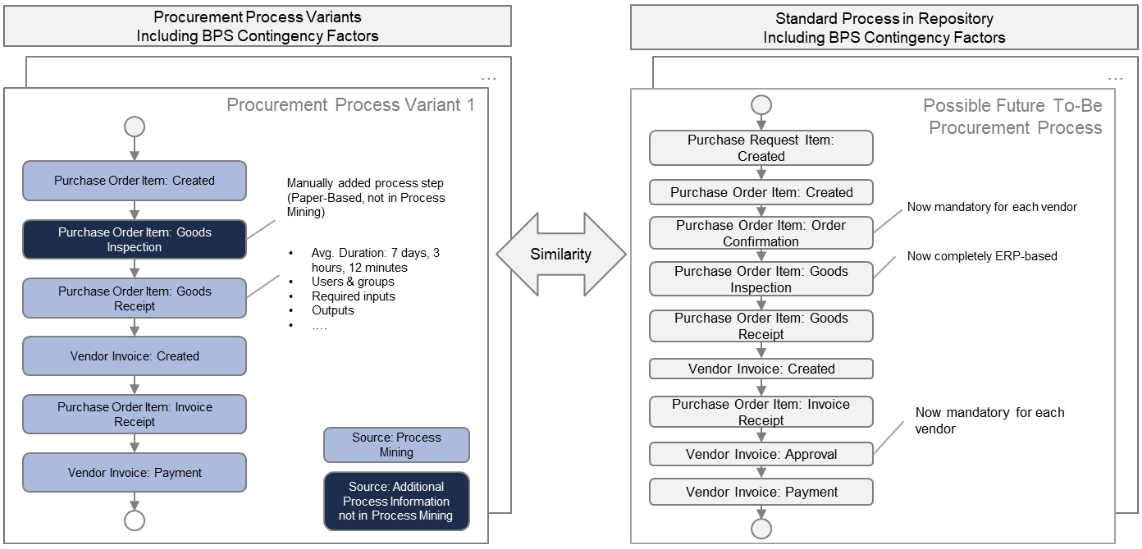
Figure 62: Concept of similarity matching for selecting BPs based on contingency factors



In order to select a suitable standard from multiple different process designs based on similarity (right-hand-side of figure 63), each standard BP needs to be compared against each of the individual as-is process variants (left-hand-side of figure 63) (possibly across different companies) to decide on the fit between the as-is and the to-be standard process ("fit-gap analysis"). However, in practice, this comparison is highly labor-intensive and therefore possibly benefits from a DSS to semi-automatically determine the "fit" between process models and BPS contingency factors.

As reported in Fleig, Augenstein and Maedche (2018c), the SAP purchase-to-pay ("procurement") and the order-to-cash ("sales") processes were selected by the application of KeyPro in DSR project 2 for implementation in a process mining application, as these BPs of the industry partner companies exhibited the highest number of executions, a comparably high number of employees involved in the processes, and a high degree of external partners involved. For mining and comparing BPs and their variants, the manufacturing corporation implemented a process mining solution in a proof of concept project for the SAP Purchase-to-Pay ("Purchasing") and the Order-to-Cash ("Sales") processes. However, despite the automatic availability of process models from process mining, several issues for selecting a standard process for the SAP S/4 HANA system occurred.

Figure 63: Example for variant-level comparison of as-is process against to-be process designs (based on (Fleig, Augenstein and Maedche, 2018c))



First, the expected number of variants of the as-is process to be analyzed and compared against the standard process repository was significantly higher than expected (e.g., ~2.540 to 20.670 variants in the purchase-to-pay and ~20.870 to 35.320 variants in the order-to-cash processes in the different companies). Second, numerous BPS contingency factors derived in sections 2.3.3.3 and 2.3.3.4 cannot be retrieved automatically from data and process mining and therefore need to be attached manually to the process models. Therefore, only the most important variants which cover at least 80% of cases of the as-is process could be enriched with the additional non-data-driven BPS contingency factors. Besides a high number of variants in the as-is process, the effort for the process selection is further increased by a high number of possible to-be standard process designs. For example, for the purchase-to-pay process, the "SAP Best Practices Explorer" used as standard process repository delivers 12 different standard process specifications in BPMN 2.0 notation in the "Operational Purchasing" domain for the on-premise version of SAP S/4 HANA. Third, to effectively match to-be standard process designs, standard processes in the repository need to be assigned the BPS contingency factors before process selection.

6.3.2 Suggestion: Design Requirements

6.3.2.1 Meta Requirements

Design requirements were derived and published in Fleig, Augenstein and Maedche (2018a). This section explains the design requirements as the conceptual foundations for the DSS.

As introduced in sections 2.3.3.3 and 2.3.5., information on BPs and BPS contingency factors might either be stored in prescriptive, non-data-driven sources such as the tacit knowledge of process participants, or be stored in descriptive data sources such as application systems. As each of these two types and sources of contingency factors has individual strengths, weaknesses, and limitations, the DSS needs to retrieve and combine BPS contingencies from different sources. A potential source of contingency factors is data-driven process information stored in application systems such as ERP systems which can be retrieved by technologies such as process mining. These sources include data generated by systems during the process execution, such as event log tables within the ERP systems. The first MR1 on data-driven BPS contingency factors is formulated accordingly:

MR1: The DSS needs to incorporate data-driven BPS contingency factors.

However, an exclusive reliance upon data from application systems in decision-making for BPS yields merely a partial excerpt of process realities (cf. section 2.3.5). For example, some BPS contingency factors which cannot be retrieved from data as these process elements are not executed or captured within the application system. Examples include paper-based process steps, other related application systems, intangible inputs, outputs, strategy, governance, training, people and knowledge, culture or legal factors (cf. section 2.3.3.3). Process mining in particular captures only information on process activities within the application systems (van der Aalst, 2011), and event logs merely contain a subset of all possible process facets (van der Aalst, 2011, 2014). Therefore, insights on BPS contingencies gained from data-driven sources might be incomplete and the DSS needs to incorporate non-data-driven BP contingency factors in addition to the data-driven BPS. MR2 on non-data-driven BPS contingencies requires accordingly:

MR2: The DSS needs to incorporate non-data-driven BPS contingency factors.

As a direct requirement of MR1 and MR2, both sources of information on BPS contingencies need to be merged and combined in a single comprehensive as-is process model before decision-making which ensures comprehension of decision-makers (cf. sections 2.6 and 1.1.3). Consequently, MR3 requires:

MR3: The DSS needs to merge both data-driven and non-data-driven BPS contingency factors in an as-is process model for decision-making.

In addition to these MRs to derive a comprehensive as-is process model that combines the different BPS contingencies, an additional MR is established concerning the possible different selection alternatives of standard processes. To select among different standard processes based on BPS contingency factors, the DSS needs to possess a repository of potential standard process specifications. MR4 thus requires a standard process repository:

MR4: The DSS needs to provide a repository of different standard process design alternatives including BPS contingency factors.

In the DSS, the as-is process model including BPS contingency factors is to be matched against these standard process design alternatives from the repository to derive a standard process recommendation. As initially motivated, the DSS relies on BP similarity to minimize the distance between the BPS contingency factors (MR1 and MR2) of the as-is process model (MR3) and the different to-be standard BP models (Martens, Fettke and Loos, 2014) in the repository (MR4). The final MR5 requires accordingly:

MR5: The DSS needs to provide a matching algorithm to select an appropriate standard process design based on BPS contingency factors.

6.3.2.2 Design Principles

MRs from the previous section are translated into DPs to steer the development of the software artifact and to modularize the components of the DSS. According to MR1, the DSS is required to incorporate data-driven BPS contingency factors which can be retrieved from process mining such as process models, BM-related BPS contingency factors (cf. section 2.3.3.4) from DSR project 1 on BMM (cf. section 4), or process-related BPS contingency factors such as process inputs and outputs (cf. section 2.3.3.3). In turn, this requires to extract relevant process data from application systems and to process the information in process mining and an event log database. Further, the event log needs to be visualized in a graphical process model such as a BPMN representation. Thus, DP1.1 is formulated as follows:

DP1.1: The DSS needs to provide a process mining layer to retrieve process models and data-driven BPS contingency factors from application systems.

Further, MR2 requires the DSS to incorporate non-data-driven BPS contingency factors from the BM (cf. section 2.3.3.4) and BPs (cf. section 2.3.3.3) into process models (MR3), which requires the provision of a user interface to enrich the data-driven process mining models with additional non-data-driven information. DP2.1 therefore requires:

DP2.1: The DSS needs to provide the ability to enter additional non-data-driven BPS contingency factors into decision-making.

In addition to the incorporation of data-driven (MR1) and non-data-driven (MR2) process information, MR3 requires to combine both types of contingency factors in process models which ensure PMC of users (cf. sections 2.3.4, 2.6.1 and 6.2.1) before decision-making in the algorithm (MR5) to determine the most suited standard process. DP3.1 is established accordingly.

DP3.1: The DSS needs to combine process mining models and data-driven BPS contingency factors with non-data-driven BPS contingency factors in a single process model of the as-is process that ensures comprehension of users.

In order to propose a standard process specification based on a similarity comparison (MR5) , the enriched as-is process model needs to be matched against the different possible process designs as required by MR4. To implement the requirement, DP4.1 is formulated accordingly:

DP4.1: The DSS needs to provide a repository of different standard processes designs including BPS contingency factors.

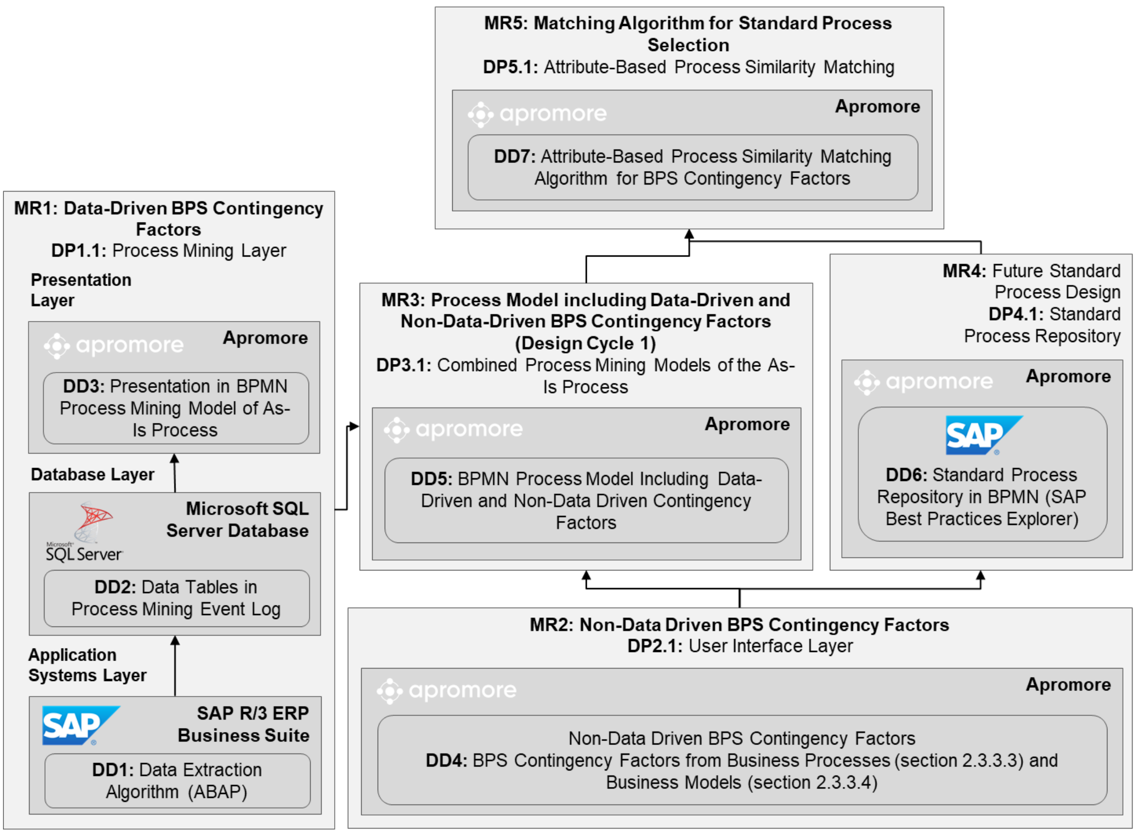
Finally, the last requirement MR5 refers to the need for a matching algorithm which determines the similarity (“conformance”) of the as-is process model (MR3) for each of the candidate standard process models in the process repository (MR4) to recommend a target model for implementation. DP5.1 is formulated as follows:

DP5.1: The DSS needs to provide a similarity-based process matching algorithm to select a standard process design from the process repository based on the similarity of BPS contingency factors.

6.3.3 Development: Instantiation of the Process Mining DSS in Apromore (Design Decisions)[22]

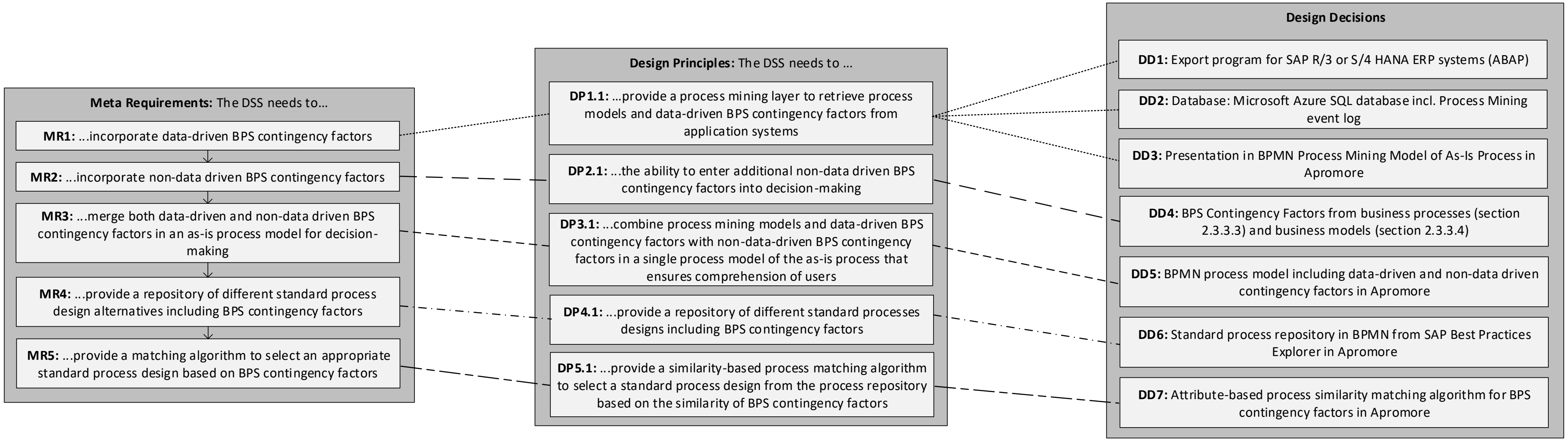
The development phase of the second design cycle implements a prototype instantiation in the open-source process analytics platform Apromore. Apromore is an open-source collaborative online BP analytics platform provided by the Apromore Initiative (The Apromore Initiative, 2018) that provides a number of benefits such as the broad acceptance in the community and the numerous functionalities provided by a research-oriented community. Figure 64 provides an overview of the final implementation in SAP R/3 ERP systems, Microsoft SQL Server, and Apromore, which is described in the following. Figure 65 summarizes design requirements including MRs, DPs, and DDs.

Figure 64: Final implementation according to design requirements (taken from (Fleig, Augenstein and Maedche, 2019))



[22] The implementation and technical development of the similarity matching algorithm in Apromore (DD7) was conducted in collaboration with a supervised master student in Zhang (2018).

Figure 65: Overview over design requirements (meta requirements, design principles, and design decisions)



For the DSS implementation. the Apromore DSS uses real-world data for the purchase-to-pay and order-to-cash processes which were determined as the most important processes by DSR project 2 from three SAP R/3 ERP systems across the three sub-companies of the manufacturing corporation. The dataset is described in the evaluation with a field showcase at the industry partner to demonstrate technical feasibility (cf. section 6.3.4).

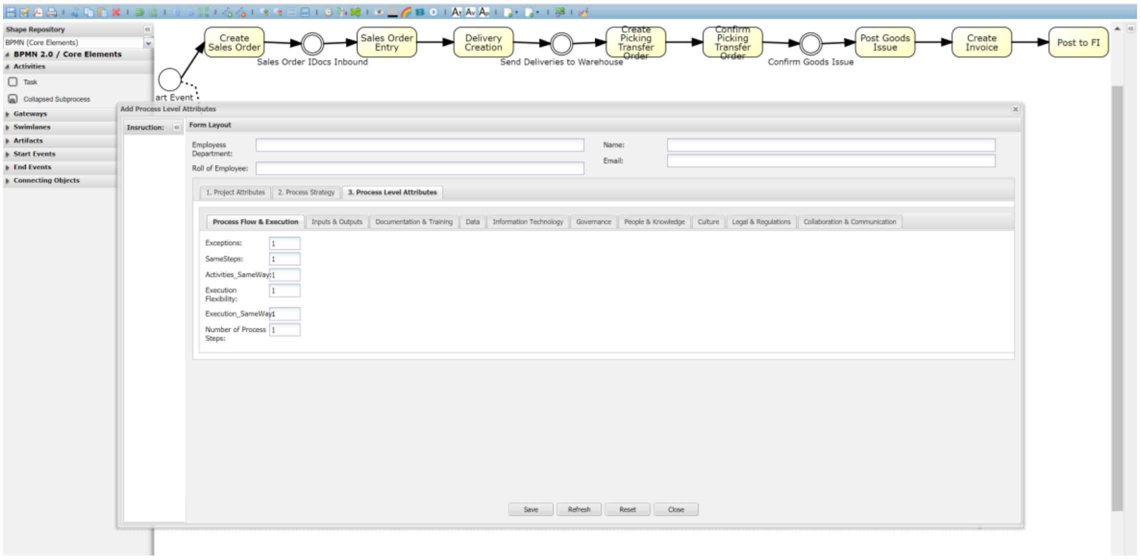
To account for DP1.1 and to retrieve the data-driven BPS contingency factors, the process mining layer contains an application systems-, a database- as well as a presentation layer. In the application systems layer of the DSS, the ABAP data extraction program for SAP R/3 and S/4 HANA ERP systems from the previous DSR projects (cf. sections 4.2.2 and 5.2.2.1) was implemented in each of the SAP R/3 systems of the industry partner to extract the relevant data tables required for process mining as .csv-files (DD1). Further, the raw data from the individual .csv files from the application systems need to be imported and transformed into a process mining event log. Therefore, the database layer imports all relevant data into a Microsoft SQL Server database to perform the event log generation by a SQL transformation script. To perform the event log generation, a German process mining company (project partner) provided the transformation scripts for the purpose of this research to generate the event log from the SAP ERP raw data for the purchase-to-pay and order-to-cash (DD2). In principle, however, the system might be implemented for any process mining solution if it adheres to the following Apromore requirements for BPMN process models. Finally, the database layer exports all relevant information in a structured format from the event log into .xes-files for the BPMN visualization engine in Apromore to create BPMN process models (DD3). An exemplary BPMN process mining model in the DSS is illustrated in figure 66 for a variant of the SAP order-to-cash process (without additional BPS contingency factors attached).

Figure 66: Example of a BPMN process model from Process Mining for the SAP order-to-cash process variant in Apromore (DD3) (taken from (Zhang, 2018))

Further, the DSS needs to provide a graphical user interface as required by DP2.1 to attach non-data-driven BPS contingency factors to the process models from process mining

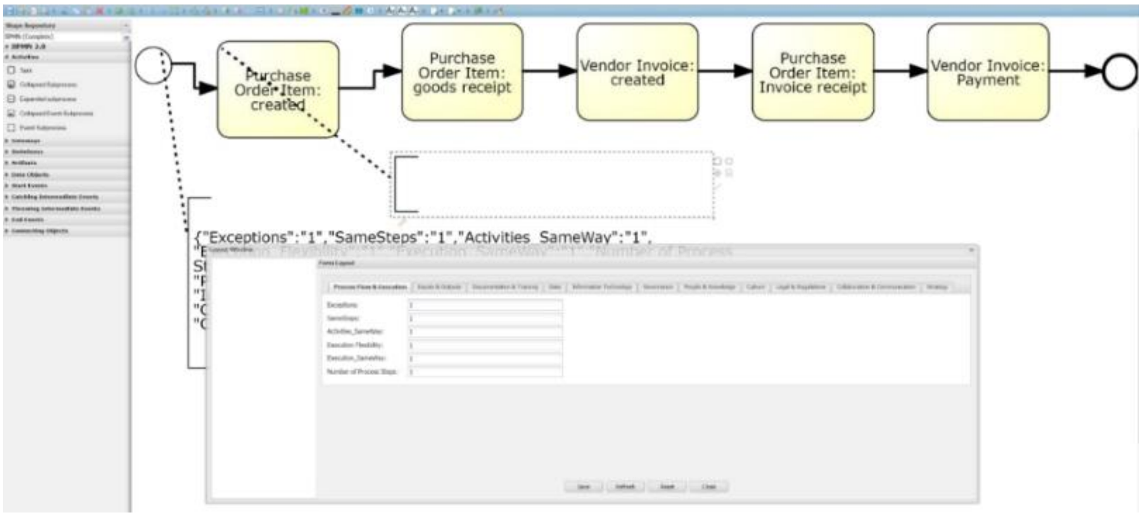
(DP1.1). The user interface allows attaching standardization attributes that are valid for either the entire process, a particular process variant, or a specific task (DD4). The user interface provides an entry mask for the BPS contingency factors identified in BPM in section 2.3.3.3 and from BM literature in section 2.3.3.4. The user interface is illustrated in figure 67.

Figure 67: Graphical user interface in Apromore to enter non-data-driven BPS contingency factors (DD4) (taken from (Zhang, 2018))



In order to account for DP3.1 for a BPMN process model of the as-is process that represents both data-driven and non-data-driven BPS contingency factors and ensures PMC, findings from the laboratory experiment on comprehension in the first design cycle were incorporated by enhancing the Apromore BPMN visualization engine. As decided in section 6.2.3.2.9, a combination of the static (integrated process modeling) and the guided (visual guidance) process model variant was implemented which allows users to display all BPS contingency factors by branches assigned to the BPMN model (static variant) as well as to display factors in a structured graphical window with tabs (guided variant) (DD5). The implementation of the process models for BPS contingency factors is illustrated in figure 68.

Figure 68: Apromore graphical user interface to attach BPS contingency factors (DD4) (taken from (Zhang, 2018))



Furthermore, the library of standard process designs required by DP4.1 for process matching was created from the SAP Best Practices Explorer[23] that provides a publicly available database of to-be standard processes in BPMN 2.0 notation for SAP S/4 HANA on-premise 1809 and by importing the library into Apromore as matching candidates. Each of the to-be process models was enriched with the standardization attributes and assigned with values in a workshop with 6 process experts to perform the process matching (DD6).

For the selection of the most similar standard process, DP5.1 requires a similarity matching algorithm. Recently, "process similarity" has gained a high degree of attention and numerous approaches to process matching have been proposed. By means of a literature review, several potential process matching techniques were identified and compared to select attribute-based similarity matching as a suited candidate to solve the problem at hand. The contribution by Becker and Laue (Becker and Laue, 2012) categorizes process similarity measures into approaches including the correspondence between process model nodes and edges, the edit distance between graphs, causal dependencies between the different activities, and similarity approaches based on trace sets. For example, the contribution by Dijkman et al. (2011) identifies five similarity dimensions to be taken into account, namely syntactic, semantic, attribute-based, type-based and contextual similarity.

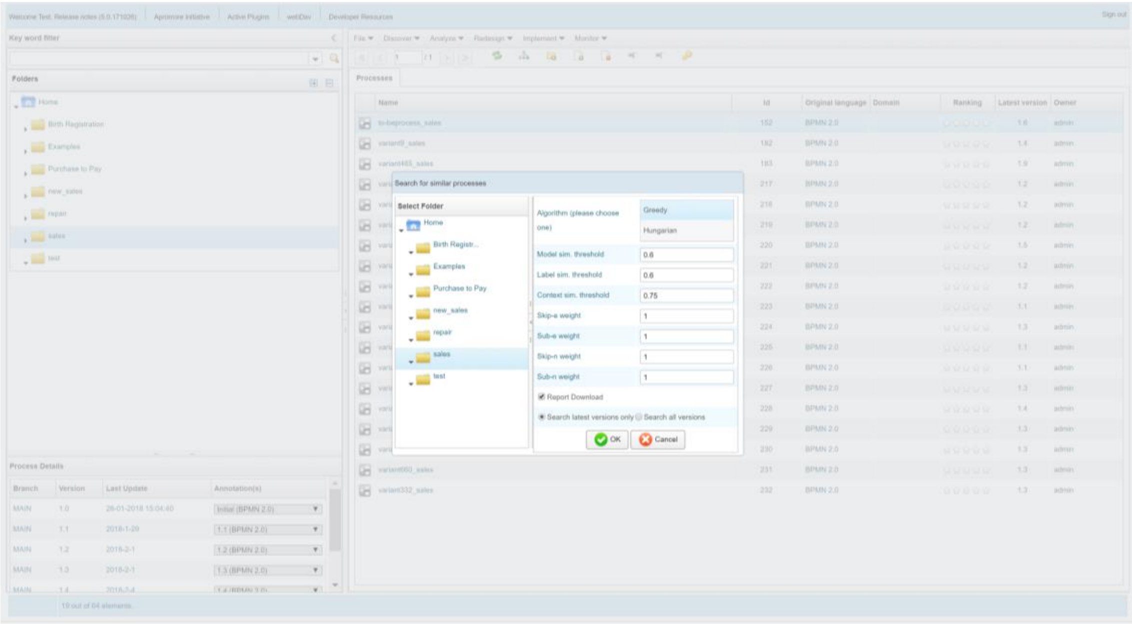
[23] https://rapid.sap.com/bp/

Therefore, the authors propose to measure the similarity from three aspects including node-matching, structural, and behavioral similarity. Besides, Thaler et al. (Thaler *et al.*, 2016) introduce the natural language, graph structure, behavior, and human estimation as determinants of model similarity. Most of these similarity matching techniques are based on the model structure or behavior and define distance metrics between a pair of process models to quantify the similarity. The authors in Li et al. (2008) provide an approach to measure the structural similarity between BPs based on the number of transformation operations such as adding, deleting or moving to change the structure from one BP to the other. A frequent challenge in process matching is differing labeling styles between process models. For example, a verb-object label like "create order" refers semantically to the same task as the action-noun style "creation of order". The algorithm relies on natural language processing to address this issue. Thus, the "BPMNDiffViz" by Ivanov et al. (2015) compares process models in BPMN 2.0 language using label matching and structural matching metrics. The ICoP Framework by Weidlich et al. uses structural similarity to identify matches and correspondences between BPs (Weidlich, Dijkman and Mendling, 2010). In sum, the calculation of process model similarity needs to take into account heterogeneity of behavioral representation, labeling styles and terminology (Dijkman *et al.*, 2013), as well as process model structure (Dijkman *et al.*, 2011).

However, for the proposed DSS, the measurement of similarity needs to be extended to take into account process model attributes such as the BPS contingency factors. Thus, standard process recommendations are derived through an attribute-based similarity matching algorithm which calculates process model similarity for each variant of the as-is process model against the to-be standard process models in the repository based on BPS contingency factors, behavior, process model structure, and text processing of labels.

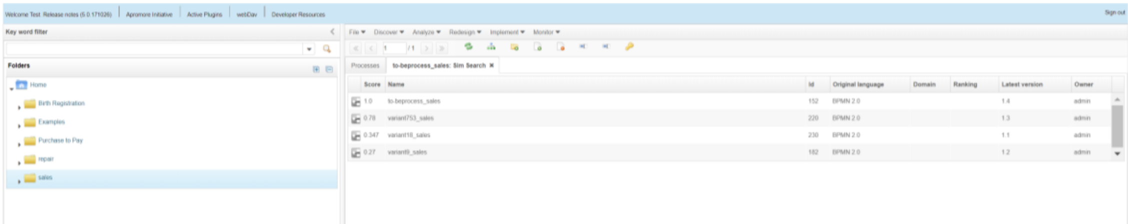
For realization in Apromore, a new similarity-based matching plugin based on the existing "similarity search" plugin in Apromore was developed as illustrated in figure 69. The algorithm for similarity matching developed by Zhang (2018) performs matching in three steps. The first-level matcher performs matching of attributes at the process-level. Further, the algorithm ensures that the as-is process is matched against the correct domain of the to-be processes such as sales or procurement processes in the repository and considers process-level BPS contingency factors. The algorithm first calculates the similarity score based on commonly shared attributes ("contingency factors") of the as-is and the to-be process models. Second, the algorithm calculates the cosine similarity according to the attribute values to measure similarity between the process-level BPS contingency factors such as strategy, governance, or culture (Wurm *et al.*, 2018).

Figure 69: Similarity matching algorithm in Apromore (DD7) (taken from (Zhang, 2018))



Further, each variant of the as-is process differs from the other variants in terms of graph structure, variant behavior, and contingency factors such as executions or inputs and outputs (cf. table 2). Thus, the second variant-level matcher calculates the similarity of each variant of the as-is process according to behavior via graph dependency, graph structure of the variant via graph edit distance, and the difference between attribute values of the contingency factors. Third, the task-level matches the similarity of tasks and attributes via syntactic and linguistic similarity of the activity labels. For each non-data-driven attribute, the numeric distance is calculated. The overall similarity for a to-be standard BP in the repository is calculated by the sum of variant similarities weighted by the number of variant occurrences. The final result of the attribute-based similarity-matching algorithm in the DSS is thus a similarity measure between 0 and 1 (1= perfect similarity) for each of the to-be standard BPs in the repository. Thus, decision-makers receive a list of all standard processes ordered by descending similarity to the as-is process as depicted in figure 70, such that the standard BP with the highest similarity is the selected process for implementation.

Figure 70: Results of the attribute-based similarity matching algorithm in Apromore (DD7)



6.3.4 Evaluation: Field Show Case of the DSS in Manufacturing

In order to demonstrate the feasibility of the artifact instantiation in a real-life setting, the DSS was applied in the BPS and S/4 HANA migration project at the industry partner in three manufacturing companies and three different SAP R/3 ERP systems. The industry partner provided a process mining event log for the SAP R/3 ERP purchase-to-pay ("purchasing") and the order-to-cash ("sales") process for the period from January 2016 to July 2017. An overview of the event log is provided in table 60. In the showcase evaluation for technical feasibility, the number of variants to cover a threshold of at least 80% of cases for each process was considered.

Table 60: Overview of event log (taken from (Fleig, Augenstein and Maedche, 2018a))

	SAP R/3 ERP end-to-end processes					
	Purchase-to-Pay ("Purchasing")			Order-to-Cash ("Sales")		
Company	**Alpha**	**Beta**	**Gamma**	**Alpha**	**Beta**	**Gamma**
Period	01.01.2016 - 31.07.2017					
Number of cases	998.80 Thsd.	432.21 Thsd.	108.54 Thsd.	15.8 Mil.	65.377	155.125
Number of process variants [Thsd.]	20.67	10.47	2.54	35.32	39.82	20.87
Total number of process steps [Millions]	4.13	2.15	0.34774	106.52	50.49	6.07
Avg. number of process steps	4.13	4.98	4.42	6.74	6.02	8.37
Distinct process steps	30	154	54	21	21	22

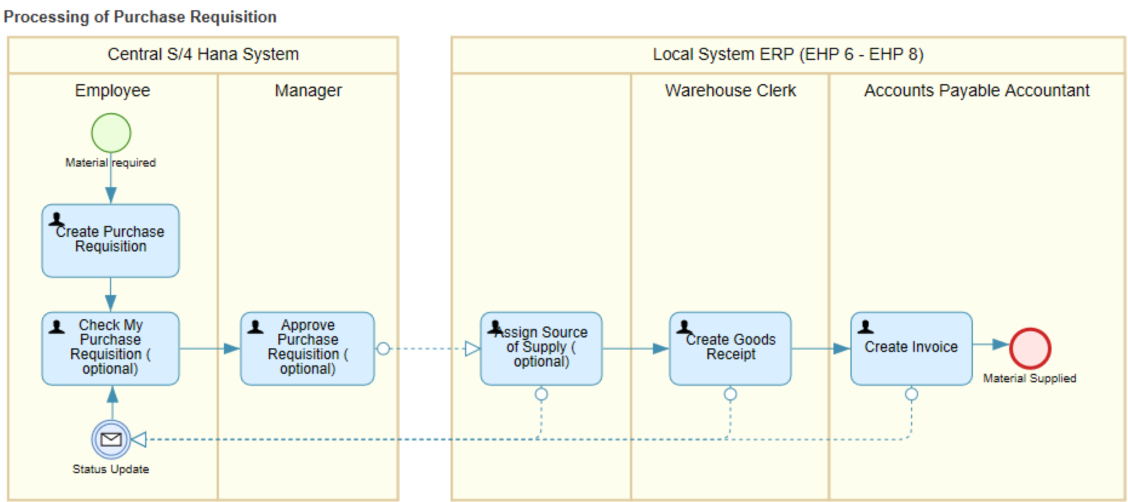
For the purchasing process of company A, 41 process variants were taken into account which covers a number of 869.63 thousand purchase orders and assigned with the standardization attributes on the process-, variant-, and task-level in a workshop with three purchasing process experts. After the application of the similarity matching algorithm, the proposed target standard process was the standard end-to-end procurement process from SAP which achieved the highest similarity score of 0.87. Likewise, for the sales process of the company, 56 variants were processed to cover 12.74 million sales orders. As the as-is process contains a large number of customer-specific adaptations, the algorithm produced a comparably low degree of similarity of 0.68 for the SAP standard process specification "Sales from Stock Direct Sales" for the new S/4 HANA ERP system. Table 61 presents results for the application of the DSS for the purchase-to-pay and the order-to-cash processes for one sub-company of the manufacturing corporation.

Table 61: Results of DSS application in company Alpha (taken from (Fleig, Augenstein and Maedche, 2018a))

	Process	
	Purchase-to-Pay ("Purchasing")	**Order-to-Cash ("Sales")**
Number of cases considered	869.63 Thsd.	12.74 Mil.
Number of variants considered	41	56
Number of different tasks	30	15
Similarity score of proposed standard process	0.87	0.68
Proposed target standard	SAP_E2E_P2P Standard_Procurement	SAP_E2E_O2C Sales_from_stock_Direct_Sales

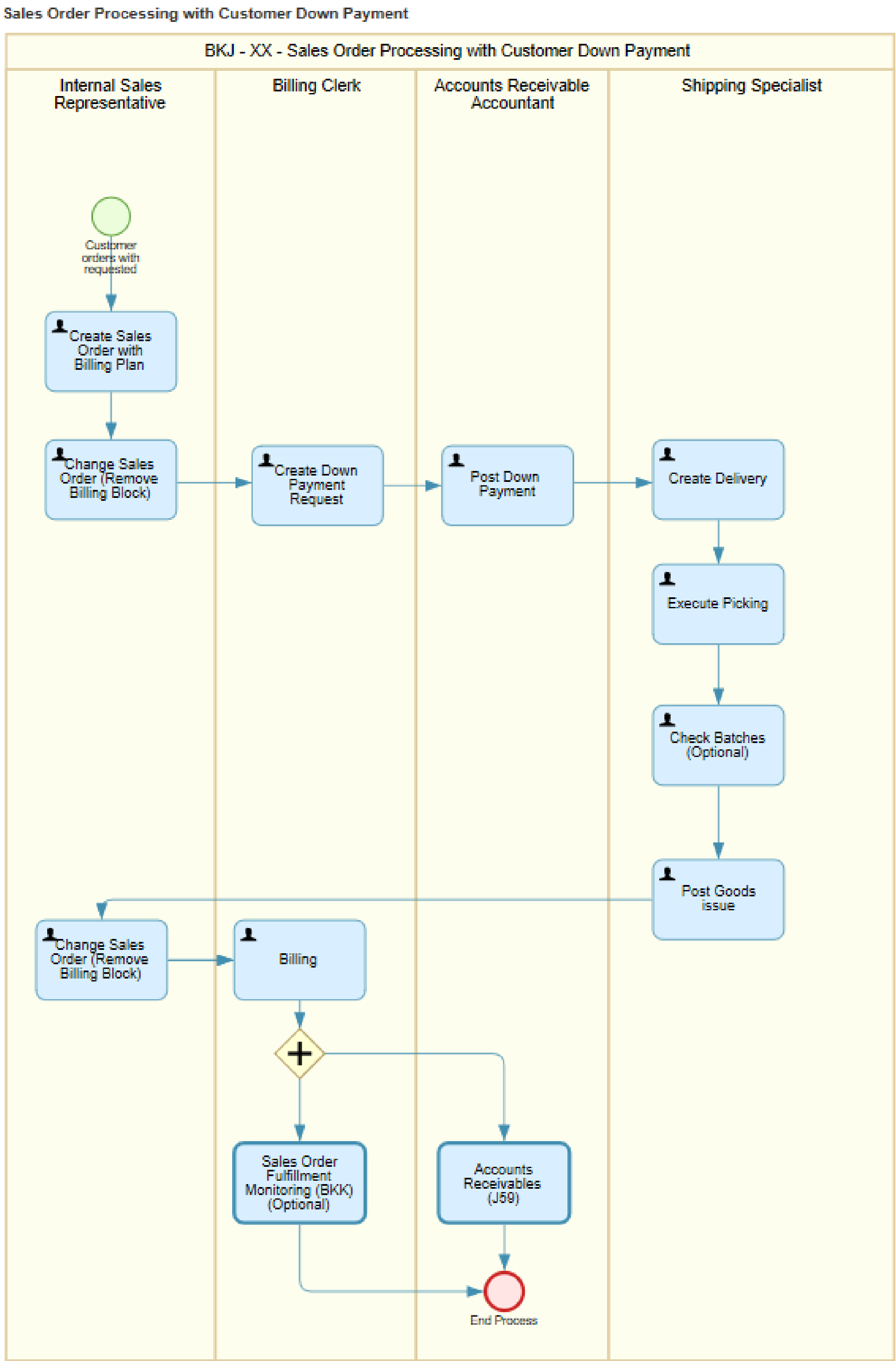
The new standard process designs selected by the DSS and to be implemented for the organization that maximize the similarity and the degree of fit between the as-is standard BP and the to-be process designs under consideration of the BPS contingency factors are illustrated in figure 71 and figure 72.

Figure 71: DSS result (selected standard BP design) for the purchase-to-pay process (source: SAP Best Practices Explorer for S/4 HANA)[24]



[24] https://rapid.sap.com/bp/

Figure 72: DSS result (selected standard BP design) for the order-to-cash process (source: SAP Best Practices Explorer for S/4 HANA)



7 Discussion[25]

This section discusses findings from the DSR projects and provides theoretical and practical contributions as well as limitations and avenues for future research.

7.1 DSR Project 1: Design of a Business Model Mining System

BMs have become an essential concept in both academia and practice since the late 1990s (Andreini and Bettinelli, 2017; Demil and Lecocq, 2010) to translate the abstract organizational strategy into specific arrangements (Osterwalder, Pigneur and Tucci, 2005). In BPS initiatives, BMs provide numerous contingency factors that need to be taken into account for selecting appropriate standard process designs (cf. section 2.3.3.4).

Traditional non-data-driven approaches to business modeling such as the BMC are decoupled from application systems and typically follow a data-independent, manual approach. To better comprehend and retrieve BM-related BPS contingency factors, DSR project 1 designs a data-driven BMM system that automatically identifies, retrieves, and represents BMs from data in application systems such as SAP R/3 or S/4 HANA ERP systems. First, the project derives design requirements and conceptualization for BMM systems and suggests an open, standardized reference data model for BMM independent from specific application systems. The DSR project instantiates the software artifact BM-Miner and demonstrates technical feasibility by using data from an educational SAP S/4 HANA system of a fictitious bicycle company, a public reference dataset “Adventure-Works”, and three real-life SAP R/3 ERP systems of a German manufacturing corporation. A field study evaluates the BM-Miner and finds significant differences between data-driven BMCs and BMCs created by managers. A laboratory experiment finds significant beneficial impacts of the BM-Miner on the objective and subjective comprehension of BMs. Thus, DSR project 1 provides a new data-driven class of BMM applications to support comprehension of BM-related contingency factors in BPS initiatives.

[25] This chapter contains content previously published in Fleig (2017), Fleig, Augenstein and Maedche (2018a, 2018b, 2018c, 2018d), Wurm *et al.* (2018); Fleig, Augenstein and Maedche (2019).

In addition to the applicability of the artifact and findings within the context of BPS, DSR project 1 provides further contributions to support the more general decision-making, modeling, monitoring, transformation, and comprehension in BM management. In particular, the field evaluation of the artifact provides evidence that differences exist between non-data-driven and data-driven BMs such that mining BMs from application systems might provide an alternative source of knowledge on organizational BMs. As revealed by the field study, these benefits are particularly prominent for BM elements that involve a high amount of data or which span beyond boundaries of organizational units. However, as discovered in the field evaluation, both approaches exhibit specific strengths and weaknesses. Thus, BMM remains a complementary rather than an alternative technique for business modeling to "enrich" non-data-driven human knowledge with data-driven insights. The subsequent laboratory evaluation with non-experts further reveals three beneficial impacts of a BMM software on BM comprehension by users, even if these users are unfamiliar with the organizational BM and business modeling in general. First, participants using the BM-Miner were able to increase the number of correctly answered questions regarding the status-quo BM, i.e. to increase their effectiveness when gaining an understanding of the current BM. Second, the evaluation revealed that the artifact reduces the time required to gain information on specific aspects of the current BM, thereby increasing user efficiency. Third, compared to data analyses without BM-Miner, the use of the artifact improves the relative efficiency of users, i.e. it increases the effectiveness per given time.

7.1.1 Theoretical Contribution

Conceptualizing a system that helps to comprehend a status-quo BM from data, i.e. to build a clear understanding of the organization's current BM from operational data within application systems, gives rise to immediate implications for research. First, DSR project 1 introduces BMM as a promising new field of research to link existing research from business modeling to "Big Data" (de Camargo Fiorini *et al.*, 2018) and mining techniques such as process mining (van der Aalst *et al.*, 2011; van der Aalst, 2013, 2018). Nevertheless, research lacks actionable knowledge on how to gain insights on the status-quo BM systematically (Szopinski *et al.*, 2019). While extant research on business modeling has focused on strategic and human-centric approaches to building an understanding of the BM (Ebel, Bretschneider and Leimeister, 2016), using new technologies, available data sources and internal application systems remains a largely untapped field of research. DSR project 1 complements existing research in this area as it designs and demonstrates how such an approach may be conducted. Thus, DSR project 1 answers calls for research on the use of data-driven technologies in organizational decision-making (Szopinski *et al.*, 2019).

Besides, DSR project 1 contributes to adjacent research disciplines. For instance, BM transformation (BMT) and related concepts such as BM innovation have been recognized as paramount in disciplines such as IS research and many others such as BPM or entrepreneurship (Al-Debei and Avison, 2010; Szopinski *et al.*, 2019). BMT is the process in which the organization actively aligns the BM with a continually changing internal and external environment (Saebi, Lien and Foss, 2017). BMT thereby comprises the entire spectrum of modifications and refinements which are found to have an impact on the current BM, and which leads to a new or adapted BM (Laudien and Daxböck, 2016). However, BMT implies significant challenges and high risks for organizations (Kalakota and Robinson, 2001; Pateli and Giaglis, 2005). Therefore, decision-making in BMT requires a robust and exhaustive understanding of the current status-quo BM, which is supported by the artifact and concept in DSR project 1. To support this, BMs and associated methods, techniques and tools are becoming increasingly important (Osterwalder and Pigneur, 2013).

7.1.2 Practical Contribution

To the best of knowledge, DSR project 1 on BMM is the first to conceptualize an approach to increase comprehension of status-quo BMs successfully and to provide a "mining" application for BMs from data. While current approaches to understanding BMs such as the BMC are primarily paper- and workshop-based and unrelated to data (Fleig, Augenstein and Maedche, 2018d), the artifact supports practitioners in understanding and defining BMs. For instance, 60% of respondents in a practitioner survey of 3.000 executives found the definition of BMs among the top organizational challenges (General Electrics, 2014; Szopinski *et al.*, 2019). Increasing the comprehension of users while decreasing the time required to capture the status-quo BM may have a significant impact in organizational practice by improving the performance of BM projects. The proposed BMM concept and prototype existing business modeling practices, often pursued in non-data-driven analyses, with a novel data-driven approach using the BM-Miner and the BMM concept in general. As discovered in the series of interviews with business experts, gaining a profound understanding of the status-quo BM is a time-consuming process and error-prone process which requires experienced BM transformation teams.

Further, to ensure a profound basis for decision-making in BM-related projects, practitioners are required to have a precise and exhaustive understanding of the organization's status-quo BM. Thus, BM comprehension constitutes an increasingly important skill for organizations as a prerequisite for BMT and to keep pace with environmental changes in the market. By providing BMM as a novel and data-driven approach to increase the comprehension in terms of a more in-depth and faster understanding of the BM, DSR project 1 contributes to achieving strategic flexibility for the organization. In particular, BMM thus contributes to "*the ability of the organization to adapt to substantial, uncertain, and fast-occurring environmental changes that have a meaningful impact on the organization's performance*" (Aaker and Mascarenhas, 1984) and the "*ex-ante ability to rapidly reallocate and reconfigure resources and processes*" (Bock *et al.*, 2012).

7.1.3 Limitations and Future Research

However, the concept of BMM in IS such as ERP systems encounters several limitations. Comparable to shadow process steps in process mining (van der Aalst, 2016), BMM is unable to discover elements of BMs which are not captured in data in IS of the organization. BMM fails to include BM-related elements outside of systems such as paper-based processes, or intangible parts of the value proposition which are not documented or detectable in application systems. Additionally, BMM in application systems is generally only able to detect BM components from application systems that are part of the organization, while components from networks or upstream and downstream partners can only be mined if the organization has a connection to the partner systems. Besides, organizations might have more than one BM, which requires to identify and distinguish among different sub-BMs (Veit *et al.*, 2014). As a take-away from these limitations, BMM is positioned as a data-driven "stimulus" to enrich and to complement the traditional non-data-driven, human-centered approaches to business modeling. BMM complements rather than replaces traditional "de-jure" BMM techniques with a "de facto" and data-driven approach to retrieve the BM automatically from application systems.

Therefore, DSR project 1 opens several avenues for future research. First and to overcome the outlined weaknesses in mining the BM components, more elaborate techniques such as data mining (Aggarwal, 2015), process mining (van der Aalst, 2018), machine learning (Kubat, 2017; Rebala, Ravi and Churiwala, 2019), or artificial intelligence (Flasiński, 2016) can be applied to discover the intangible BM components which have been identified as harder to identify in the field study such as the value proposition (Augenstein, Fleig and Dellermann, 2018). For example, the "mining" capabilities of the tool can be improved. For instance, by means of artificial intelligence some of the current "reporting" functionality might be enhanced with BM discovery techniques to automatically identify and link BM-related data and elements instead of relying on a predetermined data model.

Further, the developed SAP table extraction program (DD1) allows exporting data close to real-time. Thus, future research or practitioners might provide another version of the BM-Miner to support "Real-Time BMM" to support decision-makers in daily operations by monitoring the BM in interactive dashboards instead of ad-hoc analyses. Furthermore, the design of dashboards possibly impacts comprehension and the understanding of users (Yigitbasioglu and Velcu, 2012). Therefore, future research might concentrate on the development and improvement of the artifact dashboard to further increase comprehension.

7.2 DSR Project 2: Design of a DSS to Discover Important Organizational BPs

BPs are paramount to organizational value creation (Gibb, Buchanan and Shah, 2006), strategy, and BMs (cf. section 2.3). However, "traditional", non-data-driven methods of process analysis possibly suffer from deviations from process reality, high costs and consumption of organizational resources such as employees and time, and proneness to errors (Fleig, Augenstein and Maedche, 2018b; Indulska *et al.*, 2009; van der Aalst, 2011, 2014). To overcome these limitations of human "de-jure" process perceptions, DSR project 2 proposes to utilize "de facto" and data-driven process analysis techniques such as process mining (van der Aalst, 2010; van der Aalst and Weijters, 2004) to automatically discover the set of BPs in organizations, and to quantify the importance of individual BPs from data stored in application systems for process prioritization. Thereby, DSR project 2 designs a prototype which intends to ensure that decision-makers base process decisions on a comprehensive list of BPs in the organization and focus BPM initiatives on BPS that are important for the organization.

7.2.1 Theoretical Contribution

Thereby, DSR project 2 contributes to several disciplines within BPM. First, the approach contributes to the field of process mining and the area of process discovery (cf. section 2.3.5). While existing process mining approaches focus on the vertical, in-depth “mining” of one specific BP, such as the purchase-to-pay or order-to-cash process and on the provision of process-specific analyses such as KPIs or process variants, DSR project 2 pursues a horizontal complementary approach. Second, prioritization of process decision-making is a critical element in BPM activities such as BPS projects, resource allocation, or process monitoring (Fleig, Augenstein and Maedche, 2018b). However, existing literature in academics does not provide an exhaustive answer to a definition of process importance, and to the question of how the importance of BPs can be measured objectively from data and different, partially contradictory viewpoints. Thus, DSR project 2 provides a collection of process importance metrics to derive BP importance data-driven from data stored in application systems.

7.2.2 Practical Contribution

DSR project 2 provides practitioners with an applicable data-driven DSS for the analysis and discovery of the process landscape and the automatic calculation of process importance metrics for SAP R/3 ERP and S/4 HANA systems. As revealed by the field study, the data-driven approach in DSR project 2 possibly discovers additional BPs of which human decision-makers are not aware such as BPs spanning organizational units and boundaries, or BPs which are executed automatically without human involvement such as master data governance processes.

Depending on the organization, the share of “hidden” BPs in the “long tail” (Imgrund *et al.*, 2018) ranges between 6.50% and 30.13%. Besides, the two field interviews in Finance and Controlling indicated a different perception between process importance metrics by human decision-makers and by the data-driven KeyPro analysis.

Through the application of KeyPro in BPM initiatives throughout the different phases of the BPM lifecycle (cf. section 2.3), DSR project 2 responds to calls for evidence-based management and the trend towards the incorporation of data into organizational decision-making (Kroker, 2017). For example, KeyPro might provide ad-hoc or project-related analyses as well as the continuous analysis of processes with dashboards for daily operations. Besides, by providing a data model in the data management layer, different data sources and different system types can be combined across the systems landscape. At the same time, KeyPro allows for trend analyses by providing time-related process data. Further, the BI functionality of the artifact allows filtering, aggregating, or drilling-down throughout the process hierarchy and calculate all importance metrics for the respective level of analysis.

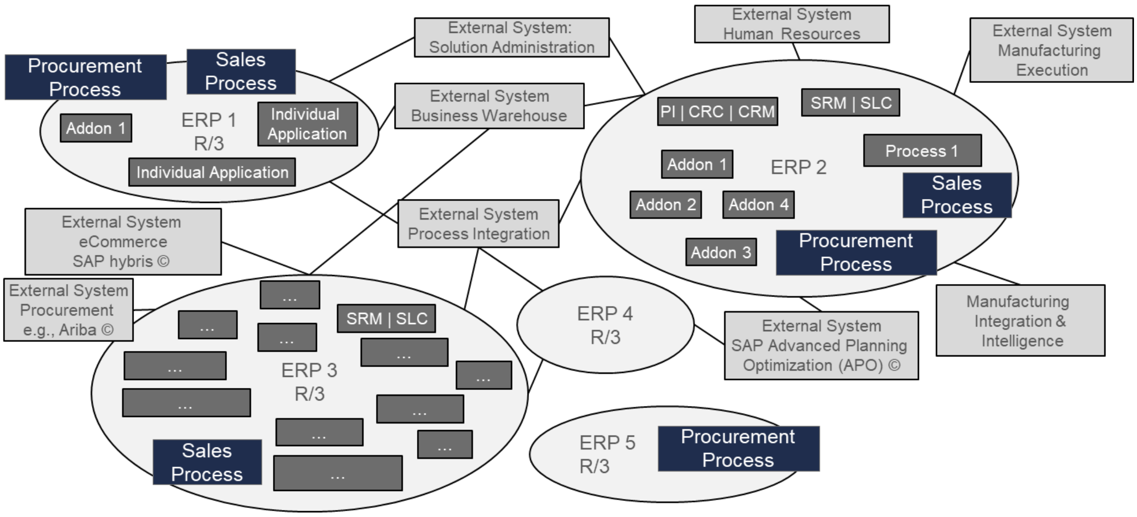
7.2.3 Limitations and Future Research

The approach to retrieve the set of BPs in the organization and to calculate objective importance metrics from application systems by matching the executed transactions within the system to a reference library of BPs encounters several limitations.

First, DSR project 2 and the KeyPro artifact concentrates on providing only process importance metrics which can be objectively determined from data, while “shadow processes” (van der Aalst, 2018) and metrics which cannot be captured from data are not retrieved. KeyPro is in its current implementation state only able to determine BPs from application systems. However, the data-driven approach does not take into account paper-based or off-system processes such as the development of vision and strategy from the APQC framework, or purely managerial processes (APQC, 2017). For example, as opposed to manufacturing organizations, service organizations generally exhibit a higher share of intangible and non-repetitive BPs which are not implemented in application systems, and thus do not produce system records for KeyPro process matching. Therefore, the artifact is intended as a complement to human process knowledge and analyses. Nevertheless, in principle KeyPro is able to handle any log file which contains a timestamp, a transaction or process identifier, as well as information about the dimensions of process importance such as the user executing the process. Thus, a future implementation might also include other application systems and “shadow processes” (van der Aalst, 2016) as well as non-data-driven process importance information.

Second, organizational process landscapes of application systems are inherently complex due to a high number of different systems, addons, satellite systems, customizing, “shadow IT” (Silic and Back, 2014), or organization-specific individual “Z-” developments (Fleig, Augenstein and Maedche, 2018c). For mining and discovering the entire process landscape correctly, all systems (beyond the currently implemented SAP ERP systems) need to be integrated into the KeyPro application. For example, the set of BP-related application systems involved in the BPS project at the industry partner is illustrated in figure 73.

Figure 73: Application systems involved in the execution of BPs in the BPS and SAP S/4 HANA migration project at the industry partner (taken from (Fleig, Augenstein and Maedche, 2018c)



Third, many BPs are organization-specific. Thus, DSR project 2 had to retrieve a specific list of BPs from the different sub-companies at the industry partner to apply the artifact and to conduct the evaluation. These BPs represent a rather specific view of manufacturing organizations. To increase generalizability, KeyPro needs to “learn” the matching of additional BPs from other organizations and industries and be able to match transactions against other reference process lists such as the implemented APQC Process Framework (APQC, 2017) in future.

DSR project 2 and the evaluations revealed the potential to pursue several directions for future research into the data-driven “horizontal” discovery of the set of BPs in an organization and the automatic calculation of process importance. Most importantly, the construct of process importance depends on non-data-driven as well as data-driven dimensions (Fleig, Augenstein and Maedche, 2018b). In future research, the metrics used for determining process importance may be extended by non-data-driven metrics. In particular, the design of dashboards constitutes a research branch of its own and has been determined as a critical impact variable on user understanding (Few, 2013; Yigitbasioglu and Velcu, 2012). Thus, this research stream might be consulted to optimize KeyPro to increase comprehension by dashboard design.

7.3 DSR Project 3: Design of a Process Mining DSS for Data-Driven BPS

DSR project 3 designs a process mining DSS which combines process models with BPS contingency factors to increase comprehension and then employs an attribute-based process similarity matching algorithm to recommend a process design from a repository of standard BPs.

7.3.1 Theoretical Contribution

Although state-of-the-art application systems increasingly provide organizations with tremendous amounts of process data, and process mining delivers mature techniques to turn data into process information, turning information into actual process decisions and ensuring decision-makers comprehend the process deeply (i.e., effectiveness) and quickly (i.e., efficiency) remains a substantial challenge. At the same time, BPS depends on numerous different contingency factors (cf. section 2.3.3). Although process models provide a promising means to communicate process information, decision-making depends upon the appropriate representation of contingency factors to both increase and ensure PMC. Therefore, the first design cycle consults existing literature on PMC to design four different process model variants for representing BPS contingency factors which are subsequently evaluated in a controlled laboratory experiment. However, findings might be transferable to other and broader contexts beyond BPS such as any process changes (cf. section 2.3.2) which require to represent process information such as contingency factors in process models. Current notations such as BPMN might be improved by displaying information and process contingency factors according to the findings in the first design cycle. Further, it might be expected that findings from the positive impact on comprehension are generic and further valid beyond a BPS contingency factor-context and that process model variants might be used for representing any type of process information.

First, findings in the laboratory experiment on effectiveness in terms of a qualitative understanding of process model content and BPS contingency factors indicate that the process model variant which relies on visual guidance of users by features such as icons and structured tabs improves PMC. This finding yields broader implications for the design of BPM applications that rely on process models and additional information attached such as KPIs or process attributes such as systems, users, inputs or outputs. For example, process mining applications such as Celonis© might utilize findings to design appropriate, visually guided process models for representing process information to ensure the effectiveness of users when interacting with results. At the same time, the tabular process model variant achieved surprisingly good results for effectiveness, while the dynamic variant which provides interactive features achieved the lowest value. This finding possibly indicates a distraction of users from process model contents by these features.

Second, process model design impacts PMC in terms of efficiency, i.e., the time required to retrieve and comprehend information. Interactive features require time for users to explore and learn the handling of interactive models. Besides, although the dynamic variant was intended to reduce the cognitive load and information density of the process model, a negative impact might be that information remains hidden and unnoticed by users. Variants with interactive features such as the dynamic decomposition variant or a high density of information within one element such as a table lead to users requiring more time to comprehend models, while the static process model that displays process attributes such as the contingency factors with branches directly at the location of relevance achieved the best result. For the design of BPM applications, this finding likewise contributes to the body of knowledge on how to link process attributes to process models. In current implementations, additional process information is usually presented as a detached element such as a separate dashboard next to the graphical process model. Thus, linking information such as a task-level KPI directly to the corresponding element in the process model (e.g., by branches such as in the static variant) without interactive features possibly reduces the time required for users to comprehend the model.

Third, these findings translate into the quality-time ratio and trade-off measured by relative efficiency. For instance, the finding yields further support for a process model design that refrains from interactive features but links process attributes to the place of occurrence or provides information in a structured way such as the guided variant.

7.3.2 Practical Contribution

Regarding emerging technologies such as process mining which provide powerful methodologies to retrieve and represent process information in-depth from numerous sources, the question of how to appropriately represent this information in process models to contribute to comprehension becomes further important from a practical point of view.

For practitioners, the DSS might considerably improve the ability to standardize BPs. By proposing a standard BP design based on the similarity between the BPS contingency factors of the as-is process design and the to-be standard processes, the DSS aims to reduce the overall costs of BPS, to optimize the degree of fit between the organization and the implemented processes, and to minimize the degree of organizational change required in BPS projects such as ERP implementations. Reducing the misfits between BPs and the ERP system at the same time increases the likelihood of ERP implementation project success (cf. section 2.4). At the same time, the reduction of misfit between BPs and the ERP system alleviates possible technochange during the implementation project (Fischer *et al.*, 2017). Besides, by using process mining and by deciding on process models that ensure PMC and contain numerous BPS contingency factors, decision-making in BPS relies on more information than without the DSS. Furthermore, the matching algorithm for selecting a standard BP in a structured way based on the similarity of contingency factors significantly reduces the effort and complexity for human decision-makers.

7.3.3 Limitations and Future Research

However, the DSS and the approach of selecting a standard BP based on the similarity of BPS contingency factors also encounters several limitations. First, , process mining itself suffers from an array of limitations. For instance, process analyses vitally depend upon data quality in the underlying application systems (Schönig *et al.*, 2016) and on process information such as BPS contingency factors to be recorded in data (cf. section 2.3.5).

Second, the DSS determines the process model with the highest degree of similarity from the repository of best-practice standard processes. Although “similarity” implies a minimization of organizational change and thus lowers tangible and intangible costs for implementation of the standard BP, the “best” candidate for implementation might be a more radical change towards a process with only a low degree of similarity to the as-is process.

Third, BPs in practice consist of numerous individual variants which lead to “Spaghetti” process models that contain numerous process variants and that are “difficult to interpret” and thus of limited value for BPM activities (Song, Günther and van der Aalst, 2009). For example, the purchase-to-pay process at the industry partner consists of ~2.54, ~10.47 and 20.67 thousand variants, while the order-to-cash process entails ~20.87, ~35.32 and ~39.82 thousand variants in the three manufacturing companies (cf. table 60). At the same time, BP variants differ in terms of BPS contingency factors such as execution, inputs, outputs, data, people and knowledge, which requires an analysis on the variant level before matching (cf. section table 2). Further, while some variants are business-essential deviations from an ideal to-be standard design (e.g., the production of a product variant for a particular customer or individual arrangements), other variants might constitute undesired deviations with a detrimental impact on the organization or process performance. As a consequence, the question of which variants need to be reflected in the future process design arises and requires process owners to analyze each process variant individually. Further, the difficulty of distinguishing between important or business-critical versus unimportant and non-critical process variants arises (Schrepfer *et al.*, 2015) before the DSS can effectively be applied on a selected number of essential variants. However, the effort to screen each variant in the pool of several thousand different variants and determine their individual business criticality is virtually impossible. Therefore, decision-makers need to prioritize BP variants when assigning BPS contingency factors to the variants.

However, comparably to the determination of the importance and the organizational impact of an entire BP (DSR Project 2) (Mani, Barua and Whinston, 2006), the determination of the importance of an individual BP variant likewise poses a significant challenge. For example, the importance and criticality of a BP variant varies depending on the organizational context and contingencies (vom Brocke, Zelt and Schmiedel, 2016; Zelt, Schmiedel and vom Brocke, 2018), the business environment (Milani *et al.*, 2016), the impact on organizational performance (Carpinetti, Gerólamo and Dorta, 2000), the impact on value or competitiveness (Zelt, Schmiedel and vom Brocke, 2018), frequency of occurrence (Schrepfer *et al.*, 2015), costs (Mani, Barua and Whinston, 2006), the number of problems within the process or variant (Melnyk and Christensen, 2000), the relationship to the vision statement of the organization (Meade and Rogers, 2001) or complexity (Zelt, Schmiedel and vom Brocke, 2018) of the environment (Helkiö and Tenhiälä, 2013). Therefore, this task usually requires manual screening and expert knowledge on the process, the variant as well as the organization (Huxley and Stewart, 2004; Meade and Rogers, 2001). Furthermore, the risk of "forgetting" a business-essential variant remains, even though the process mining application provided the number of variant occurrences as a metric for which variant should be analyzed and assigned with the BPS contingency factors. Thus, a future implementation needs to provide a more elaborate measure of the importance of a particular variant.

Third, in order to match BPs against models in the repository, the to-be standard models need to be attached with non-data-driven BPS contingency factors, which might differ between organizations and thus not generalize.

In addition to limitations and future research from the DSS implementation and the underlying approaches, the chosen evaluation strategy encounters several limitations. Thus, future research needs to concentrate on the evaluation of the artifact and modules within the DSS (cf. figure 64). Primarily, since the DSSs designed within the DSR projects intend to provide an understanding of the BM (cf. table 3; DSR project 1) and BPs (cf. table 2) for decision-making in the selection of a standard for an important BP (DSR project 2), the evaluation of the DSS concentrates on comprehension (understanding (Morana *et al.*, 2019)) as the dependent variable (cf. section 2.6). However, in addition to comprehension of the decision, the decision and the DSS needs to be assessed by quality variables such as performance, time, learning, trust, adoption and use, or cognitive effort (Morana *et al.*, 2019). For instance, the DSS intends to select an appropriate standard BP design based on BPS contingency factors by means of a process similarity algorithm. Nevertheless, the evaluation of the "quality" of a process selection (i.e., whether the selected standard BP was the correct choice) and the determination of the contribution to organizational performance imposes a significant challenge. For instance, to determine whether the DSS selected the correct standard BP design or whether an organization that relies on the DSS conducts better standard BP selection than an organization without DSS support requires an otherwise identical baseline for comparison (i.e., another organization which is identical in terms of the BPS contingency factors). Furthermore, whether a standard BP selection was beneficial for the organization can only be determined in hindsight, which requires significant time for the implementation and effects of process change to materialize.

Future artifact evaluations might concentrate on the process models in the DSS (DD5). For the implementation of the process model variants in the first design cycle, the influence factors integrated visualization, decomposition and visual guidance were selected for implementation based on PMC literature. Although the experiment was intendedly constructed as a within-subject design and significant impact factors on PMC were controlled and kept constant across the process model variants (Patig, 2008), there might be alternative explanatory factors which might impose threats to the internal validity of the findings in the evaluation (Wohlin *et al.*, 2012). Besides, the laboratory evaluation might suffer from threats to external validity such as the representativeness of the experiment sample or the standard process models (Mendling, Strembeck and Recker, 2012) which limit transferability of results to a non-laboratory setting (Wohlin, Höst and Henningsson, 2003). For example, although process models and BPS contingency factors in the evaluation were carefully designed in average complexity from industry practice (Recker, 2013) and retrieved from the industry partner, real-life process models and associated contingency factors might entail significantly higher complexity (Rodrigues *et al.*, 2015). Findings in the laboratory experiment with the rather inexperienced student sample might differ between novices and experts, while experience in process modeling has been found to significantly impact PMC (Schrepfer *et al.*, 2015). Therefore, distinguishing experts and novices remains a significant challenge and PMC is impacted by numerous constructs such as familiarity, intensity or knowledge (Mendling *et al.*, 2018).

Another evaluation needs to target the similarity matching algorithm (DD7) at the heart of the process selection as proposed by Dijkman *et al.* (2011) to ensure the selection is appropriate from a technical point of view.

Finally, after the selection of a standard BP, the DSS might further be improved to discover deviations from standard BPs for ongoing monitoring of process conformance to the standard BP specification instead of a one-time standard BP selection. For example, the literature proposes two possible migration scenarios for BPs in an ERP implementation. On the one hand, BPs might be transformed a priori to the implementation, and be aligned with the standards imposed by the new ERP. On the other hand, the ERP might be customized a posteriori to support the original BP design (Buonanno *et al.*, 2005; Chen, 2001). With regard to the first case, the DSS might highlight how the current process needs to be changed. With regard to the second case, the DSS might discover which changes need to be made to the process to conform to the standard process.

Future research might additionally analyze the phenomena in different industries which have been found to differ in terms of transformation such as BPS (e.g., manufacturing and automotive (Dremel *et al.*, 2017), late-comer industries and utilities (Kohli and Johnson, 2011), or healthcare (Sağiroğlu and Özturan, 2006)). Besides, organization size has been determined as a critical contingency factor by studies presenting contradictory evidence in the context of contingency theory in BPM (e.g., (Pratono, 2016; van Looy and van den Bergh, 2018)). For example, studies find large organizations to encounter difficulties in management and leadership of human resources during transformations (Dremel *et al.*, 2017; Sağiroğlu and Özturan, 2006) while smaller organizations tend to additionally encounter difficulties in technical capabilities (Balaji, Ranganathan and Coleman, 2011).

8 Conclusion[26]

Organizations operate in increasingly dynamic environments of intense competition and fundamental change in technology, economics, society, customers, regulations and even the natural environment. These far-reaching changes in the internal and external environment fundamentally alter the economics of markets and require organizations to engage in BPS to thrive and survive. However, BPS depends on numerous contingency factors from different layers of the organization such as strategy, BMs, BPs and application systems which need to be taken into account for selecting appropriate standard BP designs that match the organization. Besides, currently prevailing "de-jure" approaches to BPS are non-data-driven and often do not utilize the increasingly available data from numerous sources within and outside of organizations. Organizations that fail to develop such "big data" capabilities might potentially lose competitive advantage (de Camargo Fiorini *et al.*, 2018; Erevelles, Fukawa and Swayne, 2016). Therefore, this thesis addresses the following research question: *"How to design data-driven decision support systems to increase the comprehension of contingency factors on business process standardization?"*

Theoretically grounded in organizational contingency theory as a kernel theory, this thesis conducts three DSR projects to design data-driven DSSs to increase comprehension of the contingency factors of business process standardization for organizational decision-makers. DSR projects are conducted at an industry partner within the context of a BPS and SAP S/4 HANA transformation, strategy and roadmap project at a global Germany-based manufacturing corporation of five companies in 22 countries with around 8.200 employees and a turnover of about 1.4bn Euro.

First, in order to retrieve and comprehend BM-related BPS contingency factors, DSR project 1 employs a DSR approach to design a data-driven "Business Model Mining" system that automatically identifies, retrieves and represents BMs from data in application systems such as ERP systems in a BMC implemented in a BI dashboard. Traditional non-data-driven approaches to business modeling such as the "Business Model Canvas"

[26] This chapter builds on content from previous publications in Fleig (2017), Fleig, Augenstein and Maedche (2018a, 2018b, 2018c, 2018d, 2019).

(BMC) are decoupled from application systems and typically follow a data-independent, manual approach. The project derives generic design requirements and a blueprint conceptualization for BMM systems and suggests an open, standardized reference data model for BMM to "mine" a BMC independently from underlying application systems. Further, the project implements the software artifact "Business Model Miner" in Microsoft Azure and PowerBI and demonstrates technical feasibility by using data from an educational SAP S/4 HANA system of a fictitious bicycle company, a public reference dataset "Adventure-Works", and three real-life SAP R/3 ERP systems of a German manufacturing corporation. A field study at a manufacturing corporation with 21 managers evaluates the Business Model Miner and finds differences between data-driven BMCs and BMCs created by managers and the potential for a complementary role of BMM tools to enrich the understanding of BMs. Further, a controlled laboratory experiment with 142 students finds significant beneficial impacts of the artifact on subjective and objective comprehension in terms of effectiveness, efficiency, and relative efficiency. Thus, DSR project 1 provides a new data-driven class of BMM applications and usable software for SAP R/3 and S/4 HANA ERP systems to support decision-making, modelling, monitoring, transformation, and comprehension in BM management beyond a BPS context.

Second, DSR project 2 designs a data-driven process mining DSS "KeyPro" to automatically discover and prioritize the set of BPs occurring in an organization from log data in application systems to concentrate BPS initiatives on the important BPs given limited organizational resources. The project derives objective and quantifiable BP importance metrics from BM and BPM literature and provides generic design requirements for the DSS. The project further implements the "KeyPro" artifact for SAP R/3 ERP and S/4 HANA systems in Microsoft SQL Server / Azure and interactive Microsoft PowerBI dashboards. To apply KeyPro at the industry partner and demonstrate technical feasibility, 220 processes are retrieved from 52 functional process owners across four manufacturing companies. 773 individual SAP R/3 ERP transactions are matched to a global process list of the industry partner to measure which BPs constitute "important" processes along with the importance metrics identified in BM and BPM literature. A field evaluation at the industry partner compares BPs detected manually by human decision-makers against BPs discovered from data by KeyPro and reveals significant differences between data-driven and non-data-driven analyses and a complementary role of the artifact to deliver additional insights into the set of BPs in the organization. In a controlled laboratory experiment with 30 students, the dashboards with the lowest comprehension are identified for further development of the artifact.

Third, following an understanding of the organizational BM and the selection of important BPs for BPS initiatives, contingency theory requires decision-makers to select a standard BP design that matches BPS contingency factors to reduce the costs of BPS, to optimize the fit between the organization and the implemented to-be standard BP, and to minimize the degree of organizational change required for implementation. Thus, DSR project 3 designs a process mining DSS to select a standard BP from a repository of different alternative designs based on the similarity of BPS contingency factors of the as-is process and the different to-be standard processes. DSR project 3 thus derives four different process model variants for representing BPS contingency factors that vary according to determinant factors of process model comprehension (PMC). In a controlled laboratory evaluation with 150 students, significant differences in PMC between the tabular, static, dynamic and the guided variant are identified. Based on laboratory findings, the DSS is implemented in the BPM platform “Apromore” to select standard BP reference models from the SAP Best Practices Explorer for SAP S/4 HANA and applied in a showcase for the purchase-to-pay and order-to-cash process of a manufacturing company at the industry partner.

9 References

Aaker, D.A. and Mascarenhas, B. (1984) 'The Need for Strategic Flexibility', *Journal of Business Strategy*, 5(2), pp. 74–82. doi: 10.1108/eb039060

Acharya, A. *et al.* (2018) 'Big data, knowledge co-creation and decision making in fashion industry', *International Journal of Information Management*, 42, pp. 90–101. doi: 10.1016/j.ijinfomgt.2018.06.008

Aggarwal, C.C. (2015) *Data Mining*. Cham: Springer International Publishing.

Agrawal, R., De, P. and Sinha, A.P. (1999) 'Comprehending object and process models: An empirical study', *IEEE Transactions on Software Engineering*, 25(4), pp. 541–556. doi: 10.1109/32.799953

Agrawal, R., Gunopulos, D. and Leymann, F. (1998) 'Mining process models from workflow logs', in *Advances in Database Technology — EDBT'98: EDBT 1998.* Lecture Notes in Computer Science. (1377): Springer Berlin Heidelberg.

Aldea, A., Iacob, M.-E. and Quartel, D. (2018) 'From Business Strategy to Enterprise Architecture and Back', *2018 IEEE 22nd International Enterprise Distributed Object Computing Workshop (EDOCW), 2018 IEEE 22nd International Enterprise Distributed Object Computing Workshop (EDOCW),* Stockholm, 10/16/2018 - 10/19/2018: IEEE, pp. 145–152. doi: 10.1109/EDOCW.2018.00029

Al-Debei, M.M. and Avison, D. (2010) 'Developing a unified framework of the business model concept', *European Journal of Information Systems*, 19(3), pp. 359–376. doi: 10.1057/ejis.2010.21

Al-Debei, M.M., El-Haddadeh, R. and Avison, D. (2008) 'Defining the Business Model in the New World of Digital Business', *14th Americas Conference on Information Systems, Toronto, Canada*. Available at: https://aisel.aisnet.org/amcis2008/300/.

American Productivity & Quality Center (APQC) (2017) *Process Classification Framework*. (PCF). Available at: https://www.apqc.org/pcf (Accessed: 18 November 2017).

Amit, R. and Zott, C. (2015) 'Crafting Business Architecture: the Antecedents of Business Model Design', *Strategic Entrepreneurship Journal*, 9(4), pp. 331–350. doi: 10.1002/sej.1200

Andersson, B., Bergholtz, M. and Gregoire, B. (2006) 'From Business to Process Models - a Chaining Methodology', *International Conference on Advanced Information Systems Engineering: Proceedings of CAISE'06 Workshops and Doctoral Consortium*, 211-218.

Andreini, D. and Bettinelli, C. (2017) *Business Model Innovation: From Systematic Literature Review to Future Research Directions / Daniela Andreini, Cristina Bettinelli*. (International series in advanced management studies). Cham, Switzerland: Springer.

Anning-Dorson, T. (2018) ‘Customer involvement capability and service firm performance: The mediating role of innovation’, *Journal of Business Research*, 86, pp. 269–280. doi: 10.1016/j.jbusres.2017.07.015

Antunes, G. *et al.* (2015) ‘The process model matching contest 2015’, *Enterprise modelling and information systems architectures*, pp. 127–155. Available at: https://dl.gi.de/handle/20.500.12116/2041.

Arán Carrión, J. *et al.* (2008) ‘Environmental decision-support systems for evaluating the carrying capacity of land areas: Optimal site selection for grid-connected photovoltaic power plants’, *Renewable and Sustainable Energy Reviews*, 12(9), pp. 2358–2380. doi: 10.1016/j.rser.2007.06.011

Aranda, J. *et al.* (2007) ‘A Framework for Empirical Evaluation of Model Comprehensibility’, in *International Workshop on Modeling in Software Engineering (MISE'07)*. Available at: http://dl.acm.org/ft_gateway.cfm?id=1269010&type=pdf.

Arnott, D. (2006) ‘Cognitive biases and decision support systems development: a design science approach’, *Information Systems Journal*, 16(1), pp. 55–78. doi: 10.1111/j.1365-2575.2006.00208.x

Aspara, J. *et al.* (2013) ‘Corporate Business Model Transformation and Inter-Organizational Cognition: The Case of Nokia’, *Long Range Planning*, 46(6), pp. 459–474. doi: 10.1016/j.lrp.2011.06.001

Augenstein, D. and Fleig, C. (2017) ‘Exploring Design Principles for a Business Model Mining Tool’, *International Conference on Information Systems, Seoul, Republic of Korea*. Available at: http://aisel.aisnet.org/icis2017/DataScience/Presentations/4/ (Accessed: 9 February 2018).

Augenstein, D. and Fleig, C. (2018) ‘Designing for Business Model Comprehension - Principles for an Extended Business Model Tool’, *26th European Conference on Information Systems, Portsmouth, United Kingdom*, Research-in-Progress Papers. Available at: https://aisel.aisnet.org/ecis2018_rip/56.

Augenstein, D., Fleig, C. and Dellermann, D. (2018) ‘Towards Value Proposition Mining - Exploration of Design Principles’, *39th International Conference on Information Systems, San Francisco, San Francisco, United States*.

Autio, E. (2017) ‘Strategic Entrepreneurial Internationalization: A Normative Framework’, *Strategic Entrepreneurship Journal*, 11(3), pp. 211–227. doi: 10.1002/sej.1261

Aysolmaz, B. and Reijers, H.A. (2016) ‘Towards an Integrated Framework for Invigorating Process Models: A Research Agenda’, in Reichert, M. and Reijers, H.A. (eds.) *Business Process Management Workshops: BPM 2016.* Lecture Notes in Business Information Processing. (256). Cham: Springer, pp. 552–558.

Bagnoli, C. *et al.* (2018) ‘Defining The Concept Of Business Model’, *International Journal of Knowledge and Systems Science*, 9(3), pp. 48–64. doi: 10.4018/IJKSS.2018070104

Bala, H. and Venkatesh, V. (2007) ‘Assimilation of Interorganizational Business Process Standards’, *Information Systems Research*, 18(3), pp. 340–362. doi: 10.1287/isre.1070.0134

Balaji, S., Ranganathan, C. and Coleman, T. (2011) ‘IT-Led Process Reengineering: How Sloan Valve Redesigned its New Product Development Process’, *MIS Quarterly Executive*, 10(2), pp. 81–92.

Bask, A.H., Tinnilä, M. and Rajahonka, M. (2010) ‘Matching service strategies, business models and modular business processes’, *Business Process Management Journal*, 16(1), pp. 153–180. doi: 10.1108/14637151011017994

Baskerville, R.L. and Pries-Heje, J. (2010) ‘Explanatory Design Theory’, *Business & Information Systems Engineering*, 2(5), pp. 271–282. Available at: https://aisel.aisnet.org/bise/vol2/iss5/2.

Bass, J.M., Allison, I. and Banerjee, U. (2013) ‘Agile method tailoring in a CMMI level 5 organization’, *Addressing the paradox*, 22(4), pp. 77–98.

Beck, D.J. (2018) *Process Mining for Process Standardisation: Designing Standardisation Attributes-Enriched Process Models for Higher Comprehension: Supervised Master Thesis*. Master-Thesis. Karlsruhe Institute of Technology.

Becker, J., Rosemann, M. and von Uthmann, C. (2000) ‘Guidelines of Business Process Modeling’, in van der Aalst, W.M.P., Desel, J. and Oberweis, A. (eds.) *Business Process Management: Models, Techniques, and Empirical Studies.* (Lecture Notes in Computer Science, 1806). Berlin: Springer, pp. 30–49.

Becker, M. and Laue, R. (2012) ‘A comparative survey of business process similarity measures’, *Process / Workflow Mining*, 63(2), pp. 148–167.

Beimborn, D. *et al.* (2009) ‘The Role of Process Standardization in Achieving IT Business Value’, *42nd Hawaii International Conference on System Sciences (*1p). doi: 10.1109/HICSS.2009.453

Benbasat, I. and Zmud, R.W. (1999) ‘Empirical Research in Information Systems: The Practice of Relevance’, *Management Information Systems Quarterly*, 23(1), pp. 3–16.

Benders, J., Batenburg, R. and van der Blonk, H. (2006) ‘Sticking to standards; technical and other isomorphic pressures in deploying ERP-systems’, *Information & Management* (43(2)), pp. 194–203.

Berkovits, I., Hancock, G.R. and Nevitt, J. (2000) ‘Bootstrap Resampling Approaches for Repeated Measure Designs: Relative Robustness to Sphericity and Normality Violations’, *Educational and Psychological Measurement*, 60(6), pp. 877–892. doi: 10.1177/00131640021970961

Berre Arne- Jørgen, de Man Henk and Lindgren, P. (2013) ‘Business Model Innovation with the NEFFICS platform and VDML’, *CEUR Workshop Proceedings*, 1006, pp. 24–30.

Bessai, K. *et al.* (2008) ‘Context-aware Business Process Evaluation Redesign’, *Proceedings of BPMDS'08*, pp. 86–95.

Besson, P. and Rowe, F. (2012) ‘Strategizing information systems-enabled organizational transformation: A transdisciplinary review and new directions’, *The Journal of Strategic Information Systems*, 21(2), pp. 103–124.

Bharadwaj, A. *et al.* (2013) ‘Digital Business Strategy: Toward a Next Generation of Insights’, *Management Information Systems Quarterly*, 37(2), pp. 471–482. doi: 10.25300/MISQ/2013/37:2.3

Bider, I. and Perjons, E. (2017) ‘Using a Fractal Enterprise Model for Business Model Innovation’, *BPMDS’17 Working Conference Business process modeling, development and support*, 1859, pp. 20–29. Available at: http://ceur-ws.org/Vol-1859/bpmds-02-paper.pdf.

Bieger, T. and Reinhold, S. (2011) ‘Das wertbasierte Geschäftsmodell – Ein aktualisierter Strukturierungsansatz’, in Bieger, T., Knyphausen-Aufseß, D. zu and Krys, C. (eds.) *Innovative Geschäftsmodelle.* Berlin, Heidelberg: Springer Berlin Heidelberg, pp. 13–70.

Bock, A.J. *et al.* (2012) ‘The Effects of Culture and Structure on Strategic Flexibility during Business Model Innovation’, *Journal of Management Studies*, 49(2), pp. 279–305. doi: 10.1111/j.1467-6486.2011.01030.x

Bodart, F. *et al.* (2001) ‘Should Optional Properties Be Used in Conceptual Modelling? A Theory and Three Empirical Tests’, *Information Systems Research*, 12(4), pp. 384–405. doi: 10.1287/isre.12.4.384.9702

Bohnsack, R., Pinkse, J. and Kolk, A. (2014) ‘Business models for sustainable technologies: Exploring business model evolution in the case of electric vehicles’, *Research Policy*, 43(2), pp. 284–300. doi: 10.1016/j.respol.2013.10.014

Bolton, R. and Hannon, M. (2016) ‘Governing sustainability transitions through business model innovation: Towards a systems understanding’, *Research Policy*, 45(9), pp. 1731–1742. doi: 10.1016/j.respol.2016.05.003

Bonakdar, A. *et al.* (2013) ‘Transformative Influence of Business Processes on the Business Model: Classifying the State of the Practice in the Software Industry’, *2013 46th Hawaii International Conference on System Sciences, 2013 46th Hawaii International Conference on System Sciences (HICSS)*, Wailea, HI, USA, 1/7/2013 - 1/10/2013: IEEE, pp. 3920–3929. doi: 10.1109/HICSS.2013.573

Bortz, J. and Schuster, C. (2010) *Statistik für Human- und Sozialwissenschaftler*. 7th edn. (Springer-Lehrbuch). Berlin, Heidelberg: Springer-Verlag Berlin Heidelberg.

Botta-Genoulaz, V., Millet, P.A. and Grabot, B. (2005) ‘A survey on the recent research literature on ERP systems’, *Computers in Industry* (56(6)), pp. 510–522.

Botzkowski, T. (2018) *Digitale Transformation von Geschäftsmodellen im Mittelstand*. Wiesbaden: Springer Fachmedien Wiesbaden.

Bousquet, F., Fomin, V.V. and Drillon, D. (2011) ‘Anticipatory Standards Development and Competitive Intelligence’, *International Journal of Business Intelligence Research*, 2(1), pp. 16–30. doi: 10.4018/jbir.2011010102

Brandão, B., Santoro, F. and Azevedo, L.G. (2015) ‘Towards Aspects Identification in Business Process Through Process Mining’, *Anais do XI Simpósio Brasileiro de Sistemas de Informação.* Porto Alegre, RS, Brasil: SBC, pp. 741–748. Available at: https://sol.sbc.org.br/index.php/sbsi/article/view/5883.

Brown, J.D. (1988) *Understanding Research in Second Language Learning: A Teacher's Guide to Statistics and Research Design*: Cambridge University Press.

Bühl, A. (2016) *SPSS 23: Einführung in die moderne Datenanalyse*. 15th edn. (st - scientific tools). Hallbergmoos: Pearson.

Buonanno, G. *et al.* (2005) ‘Factors affecting ERP system adoption’, *Journal of Enterprise Information Management*, 18(4), pp. 384–426. doi: 10.1108/17410390510609572

Burton-Jones, A. and Meso, P. (2002) ‘How Good Are These UML Diagrams? An Empirical Test of the Wand and Weber Good Decomposition Model’, in *Twenty-Third International Conference on Information Systems*.

Burton-Jones, A. and Meso, P. (2008) ‘The Effects of Decomposition Quality and Multiple Forms of Information on Novices’ Understanding of a Domain from a Conceptual Model’, *Journal of the Association for Information Systems*, 9(12), pp. 748–802. doi: 10.17705/1jais.00179

Cao, G. and Duan, Y. (2017) ‘How do top- and bottom-performing companies differ in using business analytics?’ *Journal of Enterprise Information Management*, 30(6), pp. 874–892. doi: 10.1108/JEIM-04-2016-0080

Capecchi, S. and Pisano, P. (2014) ‘Reputation by Design: Using VDML and Service ML for Reputation Systems Modeling’, *2014 IEEE 11th International Conference on e-Business Engineering, 2014 IEEE 11th International Conference on e-Business Engineering (ICEBE),* Guangzhou, China, 5/11/2014 - 7/11/2014: IEEE, pp. 191–198.

Caron, F., Vanthienen, J. and Baesens, B. (2013) ‘Comprehensive rule-based compliance checking and risk management with process mining’, *Decision Support Systems,* 54(3), pp. 1357–1369. doi: 10.1016/j.dss.2012.12.012

Carpinetti, L.C.R., Gerólamo, M.C. and Dorta, M. (2000) ‘A conceptual framework for deployment of strategy-related continuous improvements’, *The TQM Magazine,* 12(5), pp. 340–349. doi: 10.1108/09544780010341950

Casadesus-Masanell, R. and Ricart, J.E. (2010) ‘From Strategy to Business Models and onto Tactics’, *Long Range Planning,* 43(2-3), pp. 195–215. doi: 10.1016/j.lrp.2010.01.004

Caspar, J. *et al.* (2013) ‘Vom Geschäftsmodell zum Geschäftsprozess und zurück’, *HMD Praxis der Wirtschaftsinformatik*, 50(4), pp. 13–22. doi: 10.1007/BF03340830

Cayoglu, U. *et al.* (2013) ‘Report: The process model matching contest 2013’, *International Conference on Business Process Management.* Springer-Verlag GmbH, pp. 442–463.

Champy, J. (2003) *X-engineering the corporation: Reinventing your business in the digital age*: Warner Business.

Chase, R.B. (1981) ‘The Customer Contact Approach to Services: Theoretical Bases and Practical Extensions’, *Operations Research*, 29(4), pp. 698–706.

Chen, I.J. (2001) ‘Planning for ERP systems: analysis and future trend’, *Business Process Management Journal*, 7(5), pp. 374–386. doi: 10.1108/14637150110406768

Chen, Y. *et al.* (2017) ‘IT capability and organizational performance: The roles of business process agility and environmental factors’, *European Journal of Information Systems*, 23(3), pp. 326–342. doi: 10.1057/ejis.2013.4

Chesbrough, H. (2002) ‘The role of the business model in capturing value from innovation: evidence from Xerox Corporation's technology spin-off companies’, *Industrial and Corporate Change,* 11(3), pp. 529–555. doi: 10.1093/icc/11.3.529

Chinces, D. and Salomie, I. (2013) ‘Business process mining algorithms’, *9th IEEE International Conference on Intelligent Computer Communication and Processing (ICCP), Cluj-Napoca, Romania*, pp. 271–277. doi: 10.1109/ICCP.2013.6646120

Christensen, L.B., Johnson, R.B. and Turner, L.A. (2011) *Research Methods, Design, and Analysis*. 11th edn. Boston Mass.: Allyn & Bacon Pearson Education.

Christin Jurisch, M. *et al.* (2014) ‘Which capabilities matter for successful business process change?’ *Business Process Management Journal*, 20(1), pp. 47–67. doi: 10.1108/BPMJ-11-2012-0125

CIO (2017) *15 famous ERP disasters, dustups and disappointments*. Available at: https://www.cio.com/article/2429865/enterprise-resource-planning/enterprise-resource-planning-10-famous-erp-disasters-dustups-and-disappointments.html.

Clark-Carter, D. (2004) *Quantitative Psychological Research: A Student's Handbook*. 2nd edn. London, UK: Psychology Press.

Clark-Carter, D. (2009) *Quantitative Psychological Research: The Complete Student's Companion,, 3rd Edition: The Complete Student's Companion*: Taylor & Francis.

Cohen, J. (1992) ‘A Power Primer’, *Psychological Bulletin*, 112(1), pp. 155–159. doi: 10.1037/0033-2909.112.1.155

Curiazzi, R. *et al.* (2016) ‘Process Standardization to Support Service Process Assessment and Re-engineering’, *Procedia CIRP*, 47, pp. 347–352. doi: 10.1016/j.procir.2016.03.104

Curtis, B., Kellner, M.I. and Over, J. (1992) ‘Process Modeling’, *Communications of the ACM*, 35(9), pp. 75–90. doi: 10.1145/130994.130998

Daft, R.L., Murphy, J. and Willmott, H. (2010) *Organization theory and design: An international persepective*. Andover: CENGAGE Learning Business Press.

Davenport, T.H. (1993) *Process Innovation: Reengineering Work through Information Technology*. 5th edn. Boston, Mass.: Harvard Business School Press.

Davenport, T.H. (2005) ‘The coming commoditization of processes’, *Harvard Business Review*, 83(6), pp. 101–108.

Davenport, T.H. (2014) ‘How strategists use “big data” to support internal business decisions, discovery and production’, *Strategy & Leadership*, 42(4), pp. 45–50. doi: 10.1108/SL-05-2014-0034

Davenport, T.H. and Short, J.E. (1990) ‘The new industrial engineering: information technology and business process redesign’, *Sloan Management Review*, Summer 1990(31), pp. 11–27. Available at: https://is.ieis.tue.nl/education/bpmcourse/papers/Davenport%20(1990)%20-%20The%20New%20Industrial%20Engineering.pdf (Accessed: 30 July 2019).

David, J.S., McCarthy, W.E. and Sommer, B.S. (2003) ‘Agility - The Key to Survival of the Fittest in the Software Market’, *Communications of the ACM*, 46(5), pp. 65–69. doi: 10.1145/769800.769803

de Bruin, T. and Rosemann, M. (2007) ‘Using the Delphi Technique to Identify BPM Capability Areas’, *18th Australasian Conference on Information Systems*.

de Camargo Fiorini, P. *et al.* (2018) 'Management theory and big data literature: From a review to a research agenda', *International Journal of Information Management*, 43, pp. 112–129. doi: 10.1016/j.ijinfomgt.2018.07.005

de Weerdt, J. *et al.* (2012) 'A multi-dimensional quality assessment of state-of-the-art process discovery algorithms using real-life event logs', *Information Systems*, 37(7), pp. 654–676. doi: 10.1016/j.is.2012.02.004

de Weerdt, J., van den Broucke, S.K.L.M. and Caron, F. (2015) 'Bidimensional Process Discovery for Mining BPMN Models', in Fournier, F. and Mendling, J. (eds.) *Business Process Management Workshops: BPM 2014.* Lecture Notes in Business Information Processing. (202). Cham: Springer International Publishing, pp. 529–540.

Del Giudice, M. (2016) 'Discovering the Internet of Things (IoT) within the business process management', *Business Process Management Journal*, 22(2), pp. 263–270. doi: 10.1108/BPMJ-12-2015-0173

Deloitte (2015) *Your guide to a successful ERP journey: Top 10 change management challenges for Enterprise Resource Planning Implementations*. Available at: https://www2.deloitte.com/content/dam/Deloitte/mx/Documents/human-capital/01_ERP_Top10_Challenges.pdf.

Demil, B. and Lecocq, X. (2010) 'Business Model Evolution: In Search of Dynamic Consistency', *Long Range Planning*, 43(2-3), pp. 227–246. doi: 10.1016/j.lrp.2010.02.004

Demirkan, H. and Delen, D. (2013) 'Leveraging the capabilities of service-oriented decision support systems: Putting analytics and big data in cloud', *Decision Support Systems*, 55(1), pp. 412–421. doi: 10.1016/j.dss.2012.05.048

Di Valentin, C. *et al.* (2012) 'Towards a Framework for Transforming Business Models into Business Processes', *18th Americas Conference on Information Systems, Seattle, Washington, USA*, 1.

Dijkman, R.M. (2007) 'A Classification of Differences between Similar Business Processes', *Enterprise Distributed Object Computing Conference (EDOC), Annapolis, MD, USA*. doi: 10.1109/EDOC.2007.24

Dijkman, R.M. *et al.* (2011) 'Similarity of business process models: Metrics and evaluation', *Information Systems*, 36(2), pp. 498–516.

Dijkman, R.M. *et al.* (2013) 'A Short Survey on Process Model Similarity: Seminal Contributions to Information Systems Engineering: 25 Years of CAiSE', pp. 421–427.

Dikici, A., Turetken, O. and Demirors, O. (2018) 'Factors influencing the understandability of process models: A systematic literature review', *Information and Software Technology*, 93, pp. 112–129 (Accessed: 22 December 2017).

Döhring, M., Reijers, H.A. and Smirnov, S. (2014) ‘Configuration vs. adaptation for business process variant maintenance: An empirical study’, *Information Systems,* 39, pp. 108–133. doi: 10.1016/j.is.2013.06.002

Donaldson, L. (2001) *The Contingency Theory of Organizations*. (Foundations for organizational science). Thousand Oaks, California: SAGE Publications, Inc.

Donaldson, L. (2006) ‘The Contingency Theory of Organizational Design: Challenges and Opportunities’, in Burton, R.M. *et al.* (eds.) *Organization Design: The evolving state-of-the-art.* (Information and Organization Design Series, 6). Boston, MA: Springer Science+Business Media LLC, pp. 19–40.

Dremel, C. *et al.* (2017) ‘How AUDI AG Established Big Data Analytics in its Digital Transformation’, *MIS Quarterly Executive,* 16, pp. 81–100.

Duan, C., Grover, V. and Balakrishnan, N.R. (2009) ‘Business Process Outsourcing: An event study on the nature of processes and firm valuation’, *European Journal of Information Systems,* 18(5), pp. 442–457.

Dumas, M. *et al.* (2012) ‘Understanding Business Process Models: The Costs and Benefits of Structuredness’, in Ralyté, J. *et al.* (eds.) *Advanced Information Systems Engineering: CAiSE 2012.* Lecture Notes in Computer Science. (7328): Springer Berlin Heidelberg, pp. 31–46.

Dumas, M. *et al.* (2013) *Fundamentals of Business Process Management*. Berlin, Heidelberg: Springer Berlin Heidelberg.

Dunn, O.J. (1964) ‘Multiple Comparisons Using Rank Sums’, *Technometrics,* 6(3), p. 241. doi: 10.2307/1266041

Eames, C. (1972) 'What is Design'. Interview with Charles Eames. Interview by Madame L’Amic, 1972.

Ebel, P., Bretschneider, U. and Leimeister, J.M. (2016) ‘Leveraging virtual business model innovation: a framework for designing business model development tools’, *Information Systems Journal,* 26(5), pp. 519–550. doi: 10.1111/isj.12103

Ehie, I. and Madsen, M. (2005) ‘Identifying critical issues in enterprise resource planning (ERP) implementation’, *Computers in Industry* (56(6)), pp. 545–557.

El Kharbili, M. (2012) ‘Business Process Regulatory Compliance Management Solution Frameworks: A Comparative Evaluation’, *Conferences in Research and Practice in Information Technology Series*, 130.

Erevelles, S., Fukawa, N. and Swayne, L. (2016) ‘Big Data consumer analytics and the transformation of marketing’, *Journal of Business Research,* 69(2), pp. 897–904. doi: 10.1016/j.jbusres.2015.07.001

Fahland, D. *et al.* (2009) 'Declarative versus Imperative Process Modeling Languages: The Issue of Understandability: The issue of understandability', in Halpin, T. (ed.) *Enterprise, Business-Process and Information Systems Modeling: BPMDS 2009, EMMSAD 2009.* Lecture Notes in Business Information Processing. (29): Springer Berlin Heidelberg, pp. 353–366.

Fan, W. and Gordon, M.D. (2014) 'The power of social media analytics', *Communications of the ACM,* 57(6), pp. 74–81. doi: 10.1145/2602574

Féris, M.A.A., Zwikael, O. and Gregor, S. (2017) 'QPLAN: Decision support for evaluating planning quality in software development projects', *Decision Support Systems,* 96, pp. 92–102. doi: 10.1016/j.dss.2017.02.008

Fernandez, J. and Bhat, J. (2010) 'Addressing the Complexities of Global Process Harmonization', in Wang, M. and Sun, Z. (eds.) *Handbook of research on complex dynamic process management: Techniques for adaptability in turbulent environments.* Hershey, Pa: IGI Global (701 E. Chocolate Avenue Hershey Pennsylvania 17033 USA), pp. 368–385.

Few, S. (2013) *Information dashboard design: Displaying data for at-a-glance monitoring*. 2nd edn. Burlingame, CA: Analytics Press.

Field, A.P., Miles, J. and Field, Z. (2012) *Discovering statistics using R*. London: Sage.

Figl, K. (2017) 'Comprehension of Procedural Visual Business Process Models: A literature review', *Business & Information Systems Engineering*, 59(1), pp. 41–67.

Figl, K. and Laue, R. (2011) 'Cognitive Complexity in Business Process Modeling', in Mouratidis, H. and Rolland C. (eds.) *Advanced Information Systems Engineering: CAiSE 2011.* Lecture Notes in Computer Science. (6741): Springer Berlin Heidelberg, pp. 452–466.

Figl, K. and Laue, R. (2015) 'Influence factors for local comprehensibility of process models', *International Journal of Human-Computer Studies*, 82, pp. 96–110. doi: 10.1016/j.ijhcs.2015.05.007

Figl, K., Mendling, J. and Strembeck, M. (2013) 'The Influence of Notational Deficiencies on Process Model Comprehension', *Journal of the Association for Information Systems*, 14(6), pp. 312–388.

Figl, K. and Recker, J. (2016a) 'Exploring cognitive style and task-specific preferences for process representations', *Requirements Engineering*, 21(1), pp. 63–85. doi: 10.1007/s00766-014-0210-2

Figl, K. and Recker, J. (2016b) 'Process innovation as creative problem solving: An experimental study of textual descriptions and diagrams', *Information & Management*, 53(6), pp. 767–786. doi: 10.1016/j.im.2016.02.008

Figl, K., Recker, J. and Mendling, J. (2013) 'A study on the effects of routing symbol design on process model comprehension', *Decision Support Systems*, 54(2), pp. 1104–1118. doi: 10.1016/j.dss.2012.10.037

Figl, K. and Strembeck, M. (2015) 'Findings from an Experiment on Flow Direction of Business Process Models', in Kolb, J., Leopold, H. and Mendling, J. (eds.) *Enterprise modelling and information systems architectures. Bonn: Gesellschaft für Informatik e.V.*, pp. 59–73.

Financial Reporting Council (2018) *Guidance on the Strategic Report*. Accounting and Reporting. Available at: https://www.frc.org.uk/getattachment/fb05dd7b-c76c-424e-9daf-4293c9fa2d6a/Guidance-on-the-Strategic-Report-31-7-18.pdf (Accessed: 18 August 2019).

Finestone, N. and Snyman, R. (2005) 'Corporate South Africa: making multicultural knowledge sharing work', *Journal of Knowledge Management*, 9(3), pp. 128–141. doi: 10.1108/13673270510602827

Finney, S. and Corbett, M. (2007) 'ERP implementation: a compilation and analysis of critical success factors', *Business Process Management Journal*, 13(3), pp. 329–347. doi: 10.1108/14637150710752272

Fischer, M. *et al.* (2017) 'Assessing Process Fit in ERP Implementation Projects: A Methodological Approach', *12th International Conference on Design Science Research in Information Systems and Technology, Karlsruhe, Germany*.

Flasiński, M. (2016) *Introduction to Artificial Intelligence*. Cham: Springer International Publishing.

Fleig, C. (2017) 'Towards the Design of a Process Mining-Enabled Decision Support System for Business Process Transformation', *International Conference on Advanced Information Systems Engineering: Forum and Doctoral Consortium Papers, Essen, Germany*, pp. 170–178 (Accessed: 12 November 2017).

Fleig, C., Augenstein, D. and Maedche, A. (2018a) 'Designing a Process Mining-Enabled Decision Support System for Business Process Standardization in ERP Implementation Projects', in Weske, M. *et al.* (eds.) *Business Process Management Forum.* (Lecture Notes in Business Information Processing). Cham: Springer International Publishing, pp. 228–244.

Fleig, C., Augenstein, D. and Maedche, A. (2018b) 'KeyPro - A Decision Support System for Discovering Important Business Processes in Information Systems: Information Systems in the Big Data Era', *International Conference on Advanced Information Systems Engineering*, Information Systems in the Big Data Era, pp. 90–104.

Fleig, C., Augenstein, D. and Maedche, A. (2018c) 'Process Mining for Business Process Standardization in ERP Implementation Projects – An SAP S/4 HANA Case Study from Manufacturing', *International Business Process Management Conference, Sydney, New South Wales, Australia*. doi: 10.5445/IR/1000084169

Fleig, C., Augenstein, D. and Maedche, A. (2018d) ‘Tell Me What’s My Business - Development of a Business Model Mining Software’, in Mendling, J. and Mouratidis, H. (eds.) *Information Systems in the Big Data Era.* (Lecture Notes in Business Information Processing). Cham: Springer International Publishing, pp. 105–113.

Fleig, C., Augenstein, D. and Maedche, A. (2019) ‘A Process Mining-Enabled Decision Support System for Data-Driven Business Process Standardization in ERP Implementation Projects: KIT Scientific Working Paper’, *Proceedings of the KSS Research Workshop 2017*, pp. 48–52. doi: 10.5445/IR/1000104369

Ford, F.N. (1985) ‘Decision support systems and expert systems: A comparison’, *Information & Management*, 8(1), pp. 21–26. doi: 10.1016/0378-7206(85)90066-7

Foss, N.J. and Saebi, T. (2017) ‘Fifteen Years of Research on Business Model Innovation’, *Journal of Management*, 43(1), pp. 200–227. doi: 10.1177/0149206316675927

Fox, M.S., Barbuceanu, M. and Gruninger, M. (1996) ‘An organisation ontology for enterprise modeling: Preliminary concepts for linking structure and behaviour’, *Computers in Industry*, 29(1), pp. 123–134. doi: 10.1016/0166-3615(95)00079-8

França, C.L. (2017) *Business Model Design for Strategic Sustainable Development: Blekinge Institute of Technology Doctoral Dissertation Series*. Doctoral thesis, comprehensive summary. Blekinge Tekniska Högskola. Available at: https://www.google.de/url?sa=t&rct=j&q=&esrc=s&source=web&cd=1&ved=2ahUKEwiNhu2JzeDmAhVPZVAKHWg9DXgQFjAAegQIAxAC&url=https%3A%2F%2Fwww.diva-portal.org%2Fsmash%2Fget%2Fdiva2%3A1060784%2FFULLTEXT03.pdf&usg=AOvVaw0k-r2tORUdxDYQBOCvIz58.

Friedman, M. (1937) ‘The Use of Ranks to Avoid the Assumption of Normality Implicit in the Analysis of Variance’, *Journal of the American Statistical Association*, 32(200), p. 675. doi: 10.2307/2279372

Gabryelczyk, R. and Jurczuk, A. (2017) ‘Does Experience Matter? Factors Affecting the Understandability of the Business Process Modelling Notation’, *Procedia Engineering*, 182, pp. 198–205. doi: 10.1016/j.proeng.2017.03.164

Garretson, P. and Harmon, P. (2005) ‘How Boeing A&T Manages Business Processes’, *BPTrends*, November. Available at: https://www.bptrends.com/publicationfiles/11-05-WP-BoeingATBPM-Garretson-Harmon.pdf (Accessed: 18 August 2019).

Gassmann, O., Frankenberger, K. and Csik, M. (2014) *The business model navigator: 55 models that will revolutionise your business / Oliver Gassmann, Karolin Frankenberger, Michaela Csik*. Harlow: Financial Times.

Gattiker, T.F. and Goodhue, D.L. (2005) ‘What Happens after ERP Implementation: Understanding the Impact of Interdependence and Differentiation on Plant-Level Outcomes’, *Management Information Systems Quarterly*, 29(29(3)), pp. 559–585.

Gebauer, J. and Lee, F. (2008) ‘Enterprise System Flexibility and Implementation Strategies: Aligning Theory with Evidence from a Case Study’, *Information Systems Management*, 25(1), pp. 71–82. doi: 10.1080/10580530701777198

Gebauer, J. and Schober, F. (2006) ‘Information System Flexibility and the Cost Efficiency of Business Processes’, *Journal of the Association for Information Systems* (Vol. 7, No. 3), pp. 122–147.

Gemino, A. and Wand, Y. (2003) ‘Evaluating modeling techniques based on models of learning’, *Communications of the ACM*, 46(10), p. 79. doi: 10.1145/944217.944243

Gemino, A. and Wand, Y. (2004) ‘A framework for empirical evaluation of conceptual modeling techniques’, *Requirements Engineering*, 9(4), pp. 248–260. doi: 10.1007/s00766-004-0204-6

Gemino, A. and Wand, Y. (2005) ‘Complexity and clarity in conceptual modeling: Comparison of mandatory and optional properties’, *Data & Knowledge Engineering*, 55(3), pp. 301–326. doi: 10.1016/j.datak.2004.12.009

General Electrics (2014) *Global Innovation Barometer 2014*. Available at: https://www.ge.com/reports/ge-innovation-barometer-2014-2/.

Genero, M., Poels, G. and Piattini, M. (2008) ‘Defining and validating metrics for assessing the understandability of entity–relationship diagrams’, *Data & Knowledge Engineering*, 64(3), pp. 534–557. doi: 10.1016/j.datak.2007.09.011

Gepp, M., Khomut, M. and Vollmar, J. (2012) ‘Success Factors of Standardization: An Empirical Study’, *23rd International DAAAM Symposium*, 23(1).

Gibb, F., Buchanan, S. and Shah, S. (2006) ‘An integrated approach to process and service management’, *International Journal of Information Management*, 26(1), pp. 44–58. doi: 10.1016/j.ijinfomgt.2005.10.007

Giessmann, A. and Legner, C. (2016) ‘Designing business models for cloud platforms’, *Information Systems Journal*, 26(5), pp. 551–579. doi: 10.1111/isj.12107

Girod, S.J.G. and Bellin, J.B. (2011) ‘Revisiting the “Modern” Multinational Enterprise Theory: An Emerging-market Multinational Perspective’, in Ramamurti, R. and Hashai, N. (eds.) *The Future of Foreign Direct Investment and the Multinational Enterprise*. (Research in Global Strategic Management): Emerald Group Publishing Limited, pp. 167–210.

Goes, P.B. (2014) ‘Big data and IS research’, *Management Information Systems Quarterly*, 38, pp. 3–8.

Gopal, R., Marsden, J.R. and Vanthienen, J. (2011) 'Information mining — Reflections on recent advancements and the road ahead in data, text, and media mining', *Decision Support Systems*, 51(4), pp. 727–731. doi: 10.1016/j.dss.2011.01.008

Grant, M.J. and Booth, A. (2009) 'A typology of reviews: an analysis of 14 review types and associated methodologies', *Health Information and Libraries Journal*, 26(2), pp. 91–108. doi: 10.1111/j.1471-1842.2009.00848.x

Graupner, E., Urbitsch, E. and Maedche, A. (2015) 'A Conceptualization and Operationalization of Process Visibility Capabilities', *Wirtschaftsinformatik 2015*. Available at: https://aisel.aisnet.org/wi2015/38.

Green, P. and Rosemann, M. (2000) 'Integrated process modeling: An ontological evaluation', *Information Systems*, 25(2), pp. 73–87. doi: 10.1016/S0306-4379(00)00010-7

Gregor, S. and Hevner, A.R. (2013) 'Positioning and Presenting Design Science Research for Maximum Impact', *Management Information Systems Quarterly*, 37(2), pp. 337–355. doi: 10.25300/MISQ/2013/37.2.01

Griffith, D.A., Chandra, A. and Ryans, J.K. (2003) 'Examining the Intricacies of Promotion Standardization: Factors Influencing Advertising Message and Packaging', *Journal of International Marketing*, 11(3), pp. 30–47. doi: 10.1509/jimk.11.3.30.20160

Gross, A. and Doerr, J. (2009) 'EPC vs. UML Activity Diagram - Two Experiments Examining their Usefulness for Requirements Engineering', *17th IEEE International Requirements Engineering Conference*, pp. 47–56. doi: 10.1109/RE.2009.30

Grover, V. and Markus, M.L. (eds.) (2016) *Business process transformation*. London: Routledge (Advances in management information systems).

Haisjackl, C. *et al.* (2017) 'Visualization of the Evolution of Layout Metrics for Business Process Models', in Dumas, M. and Fantinato, M. (eds.) *Business Process Management Workshops.* (Lecture Notes in Business Information Processing). Cham: Springer International Publishing, pp. 449–460.

Hall, J.M. and Johnson, M.E. (2009) 'When Should a Process Be Art, Not Science?' *Harvard Business Review*, 87(3), pp. 58–65.

Hammer, M. (2010) 'What is Business Process Management?' in vom Brocke, J. and Rosemann, M. (eds.) *Introduction, Methods, and Information Systems.* (Handbook on business process management, 1). New York: Springer, pp. 3–16.

Hammer, M. and Champy, J. (1993) *Reengineering the corporation: A manifesto for business revolution*. New York: HarperBusiness.

Hammer, M. and Stanton, S. (1999) 'How Process Enterprises Really Work', *Harvard Business Review*, 77(6), pp. 108–120.

Harel, D. (1988) ‘On visual formalisms’, *Communications of the ACM*, 31(5), pp. 514–530. doi: 10.1145/42411.42414

Harmon, P. (2010) *Business Process Change, 2nd Edition: A Guide for Business Managers and BPM and Six Sigma Professionals*: Morgan Kaufmann.

Harmon, P. (2015) ‘The Scope and Evolution of Business Process Management’, in vom Brocke, J. and Rosemann, M. (eds.) *Handbook on Business Process Management 1: Introduction, Methods, and Information Systems.* Berlin, Heidelberg: Springer Berlin Heidelberg, pp. 37–80.

Hassani, A. and Gahnouchi, S.A. (2017) ‘A framework for Business Process Data Management based on Big Data Approach’, *Procedia Computer Science*, 121, pp. 740–747. doi: 10.1016/j.procs.2017.11.096

Hatch, M.J. and Cunliffe, A.L. (2013) *Organization theory: Modern, symbolic, and postmodern perspectives*. Oxford: Oxford University Press.

Havemo, E. (2018) ‘A visual perspective on value creation: Exploring patterns in business model diagrams’, *European Management Journal*, 36(4), pp. 441–452. doi: 10.1016/j.emj.2017.12.002

Hayashi, A.M. (2014) ‘Thriving in a big data world’, *MIT sloan management review*, 55(2), p. 35.

Hedman, J. and Kalling, T. (2003) ‘The business model concept: theoretical underpinnings and empirical illustrations’, *European Journal of Information Systems*, 12(1), pp. 49–59. doi: 10.1057/palgrave.ejis.3000446

Heggset, M., Krogstie, J. and Wesenberg, H. (2015) ‘The Influence of Syntactic Quality on Pragmatic Quality of Enterprise Process Models’, *CEUR Workshop Proceedings*, 1367.

Heikkilä, M. *et al.* (2016) ‘Business Model Innovation Paths and Tools’, *Bled 2016*.

Helkiö, P. and Tenhiälä, A. (2013) ‘A contingency theoretical perspective to the product-process matrix’, *International Journal of Operations & Production Management*, 33(2), pp. 216–244. doi: 10.1108/01443571311295644

Hess Jr., R.L., Ganesan, S. and Klein, N.M. (2003) ‘Service Failure and Recovery: The Impact of Relationship Factors on Customer Satisfaction’, *Journal of the Academy of Marketing Science*, 31(2), pp. 127–145. doi: 10.1177/0092070302250898

Hevner, A.R. *et al.* (2004) ‘Design Science in Information Systems Research’, *Management Information Systems Quarterly*, 28(1), pp. 75–105.

Hevner, A.R. (2007) ‘A Three Cycle View of Design Science Research’, *Scandinavian Journal of Information Systems*, 19(2), pp. 87–92.

Hevner, A.R. and Chatterjee, S. (2010) *Design Research in Information Systems*: New York: Springer.

Hinkelmann, K. *et al.* (2016) 'A new paradigm for the continuous alignment of business and IT: Combining enterprise architecture modelling and enterprise ontology', *Computers in Industry*, 79, pp. 77–86. doi: 10.1016/j.compind.2015.07.009

Hipp, M. *et al.* (2015) 'Enabling a User-Friendly Visualization of Business Process Models', in Fournier, F. and Mendling, J. (eds.) *Business Process Management Workshops: BPM 2014.* Lecture Notes in Business Information Processing. (202). Cham: Springer International Publishing, pp. 395–407.

Hofstede, G.H. (1997) *Cultures and organizations: Software of the mind*. New York: McGraw-Hill.

Hosack, B. *et al.* (2012) 'A Look Toward the Future: Decision Support Systems Research is Alive and Well', *Journal of the Association for Information Systems*, 13(5), pp. 315–340. doi: 10.17705/1jais.00297

Houy, C., Fettke, P. and Loos, P. (2012) 'Understanding Understandability of Conceptual Models – What Are We Actually Talking about?' in Atzeni, P., Cheung, D. and Ram, S. (eds.) *Conceptual modeling: 31st international conference, ER 2012, Florence, Italy, October 15 - 18, 2012 ; proceeding.* (Lecture Notes in Computer Science, 7532). Berlin: Springer, pp. 64–77.

Houy, C., Fettke, P. and Loos, P. (2014) 'On the theoretical foundations of research into the understandability of business process models', in *ECIS 2014 Proceedings - 22nd European Conference on Information Systems*.

Houy, C., Fettke, P. and Loos, P. (2015) 'Business Process Frameworks', in vom Brocke, J. and Rosemann, M. (eds.) *Handbook on Business Process Management 2: Strategic Alignment, Governance, People and Culture.* Berlin, Heidelberg: Springer Berlin Heidelberg, pp. 153–175.

Hummel, G. (2019) *KeyPro 2.0 - Enhancement and Evaluation of a Decision Support System for the Identification of Important Organizational Business Processes: Supervised Master Thesis*. Master-Thesis. Karlsruhe Institute of Technology.

Hussy, W., Schreier, M. and Echterhoff, G. (2013) *Forschungsmethoden in Psychologie und Sozialwissenschaften für Bachelor*. 2nd edn. (Springer-Lehrbuch). Berlin, Heidelberg: Springer Berlin Heidelberg.

Hutchison, D. *et al.* (2005) 'Applications and Theory of Petri Nets 2005', *26th International Conference on Application and Theory of Petri Nets and Other Models of Concurrency, Miami, Florida, USA*, 3536 (474pp). doi: 10.1007/b136988

Huxley, C. and Stewart, G. (2004) 'Identifying Core Processes and Critical Processes for the IT Decision Process', *15th Australasian Conference on Information Systems*. Available at: https://aisel.aisnet.org/acis2004/59.

Hwang, D. and Min, H. (2015) ‘Identifying the drivers of enterprise resource planning and assessing its impacts on supply chain performances’, *Industrial Management & Data Systems*, 115(3), pp. 541–569.

Hwang, S.-Y. and Yang, W.-S. (2002) ‘On the discovery of process models from their instances’, *Decision Support Systems*, 34(1), pp. 41–57. doi: 10.1016/S0167-9236(02)00008-8

Imai, M. (1997) *Gemba kaizen: A commonsense, low-cost approach to management / Masaaki Imai*. New York: McGraw-Hill.

Imgrund, F. *et al.* (2018) ‘Conceptualizing a Framework to Manage the Short Head and Long Tail of Business Processes’, *International Business Process Management Conference, Sydney, New South Wales, Australia*, 11080, pp. 392–408. doi: 10.1007/978-3-319-98648-7_23

Indulska, M. *et al.* (2009) ‘Business Process Modeling: Perceived Benefits’, in Laender, A.H.F. *et al.* (eds.) *Conceptual Modeling - ER 2009: ER 2009.* Lecture Notes in Computer Science. (5829): Springer Berlin Heidelberg, pp. 458–471.

Ingvaldsen, J.E. *et al.* (2005) ‘Empirical Business Models’, *International Conference on Advanced Information Systems Engineering: Proceedings of CAISE’05 Short Papers*.

Ivanov, S.Y., Kalenkova, A.A. and van der Aalst, W.M.P. (2015) ‘BPMNDiffViz : a tool for BPMN models comparison’, *13th International Conference on Business Process Management, Innsbruck, Austria*.

Jacobides, M.G. and Winter, S.G. (2012) ‘Capabilities: Structure, Agency, and Evolution’, *Organization Science*, 23(5), pp. 1365–1381. doi: 10.1287/orsc.1110.0716

Jang, Y. and Lee, J. (1998) ‘Factors influencing the success of management consulting projects’, *International Journal of Project Management*, 16(2), pp. 67–72. doi: 10.1016/S0263-7863(97)00005-7

Johannsen, F., Leist, S. and Braunnagel, D. (2014) ‘Testing the Impact of Wand and Weber’s Decomposition Model on Process Model Understandability’, in *35th International Conference on Information Systems (ICIS 2014), Auckland, New Zealand*.

Johannsen, F., Leist, S. and Tausch, R. (2014) ‘Wand and Weber's good decomposition conditions for BPMN: An interpretation and differences to Event-Driven Process Chains’, *Business Process Management Journal*, 20(5), pp. 693–729.

Jones, D. and Gregor, S. (2008) ‘The Anatomy of a Design Theory’, *Journal of the Association for Information Systems*, 8(5). Available at: http://aisel.aisnet.org/jais/vol8/iss5/1.

Jošt, G. *et al.* (2016) 'An empirical investigation of intuitive understandability of process diagrams', *Computer Standards & Interfaces*, 48, pp. 90–111. doi: 10.1016/j.csi.2016.04.006

Joyce, A. and Paquin, R.L. (2016) 'The triple layered business model canvas: A tool to design more sustainable business models', *Journal of Cleaner Production*, 135, pp. 1474–1486.

Kalakota, R. and Robinson, M. (2001) *M-business: The race to mobility*. New York: McGraw-Hill.

Kamis, A., Koufaris, M. and Stern, T. (2008) 'Using an Attribute-Based Decision Support System for User-Customized Products Online: An Experimental Investigation', *Management Information Systems Quarterly* (Vol. 32 No. 1), pp. 159–177.

Kampker, A. *et al.* (2014) 'Standardization and innovation: Dissolving the contradiction with modular production architectures', *4th International Electric Drives Production Conference*. doi: 10.1109/EDPC.2014.6984429

Kanter, R.M. (1994) 'Collaborative advantage: The art of alliances', *Harvard Business Review*, 72(4), pp. 96–108.

Kaplan, R.S. and Norton, D.P. (2004) *Strategy maps: Converting intangible assets into tangible outcomes*. Boston: Harvard Business School Press.

Kerremanns, M. (2013) 'VisionWavees: Algining Business Process Management and Performance Management to Achieve Business (Process) Excellence'.

Kettenbohrer, J. and Beimborn, D. (2014) 'What you can do to inhibit business process standardization', *20th Americas Conference on Information Systems, Savannah, Georgia, USA*, pp. 1–11.

Kettenbohrer, J., Beimborn, D. and Kloppenburg, M. (2013) 'Developing a procedure model for business process standardization', *International Conference on Information Systems, Milano, Italy*, 2, pp. 1124–1134.

Kettinger, W.J. and Grover, V. (1995) 'Special Section: Toward a Theory of Business Process Change Management', *Journal of Management Information Systems*, 12(1), pp. 9–30. doi: 10.1080/07421222.1995.11518068

Khanagha, S., Volberda, H. and Oshri, I. (2014) 'Business model renewal and ambidexterity: structural alteration and strategy formation process during transition to a Cloud business model', *R&D Management*, 44(3), pp. 322–340. doi: 10.1111/radm.12070

Kim, P. *et al.* (2009) 'Effects of episodic variations in web-based avian influenza education: influence of fear and humor on perception, comprehension, retention and behavior', *Health Education Research*, 24(3), pp. 369–380. doi: 10.1093/her/cyn031

Kim, Y.J. and Lee, J. (1993) ‘Manufacturing Strategy and Production Systems: An Integrated Framework’, *Journal of Operations Management,* 11(1), pp. 3–15.

Kitchenham, B.A. (2004) ‘Procedures for Performing Systematic Reviews’, *Joint Technical Report Keele University and National ICT Australia Ltd.* (TR/SE-0401).

Kley, F., Lerch, C. and Dallinger, D. (2011) ‘New Business Models for Electric Cars—A Holistic Approach’, *Energy policy,* 39(6), pp. 3392–3403.

Ko, R.K.L. (2009) ‘A Computer Scientist’s Introductory Guide to Business Process Management (BPM)’, *Crossroads,* 15(4), pp. 11–18. doi: 10.1145/1558897.1558901

Kocaoglu, B. and Acar, A.Z. (2015) ‘Developing an ERP Triggered Business Process Improvement Cycle from a Case Company’, *Procedia - Social and Behavioral Sciences,* 181, pp. 107–114.

Kock, N. *et al.* (2009) ‘Communication flow orientation in business process modeling and its effect on redesign success: Results from a field study’, *Decision Support Systems,* 46(2), pp. 562–575. doi: 10.1016/j.dss.2008.10.002

Kock, N., Danesh-Pajou, A. and Komiak, P. (2008) ‘A Discussion and Test of a Communication Flow Optimization Approach for Business Process Redesign’, *Knowledge and Process Management,* 15(1), pp. 72–85. doi: 10.1002/kpm.301

Kohli, R. and Johnson, S. (2011) ‘Digital transformation in latecomer industries: CIO and CEO leadership lessons from Encana Oil & Gas (USA) Inc’, *MIS Quarterly Executive,* 10.

Koppenhagen, N. *et al.* (2012) ‘Design Science Research in Action - Anatomy of Success Critical Activities for Rigor and Relevance’, *20th European Conference on Information Systems, Barcelona, Spain, June 10-13, 2012*.

Koschmider, A. *et al.* (2015) ‘Revising the Vocabulary of Business Process Element Labels’, in Zdravkovic, J., Kirikova, M. and Johannesson, P. (eds.) *Advanced Information Systems Engineering: CAiSE 2015.* Lecture Notes in Computer Science. (9097). Cham: Springer, pp. 69–83.

Koschmider, A., Kriglstein, S. and Ullrich, M. (2013) ‘Investigations on User Preferences of the Alignment of Process Activities, Objects and Roles’, in *On the Move to Meaningful Internet Systems: OTM 2013 Conferences*.

Koubarakis, M. and Plexousakis, D. (2001) ‘A formal framework for business process modelling and design’, *Information Systems* (27), pp. 299–319.

Krause, F., Bewernik, M.-A. and Fridgen, G. (2013) ‘Valuation of manual and automated process redesign from a business perspective’, *Business Process Management Journal*, 19(1), pp. 95–110. doi: 10.1108/14637151311294886

Krogstie, J. (2012) *Model-Based Development and Evolution of Information Systems: A quality approach*. London: Springer.

Kroker, M. (2017) *Weltweite Datenmengen verzehnfachen sich bis zum Jahr 2025 gegenüber heute*. Available at: https://blog.wiwo.de/look-at-it/2017/04/04/weltweite-datenmengen-verzehnfachen-sich-bis-zum-jahr-2025-gegenueber-heute/.

Kruskal, W.H. and Wallis, W.A. (1952) 'Use of Ranks in One-Criterion Variance Analysis', *Journal of the American Statistical Association*, 47(260), p. 583. doi: 10.2307/2280779

Kubat, M. (2017) *An Introduction to Machine Learning*. Cham: Springer International Publishing.

Kudo, M. *et al.* (2013) 'Business Process Analysis and Real-world Application Scenarios', in *2013 International Conference on Signal-Image Technology & Internet-Based Systems*, pp. 983–989.

Kuechler, B. and Vaishnavi, V.K. (2008) 'On theory development in design science research: Anatomy of a research project', *European Journal of Information Systems*, 17(5), pp. 489–504. doi: 10.1057/ejis.2008.40

Kumar, V. and Petersen, J.A. (2005) 'Using a Customer-Level Marketing Strategy to Enhance Firm Performance: A Review of Theoretical and Empirical Evidence', *Journal of the Academy of Marketing Science*, 33(4), pp. 504–519.

Kummer, T.-F., Recker, J. and Mendling, J. (2016) 'Enhancing understandability of process models through cultural-dependent color adjustments', *Decision Support Systems*, 87, pp. 1–12. doi: 10.1016/j.dss.2016.04.004

Kummer, T.-F. and Schmiedel, T. (2016) 'Reviewing the Role of Culture in Strategic Information Systems Research: A Call for Prescriptive Theorizing on Culture Management', *Communications of the Association for Information Systems*, 38, pp. 122–144. doi: 10.17705/1CAIS.03805

Kundu, S., Datta, S.K. and Vyas, V. (2012) 'E-banking process standardization - An evaluation of customer perception and satisfaction', *WSEAS Transactions on Business and Economics*, 9(4), pp. 171–187.

Kunze, M. *et al.* (2011) 'Towards Understanding Process Modeling: The Case of the BPM Academic Initiative', in *Business process model and notation : third international workshop, BPMN 2011, Lucerne, Switzerland, November 21-22, 2011 ; proceedings*. Berlin: Springer, pp. 44–58.

Kwak, C., Lee, J. and Lee, H. (2016) 'Effects of Information Technology on Team Innovation and Inter-Team Coordination: An Exploratory Investigation of Process Ambidexterity', in *49th Hawaii International Conference 2016*, pp. 5309–5318.

Laudien, S.M. and Daxböck, B. (2016) 'Path dependence as a barrier to business model change in manufacturing firms: insights from a multiple-case study', *Journal of Business Economics*, 86(6), pp. 611–645.

Laue, R. and Gadatsch, A. (2011) 'Measuring the Understandability of Business Process Models - Are We Asking the Right Questions?' in Zur Muehlen, M. and Su, J. (eds.) *Business Process Management Workshops: BPM 2010.* Lecture Notes in Business Information Processing. (66): Springer Berlin Heidelberg, pp. 37–48.

Laughlin, S.P. (1999) 'An ERP Game Plan', *Journal of Business Strategy*, 20(1), pp. 32–37.

Laumer, S., Maier, C. and Eckhardt, A. (2015) 'The impact of business process management and applicant tracking systems on recruiting process performance: an empirical study', *Journal of Business Economics*, 85(4), pp. 421–453. doi: 10.1007/s11573-014-0758-9

Lawrence, P.R. and Lorsch, J.W. (1967) 'Differentiation and Integration in Complex Organizations', *Administrative Science Quarterly*, 12(1), p. 1. doi: 10.2307/2391211

Lederer, M. *et al.* (2017) 'Some say Digitalization - others say IT-enabled Process Management thought through to the End', *Proceedings of the 9th Conference on Subject-oriented Business Process Management - S-BPM ONE '17, the 9th Conference*, Darmstadt, Germany, pp. 1–10. doi: 10.1145/3040565.3040574

Lee, Z. and Lee, J. (2000) 'An ERP implementation case study from a knowledge transfer perspective', *Journal of Information Technology*, 15(4), pp. 281–288. doi: 10.1080/02683960010009060

Lee J., Siau, K. and Hong, S. (2003) 'Enterprise Integration with ERP and EAI', *Communications of the ACM* (46(2)), pp. 54–60.

Lei, Z., Naveh, E. and Novikov, Z. (2016) 'Errors in Organizations: An Integrative Review via Level of Analysis, Temporal Dynamism, and Priority Lenses', *Journal of Management*, 42(5), pp. 1315–1343. doi: 10.1177/0149206316633745

Li, C., Reichert, M. and Wombacher, A. (2008) 'On Measuring Process Model Similarity Based on High-Level Change Operations: Conceptual Modeling - ER 2008', *International Conference on Conceptual Modeling*.

Lillrank, P. (2003) 'The Quality of Standard, Routine and Nonroutine Processes', *Organization Studies*, 24(2), pp. 215–233. doi: 10.1177/0170840603024002344

Lillrank, P. and Liukko, M. (2004) 'Standard, routine and non-routine processes in health care', *International Journal of Health Care Quality Assurance*, 17(1), pp. 39–46. doi: 10.1108/09526860410515927

Limam Mansar, S. and Reijers, H.A. (2007) 'Best practices in business process redesign: use and impact', *Business Process Management Journal*, 13(2), pp. 193–213. doi: 10.1108/14637150710740455

Lindgren, P. and Rasmussen, O.H. (2013) ‘The Business Model Cube’, *Journal of Multi Business Model Innovation and Technology*, 1(3), pp. 135–182.

Lindland, O.I., Sindre, G. and Solvberg, A. (1994) ‘Understanding Quality in Conceptual Modeling’, *IEEE Software*, 11(2), pp. 42–49. doi: 10.1109/52.268955

Lockamy, A. and Smith, W.I. (1997) ‘A strategic alignment approach for effective business process reengineering: Linking strategy, processes and customers for competitive advantage’, *International Journal of Production Economics*, 50(2-3), pp. 141–153. doi: 10.1016/S0925-5273(97)00038-8

Loebbecke, C. and Picot, A. (2015) ‘Reflections on societal and business model transformation arising from digitization and big data analytics: A research agenda’, *The Journal of Strategic Information Systems*, 24(3), pp. 149–157.

Loh, T.C. and Koh, S.C.L. (2004) ‘Critical elements for a successful enterprise resource planning implementation in small-and medium-sized enterprises’, *International Journal of Production Research*, 42(17), pp. 3433–3455.

Lyytinen and King (2006) ‘Standard Making: A Critical Research Frontier for Information Systems Research’, *Management Information Systems Quarterly*, 30, p. 405. doi: 10.2307/25148766

Magretta, J. (2002) ‘Why Business Models Matter’, *Harvard Business Review*, 80(5), pp. 86–92.

Malinova, M., Leopold, H. and Mendling, J. (2015) ‘An Explorative Study for Process Map Design’, in Nurcan, S. and Pimenidis, E. (eds.) *Information Systems Engineering in Complex Environments: CAiSE Forum 2014, Thessaloniki, Greece, June 16-20, 2014, Selected Extended Papers.* (Lecture Notes in Business Information Processing, 204). Cham: Springer International Publishing, pp. 36–51.

Mani, D., Barua, A. and Whinston, A. (2006) ‘Successfully Governing Business Process Outsourcing Relationships’, *MIS Quarterly Executive*, 5(1).

Mani, D., Barua, A. and Whinston, A. (2010) ‘An Empirical Analysis of the Impact of Information Capabilities Design on Business Process Outsourcing Performance’, *Management Information Systems Quarterly*, 34(1), pp. 39–62. Available at: http://www.redi-bw.de/db/ebsco.php/search.ebscohost.com/login.aspx%3fdirect%3dtrue%26db%3dbuh%26AN%3d48478140%26site%3dehost-live.

Mann, H.B. and Whitney, D.R. (1947) ‘On a Test of Whether one of Two Random Variables is Stochastically Larger than the Other’, *The Annals of Mathematical Statistics*, 18(1), pp. 50–60. doi: 10.1214/aoms/1177730491

Manrodt, K.B. and Vitasek, K. (2004) ‘Global Process Standardization: A Case Study’, *Journal of Business Logistics*, 25(1), pp. 1–23. doi: 10.1002/j.2158-1592.2004.tb00168.x

Mans, R.S. *et al.* (2013) 'A process-oriented methodology for evaluating the impact of IT: A proposal and an application in healthcare', *Information Systems*, 38(8), pp. 1097–1115. doi: 10.1016/j.is.2013.06.005

March, S.T. and Smith, G.F. (1995) 'Design and natural science research on information technology', *Decision Support Systems*, 15(4), pp. 251–266. doi: 10.1016/0167-9236(94)00041-2

Marciniak, R. *et al.* (2014) 'Does ERP integration foster Cross-Functional Awareness? Challenging conventional wisdom for SMEs and large French firms', *Business Process Management Journal*, 20(6) (865pp). doi: 10.1108/BPMJ-05-2013-0056

Margherita, A. (2014) 'Business process management system and activities', *Business Process Management Journal*, 20(5), pp. 642–662.

Markus, M.L. (2004) 'Technochange management: Using IT to drive organizational change', *Journal of Information Technology*, 19(1), pp. 4–20.

Martens, A., Fettke, P. and Loos, P. (2014) 'A genetic algorithm for the inductive derivation of reference models using minimal graph-edit distance applied to real-world business process data', *Multikonferenz Wirtschaftsinformatik*, pp. 1613–1626.

Măruşter, L. and van Beest, N.R.T.P. (2009) 'Redesigning business processes: a methodology based on simulation and process mining techniques', *Knowledge and Information Systems*, 21(3), pp. 267–297. doi: 10.1007/s10115-009-0224-0

Massa, L., Tucci, C.L. and Afuah, A. (2017) 'A Critical Assessment of Business Model Research', *Academy of Management Annals*, 11(1), pp. 73–104. doi: 10.5465/annals.2014.0072

Mayer, R.E. (2009) *Multimedia learning // Multimedia Learning*. Cambridge: Cambridge University Press. doi:10.1017/CBO9780511811678.

McLean, R. (2016) 'Alignment: Using the Balanced Scorecard to Create Corporate Synergies', *Australian Journal of Management*, 31(2), pp. 367–369. doi: 10.1177/031289620603100210

Meade, L.M. and Rogers, K.J. (2001) 'Selecting Critical Business Processes: A Case Study', *Engineering Management Journal*, 13(4), pp. 41–46. doi: 10.1080/10429247.2001.11415138

Melão, N. and Pidd, M. (2000) 'A conceptual framework for understanding business processes and business process modelling', *Information Systems Journal*, 10(2), pp. 105–129.

Melcher, J. *et al.* (2010) 'On Measuring the Understandability of Process Models', in Rinderle-Ma, S., Sadiq, S. and Leymann, F. (eds.) *Business Process Management Workshops: BPM 2009.* (Lecture Notes in Business Information Processing, 43). Berlin, Heidelberg: Springer-Verlag Berlin Heidelberg, pp. 465–476.

Melcher, J. (2012) *Process Measurement in Business Process Management: Theoretical Framework and Analysis of Several Aspects*. Zugl.: Karlsruher Institut für Technologie, KIT, Diss., 2011. Karlsruhe: KIT Scientific Publ (Accessed: 3 December 2017).

Melnyk, S.A. and Christensen, R.T. (2000) 'Value-driven process management: Using value to improve processes', *Hospital Materiel Management Quarterly*, 22(1), pp. 59–67.

Mendling, J. *et al.* (2018) 'An Empirical Review of the Connection Between Model Viewer Characteristics and the Comprehension of Conceptual Process Models', *Information Systems Frontiers*. doi: 10.1007/s10796-017-9823-6

Mendling, J., Reijers, H.A. and Recker, J. (2010) 'Activity labeling in process modeling: Empirical insights and recommendations', *Information Systems*, 35(4), pp. 467–482. doi: 10.1016/j.is.2009.03.009

Mendling, J., Reijers, H.A. and van der Aalst, W.M.P. (2010) 'Seven process modeling guidelines (7PMG)', *Information and Software Technology*, 52(2), pp. 127–136. doi: 10.1016/j.infsof.2009.08.004

Mendling, J. and Strembeck, M. (2008) 'Influence Factors of Understanding Business Process Models', in Abramowicz, W. and Fensel, D. (eds.) *Business Information Systems: 11th International Conference, BIS 2008, Innsbruck, Austria, May 5-7, 2008. Proceedings.* (Lecture Notes in Business Information Processing, 7). Berlin: Springer, pp. 142–153.

Mendling, J., Strembeck, M. and Recker, J. (2012) 'Factors of process model comprehension—Findings from a series of experiments', *Decision Support Systems*, 53(1), pp. 195–206. doi: 10.1016/j.dss.2011.12.013

Michalik, B. *et al.* (2013) 'Reducing Requirements Heterogeneity in Enterprise System Projects -- A Case Study of Harmonizing and Optimizing Business Processes', in *46th Hawaii International Conference 2013*, pp. 4084–4093.

Milani, F. *et al.* (2016) 'Modelling families of business process variants: A decomposition driven method', *Information Systems*, 56, pp. 55–72. doi: 10.1016/j.is.2015.09.003

Mocker, M., Ross, J.W. and Ciano, P. (2014) 'Building a Global Process Standard at the Most International Company on Earth: DHL Express: Teaching Case', *35th International Conference on Information Systems, Auckland, New Zealand*.

Moody, D.L. (2009) 'The "Physics" of Notations: Toward a Scientific Basis for Constructing Visual Notations in Software Engineering', *IEEE Transactions on Software Engineering*, 35(6), pp. 756–779. doi: 10.1109/TSE.2009.67

Morali, O. and Searcy, C. (2013) 'A Review of Sustainable Supply Chain Management Practices in Canada', *Journal of Business Ethics*, 117(3), pp. 635–658. Available at: http://www.jstor.org/stable/42001875.

Morana, S. *et al.* (2017) 'A review of the nature and effects of guidance design features', *Decision Support Systems*, 97, pp. 31–42. doi: 10.1016/j.dss.2017.03.003

Morana, S. *et al.* (2019) 'Designing Process Guidance Systems', *Journal of the Association for Information Systems*, pp. 499–535. doi: 10.17705/1jais.00542

Morton, N.A. and Hu, Q. (2008) 'Implications of the fit between organizational structure and ERP: A structural contingency theory perspective', *International Journal of Information Management*, 28(5), pp. 391–402. doi: 10.1016/j.ijinfomgt.2008.01.008

Moustaka, V. *et al.* (2019) 'TOMI: A Framework for Smart Tourism on the Move Innovation', *Companion Proceedings of The 2019 World Wide Web Conference on - WWW '19, Companion The 2019 World Wide Web Conference*, San Francisco, USA, 5/13/2019 - 5/17/2019. New York, New York, USA: ACM Press, pp. 123–129. doi: 10.1145/3308560.3317051

Mturi, E. and Johannesson, P. (2013) 'A context-based process semantic annotation model for a process model repository', *Business Process Management Journal*, 19(3), pp. 404–430. doi: 10.1108/14637151311319888

Münstermann, B., Eckhardt, A. and Weitzel, T. (2010) 'The performance impact of business process standardization', *Business Process Management Journal*, 16(1), pp. 29–56. doi: 10.1108/14637151011017930

Münstermann, B., Joachim, N. and Beimborn, D. (2009) 'An empirical evaluation of the impact of process standardization on process performance and flexibility', *15th Americas Conference on Information Systems, San Francisco, California, USA*, 10. Available at: http://aisel.aisnet.org/amcis2009/787/.

Münstermann, B. and Weitzel, T. (2008) 'What Is Process Standardization?' *International Conference on Information Resources Management*.

Natschläger, C. (2011) 'Deontic BPMN', in Hameurlain, A. *et al.* (eds.) *Database and Expert Systems Applications: DEXA 2011*. Lecture Notes in Computer Science. (6861): Springer Berlin Heidelberg, pp. 264–278.

Naveh, E. and Marcus, A. (2005) 'Achieving competitive advantage through implementing a replicable management standard: Installing and using ISO 9000', *Journal of Operations Management*, 24(1), pp. 1–26. doi: 10.1016/j.jom.2005.01.004

Neubauer, T. (2009) 'An empirical study about the status of business process management', *Business Process Management Journal*, 15(2), pp. 166–183. doi: 10.1108/14637150910949434

Niehaves, B. *et al.* (2014) 'BPM capability development – a matter of contingencies', *Business Process Management Journal*, 20(1), pp. 90–106. doi: 10.1108/BPMJ-07-2012-0068

Niemimaa, M. *et al.* (2019) ‘Business continuity of business models: Evaluating the resilience of business models for contingencies’, *International Journal of Information Management*, 49, pp. 208–216. doi: 10.1016/j.ijinfomgt.2019.04.010

Orosz, T. (2011) *Analysis of SAP Development tools and methods*. Available at: https://www.researchgate.net/publication/252018383_Analysis_of_SAP_Development_tools_and_methods/citation/download.

Osterwalder, A. and Pigneur, Y. (2010) *Business Model Generation: a handbook for visionaries, game changers, and challengers*: John Winley & Sons.

Osterwalder, A. and Pigneur, Y. (2013) ‘Designing Business Models and Similar Strategic Objects: The Contribution of IS’, *Journal of the Association for Information Systems*, 14(5), pp. 237–244. doi: 10.17705/1jais.00333

Osterwalder, A., Pigneur, Y. and Tucci, C.L. (2005) ‘Clarifying Business Models: Origins, Present and Future of the Concept’, *Communications of the Association for Information Systems* (Vol. 15).

Ottensooser, A. *et al.* (2012) ‘Making sense of business process descriptions: An experimental comparison of graphical and textual notations’, *Journal of Systems and Software*, 85(3), pp. 596–606. doi: 10.1016/j.jss.2011.09.023

Ould, M.A. (1995) *Business processes: Modelling and analysis for re-engineering and improvement*. Chichester: Wiley.

Panorama Consulting Solutions (2015) *Key Findings From the 2015 ERP Report*. Available at: https://www.panorama-consulting.com/key-findings-from-the-2015-erp-report/.

Pateli, A.G. and Giaglis, G.M. (2005) ‘Technology innovation-induced business model change: A contingency approach’, *Journal of Organizational Change Management*, 18(2), pp. 167–183.

Patig, S. (2008) ‘A Practical Guide to Testing the Understandability of Notations’, in *Conferences in Research and Practice in Information Technology Series*.

Peffers, K. *et al.* (2007) ‘A Design Science Research Methodology for Information Systems Research’, *Journal of Management Information Systems*, 24(3), pp. 45–77.

Peffers, K. *et al.* (2014) ‘A Design Science Research Methodology for Information Systems Research’, *Journal of Management Information Systems*, 24(3), pp. 45–77. doi: 10.2753/MIS0742-1222240302

Pero, M. and Lamberti, L. (2013) ‘The supply chain management-marketing interface in product development: An exploratory study’, *Business Process Management Journal*, 19(2), pp. 217–244. doi: 10.1108/14637151311308295

Peters, C., Blohm, I. and Leimeister, J.M. (2015) ‘Anatomy of Successful Business Models for Complex Services: Insights from the Telemedicine Field’, *Journal of Management Information Systems*, 32(3), pp. 75–104. doi: 10.1080/07421222.2015.1095034

Petre, M. (2006) ‘Cognitive dimensions ‘beyond the notation’’, *Journal of Visual Languages & Computing*, 17(4), pp. 292–301. doi: 10.1016/j.jvlc.2006.04.003

Petrusel, R., Mendling, J. and Reijers, H.A. (2016) ‘Task-specific visual cues for improving process model understanding’, *Information and Software Technology*, 79(C), pp. 63–78. doi: 10.1016/j.infsof.2016.07.003

Petrusel, R., Mendling, J. and Reijers, H.A. (2017) ‘How visual cognition influences process model comprehension’, *Decision Support Systems*, 96, pp. 1–16. doi: 10.1016/j.dss.2017.01.005

Petruzzi, G.L. and Garavelli, A.C. (2007) ‘The strategic value of the "fit" between business processes and IT management: The case of the Italian publishing industry’, *2nd IEEE/IFIP International Workshop on Business-Driven IT Management*, pp. 110–111. doi: 10.1109/BDIM.2007.375021

Pichler, P. *et al.* (2012) ‘Imperative versus Declarative Process Modeling Languages: An Empirical Investigation’, in Daniel, F., Barkaoui, K. and Dustdar, S. (eds.) *Business Process Management Workshops.* (Lecture Notes in Business Information Processing). Berlin, Heidelberg: Springer Berlin Heidelberg, pp. 383–394.

Pohle, G. and Chapman, M. (2006) ‘IBM's global CEO report 2006: business model innovation matters’, *Strategy & Leadership*, 34(5), pp. 34–40. doi: 10.1108/10878570610701531

Polpinij, J., Ghose, A. and Dam, H.K. (2015) ‘Mining business rules from business process model repositories’, *Business Process Management Journal*, 21(4), pp. 820–836. doi: 10.1108/BPMJ-01-2014-0004

Porter, M.E. (1985) *The Competitive Advantage: Creating and Sustaining Superior Performance*. New York: Free Press.

Porter, M.E. and Millar, V.E. (1985) ‘How information gives you competitive advantage’, *Harvard Business Review*, 4(63), pp. 149–160. Available at: https://www.hbs.edu/faculty/Pages/item.aspx?num=4322.

Poston, R. and Grabski, S. (2001) ‘Financial impacts of enterprise resource planning implementations’, *International Journal of Accounting Information Systems* (2), pp. 271–294.

Pourshahid, A. *et al.* (2014) ‘A goal-oriented, business intelligence-supported decision-making methodology’, *Decision Analytics*, 1(1), B147. doi: 10.1186/s40165-014-0009-8

Pratono, A.H. (2016) ‘Strategic orientation and information technological turbulence’, *Business Process Management Journal*, 22(2), pp. 368–382. doi: 10.1108/BPMJ-05-2015-0066

Puchovsky, M., Di Ciccio, C. and Mendling, J. (2016) ‘A case study on the business benefits of automated process discovery’, *6th International Symposium on Data-Driven Process Discovery and Analysis (SIMPDA), Graz, Austria*.

Radloff, M., Schultz, M. and Nüttgens, M. (2015) ‘Extending different Business Process Modeling Languages with Domain Specific Concepts: The Case of Internal Controls in EPC and BPMN’, in Kolb, J., Leopold, H. and Mendling, J. (eds.) *Enterprise modelling and information systems architectures*. Available at: http://dl.gi.de/bitstream/20.500.12116/2036/1/45.pdf.

Rai, A. *et al.* (2012) ‘Hybrid Relational-Contractual Governance for Business Process Outsourcing’, *Journal of Management Information Systems*, 29(2), pp. 213–256. doi: 10.2753/MIS0742-1222290208

Rajagopal, P. (2002) ‘An innovation - diffusion view of implementation of enterprise resource planning (ERP) systems and development of a research model’, *Information & Management* (40), pp. 87–114.

Ray, G., Barney, J.B. and Muhanna, W.A. (2004) ‘Capabilities, business processes, and competitive advantage: choosing the dependent variable in empirical tests of the resource-based view’, *Strategic Management Journal*, 25(1), pp. 23–37. doi: 10.1002/smj.366

Rebala, G., Ravi, A. and Churiwala, S. (2019) *An Introduction to Machine Learning*. Cham: Springer International Publishing.

Recker, J. (2010) ‘Continued use of process modeling grammars: The impact of individual difference factors’, *European Journal of Information Systems*, 19(1), pp. 76–92. doi: 10.1057/ejis.2010.5

Recker, J. (2013) ‘Empirical investigation of the usefulness of Gateway constructs in process models’, *European Journal of Information Systems*, 22(6), pp. 673–689. doi: 10.1057/ejis.2012.50

Recker, J. and Dreiling, A. (2007) ‘Does It Matter Which Process Modelling Language We Teach or Use? An Experimental Study on Understanding Process Modelling Languages without Formal Education’, in Toleman, M., Cater-Steel, A. and Roberts, D. (eds.) *Proceedings of the 18th Australasian Conference on Information Systems.* Toowoomba, Qld.: University of Southern Queensland, pp. 356–366 (Accessed: 9 February 2018).

Recker, J. and Dreiling, A. (2011) ‘The Effects of Content Presentation Format and User Characteristics on Novice Developers’ Understanding of Process Models’, *Communications of the Association for Information Systems*, 28(1), pp. 65–84.

Recker, J., Reijers, H.A. and van de Wouw, S.G. (2014) 'Process Model Comprehension: The Effects of Cognitive Abilities, Learning Style, and Strategy', *Communications of the Association for Information Systems,* 34(9). doi: 10.17705/1cais.03409

Reggio, G. *et al.* (2015) 'On the comprehension of workflows modeled with a precise style: Results from a family of controlled experiments', *Software & Systems Modeling,* 14(4), pp. 1481–1504. doi: 10.1007/s10270-013-0386-9

Reijers, H.A. *et al.* (2011) 'Syntax highlighting in business process models', *Decision Support Systems,* 51(3), pp. 339–349. doi: 10.1016/j.dss.2010.12.013

Reijers, H.A. and Mendling, J. (2011) 'A Study Into the Factors That Influence the Understandability of Business Process Models', *IEEE Transactions on Systems, Man, and Cybernetics - Part A: Systems and Humans,* 41(3), pp. 449–462. doi: 10.1109/TSMCA.2010.2087017

Reijers, H.A., Mendling, J. and Dijkman, R.M. (2011) 'Human and automatic modularizations of process models to enhance their comprehension', *Information Systems,* 36(5), pp. 881–897. doi: 10.1016/j.is.2011.03.003

Reijers, H.A., Mendling, J. and Recker, J. (2010) 'Business Process Quality Management', in vom Brocke, J. and Rosemann, M. (eds.) *Introduction, Methods, and Information Systems.* (Handbook on business process management, 1). New York: Springer, pp. 167–185.

Reijers, H.A., Vanderfeesten, I. and van der Aalst, W.M.P. (2016) 'The effectiveness of workflow management systems: A longitudinal study', *International Journal of Information Management*, 36(1), pp. 126–141. doi: 10.1016/j.ijinfomgt.2015.08.003

Repa, V. (2014) 'Caring of Intentionality in Business Process Models Using Business Process Patterns', *7th Workshop on Information Logistics and Knowledge Supply,* pp. 23–34.

Reynolds, P. and Yetton, P. (2015) 'Aligning business and IT strategies in multi-business organizations', *Journal of Information Technology,* 30(2), pp. 101–118. doi: 10.1057/jit.2015.1

Richen, A. and Steinhorst, A. (2005) 'Standardization or Harmonization? You need Both', *BPTrends*. Available at: www.bptrends.com.

Rodrigues, R.D.A. *et al.* (2015) 'An Experiment on Process Model Understandability Using Textual Work Instructions and BPMN Models', *29th Brazilian Symposium on Software Engineering,* pp. 41–50. doi: 10.1109/SBES.2015.12

Rolón, E. *et al.* (2009) 'Analysis and Validation of Control-Flow Complexity Measures with BPMN Process Models', in Halpin, T. (ed.) *Enterprise, Business-Process and Information Systems Modeling. BPMDS 2009, EMMSAD 2009. Lecture Notes in Business Information Processing.* (29): Springer Berlin Heidelberg.

Romero, H.L. *et al.* (2015) 'Factors that Determine the Extent of Business Process Standardization and the Subsequent Effect on Business Performance', *Business & Information Systems Engineering,* 57(4), pp. 261–270. doi: 10.1007/s12599-015-0386-0

Romero, H.L. *et al.* (2015) 'Measures of process harmonization', *Information and Software Technology*, 63, pp. 31–43.

Rosemann, M. (2006) 'Potential pitfalls of process modeling: Part A', *Business Process Management Journal*, 12(2), pp. 249–254. doi: 10.1108/14637150610657567

Rosemann, M., Recker, J. and Flender, C. (2008) 'Contextualisation of business processes', *International Journal of Business Process Integration and Management*, 3(1), p. 47. doi: 10.1504/IJBPIM.2008.019347

Rosemann, M. and vom Brocke, J. (2010) 'The Six Core Elements of Business Process Management', in vom Brocke, J. and Rosemann, M. (eds.) *Introduction, Methods, and Information Systems.* (Handbook on business process management, 1). New York: Springer, pp. 107–122.

Rosemann, M. and vom Brocke, J. (2015) 'The Six Core Elements of Business Process Management', in vom Brocke, J. and Rosemann, M. (eds.) *Handbook on Business Process Management.* (International handbooks on information systems). New York: Springer, pp. 105–126.

Rosenkopf, L. and McGrath, P. (2011) 'Advancing the Conceptualization and Operationalization of Novelty in Organizational Research', *Organization Science,* 22, pp. 1297–1311. doi: 10.2307/41303121

Ross, J.W. (2003) 'Creating a Strategic IT Architecture Competency: Learning in Stages', *SSRN Electronic Journal*. doi: 10.2139/ssrn.416180

Saebi, T., Lien, L. and Foss, N.J. (2017) 'What Drives Business Model Adaptation? The Impact of Opportunities, Threats and Strategic Orientation', *Long Range Planning,* 50(5), pp. 567–581.

Sağiroğlu, O. and Özturan, M. (2006) 'Implementation Difficulties of Hospital Information Systems', *Information Technology Journal*, 5(5), pp. 892–899. doi: 10.3923/itj.2006.892.899

Salazar, M.d.R.P., Rivera, I. and Vázquez, I.M.C. (2013) 'ERP selection: a literature review', *International Journal of Industrial and Systems Engineering*, 13(3), p. 309. doi: 10.1504/IJISE.2013.052279

Sammut-Bonnici, T. and Galea, D. (2015) 'PEST analysis', in Cooper, C.L. (ed.) *Wiley Encyclopedia of Management.* Chichester, UK: John Wiley & Sons, Ltd, p. 1.

Sánchez-González, L. *et al.* (2010) 'Quality Assessment of Business Process Models Based on Thresholds', in Meersman, R., Dillon, T. and Herrero, P. (eds.) *On the Move to Meaningful Internet Systems: OTM 2010: OTM 2010.* Lecture Notes in Computer Science. (6426): Springer Berlin Heidelberg, pp. 78–95.

Sánchez-González, L. *et al.* (2012) ‘Quality indicators for business process models from a gateway complexity perspective’, *Information and Software Technology*, 54(11), pp. 1159–1174. doi: 10.1016/j.infsof.2012.05.001

Sánchez-González, L. *et al.* (2017) ‘A case study about the improvement of business process models driven by indicators’, *Software & Systems Modeling*, 16(3), pp. 759–788. doi: 10.1007/s10270-015-0482-0

Santos, M.Y. *et al.* (2017) ‘A Big Data system supporting Bosch Braga Industry 4.0 strategy’, *International Journal of Information Management*, 37, pp. 750–760. doi: 10.1016/j.ijinfomgt.2017.07.012

Sarkis, J., Zhu, Q. and Lai, K.-H. (2011) ‘An organizational theoretic review of green supply chain management literature’, *International Journal of Production Economics*, 130(1), pp. 1–15. doi: 10.1016/j.ijpe.2010.11.010

Sarshar, K. and Loos, P. (2005) ‘Comparing the Control-Flow of EPC and Petri Net from the End-User Perspective’, in van der Aalst, W.M.P. *et al.* (eds.) *Business Process Management: BPM 2005*. Lecture Notes in Computer Science. (Lecture Notes in Computer Science, 3649). Berlin Heidelberg: Springer-Verlag, pp. 434–439.

Schäfermeyer, M., Grgecic, D. and Rosenkranz, C. (2010) ‘Factors Influencing Business Process Standardization: A Multiple Case Study’, *43rd Hawaii International Conference on System Sciences*, 43, pp. 1–10. doi: 10.1109/HICSS.2010.207

Schäfermeyer, M. and Rosenkranz, C. (2011) ‘"To standardize or not to standardize?" - Understanding the effect of business process complexity on business process standardization’, *19th European Conference on Information Systems, Helsinki, Finland*.

Scheer, A.-W. and Habermann, F. (2000) ‘Enterprise resource planning: making ERP a success’, *Communications of the ACM*, 43(4), pp. 57–61. doi: 10.1145/332051.332073

Schneider, S. and Spieth, P. (2013) ‘Business Model Innovation: Towards an Integrated Future Research Agenda’, *International Journal of Innovation Management*, 17(1), pp. 1–34. Available at: https://econpapers.repec.org/RePEc:wsi:ijimxx:v:17:y:2013:i:01:n:s136391961340001x.

Schönig, S. *et al.* (2016) ‘A framework for efficiently mining the organisational perspective of business processes’, *Decision Support Systems*, 89, pp. 87–97. doi: 10.1016/j.dss.2016.06.012

Schrepfer, M. *et al.* (2015) ‘Why do process variants matter for process monitoring?’ *13th International Conference on Business Process Management, Innsbruck, Austria*.

Schroeder, D.M., Congden, S.W. and Gopinath, C. (1995) ‘Linking Competitive Strategy and Manufacturing Process Technology’, *Journal of Management Studies*, 32(2), pp. 163–189.

Schultz, M. and Radloff, M. (2014) ‘Modeling Concepts for Internal Controls in Business Processes – An Empirically Grounded Extension of BPMN’, in *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, pp. 184–199.

Sedera, D. and Dey, S. (2007) ‘Everyone is Different! Exploring the Issues and Problems with ERP Enabled Shared Service Initiatives’, *13th Americas Conference On Information Systems, Keystone, Colorado, USA*. Available at: http://aisel.aisnet.org/amcis2007/361.

Seethamraju, R. (2006) ‘Impact of e-commerce on business process redesign and integration’, *International Journal of Electronic Business*, 4(5), p. 380. doi: 10.1504/IJEB.2006.011326

Seethamraju, R. and Krishna Sundar, D. (2013) ‘Influence of ERP systems on business process agility’, *IIMB Management Review*, 25(3), pp. 137–149. doi: 10.1016/j.iimb.2013.05.001

Seidel, S. *et al.* (2007) ‘Modelling and Supporting Processes in Creative Environments’, *15th European Conference on Information Systems*, pp. 516–527.

Seidel, S. (2009) *PhD Thesis: A Theory of Managing Creativity-intensive Processes.* University of Muenster.

Sein, M.K. *et al.* (2011) ‘Action design research’, *Management Information Systems Quarterly* (35(1)), pp. 37–56.

Sharda, R., Barr, S.H. and McDonnell, J.C. (1988) ‘Decision Support System Effectiveness: A Review and an Empirical Test’, *Management Science*, 34(2), pp. 139–159. doi: 10.1287/mnsc.34.2.139

Sharma, C. (2015) *Business Process Transformation: The Process Tangram Framework*. New Delhi: Springer India.

Shim, J.P. *et al.* (2002) ‘Past, present, and future of decision support technology’, *Decision Support Systems*, 33(2), pp. 111–126.

Silic, M. and Back, A. (2014) ‘Shadow IT – A view from behind the curtain’, *Computers & Security*, 45, pp. 274–283. doi: 10.1016/j.cose.2014.06.007

Sim, I. *et al.* (2001) ‘Clinical decision support systems for the practice of evidence-based medicine’, *Journal of the American Medical Informatics Association : JAMIA*, 8(6), pp. 527–534. doi: 10.1136/jamia.2001.0080527

Simon, H.A. (1969) *The sciences of the artificial: 1st edition*. Cambridge, USA: The MIT Press.

Siriram, R. (2012) ‘A Soft and Hard Systems Approach to Business Process Management’, *Systems Research and Behavioral Science*, 29(1), pp. 87–100. doi: 10.1002/sres.1095

Škrinjar, R., Bosilj-Vukšić, V. and Indihar-Štemberger, M. (2008) ‘The impact of business process orientation on financial and non-financial performance’, *Business Process Management Journal*, 14(5), pp. 738–754. doi: 10.1108/14637150810903084

Škrinjar, R. and Trkman, P. (2013) ‘Increasing process orientation with business process management: Critical practices’’, *International Journal of Information Management,* 33(1), pp. 48–60.

Soffer, P., Wand, Y. and Kaner, M. (2015) ‘Conceptualizing Routing Decisions in Business Processes: Theoretical Analysis and Empirical Testing’, *Journal of the Association for Information Systems*, 16(5). Available at: http://aisel.aisnet.org/jais/vol16/iss5/2.

Song, M., Günther, C.W. and van der Aalst, W.M.P. (2009) ‘Trace Clustering in Process Mining’, in Ardagna, D., Mecella, M. and Yang, J. (eds.) *Business Process Management Workshops.* (Lecture Notes in Business Information Processing). Berlin, Heidelberg: Springer Berlin Heidelberg, pp. 109–120.

Sousa, R. and Voss, C.A. (2008) ‘Contingency research in operations management practices’, *Journal of Operations Management*, 26(6), pp. 697–713. doi: 10.1016/j.jom.2008.06.001

Sprague, R.H. (1980) ‘A Framework for the Development of Decision Support Systems’, *Management Information Systems Quarterly*, 4(4), p. 1. doi: 10.2307/248957

Stark, J., Braun, R. and Esswein, W. (2016) ‘Perceptually discriminating Chunks in Business Process Models’, *IEEE Conference on Business Informatics, Paris, France,* pp. 84–93. doi: 10.1109/CBI.2016.18

Steinfield, C., Markus, M.L. and Wigand, R.T. (2011) ‘Through a Glass Clearly: Standards, Architecture, and Process Transparency in Global Supply Chains’, *Journal of Management Information Systems*, 28(2), pp. 75–108. doi: 10.2753/MIS0742-1222280204

Stetten, A.v. *et al*. (2008) ‘Towards an Understanding of the Business Value of Business Process Standardization - A Case Study Approach’, *14th Americas Conference on Information Systems, Toronto, Canada*.

Stitzlein, C., Sanderson, P. and Indulska, M. (2013) ‘Understanding healthcare processes: An evaluation of two process model notations’, *Human Factors and Ergonomics Society Annual Meeting,* 57(1), pp. 240–244. doi: 10.1177/1541931213571053

Szopinski, D. *et al.* (2019) ‘Software tools for business model innovation: current state and future challenges’, *Electronic Markets*, 60(11), p. 2794. doi: 10.1007/s12525-018-0326-1

Tanenbaum, A.S. (2007) *So Many To Choose From*, 26 October. Available at: http://wiki.c2.com/?SoManyToChooseFrom.

Täuscher, K. and Abdelkafi, N. (2017) ‘Visual tools for business model innovation: Recommendations from a cognitive perspective’, *Creativity and Innovation Management*, 26(2), pp. 160–174. doi: 10.1111/caim.12208

Taylor, A. and Taylor, M. (2014) ‘Factors influencing effective implementation of performance measurement systems in small and medium-sized enterprises and large firms: a perspective from Contingency Theory’, *International Journal of Production Research*, 52(3), pp. 847–866. doi: 10.1080/00207543.2013.842023

Teece, D.J. (2010) ‘Business Models, Business Strategy and Innovation’, *Long Range Planning*, 43(2-3), pp. 172–194. doi: 10.1016/j.lrp.2009.07.003

Tenhiälä, A. (2011) ‘Contingency theory of capacity planning: The link between process types and planning methods’, *Journal of Operations Management*, 29(1-2), pp. 65–77. doi: 10.1016/j.jom.2010.05.003

Terrenghi, N. *et al.* (2017) ‘Business Model Management: Current Practices, Required Activities and IT Support’, *13th International Conference on Wirtschaftsinformatik, St. Gallen, Switzerland*.

Thaler, T. *et al.* (2016) ‘A Comparative Analysis of Business Process Model Similarity Measures’, *International Conference on Business Process Management Workshop Papers, Rio de Janeiro, Brazil*, pp. 310–322.

The Apromore Initiative (2018) *Apromore: Advanced Process Analytics Platform*, 7 November. Available at: http://apromore.org/about.

Timmers, P. (1998) ‘Business Models for Electronic Markets’, *Electronic Markets*, 8(2), pp. 3–8. doi: 10.1080/10196789800000016

Tiwari, A., Turner, C. and Majeed, B. (2008) ‘A review of business process mining: State-of-the-art and future trends’, *Business Process Management Journal*, 14(1), pp. 5–22. doi: 10.1108/14637150810849373

Tregear, R. (2010) ‘Business Process Standardization’, in vom Brocke, J. and Rosemann, M. (eds.) *Handbook on Business Process Management 2: Strategic Alignment, Governance, People and Culture.* (International handbooks on information systems). Berlin, Heidelberg: Springer-Verlag Berlin Heidelberg, pp. 307–327.

Tregear, R. (2015) ‘Business Process Standardization’, in vom Brocke, J. and Rosemann, M. (eds.) *Handbook on Business Process Management 2: Strategic Alignment, Governance, People and Culture.* Berlin, Heidelberg: Springer Berlin Heidelberg, pp. 421–441.

Trkman, M., Mendling, J. and Krisper, M. (2016) ‘Using business process models to better understand the dependencies among user stories’, *Information and Software Technology*, 71, pp. 58–76. doi: 10.1016/j.infsof.2015.10.006

Trkman, P. (2010) ‘The critical success factors of business process management’, *International Journal of Information Management*, 30(2), pp. 125–134.

Turban, E. *et al.* (2005) *Decision support systems and intelligent systems*. 7th edn. Upper Saddle River, NJ: Pearson/Prentice-Hall.

Turban, E. *et al.* (2008) *Decision support and business intelligence systems*. 8th edn. Upper Saddle River, N.J.: Pearson Education International.

Turdasan, A. and Petrusel, R. (2016) ‘Evaluating Knowledge of Business Processes’, *Informatica Economica*, 20(3/2016), pp. 5–15. doi: 10.12948/issn14531305/20.3.2016.01

Turetken, O. *et al.* (2016) ‘The Effect of Modularity Representation and Presentation Medium on the Understandability of Business Process Models in BPMN’, *Business Process Management.* Cham: Springer International Publishing, pp. 289–307. doi: 10.1007/978-3-319-45348-4_17

Turetken, O. *et al.* (2019) ‘The Influence of Using Collapsed Sub-processes and Groups on the Understandability of Business Process Models’, *Business & Information Systems Engineering*, 12(4), p. 383. doi: 10.1007/s12599-019-00577-4

Turetken, O., Vanderfeesten, I. and Claes, J. (2017) ‘Cognitive style and business process model understanding’, in *Lecture Notes in Business Information Processing*, pp. 72–84.

Umble, E.J., Haft, R.R. and Umble, M.M. (2003) ‘Enterprise resource planning: Implementation procedures and critical success factors’, *European Journal of Operational Research*, 146(2), pp. 241–257.

Ungan, M.C. (2006) ‘Standardization through process documentation’, *Business Process Management Journal*, 12(2), pp. 135–148. doi: 10.1108/14637150610657495

University of Duesseldorf (2019) *G*Power: Statistical Power Analyses*. Available at: http://www.psychologie.hhu.de/arbeitsgruppen/allgemeine-psychologie-und-arbeitspsychologie/gpower.html (Accessed: 13 September 2019).

Vaishnavi, V.K., Kuechler, W. and Petter, S. (2004) *Design Research in Information Systems*, 11 November. Available at: http://www.desrist.org/design-research-in-information-systems/ (Accessed: 15 July 2018).

Valiris, G. and Glykas, M. (2004) ‘Business analysis metrics for business process redesign’, *Business Process Management Journal*, 10(4), pp. 445–480. doi: 10.1108/14637150410548100 van der Aalst, W.M.P. *et al.* (2003) ‘Workflow mining: A survey of issues and approaches’, *Data & Knowledge Engineering*, 47(2), pp. 237–267. doi: 10.1016/S0169-023X(03)00066-1

van der Aalst, W.M.P. *et al.* (2007) ‘Business process mining: An industrial application’, *Information Systems*, 32(5), pp. 713–732.

van der Aalst, W.M.P. (2010) ‘Challenges in business process mining’. (to appear), *Applied Stochastic Models in Business and Industry*. Available at: https://pdfs.semanticscholar.org/2a3f/248d1c487e556b79d742953a419d9abc86fb.pdf.

van der Aalst, W.M.P. (2011) *Process mining: Discovery, conformance and enhancement of business processes*. Berlin: Springer.

van der Aalst, W.M.P. *et al.* (2011) ‘Process Mining Manifesto’, *Lecture Notes in Business Information Processing*, 99 (169pp). doi: 10.1007/978-3-642-28108-2_19

van der Aalst, W.M.P. (2013) ‘"Mine your own business": using process mining to turn big data into real value’, *21st European Conference on Information Systems, Utrecht, The Netherlands*.

van der Aalst, W.M.P. (2014) ‘Process Mining in the Large: A Tutorial’, in Zimányi, E. (ed.) *Business Intelligence.* (Lecture Notes in Business Information Processing). Cham: Springer International Publishing, pp. 33–76.

van der Aalst, W.M.P. (2016) *Process Mining: Data Science in Action*. Berlin: Springer.

van der Aalst, W.M.P. (2018) ‘Process discovery from event data: Relating models and logs through abstractions’, *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, 8(3), e1244. doi: 10.1002/widm.1244

van der Aalst, W.M.P. and Dustdar, S. (2012) ‘Process mining put into context’, *IEEE Internet Computing*, 16(1), pp. 82–86.

van der Aalst, W.M.P., ter Hofstede, A.H.M. and Weske, M. (2003) ‘Business Process Management: A Survey’, in Goos, G. *et al.* (eds.) *Business Process Management.* (Lecture Notes in Computer Science). Berlin, Heidelberg: Springer Berlin Heidelberg, pp. 1–12.

van der Aalst, W.M.P. and Weijters, A.J.M.M. (2004) ‘Process mining: a research agenda’, *Computers in Industry*, 53(3), pp. 231–244. doi: 10.1016/j.compind.2003.10.001

van der Werf, J.M.E.M., Verbeek, H.M.W. and van der Aalst, W.M.P. (2012) ‘Context-Aware Compliance Checking’, in Hutchison, D. *et al.* (eds.) *Business Process Management.* (Lecture Notes in Computer Science). Berlin, Heidelberg: Springer Berlin Heidelberg, pp. 98–113.

van Looy, A. and van den Bergh, J. (2018) 'The Effect of Organization Size and Sector on Adopting Business Process Management', *Business & Information Systems Engineering*, 60(6), pp. 479–491. doi: 10.1007/s12599-017-0491-3

van Valkenhoef, G. *et al.* (2013) 'ADDIS: A decision support system for evidence-based medicine', *Decision Support Systems*, 55(2), pp. 459–475. doi: 10.1016/j.dss.2012.10.005

Vasey, M.W. and Thayer, J.F. (1987) 'The continuing problem of false positives in repeated measures ANOVA in psychophysiology: a multivariate solution', *Psychophysiology*, 24(4), pp. 479–486. doi: 10.1111/j.1469-8986.1987.tb00324.x

Veit, D. *et al.* (2014) 'Business Models', *Business & Information Systems Engineering*, 6(1), pp. 45–53. doi: 10.1007/s12599-013-0308-y

Venable, J., Pries-Heje, J. and Baskerville, R.L. (2014) 'FEDS: A Framework for Evaluation in Design Science Research', *European Journal of Information Systems*, (1), pp. 1–13. doi: 10.1057/ejis.2014.36

Venkatesh, V. (2006) 'Where To Go From Here? Thoughts on Future Directions for Research on Individual-Level Technology Adoption with a Focus on Decision Making', *Decision Sciences*, 37(4), pp. 497–518. doi: 10.1111/j.1540-5414.2006.00136.x

Vergidis, K., Turner, C. and Tiwari, A. (2008) 'Business process perspectives: Theoretical developments vs. real-world practice', *International Journal of Production Economics*, 114(1), pp. 91–104. doi: 10.1016/j.ijpe.2007.12.009

Villani, E., Greco, L. and Phillips, N. (2017) 'Understanding Value Creation in Public-Private Partnerships: A Comparative Case Study', *Journal of Management Studies*, 54(6), pp. 876–905. doi: 10.1111/joms.12270

vom Brocke, J. *et al.* (2018) 'Future Work and Enterprise Systems', *Business & Information Systems Engineering*, 60(4), pp. 357–366. doi: 10.1007/s12599-018-0544-2

vom Brocke, J. and Rosemann, M. (eds.) (2015) *Handbook on Business Process Management 2: Strategic Alignment, Governance, People and Culture*. Berlin, Heidelberg: Springer Berlin Heidelberg.

vom Brocke, J., Zelt, S. and Schmiedel, T. (2016) 'On the role of context in business process management', *International Journal of Information Management*, 36(3), pp. 486–495. doi: 10.1016/j.ijinfomgt.2015.10.002

Vries, H.J. de, Slob, F.J.C. and van Zuid-Holland, G. (2006) 'Best Practice in Company Standardization', *International Journal of IT Standards and Standardization Research*, 4(1), pp. 62–85. doi: 10.4018/jitsr.2006010104

Vries, M. de *et al.* (2011) 'A method for identifying process reuse opportunities to enhance the operating model', *IEEE International Conference*, pp. 1005–1009. doi: 10.1109/IEEM.2011.6118067

Wagner, H.-T. and Weitzel, T. (2012) ‘How to Achieve Operational Business-IT Alignment: Insights from a Global Aerospace Firm’, *MIS Quarterly Executive,* 11(1). Available at: http://dblp.uni-trier.de/db/journals/misqe/misqe11.html.

Waller, M.A. and Fawcett, S.E. (2013) ‘Data Science, Predictive Analytics, and Big Data: A Revolution That Will Transform Supply Chain Design and Management’, *Journal of Business Logistics,* 34(2), pp. 77–84.

Walls, J.G., Widmeyer, G.R. and El Sawy, O.A. (1992) ‘Building an Information System Design Theory for Vigilant EIS’, *Information Systems Research,* 3(1), pp. 36–59. doi: 10.1287/isre.3.1.36

Wang, W. *et al.* (2017) ‘Effect of Linked Rules on Business Process Model Understanding’, in *Business Process Management*.

Wang, W. (2017) *Integrated Modeling of Business Processes and Business Rules*. PhD-Thesis. The University of Queensland. Available at: https://espace.library.uq.edu.au/view/UQ:692048.

Wang, W., Indulska, M. and Sadiq, S. (2016) ‘Cognitive efforts in using integrated models of business processes and rules’, *CEUR Workshop Proceedings*, 1612, pp. 33–40.

Weber, B. *et al.* (2015) ‘Measuring Cognitive Load During Process Model Creation’, in Davis, F.D. (ed.) *Information Systems and Neuroscience: Gmunden Retreat on NeuroIS 2015.* (Lecture Notes in Information Systems and Organisation, volume 10). Cham: Springer, pp. 129–136.

Weidlich, M., Dijkman, R.M. and Mendling, J. (2010) ‘The ICoP Framework: Identification of correspondences between process models’, *International Conference on Advanced Information Systems Engineering*, pp. 483–498.

Weill, P. and Ross, J.W. (2005) ‘A matrixed approach to designing IT governance’, *MIT sloan management review*, 46(2), pp. 26–34.

Weitlaner, D., Guettinger, A. and Kohlbacher, M. (2013) ‘Intuitive Comprehensibility of Process Models’. S-BPM ONE 2013: Running Processes, *International Conference on Subject-Oriented Business Process Management*, 360, pp. 52–71. doi: 10.1007/978-3-642-36754-0_4

Weske, M. (ed.) (2012) *Business Process Management: Concepts, Languages, Architectures*. 2nd edn. Berlin, Heidelberg: Springer Berlin Heidelberg.

Wiebring, J. and Sandkuhl, K. (2015) ‘Selecting the “Right” Notation for Business Process Modeling: Experiences from an Industrial Case’, in Matulevičius, R. and Dumas, M. (eds.) *Perspectives in business informatics research: 14th international conference, BIR 2015, Tartu, Estonia, August 26-28, 2015 : proceedings.* (Lecture Notes in Business Information Processing, 229). Cham: Springer, pp. 129–144.

Wieland, H., Hartmann, N.N. and Vargo, S.L. (2017) 'Business models as service strategy', *Journal of the Academy of Marketing Science*, 45(6), pp. 925–943. doi: 10.1007/s11747-017-0531-z

Wilcoxon, F. (1945) 'Individual Comparisons by Ranking Methods', *Biometrics Bulletin*, 1(6), p. 80. doi: 10.2307/3001968

Willaert, P. *et al.* (2007) 'The Process-Oriented Organisation: A Holistic View: Developing a Framework for Business Process Orientation Maturity', *International Conference of Business Process Management, Brisbane, Australia*, pp. 1–15.

Williams, C. and van Triest, S. (2009) 'The impact of corporate and national cultures on decentralization in multinational corporations', *International Business Review*, 18(2), pp. 156–167. doi: 10.1016/j.ibusrev.2009.01.003

Wirtz, B.W. (2018) *Business Model Management: Design - Instrumente - Erfolgsfaktoren von Geschäftsmodellen*. 4th edn. Wiesbaden: Springer Gabler.

Wohlin, C. *et al.* (2012) *Experimentation in Software Engineering*: Springer-Verlag Berlin Heidelberg.

Wohlin, C., Höst, M. and Henningsson, K. (2003) 'Empirical Research Methods in Software Engineering', in Conradi, R. and Wang, A.I. (eds.) *Empirical Methods and Studies in Software Engineering: Experiences from ESERNET*. (Lecture Notes in Computer Science, 2765). Berlin: Springer, pp. 7–23.

Wong, C.W.Y., Lai, K.-H. and Cheng, T.C.E. (2011) 'Value of Information Integration to Supply Chain Management: Roles of Internal and External Contingencies', *Journal of Management Information Systems*, 28(3), pp. 161–199. Available at: http://www.jstor.org/stable/41713846.

Woodward, J. (1970) *Industrial organization: Theory and practice*. London u.a.: Oxford University Press.

Wüllenweber, K. *et al.* (2008) 'The impact of process standardization on business process outsourcing success', *Information Systems Frontiers*, 10(2), pp. 211–224.

Wurm, B. *et al.* (2018) 'Development of a Measurement Scale for Business Process Standardization', *26th European Conference on Information Systems, Portsmouth, United Kingdom*.

Yazdani, M. *et al.* (2017) 'A group decision making support system in logistics and supply chain management', *Expert Systems with Applications*, 88, pp. 376–392. doi: 10.1016/j.eswa.2017.07.014

Yigitbasioglu, O.M. and Velcu, O. (2012) 'A review of dashboards in performance management: Implications for design and research', *International Journal of Accounting Information Systems*, 13(1), pp. 41–59. doi: 10.1016/j.accinf.2011.08.002

Yoo, S.H., Shin, H. and Park, M.-S. (2015) 'New product development and the effect of supplier involvement', *Omega*, 51, pp. 107–120.

Yoon, Y., Guimaraes, T. and Clevenson, A. (1998) 'Exploring Expert System Success Factors for Business Process Reengineering', *Journal of Engineering and Technology Management*, 15(2(3)), pp. 179–199.

Yu, A.G. and Kittler, M. (2012) 'Matching programme structure to environment: A comparative study of two IS-based change programmes', *International Journal of Project Management*, 30(6), pp. 740–749. doi: 10.1016/j.ijproman.2012.01.009

Zellner, P. and Laumann, M. (2013) 'Evaluation of Business Processes for Business Process Standardization', *Pacific Asia Conference on Information Systems (PACIS)*. Available at: https://aisel.aisnet.org/pacis2013/248.

Zelt, S. *et al.* (2018) 'A theory of contingent business process management', *Business Process Management Journal*, 75(1), p. 116. doi: 10.1108/BPMJ-05-2018-0129

Zelt, S., Schmiedel, T. and vom Brocke, J. (2018) 'Understanding the nature of processes: An information-processing perspective', *Business Process Management Journal*, 24(1), pp. 67–88. doi: 10.1108/BPMJ-05-2016-0102

Zhang, J. (2018) *Designing an Extended Similarity-Based Business Process Matching Algorithm: Supervised Master Thesis*. Master-Thesis. Karlsruhe Institute of Technology.

Zimoch, M. *et al.* (2017) 'Eye Tracking Experiments on Process Model Comprehension: Lessons Learned', *18th International Conference on Business Process Modeling, Development, and Support* (287), pp. 153–168.

Zott, C. and Amit, R. (2008) 'The fit between product market strategy and business model: implications for firm performance', *Strategic Management Journal*, 29(1), pp. 1–26. doi: 10.1002/smj.642

Zott, C., Amit, R. and Massa, L. (2011) 'The Business Model: Recent Developments and Future Research', *Journal of Management*, 37(4), pp. 1019–1042. doi: 10.1177/0149206311406265

Zugal, S. *et al.* (2015) 'Investigating expressiveness and understandability of hierarchy in declarative business process models', *Software & Systems Modeling*, 14(3), pp. 1081–1103. doi: 10.1007/s10270-013-0356-2

10 Appendix

This section provides appendices. A further digital appendix attached to this dissertation contains all related files to the DSR projects (surveys, results, tool demos, scripts, databases, literature, non-confidential industry partner project documents, among others).

10.1 DSR Project 1: Additional Business Model Miner Dashboards

The following section contains additional screenshots for the detail dashboards for the BMC in the BM-Miner artifact developed in DSR project 1 in section 4. Screenshots are based on the implementation in an education SAP R/3 ERP system of a fictitious bicycle company.

Figure 74: Business Model Miner dashboard: key partners (networks and regions)

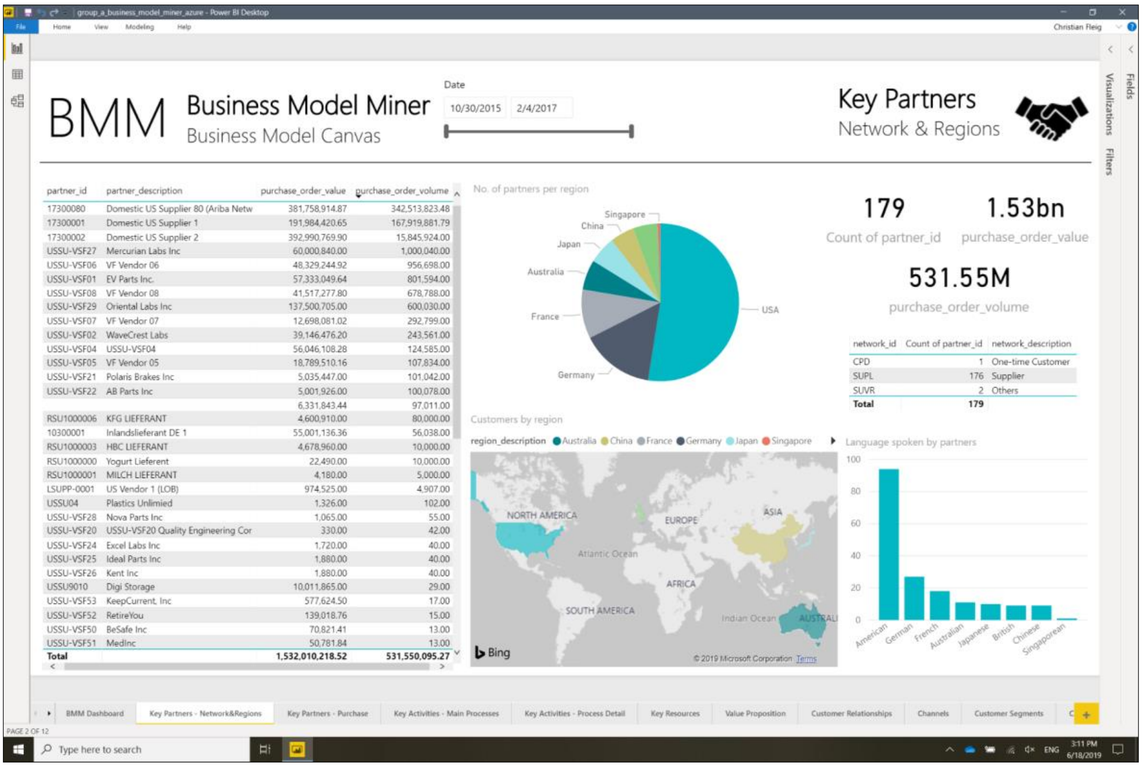


Figure 75: Business Model Miner Dashboard: key partners (filtered for partners from Germany)

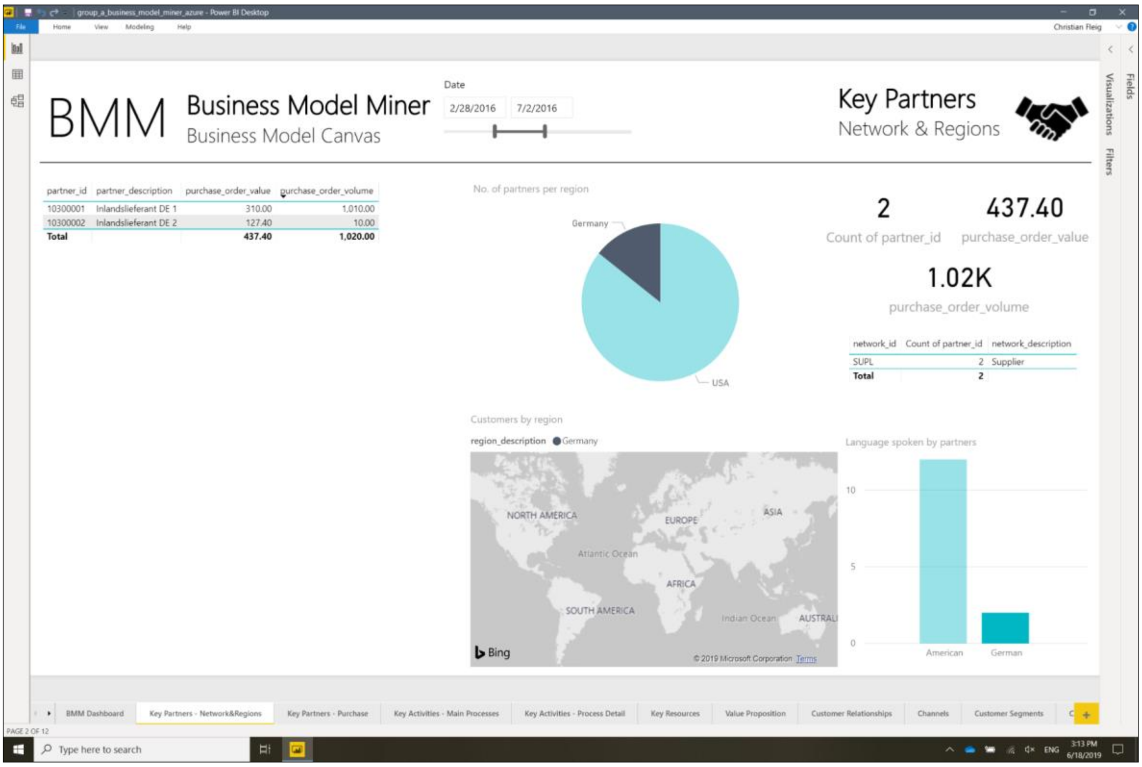


Figure 76: Business Model Miner dashboard: revenue structure

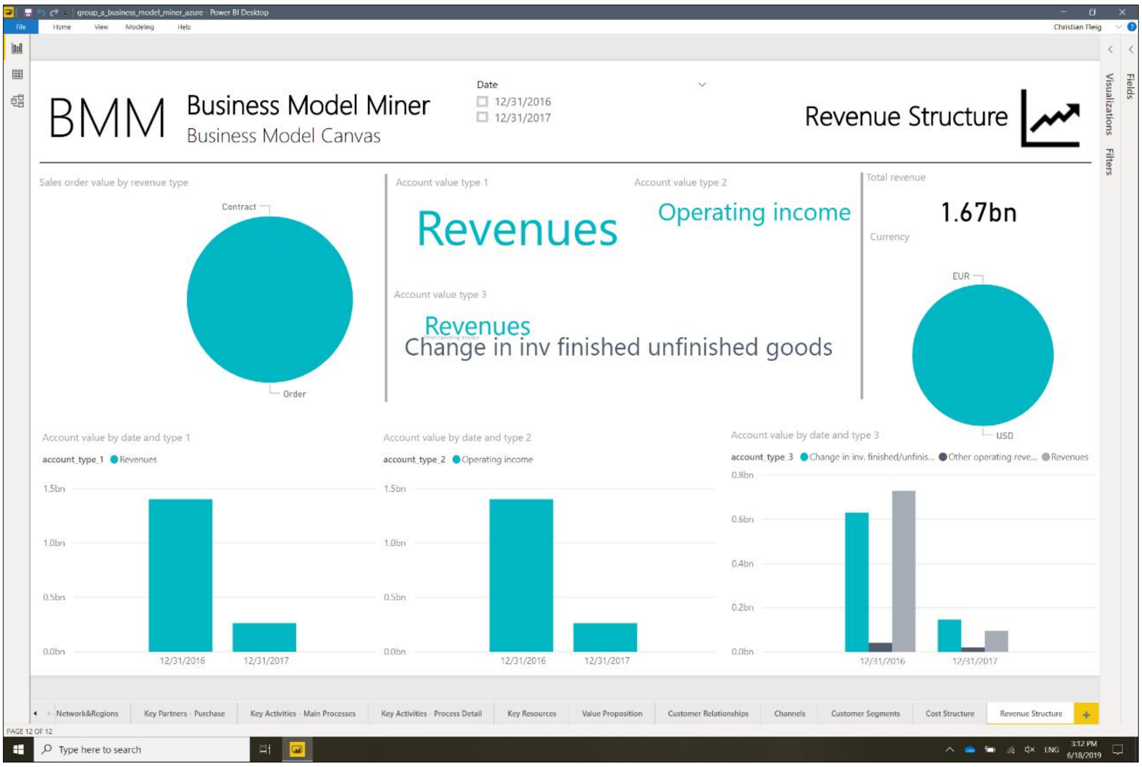


Figure 77: Business Model Miner dashboard: cost structure

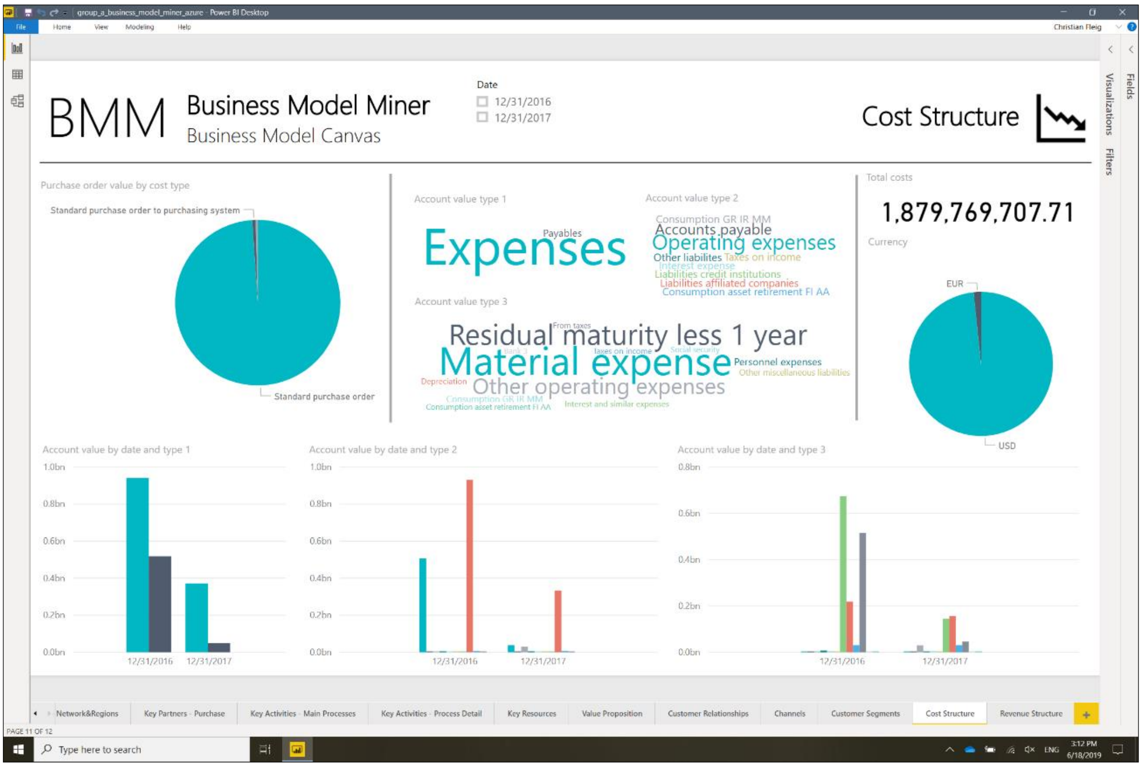


Figure 78: Business Model Miner dashboard: customer segments

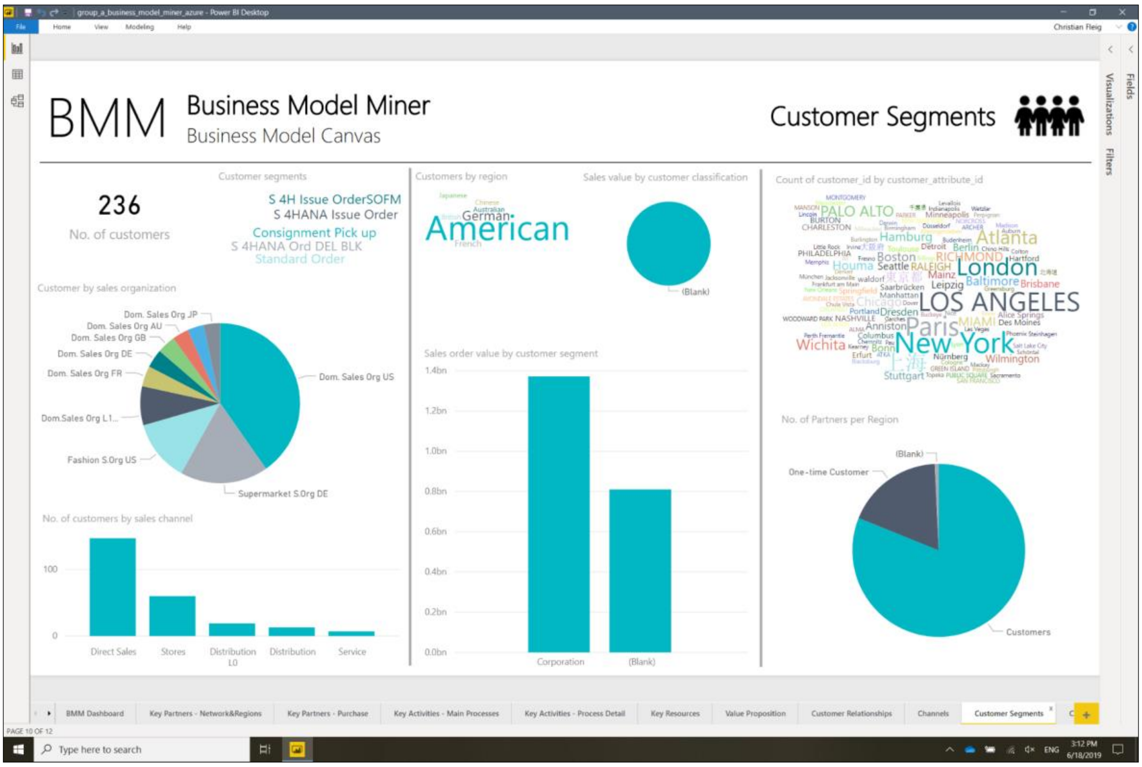


Figure 79: Business Model Miner dashboard: channels

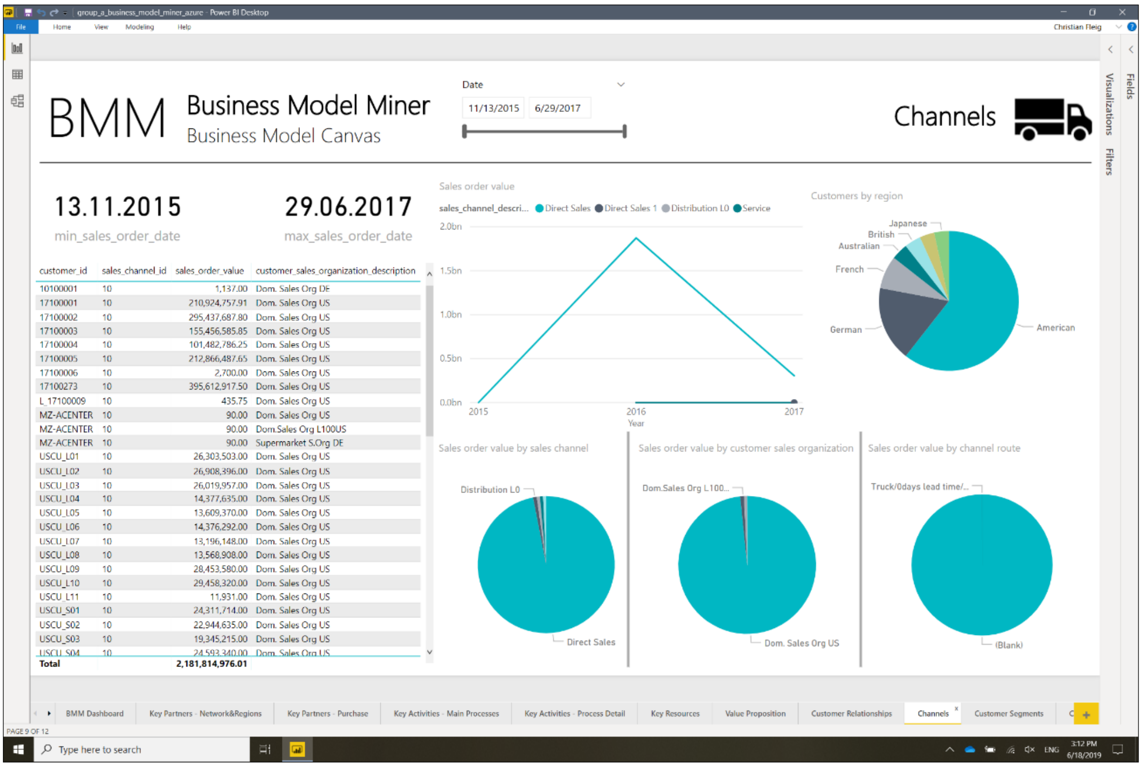


Figure 80: Business Model Miner dashboard: value proposition

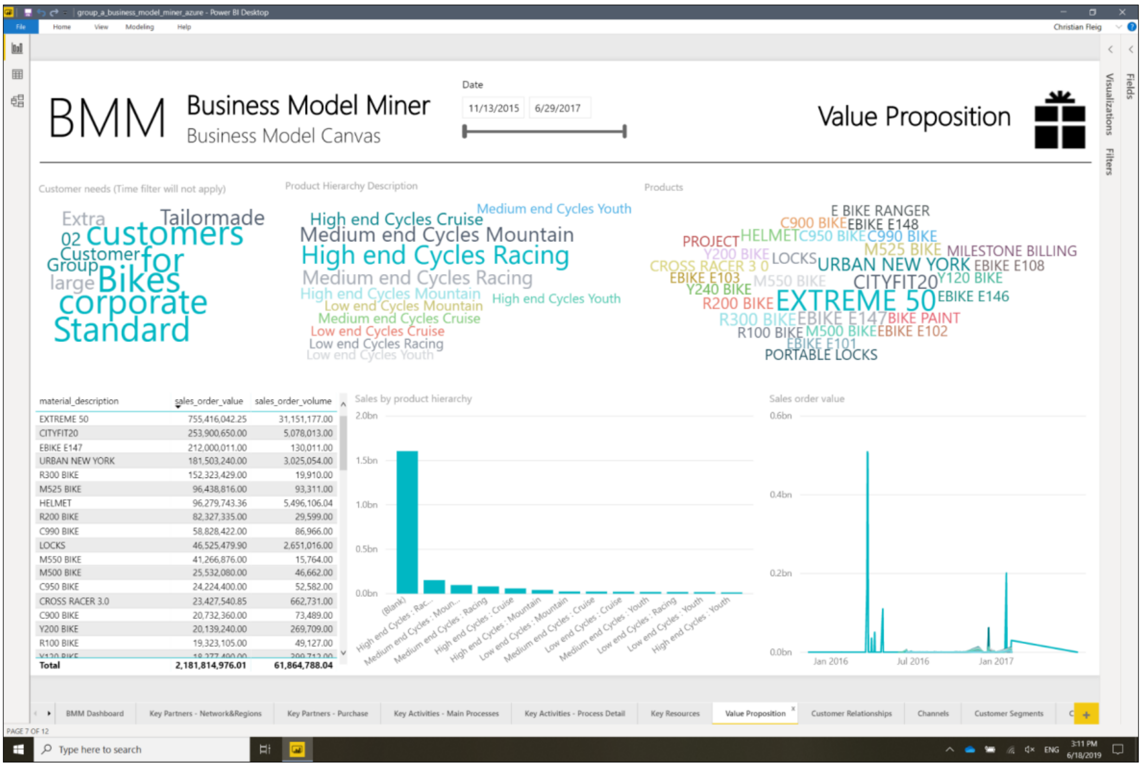


Figure 81: Business Model Miner dashboard: key resources

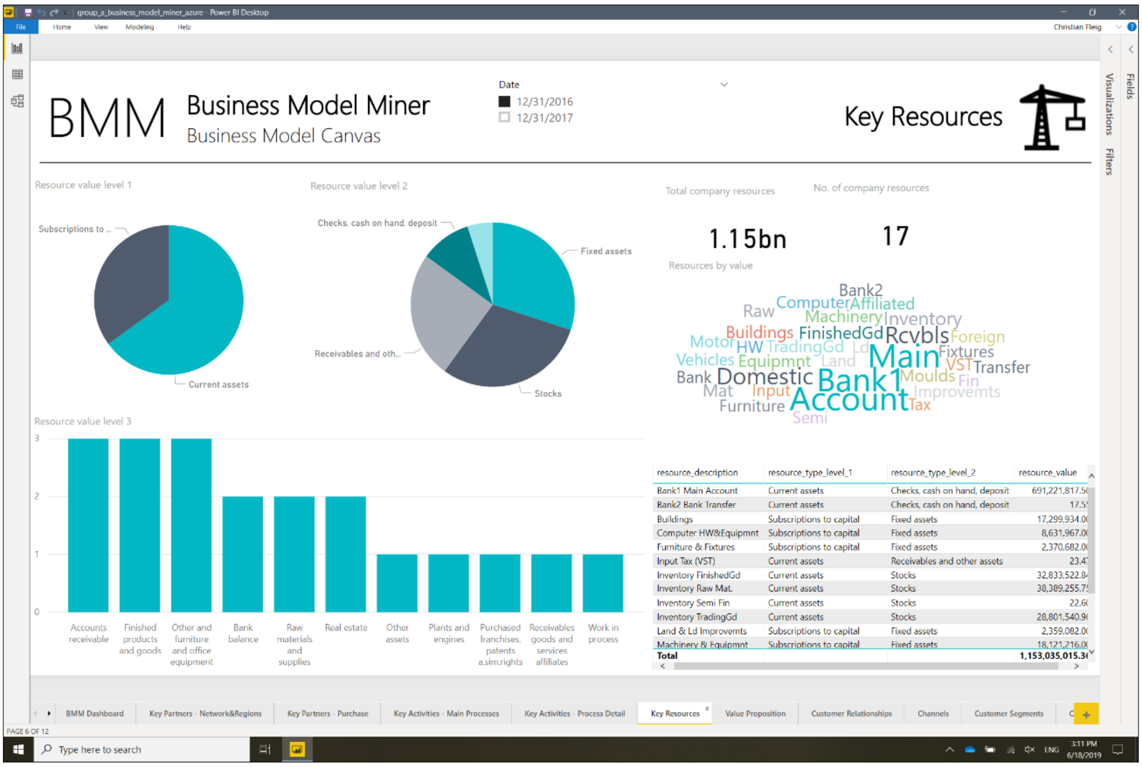
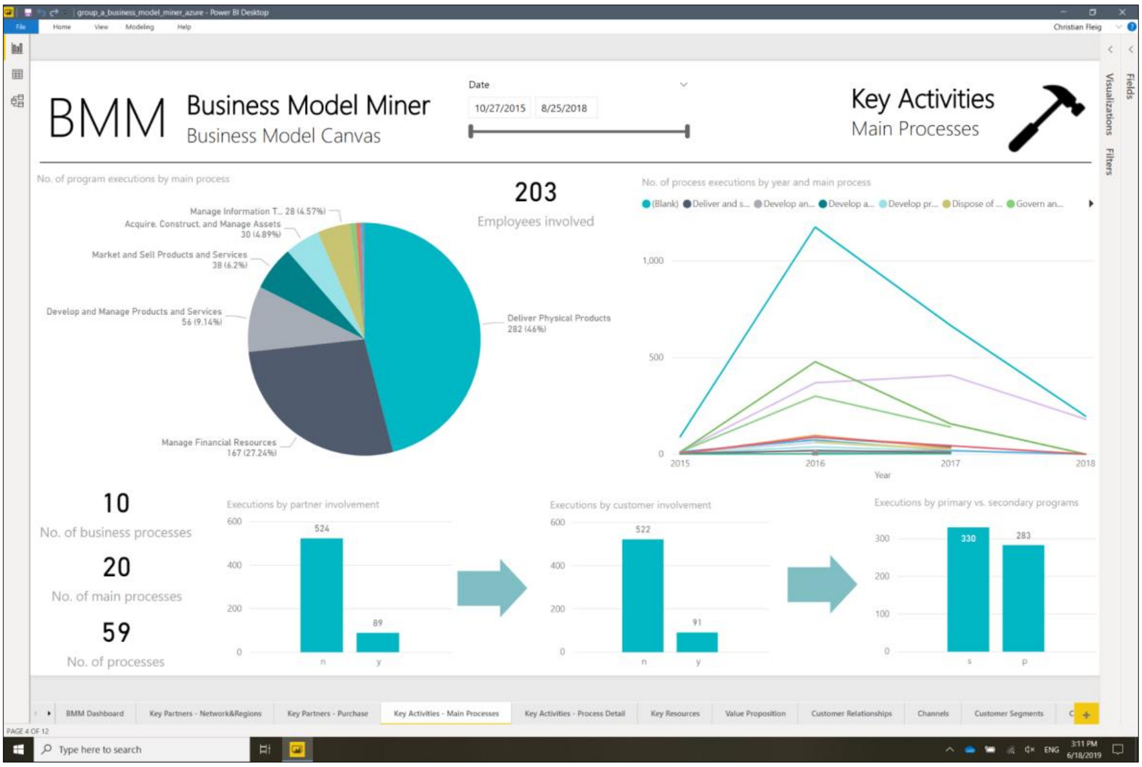
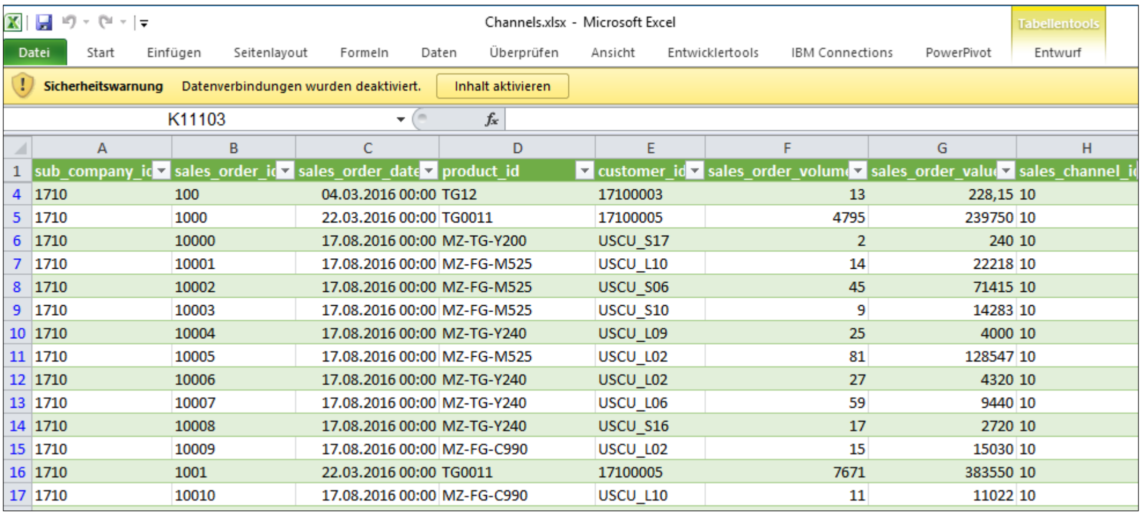


Figure 82: Business Model Miner dashboard: key activities (main processes)



10.2 DSR Project 1: Laboratory Experiment: Group Screenshots

Figure 83: Exemplary spreadsheet of groups A and D


Channels.xlsx - Microsoft Excel

	sub_company_id	sales_order_id	sales_order_date	product_id	customer_id	sales_order_volume	sales_order_value	sales_channel_id
4	1710	100	04.03.2016 00:00	TG12	17100003	13	228,15	10
5	1710	1000	22.03.2016 00:00	TG0011	17100005	4795	239750	10
6	1710	10000	17.08.2016 00:00	MZ-TG-Y200	USCU_S17	2	240	10
7	1710	10001	17.08.2016 00:00	MZ-FG-M525	USCU_L10	14	22218	10
8	1710	10002	17.08.2016 00:00	MZ-FG-M525	USCU_S06	45	71415	10
9	1710	10003	17.08.2016 00:00	MZ-FG-M525	USCU_S10	9	14283	10
10	1710	10004	17.08.2016 00:00	MZ-TG-Y240	USCU_L09	25	4000	10
11	1710	10005	17.08.2016 00:00	MZ-FG-M525	USCU_L02	81	128547	10
12	1710	10006	17.08.2016 00:00	MZ-TG-Y240	USCU_L02	27	4320	10
13	1710	10007	17.08.2016 00:00	MZ-TG-Y240	USCU_L06	59	9440	10
14	1710	10008	17.08.2016 00:00	MZ-TG-Y240	USCU_S16	17	2720	10
15	1710	10009	17.08.2016 00:00	MZ-FG-C990	USCU_L02	15	15030	10
16	1710	1001	22.03.2016 00:00	TG0011	17100005	7671	383550	10
17	1710	10010	17.08.2016 00:00	MZ-FG-C990	USCU_L10	11	11022	10

Figure 84: Tabular business model dashboards of group B

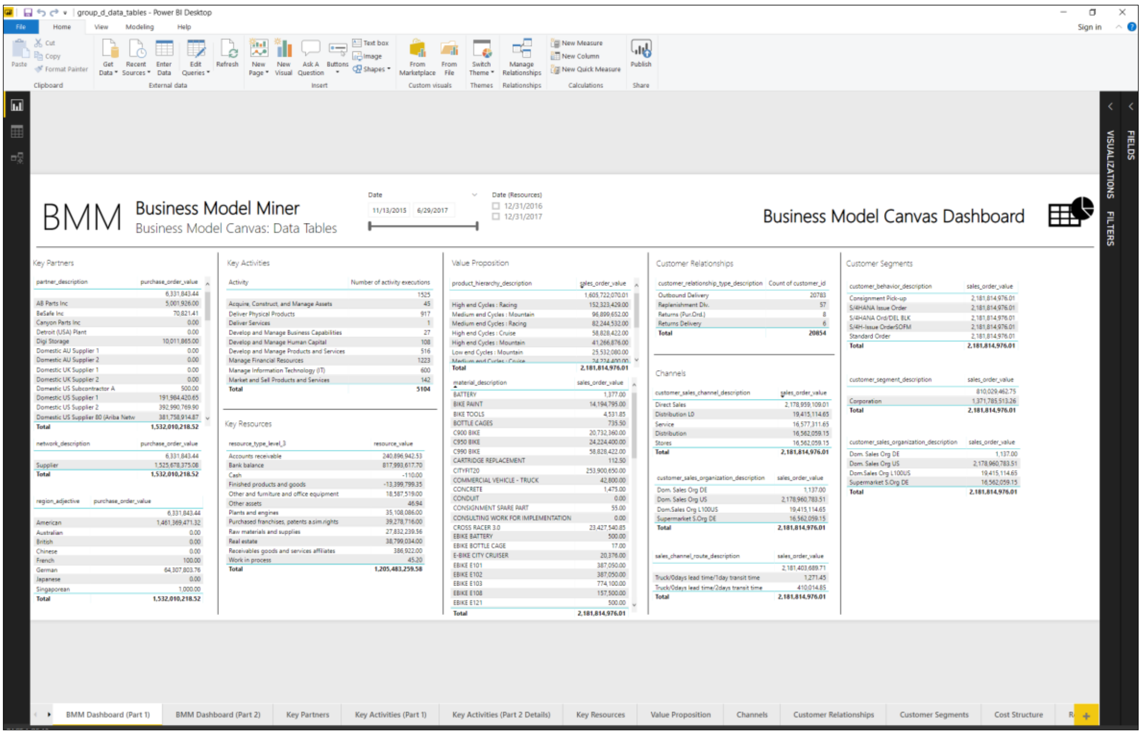
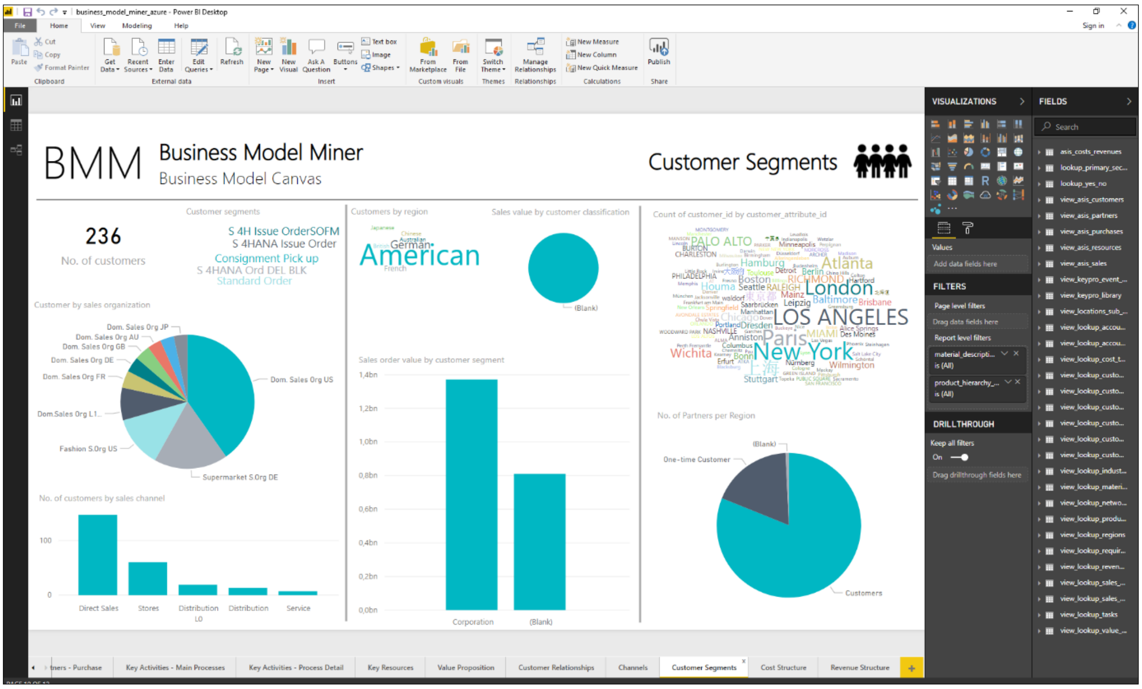


Figure 85: Business Model Miner dashboards of groups C and D



10.3 DSR Project 2: Additional KeyPro Dashboards

Figure 86: KeyPro dashboard on process performance index (PPI) (DD11) (filtered for the delivery of physical products) (in cooperation with Hummel (2019))

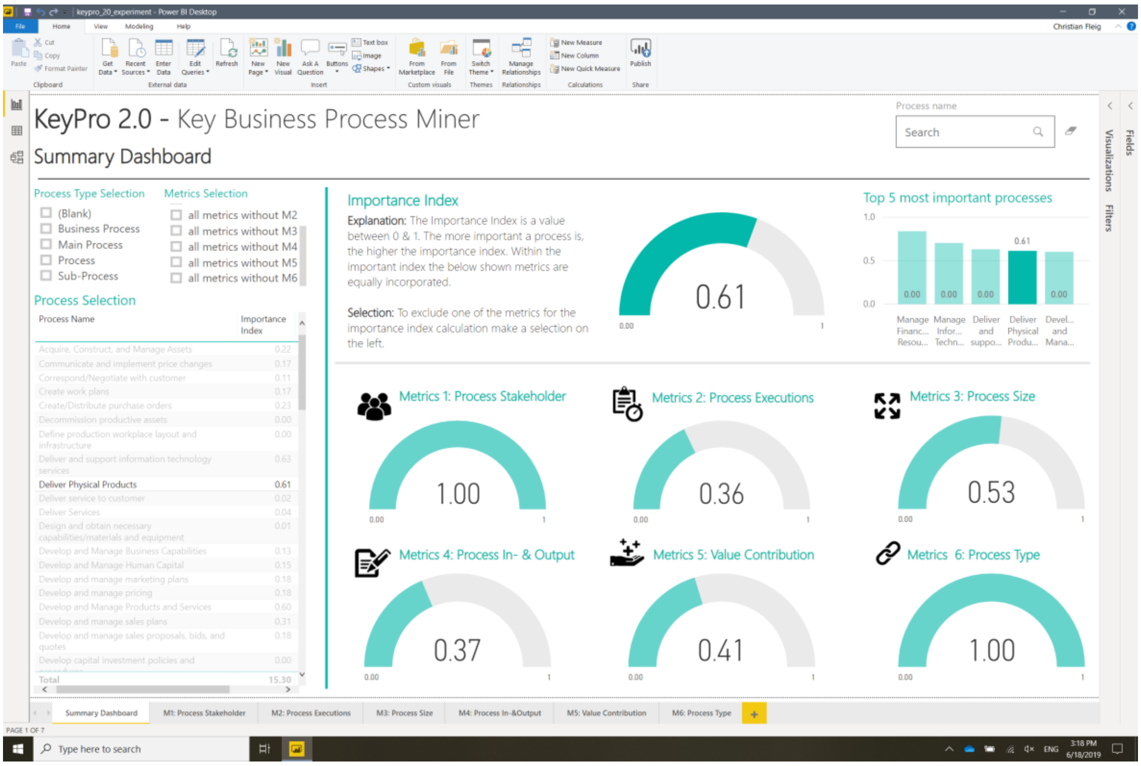


Figure 87: KeyPro dashboard on process stakeholders (DD2) (filtered for development and management of products and services) (in cooperation with Hummel (2019))

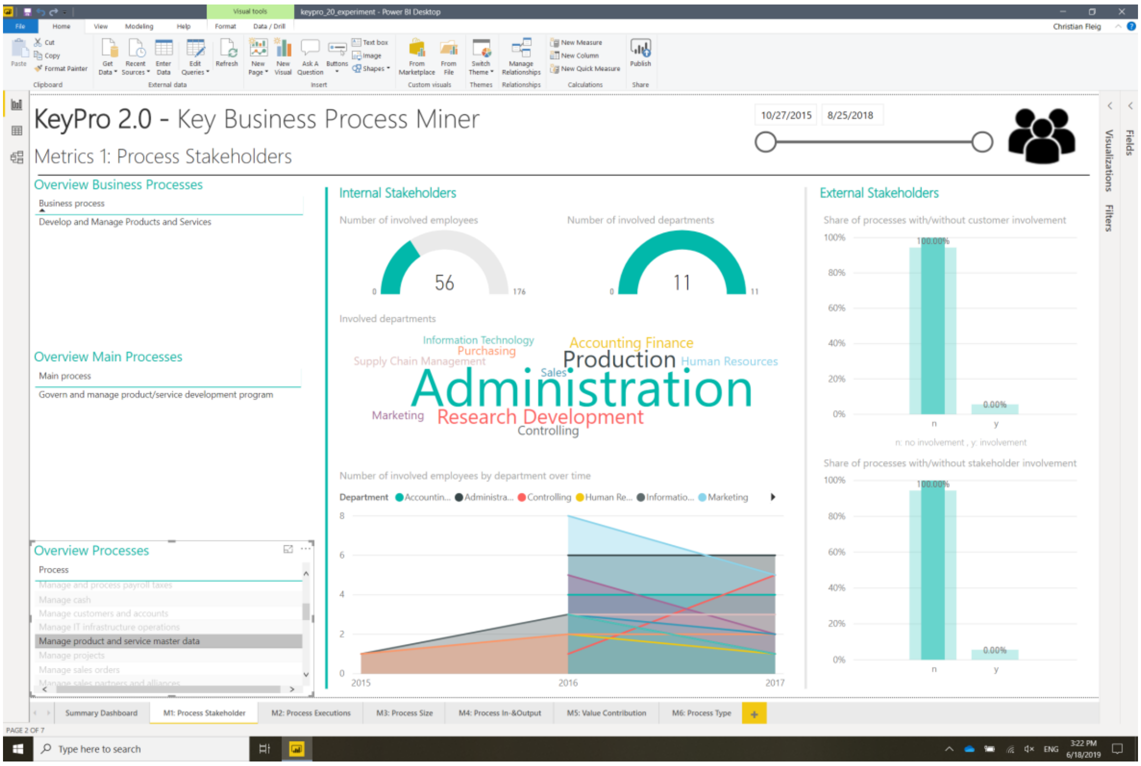


Figure 88: KeyPro dashboard on process executions (DD1) (in cooperation with Hummel (2019))

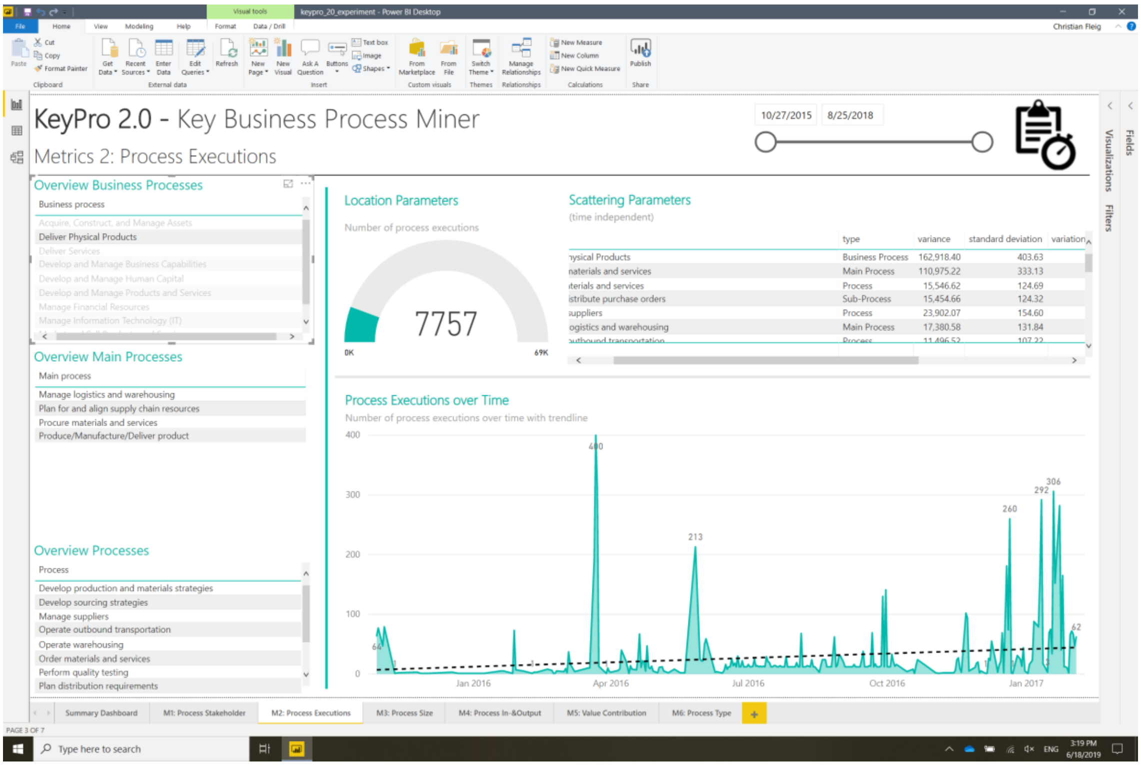


Figure 89: KeyPro dashboard on process executions(DD1) (filtered for development and management of products and services) (in cooperation with Hummel (2019))

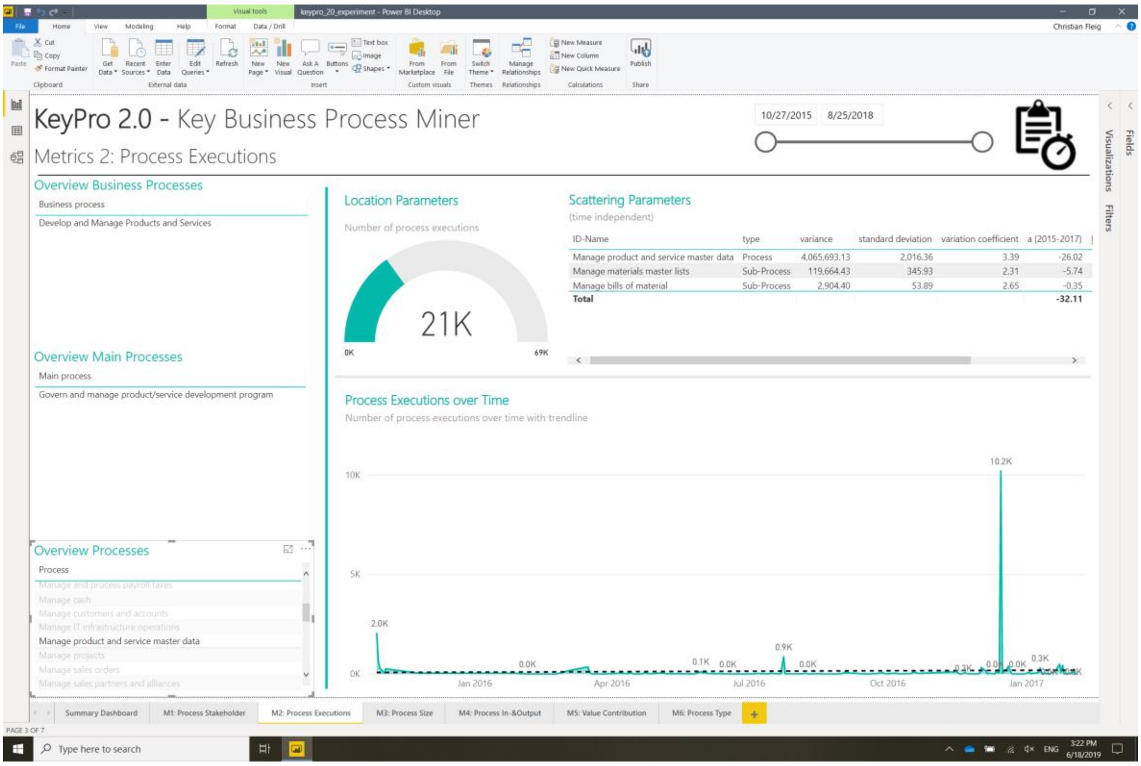


Figure 90: KeyPro dashboard on process size (DD9) (filtered for the development and management of products and services) (in cooperation with Hummel (2019))

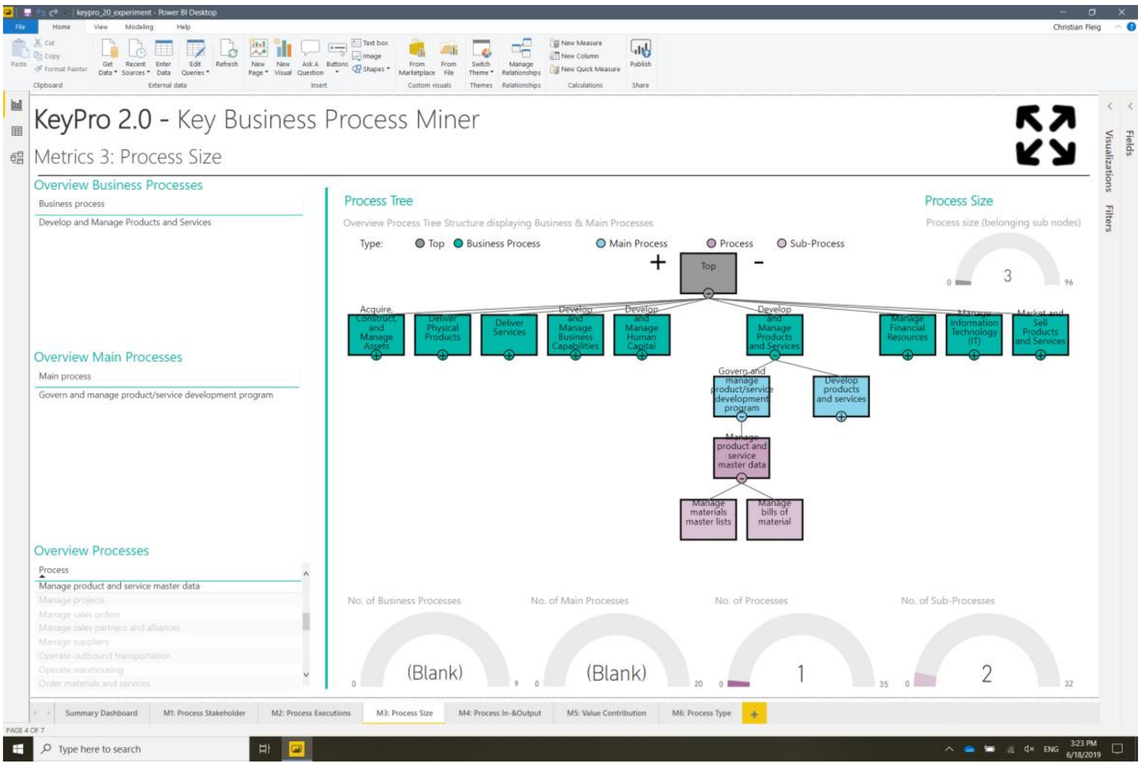


Figure 91: KeyPro dashboard on process inputs and outputs (DD10) (filtered for the development and management of products and services) (in cooperation with Hummel (2019))

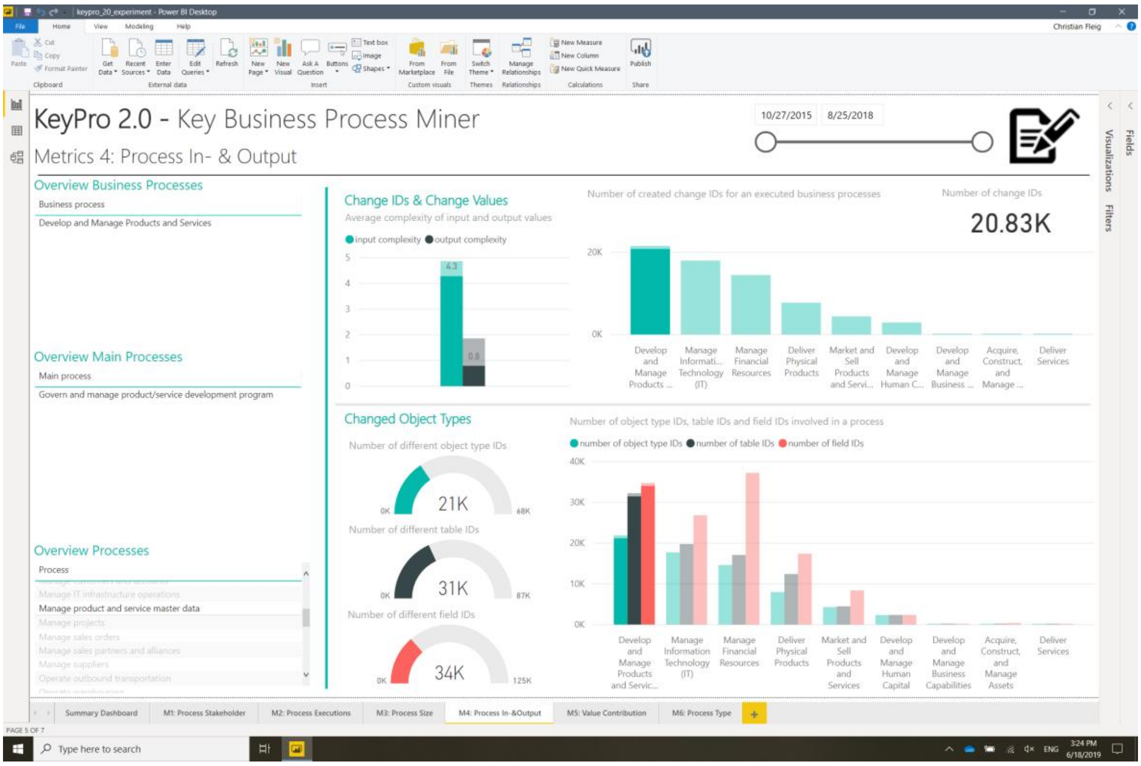
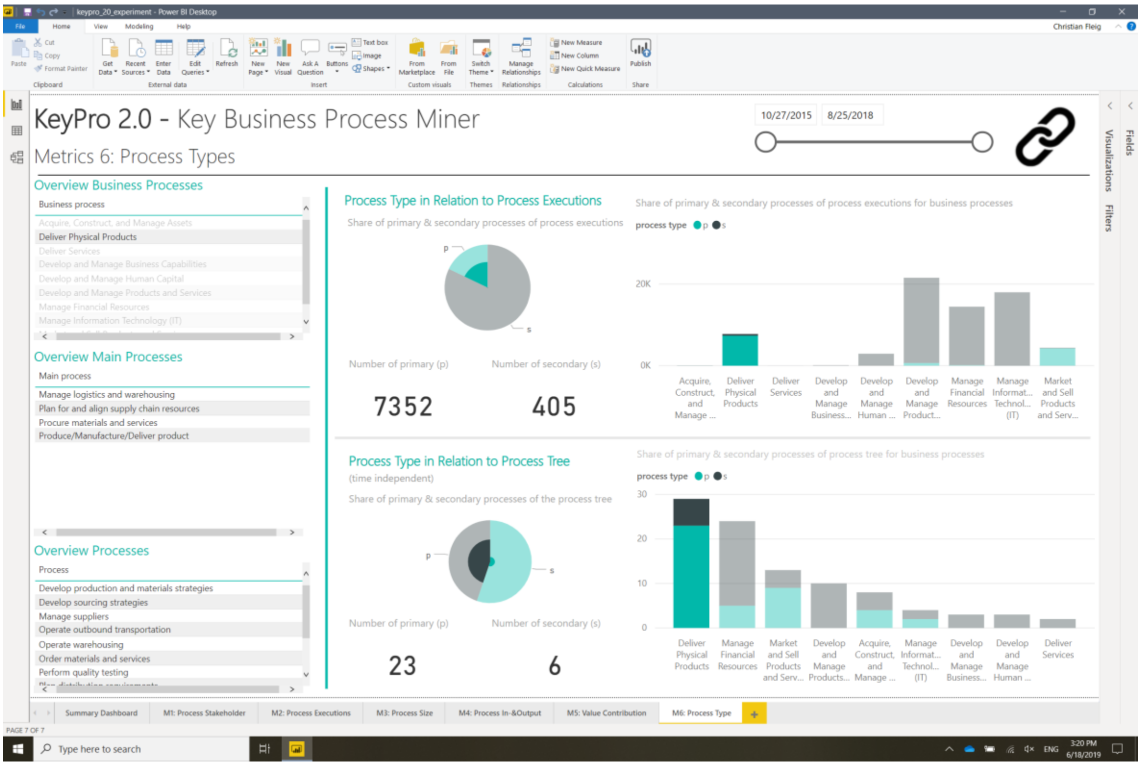


Figure 92: KeyPro dashboard on primacy (DD9) (filtered for the delivery of physical products) (in cooperation with Hummel (2019))



10.4 DSR Project 2: Laboratory Experiment Results on Dashboard Comparison

A repeated measures ANOVA tests for statistical significance of the differences between the dashboards and compares the comprehension for the metrics and the summary dashboard against each other to determine dashboards which are less comprehensible. For the validity of the experiment approach, the comparability of the questions needs to be tested to ensure that observed differences in the comprehension are not caused by different levels of difficulty in the questions. Thus, the questions are compared according to their perceived complexity, required thinking and problem-solving skills, and regarding the degree to which the questions were perceived as challenging by the subjects.

10.4.1 Results

10.4.1.1 Description

The size dashboard was discovered as the least effective dashboard. The dashboard represents the process landscape visually in an interactive tree diagram with the different levels of the process hierarchy. The nodes of the tree diagram contain information on parent and child processes. Additional semi-circle diagrams below the tree structure display the value of the process size metrics for the selected BP in the tree. Although the tree structure enables users to achieve a high comprehension in terms of effectiveness, further improvements of KeyPro might thus concentrate on a reduction of the time required to retrieve information on process size. For example, further development might concentrate on reducing the cognitive overload of users.

Figure 93 - Least efficient and relatively efficient dashboard: process size

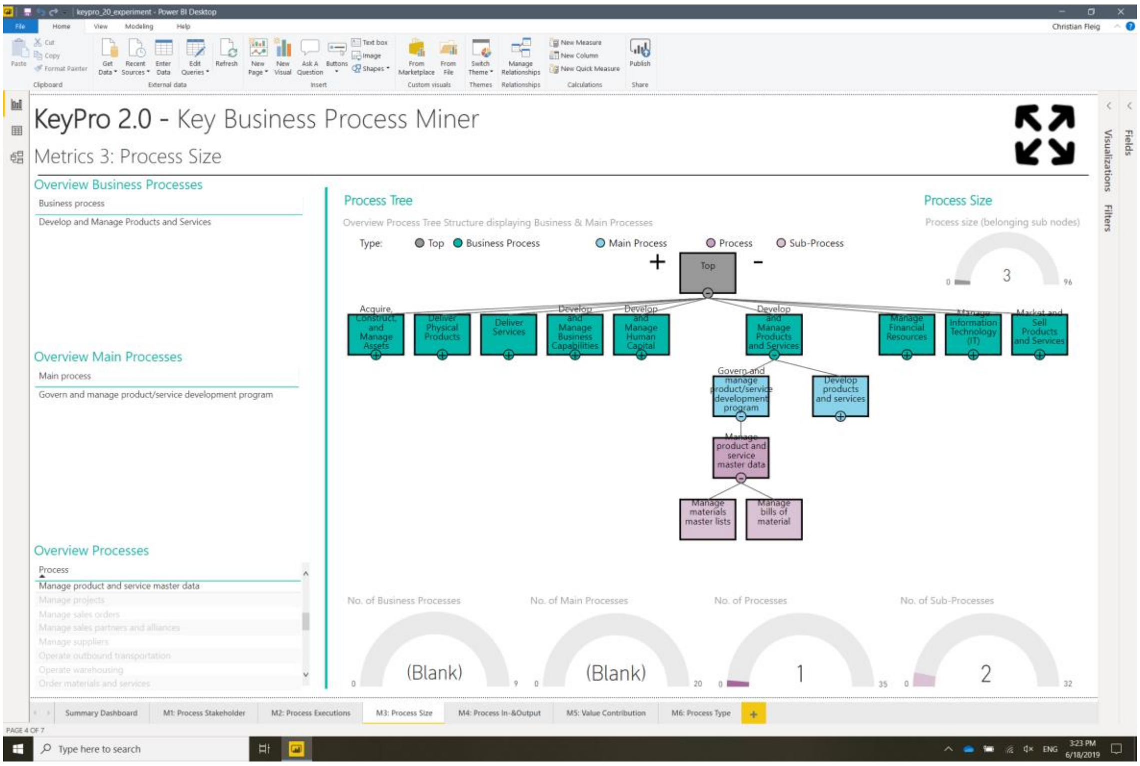
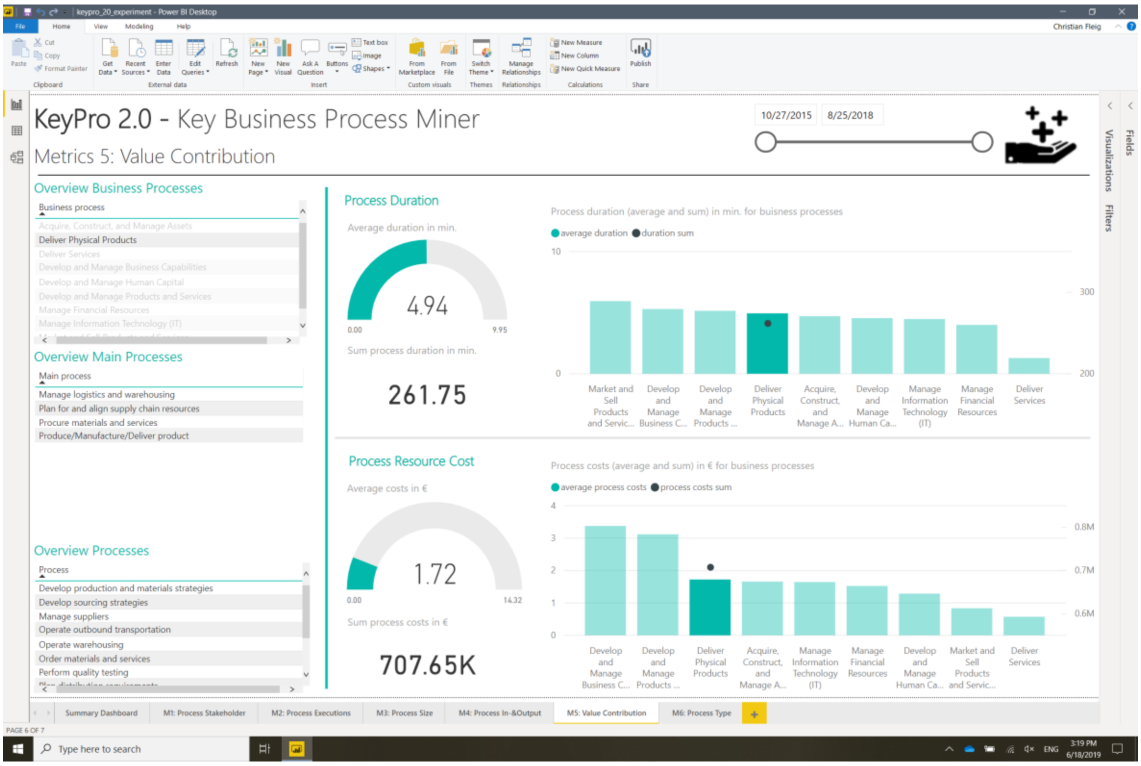


Figure 94 - Least effective dashboard: value creation



A potential reason for the comparably low performance of the value creation dashboard might be an overload by the two bar charts which contain the average and the sum of process costs or process duration at the same time (Yigitbasioglu and Velcu, 2012). Thus, a future design cycle might focus on the improvement of the effectiveness of the value creation dashboard.

10.4.1.2 Assumptions Testing and Test Selection

The assumptions testing conducts Shapiro-Wilk tests for normality, skewness/kurtosis tests, and Levene tests for homogeneity of variances. As revealed in table 62, data on effectiveness and efficiency in most cases does not satisfy the assumption of normal distributions.

Table 62 Overview over assumptions tests

	Shapiro-Wilk				Skewness & Kurtosis		Hypothesis of Normality
	W'	V'	z	Prob > z	Pr (Skewness)	Pr (Kurtosis)	
Effectiveness							
Total	0.98171	0.581	-1.121	0.86887	0.9451	0.6309	Supported
Metric 1: Stakeholders	0.90067	3.157	2.377	0.00872	0.0388	0.6230	Not supported
Metric 2: Executions	0.84098	5.054	3.350	0.00040	0.0012	0.4068	Not supported
Metric 3: Size	0.88712	3.588	2.642	0.00413	0.0000	0.0000	Not supported
Metric 4: Inputs & Outputs	0.68082	10.145	4.791	0.00000	0.0000	0.0107	Not supported
Metric 5: Value Creation	0.92157	2.493	1.889	0.02947	0.3245	0.5064	Not supported
Metric 6: Primacy	0.94598	1.717	1.118	0.13181	0.0356	0.0129	Supported
Summary Dashboard	0.87264	4.048	2.891	0.00192	0.0351	0.9126	Not supported
Efficiency							
Total	0.95536	1.419	0.723	0.23473	0.1368	0.9563	Supported
Metric 1: Stakeholders	0.95776	1.343	0.609	0.27119	0.1514	0.7724	Supported
Metric 2: Executions	0.85682	4.551	3.133	0.00086	0.0107	0.3874	Not supported
Metric 3: Size	0.86453	4.306	3.019	0.00127	0.0009	0.0091	Not supported
Metric 4: Inputs & Outputs	0.88576	3.631	2.666	0.00383	0.0035	0.0322	Not supported
Metric 5: Value Creation	0.92664	2.332	1.750	0.04002	0.0454	0.6188	Not supported
Metric 6: Primacy	0.85868	4.492	3.106	0.00095	0.0036	0.1158	Not supported

	Shapiro-Wilk				Skewness & Kurtosis		Hypothesis of Normality
	W’	V’	z	Prob > z	Pr (Skewness)	Pr (Kurtosis)	
Summary Dashboard	0.93681	2.008	1.442	0.07465	0.0465	0.4501	Supported
Relative Efficiency							
Total	0.95614	1.394	0.687	0.24598	0.4070	0.2623	Supported
Metric 1: Stakeholders	0.93259	2.143	1.576	0.05754	0.1793	0.3398	Supported
Metric 2: Executions	0.96336	1.165	0.315	0.37632	0.4206	0.4426	Supported
Metric 3: Size	0.97052	0.937	-0.135	0.55352	0.1635	0.7830	Supported
Metric 4: Inputs & Outputs	0.98198	0.573	-1.153	0.87552	0.8973	0.4817	Supported
Metric 5: Value Creation	0.80498	6.199	3.772	0.00008	0.0007	0.0318	Not supported
Metric 6: Primacy	0.93114	2.189	1.620	0.05264	0.0337	0.4075	Supported
Summary Dashboard	0.89023	3.489	2.584	0.00488	0.0013	0.0034	Not supported

The assumption of sphericity (the variances of the differences in all possible combinations of the related groups are equal) is tested in tables 63, 64, and 65 in Levene tests. As revealed by Levene tests, data for effectiveness, efficiency, and relative efficiency does not support the assumption of variance homogeneity.

Table 63 – Assumptions tests for sphericity (Levene tests) (effectiveness)

	Stk.	Exec.	Size	In- & Outputs	Val. Contr.	Primacy	Sum. Dash.
Stakeholders	-	0.0025	0.0000	0.0001	0.3690	0.0191	0.7247
Exec.	-	-	0.0133	0.3860	0.0296	0.4686	0.0070
Size	-	-	-	0.1011	0.0000	0.0016	0.0000
In- & Outputs	-	-	-	-	0.0027	0.1134	0.0005
Val. Contr.	-	-	-	-	-	0.1414	0.5839
Primacy	-	-	-	-	-	-	0.0450
Sum. Dash.	-	-	-	-	-	-	-

Table 64 – Assumptions tests for sphericity (Levene tests) (efficiency)

	Stk.	Exec.	Size	In- & Outputs	Val. Contr.	Primacy	Sum. Dash.
Stakeholders	-	0.0973	0.0002	0.3750	0.3022	0.0004	0.6719
Exec.	-	-	0.0249	0.4350	0.5250	0.0455	0.2143
Size	-	-	-	0.0029	0.0044	0.8003	0.0007
In- & Outputs	-	-	-	-	0.8842	0.0061	0.6418
Val. Contr.	-	-	-	-	-	0.0091	0.5416
Primacy	-	-	-	-	-	-	0.0015
Sum. Dash.	-	-	-	-	-	-	-

Table 65 – Assumptions tests for sphericity (Levene tests) (relative efficiency)

	Stk.	Exec.	Size	In- & Outputs	Val. Contr.	Primacy	Sum. Dash.
Stakeholders	-	0.8222	0.0087	0.0002	0.0269	0.7791	0.5731
Exec.	-	-	0.0158	0.0003	0.0152	0.6136	0.7345
Size	-	-	-	0.2098	0.0000	0.0039	0.0368
In- & Outputs	-	-	-	-	0.0000	0.0001	0.0011
Val. Contr.	-	-	-	-	-	0.0520	0.0060
Primacy	-	-	-	-	-	-	0.3993
Sum. Dash.	-	-	-	-	-	-	-

10.4.1.3 Repeated Measures One-Way ANOVA with Correction Factors

10.4.1.3.1 Effectiveness

Table 66 reports results for effectiveness from the repeated measures one-way ANOVA with correction factors. Each of the 30 participants received all seven dashboards. Thus, the number of observations is 210. The adjusted R-squared is 15.73%. After application of the correction factors, p-values for effectiveness indicate significant differences in the number of correctly answered questions between the dashboards and metrics at $p = 0.0001$ *** (Huynh-Feldt), $p = 0.0002$ *** (Greenhouse-Geisser), and $p = 0.0214$ ** (Box's

Conservative). This finding provides evidence that the dashboards of the artifact differ in terms of their effectiveness.

Table 66 – ANOVA results for effectiveness

<table>
<tr><th colspan="6">Repeated Measures One-Way ANOVA</th></tr>
<tr><td colspan="6">Number of obs = 210
Root MSE = .51438
R-squared = 0.2985
Adj. R-squared = 0.1573
Partial η² = 0.14309557
Effect size f = 0.4086457 (determined from partial η² in G*Power (University of Duesseldorf, 2019))
Actual power at sample size 30 = 0.9975793
Required sample size = 19</td></tr>
<tr><th>Source</th><th>Partial SS</th><th>df</th><th>MS</th><th>F</th><th>Prob > F</th></tr>
<tr><td>Model</td><td>19.5857143</td><td>35</td><td>.559591837</td><td>2.11</td><td>0.0008</td></tr>
<tr><td>Subject ID</td><td>10.1952381</td><td>29</td><td>.351559934</td><td>1.33</td><td>0.1357</td></tr>
<tr><td>Dashboard</td><td>9.39047619</td><td>6</td><td>1.56507937</td><td>5.92</td><td>0.0000</td></tr>
<tr><td>Residual</td><td>46.0380952</td><td>174</td><td>.264586754</td><td colspan="2" rowspan="2"></td></tr>
<tr><td>Total</td><td>65.6238095</td><td>209</td><td>.313989519</td></tr>
</table>

<table>
<tr><th colspan="2">Correction Factors to Account for Violation of Sphericity</th></tr>
<tr><td>Between-subjects error term: Subject ID
Levels: 30 (29 df)
Lowest b.s.e. variable: Subject ID
Repeated variable: dashboard</td><td>Huynh-Feldt epsilon: 0.8050
Greenhouse-Geisser epsilon: 0.6798
Box's conservative epsilon: 0.1667</td></tr>
</table>

<table>
<tr><th colspan="3"></th><th colspan="4">Prob > F</th></tr>
<tr><th>Source</th><th>df</th><th>F</th><th>Regular</th><th>Huynh-Feldt</th><th>Greenhouse-Geisser</th><th>Box's Conservative</th></tr>
<tr><td>Dashboard</td><td>6</td><td>5.92</td><td>0.0000 ***</td><td>0.0001 ***</td><td>0.0002 ***</td><td>0.0214 **</td></tr>
<tr><td>Residual</td><td>174</td><td colspan="5"></td></tr>
</table>

10.4.1.3.2 Efficiency

Table 67 likewise reveals a strongly significant difference between the dashboards in terms of efficiency with all corrections.

Table 67 – ANOVA results for efficiency

Repeated Measures One-Way ANOVA
Number of obs = 210 Root MSE = 107.073 R-squared = 0.4308 Adj. R-squared = 0.3162 Partial η² = 0.14413639 Effect size f = 0.4103784 (determined from partial η² in G*Power (University of Duesseldorf, 2019)) Actual power at sample size 30 = 0.9977499 Required sample size = 19

Source	Partial SS	df	MS	F	Prob > F
Model	1509523.48	35	43129.2423	3.76	0.0000
Subject ID	1004414.99	29	34634.9996	3.02	0.0000
Dashboard	505108.491	6	84184.7486	7.34	0.0000
Residual	1994855.25	174	11464.6854		
Total	3504378.74	209	16767.3624		

Correction Factors to Account for Violation of Sphericity	
Between-subjects error term: Subject ID Levels: 30 (29 df) Lowest b.s.e. variable: Subject ID Repeated variable: dashboard	Huynh-Feldt epsilon: 0.7297 Greenhouse-Geisser epsilon: 0.6252 Box's conservative epsilon: 0.1667

			Prob > F			
Source	**df**	**F**	**Regular**	**Huynh-Feldt**	**Greenhouse-Geisser**	**Box's Conservative**
Dashboard	6	7.34	0.0000	0.0000	0.0000	0.0112
Residual	174					

10.4.1.3.3 Relative Efficiency

In the ANOVA tests for relative efficiency, table 68reveals significant differences at the 5%-level, which are, however, weaker than in effectiveness and efficiency. The Box’s Conservative correction yields insignificant results.

Table 68 – ANOVA results for relative efficiency

Repeated Measures One-Way ANOVA					
Number of obs = 210 Root MSE = .006985 R-squared = 0.3561 Adj. R-squared = 0.2266 Partial η² = 0.06872227 Effect size f = 0.2716496 (determined from partial η² in G*Power (University of Duesseldorf, 2019)) Actual power at sample size 30 = 0.8414943 Required sample size = 42					
Source	**Partial SS**	**df**	**MS**	**F**	**Prob > F**
Model	.004694605	35	.000134132	2.75	0.0000
Subject ID	.003788629	29	.000130642	2.68	0.0000
Dashboard	.000905976	6	.000150996	3.10	0.0066
Residual	.008488545	174	.000048785		
Total	.01318315	209	.000063077		

Correction Factors to Account for Violation of Sphericity	
Between-subjects error term: Subject ID Levels: 30 (29 df) Lowest b.s.e. variable: Subject ID Repeated variable: dashboard	Huynh-Feldt epsilon: 0.7221 Greenhouse-Geisser epsilon: 0.6196 Box's conservative epsilon: 0.1667

			Prob > F			
Source	**df**	**F**	**Regular**	**Huynh-Feldt**	**Greenhouse-Geisser**	**Box's Conservative**
Dashboard	6	3.10	0.0066	0.0155	0.0213	0.0891
Residual	174					

10.4.1.4 Friedman's ANOVA Results

The finding on effectiveness in Friedman's ANOVA contrasts with the finding from the corrected ANOVA above.

Table 69 – Friedman's ANOVA results

	Effectiveness	Efficiency	Relative Efficiency
Friedman	20.1847	82.7645	72.7645
Kendall	0.0870	0.3567	0.3136
p-value	0.8871	0.0000	0.0000

10.4.2 Post-Hoc Tests

To locate and compare the mean values of the dashboards against each other, a series of post-hoc tests including Bonferroni, Sidak, Scheffe, Tukey, Student-Newman-Keuls (SNK) and Duncan's method are conducted in table 70. P-values smaller or equal to 0.05 are highlighted. However, due to the different contents of the importance metrics, dashboards could not be created identically with the same visual elements. Thus, the analysis does not allow to conclude whether the differences in comprehension are the result of the comprehensibility of the dashboard design or the importance metrics.

Table 70 – Post-hoc test results for pairwise comparison of the individual KeyPro dashboards on effectiveness

		P > | t |					
Dashboard	**Contrast**	**Bonferroni**	**Sidak**	**Scheffe**	**Tukey**	**SNK**	**Duncan**
Executions vs. Stakeholders	0.366667	0.1340	0.1260	0.2730	0.0900	**0.0320**	**0.0110**
Size vs. Stakeholders	0.5	**0.0050**	**0.0050**	**0.0320**	**0.0040**	**0.0030**	**0.0010**
In- & Outputs vs. Stakeholders	0.433333	**0.0280**	**0.0280**	0.1070	**0.0220**	**0.0110**	**0.0030**
Value Creation vs. Stakeholders	-0.06667	1.0000	1.0000	1.0000	0.9990	0.6160	0.6160
Primacy vs. Stakeholders	0.266667	0.9700	0.6300	0.6720	0.4130	0.1130	0.0580
Summary vs. Stakeholders	0.033333	1.0000	1.0000	1.0000	1.0000	0.8020	0.8020
Size vs. Executions	0.133333	1.0000	1.0000	0.9850	0.9530	0.5750	0.3480
In- & Outputs vs. Executions	0.066667	1.0000	1.0000	1.0000	0.9990	0.6160	0.6160
Value Creation vs. Executions	-0.43333	**0.0280**	**0.0280**	0.1070	**0.0220**	**0.0110**	**0.0030**
Primacy vs. Executions	-0.1	1.0000	1.0000	0.9970	0.9890	0.4530	0.4530
Summary vs. Executions	-0.33333	0.2730	0.2400	0.3950	0.1620	0.0350	0.0170
In- & Outputs vs. Size	-0.06667	1.0000	1.0000	1.0000	0.9990	0.6160	0.6160
Value Creation vs. Size	-0.56667	**0.0010**	**0.0010**	**0.0080**	**0.0010**	**0.0010**	**0.0000**
Primacy vs. Size	-0.23333	1.0000	0.8290	0.7970	0.5790	0.2980	0.1110
Summary vs. Size	-0.46667	**0.0120**	**0.0120**	0.0610	**0.0100**	**0.0050**	**0.0010**
Value Creation vs. In- & Outputs	-0.5	**0.0050**	**0.0050**	**0.0320**	**0.0040**	**0.0030**	**0.0010**
Primacy vs. In- & Outputs	-0.16667	1.0000	0.9930	0.9540	0.8710	0.4230	0.2400
Summary vs. In- & Outputs	-0.4	0.0630	0.0610	0.1770	**0.0460**	**0.0160**	**0.0050**
Primacy vs. Value Creation	0.333333	0.2730	0.2400	0.3950	0.1620	0.0620	**0.0210**

		P > | t |					
Dashboard	**Contrast**	**Bonferroni**	**Sidak**	**Scheffe**	**Tukey**	**SNK**	**Duncan**
Summary vs. Value Creation	0.1	1.0000	1.0000	0.9970	0.9890	0.7320	0.4830
Summary vs. Primacy	-0.23333	1.0000	0.8290	0.7970	0.5790	0.0810	0.0810

In particular, the size dashboard including the tree structure of the process hierarchy and the five semi-circle diagrams is significantly better comprehensible than the dashboard on stakeholders and the summary dashboard, which contains many different types of dashboard elements and a word cloud, which might be confusing for users. Likewise, the metrics on inputs- & outputs with a higher number of "standard" elements such as bar charts and text elements are better comprehensible than stakeholders. Therefore, a future development cycle concentrates on replacing the dashboard elements with the diagram types used in the size and inputs and outputs metric. Besides, value creation is less effective compared to executions, size, and in- and outputs, which might be due to the mixture of two different information (average and sums) within diagrams.

Table 71 – Post-hoc test results for pairwise comparison of the individual KeyPro dashboards on efficiency

		P > | t |					
Dashboard	**Contrast**	**Bonfer-roni**	**Sidak**	**Scheffe**	**Tukey**	**SNK**	**Dun-can**
Executions vs. Stakeholders	17.4093	1.0000	1.0000	0.9990	0.9960	0.5300	0.5300
Size vs. Stakeholders	142.9640	**0.0000**	**0.0000**	**0.0000**	**0.0000**	**0.0000**	**0.0000**
In- & Outputs vs. Stakeholders	77.0167	0.1250	0.1170	0.2630	0.0840	**0.0460**	**0.0120**
Value Creation vs. Stakeholders	-2.0340	1.0000	1.0000	1.0000	1.0000	0.9410	0.9410
Primacy vs. Stakeholders	74.3640	0.1650	0.1520	0.3050	0.1070	**0.0390**	**0.0130**
Summary vs. Stakeholders	24.7860	1.0000	1.0000	0.9920	0.9730	0.6430	0.4030
Size vs. Executions	125.5547	**0.0000**	**0.0000**	**0.0030**	**0.0000**	**0.0000**	**0.0000**
In- & Outputs vs. Executions	59.6073	0.6810	0.5000	0.5910	0.3250	0.1400	0.0490
Value Creation vs. Executions	-19.4433	1.0000	1.0000	0.9980	0.9920	0.7620	0.5120
Primacy vs. Executions	56.9547	0.8580	0.5840	0.6440	0.3810	0.1010	0.0520
Summary vs. Executions	7.3767	1.0000	1.0000	1.0000	1.0000	0.7900	0.7900
In- & Outputs vs. Size	-65.9473	0.3810	0.3190	0.4620	0.2110	**0.0180**	**0.0180**
Value Creation vs. Size	-144.9980	**0.0000**	**0.0000**	**0.0000**	**0.0000**	**0.0000**	**0.0000**

		P > | t |					
Dashboard	**Contrast**	**Bonfer-roni**	**Sidak**	**Scheffe**	**Tukey**	**SNK**	**Dun-can**
Primacy vs. Size	-68.6000	0.2950	0.2570	0.4100	0.1730	**0.0370**	**0.0190**
Summary vs. Size	-118.1780	**0.0010**	**0.0010**	**0.0070**	**0.0010**	**0.0000**	**0.0000**
Value Creation vs. In- & Outputs	-79.0507	0.1000	0.0950	0.2320	0.0700	0.0530	**0.0110**
Primacy vs. In- & Outputs	-2.6527	1.0000	1.0000	1.0000	1.0000	0.9240	0.9240
Summary vs. In- & Outputs	-52.2307	1.0000	0.7300	0.7340	0.4900	0.1450	0.0750
Primacy vs. Value Creation	76.3980	0.1330	0.1250	0.2720	0.0890	**0.0490**	**0.0130**
Summary vs. Value Creation	26.8200	1.0000	1.0000	0.9870	0.9600	0.7670	0.3840
Summary vs. Primacy	-49.5780	1.0000	0.8040	0.7800	0.5540	0.0750	0.0750

In terms of efficiency, the size dashboard is however less comprehensible than the stakeholders dashboard. While subjects respond to the comprehension questions with higher effectiveness, subjects require significantly longer (142.96 seconds when compared to stakeholders, 125.55 seconds against executions, and 145.00 seconds against value creation). Thus, future improvement on the size metrics dashboard needs to concentrate on achieving higher efficiency.

Table 72 – Post-hoc test results for pairwise comparison of the individual KeyPro dashboards on relative efficiency

		P > | t |					
Dashboard	**Contrast**	**Bonferroni**	**Sidak**	**Scheffe**	**Tukey**	**SNK**	**Duncan**
Executions vs. Stakeholders	0.0016	1.0000	1.0000	0.9930	0.9760	0.3850	0.3850
Size vs. Stakeholders	-0.0042	0.4400	0.3590	0.4930	0.2360	0.1410	0.0370
In- & Outputs vs. Stakeholders	-0.0032	1.0000	0.8060	0.7820	0.5570	0.2820	0.1040
Value Creation vs. Stakeholders	0.0016	1.0000	1.0000	0.9920	0.9720	0.6420	0.4020
Primacy vs. Stakeholders	-0.0010	1.0000	1.0000	0.9990	0.9980	0.5750	0.5750
Summary vs. Stakeholders	-0.0017	1.0000	1.0000	0.9890	0.9630	0.6080	0.3740
Size vs. Executions	-0.0058	**0.0340**	**0.0340**	0.1220	**0.0270**	**0.0200**	**0.0040**
In- & Outputs vs. Executions	-0.0048	0.1790	0.1650	0.3190	0.1150	0.0640	**0.0160**
Value Creation vs. Executions	0.0001	1.0000	1.0000	1.0000	1.0000	0.9780	0.9780
Primacy vs. Executions	-0.0026	1.0000	0.9700	0.9140	0.7830	0.3260	0.1790
Summary vs. Executions	-0.0033	1.0000	0.7830	0.7670	0.5350	0.2660	0.0980

		P > | t |					
Dashboard	**Contrast**	**Bonferroni**	**Sidak**	**Scheffe**	**Tukey**	**SNK**	**Duncan**
In- & Outputs vs. Size	0.0010	1.0000	1.0000	1.0000	0.9980	0.5900	0.5900
Value Creation vs. Size	0.0058	**0.0310**	**0.0310**	0.1150	**0.0250**	**0.0250**	**0.0040**
Primacy vs. Size	0.0032	1.0000	0.8220	0.7920	0.5720	0.2930	0.1090
Summary vs. Size	0.0025	1.0000	0.9800	0.9280	0.8130	0.3550	0.1970
Value Creation vs. In- & Outputs	0.0048	0.1650	0.1530	0.3060	0.1070	0.0830	0.0170
Primacy vs. In- & Outputs	0.0022	1.0000	0.9950	0.9580	0.8820	0.4380	0.2510
Summary vs. In- & Outputs	0.0015	1.0000	1.0000	0.9940	0.9810	0.4030	0.4030
Primacy vs. Value Creation	-0.0026	1.0000	0.9640	0.9060	0.7680	0.4640	0.1870
Summary vs. Value Creation	-0.0033	1.0000	0.7610	0.7530	0.5160	0.3480	0.1010
Summary vs. Primacy	-0.0007	1.0000	1.0000	1.0000	1.0000	0.6970	0.6970

Finally, post-hoc tests on relative efficiency reveal only two significant differences. First, the size dashboard is relatively less efficient than executions, which is the result of the comparably low efficiency (the divisor in relative efficiency). Second, the value creation dashboard is relative more efficient than size, with the same line of argumentation.

10.4.3 Validity Tests on Question Comparability

In sum, these findings are interpreted as support for the initially stated hypothesis that there are differences in the comprehension of the individual dashboards. To ensure that the observed differences in the comprehension of the dashboards are not caused by differences in the difficulty of the survey questions, the mean values of the assessment questions for task complexity, required thinking and task challenge are compared in a Kruskal-Wallis test. Table 73 reveals insignificant probabilities for all three variables, which implies that there are no significant differences between comprehension questions.

Table 73 – Results from Kruskal-Wallis tests to compare comprehension questions

	Complexity		Required Thinking		Task Challenge	
Dashboard / Metric	**Obs.**	**Rank Sum**	**Obs.**	**Rank Sum**	**Obs.**	**Rank Sum**
Stakeholders	30	2854.50	30	2846.50	30	2873.00
Executions	30	2965.50	30	2939.50	30	3050.50
Size	30	3350.50	30	3387.50	30	3499.00

	Complexity		Required Thinking		Task Challenge	
Dashboard / Metric	**Obs.**	**Rank Sum**	**Obs.**	**Rank Sum**	**Obs.**	**Rank Sum**
In- & Outputs	30	3799.00	30	3811.50	30	3781.50
Value Contr.	30	3008.00	30	3030.50	30	2884.00
Primacy	30	3297.50	30	3092.50	30	3120.50
Summary	30	2880.00	30	3047.00	30	2946.50
	chi-squared = 6.283 with 6 d.f. **probability = 0.3922**		chi-squared = 5.931 with 6 d.f. **probability = 0.4309**		chi-squared = 6.488 with 6 d.f. **probability = 0.3708**	

10.5 DSR Project 3: Additional Results Tables

10.5.1 Effectiveness

Table 74: Effectiveness: Wilcoxon Signed-Rank post-hoc tests: dynamic vs. table

Dynamic vs. Table			
Sign	**Observations**	**Sum ranks**	**Expected**
Positive	27	2848	4199.5
Negative	47	5551	4199.5
Zero	76	2926	2926
Total	**150**	**11325**	**11325**
unadjusted variance: 284068.75 adjustment for ties: -1856.88 adjustment for zeros:-37306.50 adjusted variance: 244905.38 Ho: **Dynamic = Table** z = -2.731 **Prob > |z| = 0.0063**			

Table 75: Effectiveness: Wilcoxon Signed-Rank post-hoc tests: dynamic vs. static

Dynamic vs. Static			
Sign	**Observations**	**Sum ranks**	**Expected**
Positive	31	3143	4489.5
Negative	51	5836	4489.5
Zero	68	2346	2346
Total	**150**	**11325**	**11325**

unadjusted variance: 284068.75
adjustment for ties: -4310.38
adjustment for zeros:-26783.50
adjusted variance: 252974.88
Ho: **Dynamic = Static**
z = -2.677
Prob > |z| = 0.0074

Table 76: Effectiveness: Wilcoxon Signed-Rank post-hoc tests: dynamic vs. guided

Dynamic vs. Guided			
Sign	**Observations**	**Sum ranks**	**Expected**
Positive	17	1796.5	4348.5
Negative	61	6900.5	4348.5
Zero	72	2628	2628
Total	**150**	**11325**	**11325**

unadjusted variance: 284068.75
adjustment for ties: -1993.00
adjustment for zeros:-31755.00
adjusted variance: 250320.75
Ho: **Dynamic = Guided**
z = -5.101
Prob > |z| = 0.0000

Table 77: Effectiveness: Wilcoxon Signed-Rank post-hoc tests: static vs. table

Static vs. Table			
Sign	**Observations**	**Sum ranks**	**Expected**
Positive	32	3742.5	4237.5
Negative	43	4732.5	4237.5
Zero	75	2850	2850
Total	**150**	**11325**	**11325**

unadjusted variance: 284068.75
adjustment for ties: -3338.75
adjustment for zeros:-35862.50
adjusted variance: 244867.50
Ho: **Static = Table**
z = -1.000
Prob > |z| = 0.3172

Table 78: Effectiveness: Wilcoxon Signed-Rank post-hoc tests: static vs. guided

Static vs. Guided			
Sign	**Observations**	**Sum ranks**	**Expected**
Positive	23	2669	4161
Negative	50	5653	4161
Zero	77	3003	3003
Total	**150**	**11325**	**11325**
unadjusted variance:284068.75 adjustment for ties: -3535.50 adjustment for zeros: -38788.75 adjusted variance: 241744.50 Ho: **Static = Guided** z = -3.035 **Prob > |z| = 0.0024**			

Table 79: Effectiveness: Wilcoxon Signed-Rank post-hoc tests: table vs. guided

Table vs. Guided			
Sign	**Observations**	**Sum ranks**	**Expected**
Positive	24	2804	3660
Negative	37	4516	3660
Zero	89	4005	4005
Total	**150**	**11325**	**11325**
unadjusted variance: 284068.75 adjustment for ties: -1116.38 adjustment for zeros:-59741.25 adjusted variance: 223211.13 Ho: **Table = Guided** z = -1.812 **Prob > |z| = 0.0700**			

10.5.2 Efficiency

Table 80: Efficiency: Wilcoxon Signed-Rank post-hoc tests: dynamic vs. static

Dynamic vs. Static			
Sign	**Observations**	**Sum ranks**	**Expected**
Positive	99	7488	5662.5
Negative	51	3837	5662.5
Zero	0	0	0
Total	**150**	**11325**	**11325**
unadjusted variance: 284068.75 adjustment for ties: 0.00 adjustment for zeros: 0.00 adjusted variance: 284068.75 Ho: **Dynamic = Static** z = 3.425 **Prob > |z| = 0.0006**			

Table 81: Efficiency: Wilcoxon Signed-Rank post-hoc tests: dynamic vs. table

Dynamic vs. Table			
Sign	**Observations**	**Sum ranks**	**Expected**
Positive	49	3158.5	5662.5
Negative	101	8166.5	5662.5
Zero	0	0	0
Total	**150**	**11325**	**11325**

unadjusted variance: 284068.75
adjustment for ties: -0.13
adjustment for zeros:0.00
adjusted variance: 284068.63
Ho: **Dynamic = Table**
z = -4.698
Prob > |z| = 0.0000

Table 82: Efficiency: Wilcoxon Signed-Rank post-hoc tests: dynamic vs. guided

Dynamic vs. Guided			
Sign	**Observations**	**Sum ranks**	**Expected**
Positive	74	5306	5662.5
Negative	76	6019	5662.5
Zero	0	0	0
Total	**150**	**11325**	**11325**

unadjusted variance: 284068.75
adjustment for ties: 0.00
adjustment for zeros:0.00
adjusted variance: 284068.75
Ho: **Dynamic = Guided**
z = -0.669
Prob > |z| = 0.5036

Table 83: Efficiency: Wilcoxon Signed-Rank post-hoc tests: static vs. table

Static vs. Table			
Sign	**Observations**	**Sum ranks**	**Expected**
Positive	32	1798	5662.5
Negative	118	9527	5662.5
Zero	0	0	0
Total	**150**	**11325**	**11325**

unadjusted variance: 284068.75
adjustment for ties: 0.00
adjustment for zeros:0.00
adjusted variance: 284068.75
Ho: **Static = Table**
z = -7.251
Prob > |z| = 0.0000

Table 84: Efficiency: Wilcoxon Signed-Rank post-hoc tests: static vs. guided

Static vs. Guided			
Sign	**Observations**	**Sum ranks**	**Expected**
Positive	48	3264	5662.5
Negative	102	8061	5662.5
Zero	0	0	0
Total	**150**	**11325**	**11325**
unadjusted variance: 284068.75 adjustment for ties: 0.00 adjustment for zeros:0.00 adjusted variance: 284068.75 Ho: **Static = Guided** z = -4.500 **Prob > |z| = 0.0000**			

Table 85: Efficiency: Wilcoxon Signed-Rank post-hoc tests: table vs. guided

Table vs. Guided			
Sign	**Observations**	**Sum ranks**	**Expected**
Positive	92	7438	5662.5
Negative	58	3887	5662.5
Zero	0	0	0
Total	**150**	**11325**	**11325**
unadjusted variance: 284068.75 adjustment for ties: 0.00 adjustment for zeros: 0.00 adjusted variance: 284068.75 Ho: **Table = Guided** z = 3.331 **Prob > |z| = 0.0009**			

10.5.3 Relative Efficiency

Table 86: Relative efficiency: Wilcoxon Signed-Rank post-hoc tests: table vs. static

Table vs. Static			
Sign	**Observations**	**Sum ranks**	**Expected**
Positive	33	1464	5662.5
Negative	117	9861	5662.5
Zero	0	0	0
Total	**150**	**11325**	**11325**
unadjusted variance: 284068.75 adjustment for ties: 0.00 adjustment for zeros: 0.00 adjusted variance: 284068.75 Ho: **Table = Static** z = -7.877 **Prob > |z| = 0.0000**			

Table 87: Relative efficiency: Wilcoxon Signed-Rank post-hoc tests: table vs. dynamic

Table vs. Dynamic			
Sign	**Observations**	**Sum ranks**	**Expected**
Positive	57	4024	5662.5
Negative	93	7301	5662.5
Zero	0	0	0
Total	**150**	**11325**	**11325**

unadjusted variance: 284068.75
adjustment for ties: 0.00
adjustment for zeros: 0.00
adjusted variance: 284068.75
Ho: **Table = Dynamic**
z = -3.074
Prob > |z| = 0.0021

Table 88: Relative efficiency: Wilcoxon Signed-Rank post-hoc tests: table vs. guided

Table vs. Guided			
Sign	**Observations**	**Sum ranks**	**Expected**
Positive	48	3019	5662.5
Negative	102	8306	5662.5
Zero	0	0	0
Total	**150**	**11325**	**11325**

unadjusted variance: 284068.75
adjustment for ties: 0.00
adjustment for zeros: 0.00
adjusted variance: 284068.75
Ho: **Table = Guided**
z = -4.960
Prob > |z| = 0.0000

Table 89: Relative efficiency: Wilcoxon Signed-Rank post-hoc tests: static vs. dynamic

Static vs. Dynamic			
Sign	**Observations**	**Sum ranks**	**Expected**
Positive	99	8696	5662.5
Negative	51	2629	5662.5
Zero	0	0	0
Total	**150**	**11325**	**11325**

unadjusted variance: 284068.75
adjustment for ties: 0.00
adjustment for zeros: 0.00
adjusted variance: 284068.75
Ho: **Static = Dynamic**
z = 5.692
Prob > |z| = 0.0000

Table 90: Relative efficiency: Wilcoxon Signed-Rank post-hoc tests: static vs. guided

Static vs. Guided			
Sign	**Observations**	**Sum ranks**	**Expected**
Positive	96	7870	5662.5
Negative	54	3455	5662.5
Zero	0	0	0
Total	**150**	**11325**	**11325**
unadjusted variance: 284068.75 adjustment for ties: 0.00 adjustment for zeros: 0.00 adjusted variance: 284068.75 Ho: **Static = Guided** z = 4.142 **Prob > |z| = 0.0000**			

Table 91: Relative efficiency: Wilcoxon Signed-Rank post-hoc tests: dynamic vs. guided

Dynamic vs. Guided			
Sign	**Observations**	**Sum ranks**	**Expected**
Positive	60	4509	5662.5
Negative	90	6816	5662.5
Zero	0	0	0
Total	**150**	**11325**	**11325**
unadjusted variance: 284068.75 adjustment for ties: 0.00 adjustment for zeros: 0.00 adjusted variance: 284068.75 Ho: **Dynamic = Guided** z = -2.164 **Prob > |z| = 0.0304**			

11 List of Publications

11.1 Conference Contributions Included in This Thesis

- *Fleig, C., Augenstein, D., Maedche, A.*, „Designing a Process Mining-Enabled Decision Support System for Business Process Standardization in ERP Implementation Projects”, *Proceedings of the 16th International Conference on Business Process Management 2018 (BPM Forum), Sydney, Australia*, pp.228-244, doi:10.1007/978-3-319-98651-7_14
- *Fleig, C., Augenstein, D., Maedche, A.*, „Process Mining for Business Process Standardization in ERP Implementation Projects – An SAP S/4 HANA Case Study from Manufacturing”, *Proceedings of the 16th International Conference on Business Process Management 2018 (Industry Papers), Sydney, Australia,* pp.1-8
- *Fleig, C., Augenstein, D., Maedche, A.*, „Tell Me What‘s My Business – Development of a Business Model Mining Software”, *International Conference on Advanced Information Systems Engineering 2018 (CAiSE Forum), Tallinn, Estonia,* pp. 105–113, doi: 10.1007/978-3-319-92901-9_10
- *Fleig, C., Augenstein, D., Maedche, A.*, „KeyPro – A Decision Support System for Discovering Important Business Processes in Information Systems”, *International Conference on Advanced Information Systems Engineering 2018 (CAiSE Forum), Tallinn, Estonia,* pp.90-104, doi: 10.1007/978-3-319-92901-9_9
- *Fleig, C., Augenstein, D., Maedche, A.* „A Process Mining-Enabled Decision Support System for Data-Driven Business Process Standardization in ERP Implementation Projects”, *KIT Scientific Working Paper’, Proceedings of the KSS Research Workshop: A Selection of Talks and Presentations on Designing the Digital Transformation, Karlsruhe, Germany,* pp. 52-56, doi: 10.5445/IR/1000104369
- *Fleig, C.*, „Towards the Design of a Process Mining-Enabled Decision Support System for Business Process Transformation”, *International Conference on Advanced Information Systems Engineering (CAiSE Forum and Doctoral Consortium Papers), 2017, Essen, Germany,* pp. 170-178

11.2 Working Papers (To Be Submitted)

- *Fleig, C., Hunke, F., Maedche, A., Satzger, G., Augenstein, D.* „Design of a Business Model Mining System”, <*Journal outlet to be determined*>
- *Fleig, C., Schulz, H., Hunke, F., Maedche, A., Satzger, G.* „KeyPro – Design of a Decision Support System for Data-Driven Process Intelligence”, <*Journal outlet to be determined*>
- *Fleig, C., Beck, D.J.., Wurm, B.., Maedche, A., Mendling, J.* „KeyPro – Design of a Decision Support System for Data-Driven Process Intelligence”, *Decision Support Systems (to be confirmed)*

11.3 Co-Authored Conference Papers Included in This Thesis

- *Wurm, B.; Mendling, J.; Schmiedel, T.; Fleig, C.* „Development of a Measurement Scale for Business Process Standardization”, *Proceedings of the 26th European Conference on Information Systems 2018 (ECIS 2018) (Research in Progress), Portsmouth, United Kingdom*

- *Augenstein, D.; Fleig, C.; Dellermann, D., „*Towards value proposition mining - Exploration of design principles", *Proceedings of the International Conference on Information Systems 2018 (ICIS 2018) (Research in Progress), San Francisco, California, USA*
- *Augenstein, D., Fleig, C., Maedche, A.,* „Development of a Data-Driven Business Model Transformation Tool", *International Conference on Design Science Research (DESRIST) 2018, Chennai, India*
- *Augenstein, D.; Fleig, C.,* „ Exploring Design Principles for a Business Model Mining Tool", *Proceedings of the International Conference on Information Systems 2017 (ICIS 2017) (Research in Progress), Seoul, South Korea*

11.4 Others

- *Fleig, C.; Augenstein, D.,* „Developing a Business Model Transformation Tool", *Karlsruhe Service Summit, 2017, Karlsruhe, Germany*
- *Fleig, C.; Seeliger, A.; Knissling, A.* „Beyond Process Mining - Process Mining für Prozesstransformation und ERP-Einführungen", *IM + io Fachmagazin, 2017*
- *Fleig, C.,* „Erfolg in Digitaler Evolution – Ein ganzheitliches Strategie-Framework für Agilität und Flexibilität in Geschäftsprozessen für Digitale Transformationsprojekte", *IM + io Fachmagazin, 2018*

Affidavit

Erklärung

(gemäß §4, Abs. 4 der Promotionsordnung vom 15. August 2006)

Ich versichere wahrheitsgemäß, die Dissertation bis auf die in der Abhandlung angegebene Hilfe selbständig angefertigt, alle benutzten Hilfsmittel vollständig und genau angegeben und genau kenntlich gemacht zu haben, was aus Arbeiten anderer und aus eigenen Veröffentlichungen unverändert oder mit Abänderungen entnommen wurde.

Karlsruhe, den 05.01.2020

Christian Fleig

Eidesstattliche Versicherung

gemäß § 6 Abs. 1 Ziff. 4 der Promotionsordnung des Karlsruher Instituts für Technologie für die Fakultät für Wirtschaftswissenschaften

1. Bei der eingereichten Dissertation zu dem Thema „Design of data-driven decision support systems for business process standardization“ handelt es sich um meine eigenständig erbrachte Leistung.

2. Ich habe nur die angegebenen Quellen und Hilfsmittel benutzt und mich keiner unzulässigen Hilfe Dritter bedient. Insbesondere habe ich wörtlich oder sinngemäß aus anderen Werken übernommene Inhalte als solche kenntlich gemacht.

3. Die Arbeit oder Teile davon habe ich bislang nicht an einer Hochschule des In- oder Auslands als Bestandteil einer Prüfungs- oder Qualifikationsleistung vorgelegt.

4. Die Richtigkeit der vorstehenden Erklärungen bestätige ich.

5. Die Bedeutung der eidesstattlichen Versicherung und die strafrechtlichen Folgen einer unrichtigen oder unvollständigen eidesstattlichen Versicherung sind mir bekannt. Ich versichere an Eides statt, dass ich nach bestem Wissen die reine Wahrheit erklärt und nichts verschwiegen habe.

Karlsruhe, den 05.01.2020

Christian Fleig

Eidesstattliche Versicherung

Belehrung

Die Universitäten in Baden-Württemberg verlangen eine Eidesstattliche Versicherung über die Eigenständigkeit der erbrachten wissenschaftlichen Leistungen, um sich glaubhaft zu versichern, dass der Promovend die wissenschaftlichen Leistungen eigenständig erbracht hat.

Weil der Gesetzgeber der Eidesstattlichen Versicherung eine besondere Bedeutung beimisst und sie erhebliche Folgen haben kann, hat der Gesetzgeber die Abgabe einer falschen eidesstattlichen Versicherung unter Strafe gestellt. Bei vorsätzlicher (also wissentlicher) Abgabe einer falschen Erklärung droht eine Freiheitsstrafe bis zu drei Jahren oder eine Geldstrafe.

Eine fahrlässige Abgabe (also Abgabe, obwohl Sie hätten erkennen müssen, dass die Erklärung nicht den Tatsachen entspricht) kann eine Freiheitsstrafe bis zu einem Jahr oder eine Geldstrafe nach sich ziehen.

Die entsprechenden Strafvorschriften sind in § 156 StGB (falsche Versicherung an Eides Statt) und in § 161 StGB (fahrlässiger Falscheid, fahrlässige falsche Versicherung an Eides Statt) wiedergegeben.

§ 156 StGB: Falsche Versicherung an Eides Statt

Wer vor einer zur Abnahme einer Versicherung an Eides Statt zuständigen Behörde eine solche Versicherung falsch abgibt oder unter Berufung auf eine solche Versicherung falsch aussagt, wird mit Freiheitsstrafe bis zu drei Jahren oder mit Geldstrafe bestraft.

§ 161 StGB: Fahrlässiger Falscheid, fahrlässige falsche Versicherung an Eides Statt

Abs. 1: Wenn eine der in den § 154 bis 156 bezeichneten Handlungen aus Fahrlässigkeit begangen worden ist, so tritt Freiheitsstrafe bis zu einem Jahr oder Geldstrafe ein.

Abs. 2: Straflosigkeit tritt ein, wenn der Täter die falsche Angabe rechtzeitig berichtigt. Die Vorschriften des § 158 Abs. 2 und 3 gelten entsprechend.

Karlsruhe, den 05.01.2020

Christian Fleig