Digital processes are the backbone of an organization's digital transformation to increase its competitive advantage. Digitalization efforts have increased in recent years but target quick-paced implementation of digital technologies for short-term benefits. Core business processes usually exhibit a high digital maturity, but processes that do not directly contribute to the value stream experience less attention in an organization's digital strategy. However, these support processes do not assume a less essential role. Instead, their daily execution enables core processes and affects an organization's productivity. For example, a quick and thorough employee onboarding minimizes mistakes and decreases the time until a new employee is self-reliant.

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Jimmy Chhor

ERGEBNISSE AUS DER PRODUKTIONSTECHNIK

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der Rheinisch-Westfälischen Technischen Hochschule Aachen
zur Erlangung des akademischen Grades eines
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Abstract

Digital processes are the backbone of an organization's digital transformation to increase its competitive advantage. Digitalization efforts have increased in recent years but target quick-paced implementation of digital technologies for short-term benefits. Core business processes usually exhibit a high digital maturity, but processes that do not directly contribute to the value stream experience less attention in an organization's digital strategy. However, these support processes do not assume a less essential role. Instead, their daily execution enables core processes and affects an organization's productivity. For example, a quick and thorough employee onboarding minimizes mistakes and decreases the time until a new employee is self-reliant.

This research addresses the identified gaps, and its approach leads to the primary research question structuring the approach to this topic: How can a systematic approach to process optimization contribute to uncovering process insights for digital business processes?

This thesis aims to develop, implement, verify, and validate a systematic and structured approach to transform non-digital to digital processes, focusing on support processes and continuous data-driven optimization. Two models account for the associated tasks. The first model addresses the gap in prioritizing processes for digitalization by expanding the scope of existing process maturity models that satisfy most formulated requirements. The second model is a cyclic procedure model for process optimization originating from process mining approaches and expands designated activities to include business process management aspects and considers repeated model application to handle concept drifts due to ever-changing operation conditions.

The verification and validation in two case studies prove the models' functionality and added value, further supported by feedback from a team of experts involved in developing, implementing, and testing. The research results set the foundation for future research to expand the scope of process analysis to data streams and provide proactive operational support in process execution.

Zusammenfassung

Digitale Prozesse bilden das Fundament der digitalen Transformation eines Unternehmens, um dessen Wettbewerbsfähigkeit zu steigern. Aktuelle Bestrebungen zielen trotz der Bedeutung digitaler Prozesse auf eine schnelle Implementierung digitaler Technologien, um kurzfristige Vorteile zu erzielen. Kernprozesse weisen gegenüber Prozessen, die nicht direkt zum Wertstrom beitragen, in der Regel eine hohe digitale Reife auf. Unterstützungsprozesse erfahren weniger Aufmerksamkeit in der digitalen Unternehmensstrategie, sind aber vergleichbar bedeutsam. Ihre tägliche Ausführung ermöglicht Kernprozesse und wirkt sich positiv auf die Produktivität eines Unternehmens aus. So minimiert beispielsweise ein schnelles Onboarding neuer Mitarbeitender Fehler und verkürzt die Zeit bis zur selbstständigen Übernahme von Aufgaben.

Diese Forschungsarbeit befasst sich mit den identifizierten Lücken und setzt sich mittels folgender Forschungsfrage mit der Thematik auseinander: Wie kann ein systematischer Ansatz zur Prozessoptimierung dazu beitragen, Erkenntnisse zu digitalisierten Geschäftsprozesse zu schaffen?

Ziel dieser Arbeit ist es, einen systematischen Ansatz zur Transformation nicht-digitaler in digitale Prozesse zu entwickeln, implementieren, verifizieren und validieren. Der Fokus liegt auf Unterstützungsprozessen und ihrer kontinuierlichen, datengetriebenen Optimierung. Zwei Vorgehensmodelle strukturieren die damit verbundenen Aufgaben. Das erste Modell adressiert die Priorisierung von Prozessen für die Digitalisierung, indem es bestehende Prozessreifegradmodelle erweitert. Das zweite Modell ist ein zyklisches Vorgehensmodell zur Prozessoptimierung. Es baut auf Ansätzen des Process Mining auf, und berücksichtigt die wiederholte Anwendung, die mit Konzeptverschiebung einhergeht.

Die Verifizierung und Validierung in zwei Fallstudien sowie das Feedback des begleitenden Expertenteams, belegen die Funktionalität und den Mehrwert der entwickelten Modelle. Die Forschungsergebnisse bilden die Grundlage für zukünftige Forschungsvorhaben, um den Umfang der Prozessanalyse auf Datenströme auszuweiten und durch proaktive Unterstützung bei der Prozessausführung die Prozessperformanz zu steigern.

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List of Abbreviations and Symbols

Abbreviation	Description
ARIS	Architecture of Integrated Information System
Baldrige-EF	Baldrige Excellence Framework
BPM	Business Process Management
BPM-MA	Business Process Management Maturity Assessment by Szelagowski et al. (2021)
BPM-MF	Business Process Management Maturity Framework by Froger et al. (2019)
BPM-MM	Business Process Management Maturity Model by Rosemann et al. (2005)
BPMM-OMG	Business Process Maturity Model by OMG (2008)
BPMN	Business Process Model and Notation
cf.	confer
CMMI	Capability Maturity Model Integration
COBIT	Control Objectives for Information and Related Technologies
CRISP-DM	Cross-Industry Standard Process for Data Mining by Chapman et al. (2000)
CSV	Comma-separated values
d	days
DFSS	Design for Six Sigma
DIN	German Institute for Standardization
DMAIC	DMAIC cycle: define, measure, analyze, improve and control
DPM	Digital Process Maturity by Appelfeller et al. (2019)
EAM	Enterprise Architecture Management
EFQM-EM	EFQM Excellence Model
GPL	General Public License
h	hours
IEC	International Electrotechnical Commission
ISACA	International Information Systems Audit and Control Association

to be continued on the next page

Abbreviation	Description
ISO	The International Organization for Standardization
IT	Information Technology
ITIL	IT Infrastructure Library
L*LCM	L* Life Cycle Model by Aalst (2016)
LGPL	Lesser General Public License
MBNQA	Malcolm Baldrige National Quality Award
m	minutes
MM-DBP	Maturity Model Digital Business Processes by Bitkom (2020)
NIST	National Insitute of Standards and Technology
OMG	The Object Management Group
PDCA	PDCA cycle: plan, do, check and act
PDM	Process Diagnostics Method by Bozkaya et al. (2009)
PEMM	Process and Enterprise Maturity Model by Hammer (2007)
PM^2)	Process Mining Project Methodology by Eck et al. (2015)
PMF	Process Mining Framework by Aalst (2016)
PMM	Process Maturity Model by Schmelzer et al. (2020)
R	Requirement
RQ	Research question
SCAMPI	Standard CMMI Appraisal Method for Process Improvement
SMART	SMART objective: specific, measurable, achievable, relevant, and time-bound
TCT	Total Cycle Time
TOC	Theory of Constraints
TOGAF	The Open Group Architecture Framework
TQM	Total Quality Management
TR	Technical report
V&V	Verification and Validation
VSM	Value Stream Mapping
WFM	Workflow Management
WoPeD	Workflow Petri Net Designer
XES	Extensible Event Stream
XML	Extensible Markup Language

Symbol	Description
L	Event log
L_c	Pre-processed event log with closed cases
L_o	Pre-processed event log with open cases
L_p	Pre-processed event log (complete)
L_r	Raw event log (complete)
M	Process model
M_d	Discovered process model
M_e	Enhanced process model
M_p	Pre-processed workflow model (complete)
M_r	Raw workflow model
M_t	Pre-processed workflow model without loops/target process model

1 Introduction

The first chapter introduces the foundations of this research. Then, based on the discussion of present challenges and recent developments the industry faces, the underlying issue surfaces and depicts the motivation for the research (cf. section 1.1). The insights serve as input to define the research objectives and formulate research questions (cf. section 1.2). The research methodology in the subsequent section structures the approach to answer the research questions and fulfill the objective (cf. section 1.3).

1.1 Motivation

Volatile market conditions and unpredictable changes, uncertainty in decisions due to the lack of knowledge, increasing complexity in networked systems like global value chains, and ambiguity summarize the high-level challenges organizations face in this century[1]. The acronym VUCA condenses these four aspects into a single expression to describe this challenging state with shorter product life cycles and increasingly individualized customer products to cater to changing customer demand[2]. Organizations strife to encounter VUCA and minimize its ramifications with organizational changes supported by technical progress in the advancing digital age to increase agility and customer focus[3].

Most organizations rely on a hierarchical organizational structure to create and deliver customer value, whether it is a physical product or a service to the customer[4]. However, in recent decades, organizations have realized the added value in streamlining their activities and a process-oriented approach to managing the organization, creating more agile structures to meet the VUCA environment[5]. Core processes tied to an organization's value chain, in particular, production and logistics, exhibit the most progress in process orientation, whereas administrative and management processes still retain the most potential for improvement[6]. Nonetheless, all business processes surmise an essential role in increasing the efficiency and efficacy of the

[1] cf. Dombrowski and Henningsen 2019, pp. 1–2.
[2] cf. Schuh et al. 2020, p. 11.
[3] cf. Weinreich 2016, pp. 12–15.
[4] cf. Rüegg-Stürm and Grand 2020, pp. 70–72.
[5] cf. Hirzel et al. 2013, pp. 1–4.
[6] cf. Dombrowski et al. 2015, p. 65.

organization[7]. Business Process Management (BPM) establishes the fundamentals to enable inter-divisional cooperation through transparency and coordination.[8] At the same time, structured, and in particular, digital processes, secure a systematic approach to introduce digital technologies in organizations and pave the way for digital business transformation[9].

Digital business transformation contributes to increasing efficiency in business operations and the required organizational agility. Digital technologies embedded in digital processes facilitate inter-divisional global communications and enable collaboration through shared services. Likewise, changes manifest in digital business models, creating flexible products. Digital products accessible from anywhere at any time represent one of many developments in the digital era.[10]

The challenge for organizations is approaching and transitioning toward exploiting digital business models. This question traces back to the outset of transitioning to a process-oriented organization characterized by digital processes. This research focuses on business processes that contribute to productivity but are different from typical core processes that habitually traverse digitalization first. In the context of process management, it is vital to revise them initially in their digital transition and continuously ensure optimization to address quality deterioration over time[11].

1.2 Objective and Research Question

This scientific work aims to develop a methodology for identifying the prioritization order of eligible processes for the digital transition and ensuring continuous improvement by exploiting available process data recorded in process execution for analysis. The process insights support decision-making regarding process improvement measures. For this purpose, data-based methods are developed based on existing process data that analyze and evaluate the improvement potential of business processes. By making this knowledge available, structured process improvement is efficient and contributes to a long-term process performance increase.

The stated objective of the thesis translates to an overarching research question, which structures the subsequent research activities. This thesis derives the research question from the need for action based on motivation and therefore supports the goal orientation in the research process.

[7] cf. Koch 2015, pp. 19–20.
[8] cf. Hirzel 2013, pp. 9–10.
[9] cf. Appelfeller and Feldmann 2018, p. 5.
[10] cf. Almeida et al. 2020, pp. 97–100.
[11] cf. Roenpage et al. 2007b, p. 108.

RQ How can a systematic approach to process optimization contribute to uncovering process insights for digital business processes?

To answer the overarching research question, a decomposition into three subordinate research questions facilitates the scientific discussion in the following chapters. Section 2.5.1 expands on the background of this outline.

- *SRQ1 Which criteria support the decision-making of prioritizing business processes in digital transformation?*
- *SRQ2 How can data-driven analytical methods be aggregated in a guided procedure model to facilitate process analysis and uncover process insights?*
- *SRQ3 How can concept drift be considered in the cyclical process analysis?*

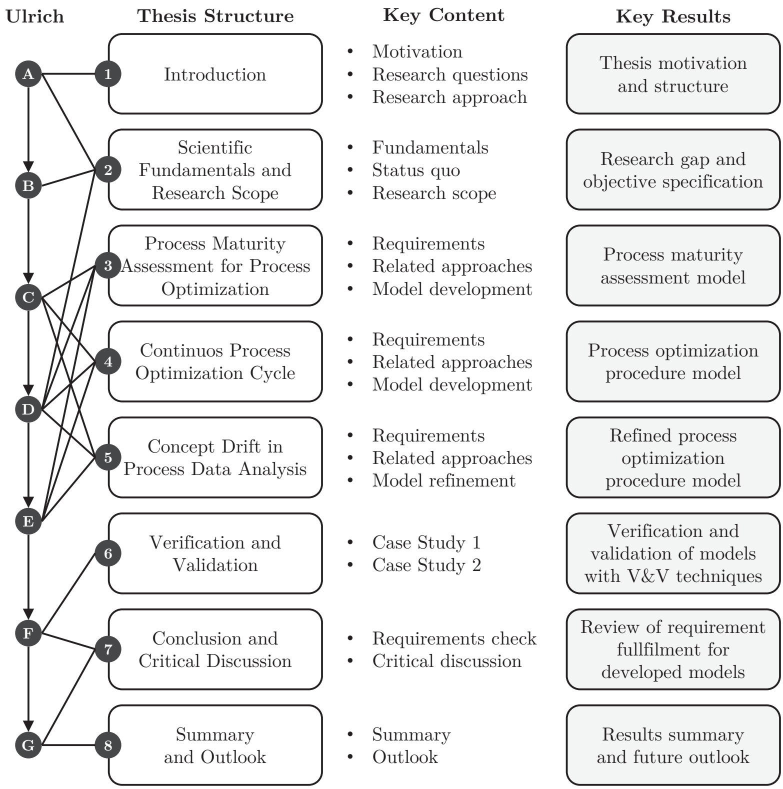
1.3 Research Methodology and Thesis Structure

The motivation and research objective assign the research work to the design sciences that incorporate the engineering discipline. In contrast to the explanatory sciences, the research in engineering pursues solution-oriented knowledge generation and its application to develop pragmatic and specific solutions in the application domain in favor of a comprehensive theoretical understanding of interrelationships.[12] This research follows the seven-step approach by ULRICH[13]. The outset and conclusion of the work start and end, respectively, with the embedding in practical application. Figure 1.1 visualizes the phases and assigns this thesis' chapters accordingly.

The fundamentals ensure a common understanding of relevant disciplines in business process management and digital processes to discuss the status quo, identify the research gap, and formulate research questions (cf. chapter 2). The research questions follow the activities in business process management for the transition of non-digital to digital processes and relate to process optimization methods. At the outset, defining metrics to assess process maturity and evaluate their prioritization for digitalization is essential. The next chapter discusses related approaches based on requirements specification and deduces a suitable assessment model(cf. chapter 3).

The transition to digital processes in information systems and their execution generate process data benefiting recent approaches for process data analysis. Developing a process optimization procedure model incorporating considerations regarding

[12] cf. AKEN 2005, pp. 20–22.
[13] cf. ULRICH 1981, pp. 3–24.
[14] cf. ibid., pp. 3–24.



Research methodology based on Ulrich
A - Identification and typing of practical problems
B - Identification and interpretation of problem-related theories and hypothesis from empirical fundamental sciences
C - Identification and specification of problem-related approaches of formal sciences
D - Identification and examination of the relevant application context
E - Deduction of assessment criteria, design rules and models
F - Test of rules and models in the context of application
G - Practice consultancy

Figure 1.1: Thesis structure following Ulrich's research methodology[14]

cyclical application for continuous improvement assures suitable and recurrent data exploitation (cf. chapter 4). The complexity that accompanies procedure models of this sort manifests as concept drift. Concept drift impacts the analysis, and its scope warrants a procedure model refined to develop appropriate measures (cf. chapter 5). The resulting procedure model requires verification and validation in a practical application context. Two application scenarios support the evaluation process (cf. chapter 6). Based on the results in the application scenarios, it is possible to formulate a conclusion regarding the research questions formulated at the outset of this research (cf. chapter 7) and develop recommendations for future research (cf. chapter 8).

2 Scientific Fundamentals and Research Scope

The application domain and its environment set the framework conditions for the research. The introduction of relevant scientific fundamentals in process management (cf. section 2.1), process digitalization (cf. section 2.2), and the status quo in German organizations 2.3 creates a common understanding about the present challenges before proceeding towards the outline and scope of the thesis that addresses identified challenges (cf. section 2.3). Framed into research questions, it presents a structured approach to incorporate and address the gaps (cf. section 2.5).

2.1 Process Management

This section introduces the topic of process management. It presents elementary definitions and process modeling notations, and displays the connection to business process management and process performance in organizations.

2.1.1 Process

A set of regularly performed activities with a defined beginning and end characterizes a process that intends to achieve an objective within predefined boundary conditions. The activities follow a logical and temporal structure to transform an input via multiple steps and iterations to the desired output. Figure 2.1 illustrates these building blocks for a process on a generic level. The degree of automation for process execution ranges from manual to fully automated.[15].

Figure 2.1: Schematic representation of a process

Every organization has processes, regardless of whether an explicit definition and documentation exist. A trigger within or outside the organization initiates a process known as a business process. Processes exhibit a varying degree of maturity in their structure and sequence of activities. Conventions for process handling and execution exist, or process participants reconcile them every time.[16]

[15]cf. Gadatsch 2015, p. 3.
[16]cf. Fleischmann et al. 2018, pp. 1–2.

DIN EN ISO 9000 describes a systematic approach to process design. It covers minimum requirements for business processes and contributes to the increasingly important process orientation in organizations (cf. section 2.3.2)[17]. Elements specified in the norm extend to:

- Definition of input and output
- Definition of process sequence and interfaces
- Definition of criteria and procedures to ensure effective implementation and control
- Definition and assurance of necessary resources
- Definition of responsibilities and roles
- Assessment of risks and opportunities
- Assessment and assurance of process success
- Continuous improvement of processes and implementation of measures

It is common to categorize business processes into three types: management, core, and support processes.[18] Following the *St. Gallen Management Model* definition, management processes comprise strategic business processes that concern an organization's design, stabilization, and advancement of value creation. Examples are budgeting, financial multi-year planning, and strategy development. Core processes differ between companies and depend on the business model. These cover all value-adding processes and create a benefit perceptible to the customer. Support processes provide infrastructures and resources critical to the success of processes of the first two categories and enable efficient process execution. Despite their characterization as support processes, their value is comparable to core processes. Separating these categories is not always possible, depending on the business strategy and model.[19]

A detailed process description and documentation are the basis for creating a shared process understanding. The minimum requirements defined in DIN EN ISO 9001 set the foundations for a sufficient process description and coincide with other sources.[20] While the norm describes the essential content, it limits the need to maintain and retain the process documentation to the bare necessities to plan, support, and execute processes.[21] Accordingly, the visualization of individual process steps in a flow chart is not required. A simple method to collect process information at a macro level that meets this requirement is the turtle method shown in figure 2.2.

[17] cf. Deutsches Institut für Normung e. V. 2015a, p. 20.
[18] cf. Fleischmann et al. 2018, pp. 1–3.
[19] cf. Rüegg-Stürm and Grand 2020, pp. 75–81.
[20] cf. Fleischmann et al. 2018, p. 5.
[21] cf. Deutsches Institut für Normung e. V. 2015a, p. 20.

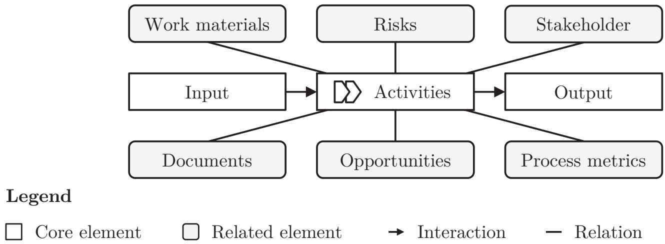


Figure 2.2: Turtle Diagram for process description

2.1.2 Process Modeling

Systematic process documentation creates a link between processes and process models. In general, processes are interlinked activities that are visible to the observer. Process models visualize essential activities in a flow chart to represent, communicate, and document a process. Following the objective, a process model either describes the natural process in an as-is process model or defines desired process steps in a target process model[22]. Figure 2.3 shows an exemplary process model as a flow chart for a simplified tender process.

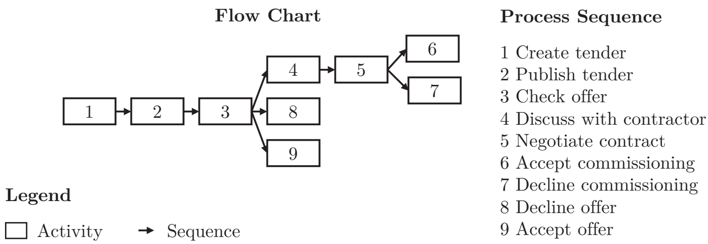


Figure 2.3: Flow chart process model for a simplified tender process

Organization and application systems design use related, yet different process models. The specific purpose determines the selection of a suitable modeling language. A modeling language dictates a formal notation and contributes to a uniform understanding of the stakeholders involved in process design and implementation.[23]

Examples corresponding to these domains further illustrate its application. Or-

[22]cf. Gadatsch 2015, p. 4.
[23]cf. Aguilar-Savén 2004, p. 143.

ganization system design intervenes in system documentation, continuous process management, and process-oriented reorganization. From an organizational point of view, it incorporates both business processes and the role of employees. Process models support the planning, execution, and control of processes. As standardized documents, process models simplify the communication between specialist departments and create transparency about the process flow. Supplementary expert knowledge supports process analysis to identify weaknesses and is a starting point for continuous process improvement up to process reorganization.[24]

In application system design, process models contribute to implementing software-based processes, commonly known as workflows. A workflow describes the technical implementation of activities in a software system and enables its automatic control on an operational level. Beyond the scope of business processes, a workflow specifies the process from an information technology perspective. Sequential activities exhibit details in their interfaces, and information on human and technical resources supplements the information content.[25]

Figure 2.4 visualizes the relationship between processes and workflows. Process implementation as a workflow usually results in creating workflow models as these support the procedure. On an operational level, it extends the description with the instantiation of a workflow. The instantiation corresponds to a single workflow iteration, also known as a case.

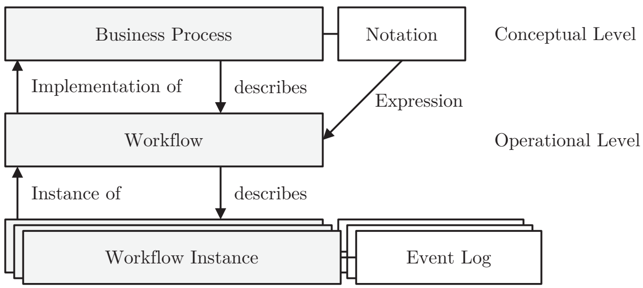


Figure 2.4: Relationship between business processes and workflows[26]

[24]cf. Rosemann et al. 2012, pp. 52–55.
[25]cf. Gadatsch 2020, pp. 11–15.
[26]own representation based on Gadatsch 2020, pp. 12–13; and Weske 2019, p. 74.

Enterprise software offers software solutions with standardized workflows for core business processes and support processes such as materials management and financial accounting that easily integrate into the present IT infrastructure. In software engineering, process models satisfy requirements for well-defined relations in data models that allow for direct transfer into code given the appropriate syntax. Thus, it also enables the simulation of dynamic system behavior to uncover process weaknesses and test countermeasures. Key performance indicators and known references support benchmarking the overall process performance.[27]

The initial task in process modeling is to determine the suitable modeling language. In organization system design, an abstract and high-level process model is sufficient to describe and analyze business processes that make use of a simple notation.[28]. In industrial practice, the standard *Business Process Modeling Notation* (BPMN) developed by the *Object Management Group* (OMG) has broad acceptance. ISO/IEC 19510:2013 describes the most recent version BPMN 2.0.[29]. BPMN adapts essential properties of modeling languages that precede it, e.g., properties of flow charts. In addition to documenting business processes, it enables the creation of models to be implemented as workflows in application system design.[30].

Figure 2.5 shows an exemplary representation in the notations BPMN (left) and Petri net (right) in direct comparison[31]. The control-flow-oriented modeling notation Petri nets is more suitable for model workflows in application system design. In contrast to event-based modeling in BPMN, it models discrete states of processes that allow for a clear differentiation between the initiation and execution of process steps, simplifying the representation of concurrent and collaborative processes. The high degree of formalism and the possibility of a mathematical representation of a Petri net corresponds to the availability of a wide variety of analysis techniques.[32]

Modeling languages are subject to a bias due to their formal notation that becomes apparent during process modeling. The interface between organization system design and application system design may require a conversion between different notations but is quickly resolved with the prevalence of dedicated algorithms.[33]

[27] cf. Rosemann et al. 2012, pp. 56–58.
[28] cf. Fleischmann et al. 2018, pp. 71–72.
[29] cf. Kossak et al. 2014, p. 1.
[30] cf. Fleischmann et al. 2018, pp. 92–93.
[31] For a detailed description of BPMN, please refer to the detailed documentation in the standard ISO/IEC 19510:2013; for the description of Petri nets, please refer to the standard ISO/IEC 15909-1:2019.
[32] cf. Aalst 2002, pp. 1–2.
[33] cf. Kalenkova et al. 2015, pp. 1019–1022.

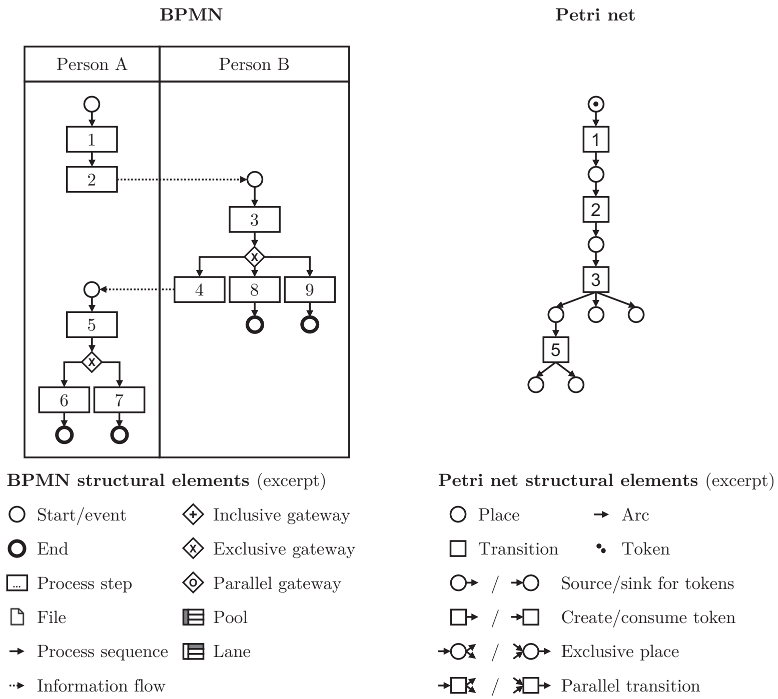


Figure 2.5: Process sequence in BPMN and Petri net notation

2.1.3 Business Process Management and Workflow Management

An integrated process management framework maximizes the performance of business processes and workflows. Figure 2.6 outlines a feasible concept on an abstract level. The strategic level in organizations defines the business strategy that comprises the business areas with essential core processes to achieve the business objectives. Key performance indicators serve as a means for planning and control. On a functional-conceptual level, necessary business processes derive from top-level strategy and specifications. Workflow management realizes the linkage to process management on an operational level. Business process models translate to workflows and enable automated execution and control in day-to-day business.[34].

[34]cf. Gadatsch 2015, pp. 8–10.

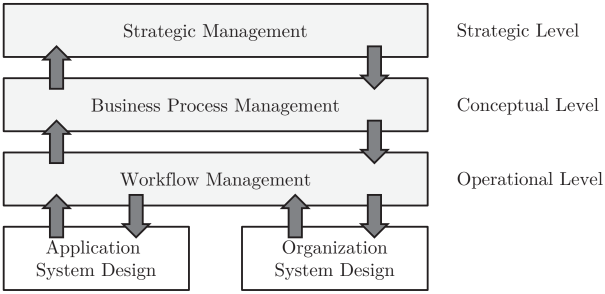


Figure 2.6: Process management in organizations[35]

The essential fields of activity on the functional-conceptual level are process management, process organization, process control, and process optimization[36]:

- **Process Governance**: The core task is to motivate employees in their attitude and behavior to increase their commitment to achieving process objectives. Accordingly, it is essential to appoint responsibilities in appropriate subareas up to whole business units within the organization (see figure 2.6), who will assume the subsequently described tasks in process management.
- **Process Organization**: The scope of process organization is broad and covers the identification, design, documentation, and organizational integration of business processes. Their implementation provides transparency about process structures and flow. It is a prerequisite to achieving a common understanding that enables control and optimization. Organizational integration addresses business process integration in the organization. Business processes create beneficial framework conditions for high process performance and resource efficiency if adequately anchored in structured organizations.
- **Process Control**: Core tasks in process control cover the definition of objectives, monitoring, and control to ensure target achievement. Essential components are process targets, performance indicators, and ensuing reporting. Process performance indicators quantify the performance concerning effectiveness and efficiency. For example, a strategic objective focuses on and expands core competencies, while an operational objective represents high customer satisfaction with the service recipient. Reports record process-

[35]own representation based on Gehring and Gadatsch 1999, pp. 1–2.
[36]cf. Schmelzer and Sesselmann 2020, pp. 15–17.

related information on performance and serve as a starting point for process optimization.

- **Process Optimization**: Process optimization targets the continuous and sustainable enhancement of process performance while considering strategic and operational objectives. The optimization differentiates between incremental process improvements and profound process reorganization. Continuous transformations contribute to steady process improvement. On the other hand, process reorganization or restructuring enables a sudden increase in process performance, bringing profound changes in the organizational structure and high expenses. Accordingly, there are exceptions to the rule.

Workflow management handles business processes' implementation and technology integration in the application system environment, also known as the workflow management system. Core tasks support operational processes, the coordination of workflows, and the management of data and persons involved in the workflow execution. The workflow management system comprises application logic, process logic, and data management layers. The processing logic corresponds to the sequence of activities defined by the process model. Application-specific adaptations and more detailed specifications affect the necessary workflow model, supplemented by information such as application interfaces and role assignments. The data collected during the workflow execution requires integrated data management to enable data backup and exchange with other information systems.[37]

Phase and life cycle models structure business processes and workflow management activities in temporal, interdependent sections. In practical application, the latter models are of interest as these reflect the concept of continuous improvement. However, life cycle models vary in their design and phase designations. In some instances, individual requirements of organizations impact their design and limit the transfer and application outside their origin.

Figure 2.7 introduces the /Business BPM Cycle that exhibits a high alignment with the structure presented in figure 2.6. It extends process management tasks with activities usually allocated to workflow management[38]:

- **Strategy and Objectives**: Strategic management defines the business strategy that sets the framework for the business model and associated business

[37]cf. Mühlen and Hansmann 2012, pp. 367–369.
[38]cf. Schmelzer and Sesselmann 2020, pp. 17–18.
[39]own representation based on ibid., p. 18.

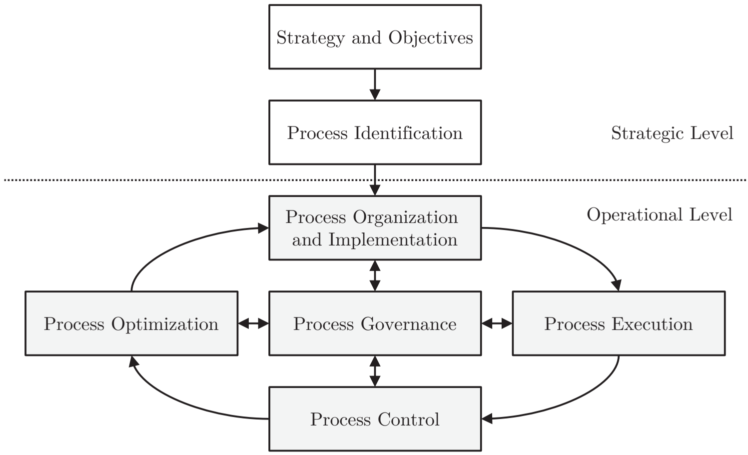


Figure 2.7: Business BPM Cycle[39]

objectives. The framework is the foundation for the process strategy that determines essential business processes with strategic and operational targets.

- **Process Identification**: Strategic specifications frame the overall process architecture that leads to the development of business processes. A process map gives an overview of their hierarchy and connecting interfaces.
- **Process Implementation**: The implementation includes integrating business processes into the organization's organizational structure and its technical implementation as workflows into corporate IT infrastructure.
- **Process Execution**: Employees interact with workflows that reflect the operational process execution in day-to-day operations. Its usage generates process-related data and allows the collection of process performance indicators that serve as input for decision-making in process management and process control.

An organization's initialization of business process management comprises the first two phases of strategy and goals and the *Business BPM Cycle* process identification. After conceptualizing and implementing the *Business BPM Cycle*, all subsequent activities convene in operations. Here, process governance represents the central control unit in the cycle. It triggers process adjustments where necessary, for instance, due to the realization of optimization potentials or changes in strategy and goals.[40]

Subsequent authors contribute to further business process management life cycle models: Gadatsch[41], Fleischmann et al.[42], Weske[43] and Kirchmer[44]. In principle, the referenced models exhibit high conformity concerning the content and predominantly differentiate in the phase structure and task assignment in individual phases.

2.1.4 Process Performance

Process performance key figures are essential to monitor and control business processes and evaluate their contribution toward process targets. Collecting and assessing indicators in day-to-day operations follow predefined key figures that condense factual information. Comparing the as-is state with the target state supports the process analysis and allows the defining of early measures for improving existing processes. Typical targets for process improvements are quick process execution, decreased process costs, or an increased quality of the process result[45]. Similar to the previous differentiation between process targets on a strategic and operational level, strategic and operational key figures coexist.[46]. Key figures give information about facts compared to indicators that correlate to a key figure or serve as a replacement for indirect measurement.[47]

The authors Helmold et al. introduce a concept to describe performance indicators from a value creation perspective in an organization. As it focuses on performance management, its deployment is on a strategic level of business process management: the concept overviews quality, cost, delivery, technology, and cross-sectoral focus performance indicators. Good performance indicators for strategic categories comprise field and service defects, non-conformities, and productivity. The cross-sectoral focus predominantly addresses indicators from the domain of Corporate Social Responsibility (CSR) that reflect the norms and values of the organization and its stakeholders.[48]. Integrating individual indicators into a key

[40]cf. Schmelzer and Sesselmann 2020, p. 18.
[41]cf. Gadatsch 2020, p. 25.
[42]cf. Fleischmann et al. 2018, pp. 1–18.
[43]cf. Weske 2019, pp. 11–17.
[44]cf. Kirchmer 2017, pp. 16–18.
[45]cf. Laue 2020, p. 81.
[46]cf. Kahl and Zimmer 2017, p. 76.
[47]cf. Hilgers 2008, p. 38.
[48]cf. Helmold and Samara 2019, pp. 7–13.

performance indicator system illustrates their interdependencies and enables a high level of information density to support strategic decision-making.[49]

Those above critical key performance indicators differ from performance indicators on an operational level, commonly known as Process Performance Indicators (PPI). The measurement happens during day-to-day operations and serves as input for periodic analyses, assessments, and audits. The definition of PPI depends on the insight objectives, target groups, and the application context. Compared to KPIs, PPIs directly link operational performance and contribute to continuous process improvement by uncovering weaknesses and improvement potentials. Organization-specific influencing factors decide PPI design, expressed in calculation and survey frequency attributes. Generally speaking, processes with a high degree of structure and automation facilitate the design and recording of PPI in contrast to weakly structured processes. Creative tasks and high intensity in collaborative activities characterize the latter.[50] Essential attributes to PPI design extend to four areas[51]:

- **Process performance key figure**: definition, description, associated processes, target value, tolerance range, intervention threshold, validity, recipien and responsibility
- **Data acquisition**: source, procedure, method and frequency
- **Data processing**: calculation method and automation degree
- **Reporting**: visualization, aggregation and archiving

Key figures at the operational level distinguish between business processes' potential, structure, and performance. Potential key figures describe the organization's ability to achieve high effectiveness and efficiency. Structure metrics point towards structural strengths and weaknesses and address process flows.[52] The dimensions of process time, process quality, and process costs allow an evaluation of process efficiency. Flexibility is increasingly vital as a performance indicator concerning dynamic influencing factors. Despite the direct correlation to operational activities, it is more of a strategic key figure that describes the organization's potential and is evident in agile process management and organization. Customer satisfaction as a performance evaluation key figure provides information about process effectiveness but occupies a similar position to flexibility as a strategic success factor.[53]

[49] cf. GADATSCH 2020, p. 79.
[50] cf. KAHL and ZIMMER 2017, pp. 77–79.
[51] cf. SCHMELZER and SESSELMANN 2020, p. 393; and KÜTZ 2009, p. 45.
[52] cf. SCHMELZER and SESSELMANN 2020, pp. 389–390.
[53] cf. ibid., pp. 364–367.

2.2 Process Digitalization

This section shares relevant information concerning digitalization, and introduces the topics business analytics and process mining.

2.2.1 Digitalization

The accelerated digital transformation and the associated transformation of processes and organizational structures increasingly impact organizations. On the one hand, technological advances in information and communication technologies (ICT) open up new digital business models and create new market opportunities. On the other hand, global competition for technology leadership and market access intensifies due to the appearance of new competitors. The drivers of the digital transformation are the flexible provision of IT resources through cloud computing, the interoperability of physical and digital objects in the Internet of Things, and the associated opportunity of collecting and analyzing large volumes of data that, as a whole, affects value chains significantly in the long run.[54]

For many organizations, value creation depends on business processes and their implementation in information systems. Improvements in business procedures yield improvements in quality and performance, creating a competitive advantage. Thus, creating active process management to flexibly adapt business processes to market demands becomes increasingly essential for process-oriented organizations.[55] The focus of consideration in business process digitalization is the process flow. Following the link between business process management and workflow management, process digitalization describes the transfer of analog process activities into digital workflows, usually integrated into enterprise resource planning (ERP) systems that facilitate communication and data transfer along the workflow.

The data basis for process digitalization is process descriptions and process models logged in knowledge management systems. Conversely, using workflows leaves digital traces in systems recorded in event logs. In addition to meta-information about the process, process logs contain process-specific information about instances of process executions that enable PPI calculation. The highly structured data in the event log allows for applying data-driven process analysis techniques and process mining (cf. section 2.2.3) to uncover process weaknesses and serve as a starting point to increase process performance. (cf. section 2.1.4)

[54] cf. Wittpahl 2017, p. 21.
[55] cf. Becker et al. 2009, pp. 1–4.

A similar yet different means of process digitalization refers to the area of process automation. Automation contributes to increased process effectiveness and, thus, process performance by minimizing the share of human intervention and increasing the degree of automation in process execution. At the same time, a high degree of process automation does not necessarily represent the pinnacle of process optimization, as it is not suitable for all types of processes and requires a high degree of standardization[56]. Robot process automation (RPA) specializes in automating workflows by deploying a software robot capable of mimicking human interaction akin to their usage of peripheral devices, thereby omitting the need for dedicated application programming interfaces (API). The inference is the particular high suitability of RPA for repetitive and standardized processes such as information retrieval from different databases, performing calculations, or analyzing and following if-then-rules that do not require human intervention.[57]

2.2.2 Business Analytics

Data-centered organizations use available data to develop business models as their foundation and success factor. The factual situation represented in data and made available through digitalization serves as the basis for business decisions on a strategic and operational level. Business analytics is the associated domain that supports decision-making by providing suitable tools and technologies to generate insights from data.[58]

Generally speaking, with increasing complexity, the depth of insights rises accordingly. The maturity of analysis capability and its competitive advantage differentiate two perspectives. The most basic techniques are a retrospective and reactive analysis of process executions. Reports aggregate calculated key figures, which provide information about the organization's performance in hindsight. This perspective's descriptive and investigative approach supports identifying cause-and-effect relationships. Underlying questions examine the factual description and investigate the root causes that led to this observation. The focus lies on the perception and reaction to these observations.[59]

Historical data evaluation provides the foundation for predicting future observations by analyzing and deriving internal cause-effect relationships. For example, suppose a particular set of factors led to a specific event in the past. It is obvious to assume

[56] cf. DUMAS et al. 2018, p. 372.
[57] cf. SCHEER 2020, pp. 118–126.
[58] cf. CHAMONI and GLUCHOWSKI 2017, pp. 9–10.
[59] cf. MCCARTHY et al. 2019, p. 11.

a systematic pattern given an extensive data set with the same observed behavior. The generalization of intrinsic data characteristics in prediction models allows a knowledge transfer to forecast trends and predict patterns.[60]

Data characteristics and analysis objectives determine the algorithm choice that generally follows a similar approach. It starts with data preparation, algorithmic pattern recognition, and interpretation in modeling, followed by prediction model deployment. During its deployment, adjustments to the trained models are necessary to properly reflect changes in the data set, leading to a cyclical restart.[61] Most commonly known process models that describe this approach are Knowledge Discovery in Databases and the industry-standard Cross-Industry Standard Process for Data Mining (CRISP-DM) (cf. section 4.2.2).

Predictive analysis has always been possible in specific domains but requires many resources and extensive expertise. With the increase in data volume and growth in both speed of recording and transmission, a manual analysis is no longer manageable. The development of new algorithms and the rise of accessible computing resources in cloud-based systems facilitate the handling and analysis of data.[62] It also serves as a precursor to prescriptive analysis that pursues the alignment to a defined target status. The underlying questions address the prediction of the event and the necessary intervention to deter undesired developments and steer toward the desired target[63].

Figure 2.8 summarizes the opportunities that data-driven analysis offers for retrospective and predictive approaches. It assigns specific terms to intermediate stages of each type and evaluates their contribution to competitive advantage and the maturity of analytic capability. Additionally, it presents information about decision-making and the degree of human interaction.

2.2.3 Process Mining

Process Mining is a recently emerged discipline of data analytics dedicated to analyzing process data. While process mining deploys and expands data mining techniques that are generally not process-centric, process mining focuses on process

[60] cf. Dinov 2023, p. 11.
[61] cf. Chamoni and Gluchowski 2017, pp. 11–12.
[62] cf. Shah 2015, pp. 207–208.
[63] cf. Nalbach et al. 2018, p. 33.
[64] own representation based on Elliott 2018, p. 1; and Brocke et al. 2017, p. 212.

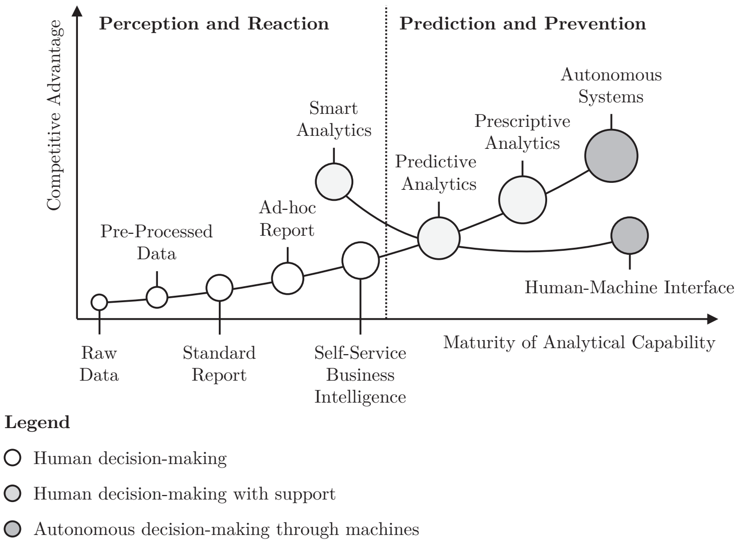


Figure 2.8: Data Analytics Stages[64]

modeling and analysis. Essential activities cover discovering, monitoring, and improving processes by knowledge extraction from event logs available in information systems. Furthermore, it is not limited to analyzing past events based on historical data but allows for predictive analytics.[65] Generally, the following process analysis perspectives are considered in the scope of analysis[66]:

- **Control-flow perspective**: The control-flow refers to the sequence of activities. The mining aims to find a suitable generalization of all possible process paths in terms of a modeling notation.
- **Organizational perspective**: The organizational perspective addresses the resources involved in the process execution and their relationship. The objective lies in uncovering their roles or depicting the social network.
- **Case perspective**: Case perspective focuses on process instances and their characteristics. Process insights on specific cases can be uncovered by analyzing their origin or path and grouping cases based on specific data attributes.
- **Time perspective**: The time perspective concerns the timing and frequency

[65] cf. Aalst et al. 2012, pp. 172–176.
[66] cf. Aalst 2016, p. 34.

of events. Process mining discovers bottlenecks, monitors resource utilization, and can predict the processing time of running cases based on past observations.

Figure 2.9 introduces the essential elements of process mining. The figure visualizes the connection between the real-world process, its implementation as a workflow in the organization's information system, the underlying process model, and the event log created during process execution. Further down, it displays the principal process mining types discovery, conformance, enhancement, and operational support with their dependency on the data inputs process model and event log. The main process mining types are defined after a brief overview of the data inputs.

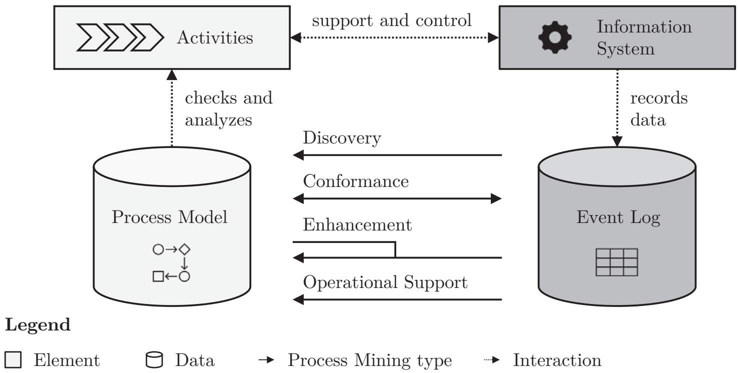


Figure 2.9: Process mining types[67]

Event logs record past process executions and are the basis for process mining. The process execution in an information system, the activity, is recorded as an event with a timestamp. Multiple events in chronological order constitute a process instance or case with peculiar attributes such as a unique identification number. Accordingly, each event can only link to one single case. Usually, the information system offers more information concerning the execution, for instance, the associated and consumed resources. As the information system requires this information to realize the workflow implementation, it is only a matter of information extraction

[67]own representation based on Aalst et al. 2012, p. 174.

to access the data.[68]

Table 2.1 presents an exemplary event log, usually available in a tabular display as a .CSV file, with the essential data required for the application of process mining. A row in the table corresponds to a singular event recorded in the event log and has a unique identifier that links interrelated events to a common sequence, here the *Case ID*. The sorting follows the chronological order defined by its timestamp. Each column represents a data attribute with information about the event.[69]

Table 2.1: Exemplary event log for a simplified tender process

Case ID	Activity	Timestamp	Resource
005	Create tender	23-03-2022, 09:58:00	Jane
005	Publish tender	23-03-2022, 10:02:00	Jane
001	Decline offer	23-03-2022, 10:21:20	Jane
004	Accept offer	24-03-2022, 07:23:00	John
005	Check offer	24-03-2022, 07:26:00	Jane
005	Discuss with contractor	24-03-2022, 14:01:00	Jane
002	Check offer	24-03-2022, 14:26:00	John
003	Check offer	24-03-2022, 15:03:20	John

The list covers essential information in an event log, of which the first three attributes represent the minimum information required to apply process mining. Additional information enables the deployment of more diverse and advanced algorithms.

- **Case ID**: The case ID is the unique identification number that connects multiple interrelated events along their sequence to form a tuple of events, also known as a trace.
- **Activity**: The activity describes the action recorded in the event log. It refers to a status change or a transition.
- **Timestamp**: The timestamp specifies the date and time of an action. Some systems offer information on the start and end times, thus yielding two timestamps.
- **Resource**: The resources associated with the activity realize its execution. Usually, this refers to the person executing the activity but may extend to consumables or resources in information systems.

Process models in process mining usually refer to the workflow model (cf. section 2.1.2 for more information on process modeling). The foundation for algorithm-based

[68]cf. Bose et al. 2013, p. 128.
[69]cf. Laue et al. 2020, pp. 170–171.

process modeling is the event log that reflects the process execution. The event log records traces constituting activity sequences. These traces include process variants as defined in the workflow implementation. An essential consideration in process modeling is that the event log does not necessarily capture all activities related to a process but only covers these executed in the information system as a workflow. Primarily, processes with manual activities account for this process type.[70]

The quality of the event log is another influencing factor for creating good process models. Event logs can be byproducts of information systems that record information automatically but not systematically. Therefore, the log is neither complete nor adequately matches reality if it can bypass recording in the information system. However, it is more common to have BPM systems with reliable and complete data-supporting notions for process instances and activities. The highest maturity level considers privacy and security concerns in the data and exhibits precise semantics and even ontology.[71]

The main process mining types are discovery, conformance, enhancement, and operational support[72]:

- **Discovery**: Creating process models based on the event log without a-priori information is the first type of process mining. With a sufficiently large event log, an algorithm such as the α algorithm[73] creates a Petri net capable of explaining the observed behavior in the event log without supplemental information. Given more information in the event log, other perspective analyses appear feasible, e.g., resource information and resource-related models to display the cooperation of people like the social network.
- **Conformance**: The second type of process mining compares a process model with the event log of the associated process. Conformance checking gives insights into whether the model conforms to the log and vice versa. It is not only limited to the control flow perspective but extends to other perspectives, e.g., the organizational perspective, to check access rights and responsibilities. Thus, conformance checking supports detecting, locating, and explaining deviations from the intended process execution reflected by the process model. It also gives an estimate of the severity of the deviation. Rozinat et al. describe an exemplary conformance checking algorithm.[74]

[70] cf. Appelfeller and Feldmann 2018, pp. 20–22.
[71] cf. Aalst et al. 2012, pp. 179–180.
[72] cf. Aalst 2016, pp. 33–34.
[73] cf. Aalst et al. 2004, pp. 1135–1137.
[74] cf. Rozinat and Aalst 2008, pp. 69–79.

- **Enhancement**: Enhancement constitutes the third type of process mining and intends to extend or improve an existing model with factual information recorded in the event log. It extends conformance checking by offering the opportunity to modify or extend a given a-priori model. One possibility is to repair a model to increase conformance with the actual process. Another possibility is to extend the model with more information to showcase other perspectives, e.g.performance metrics, by incorporating temporal information to display bottlenecks, throughput times, and frequencies.
- **Operational Support**: Operational support aims to influence process execution by providing the user with real-time recommendations, warnings, and predictions. Based on the initial application of process mining types, it is possible to perform real-time analysis, like forecasting the required time to process closure or the probability of a certain process variant.[75]

2.3 Status quo of Process Digitalization in German Companies

This section gives an overview of the present status of German companies concerning their digitalization progress, their challenges and identified key action points.

2.3.1 Status quo

The *Digital Economy and Society Index* (DESI) survey collects indicators to rank European countries' digitalization performance and has been tracking their progress since 2014. Overall, Germany ranks 11 of 27 in the digital economy and society in the latest survey from 2021. Basic digital and software skills are widespread, but overall, organizations need more ICT specialists, thus affecting the integration of digital technology in business, in which Germany ranks 18th in the European Union.[76]

This insight aligns with findings in national surveys, i.e., DIGITAL published by the *Federal Ministry for Economic Affairs and Energy* (BMWi), now *Federal Ministry for Economic Affairs and Climate Action* (BMWK), in 2020. More than two-thirds of surveyed companies integrate digitalization as a business strategy with a higher priority in service than in manufacturing industries. However, a quarter of surveyed companies also demonstrate below-average digital competency. Compared to other digital technologies, big data analytics occupies a minor role with 9% in contrast to Cloud Computing at 43%, the Internet of Things at 39%, and other Smart Services

[75] cf. Aalst 2016, p. 301.
[76] cf. DG Connect 2021, pp. 2–3.

at 29%. Around two-thirds state that most internal business processes are digital, occupying an increasingly important role in digitalizing business practices.[77]

Process digitalization significantly impacts the systematic analysis of business data, digital administrative processes, electronic invoicing, and digital documents.[78] The reasons are cross-division process collaboration and media disruptions. Few organizations boast paperless processes and may observe daily repeated manual input of identical information in information systems[79]. Still, investments in process digitalization predominantly go towards core processes, whereas digital support processes occupy a minor role[80]. Comparing different enterprise sizes discloses lagging progress for small- and medium-sized enterprises (SMEs). Only a third of SMEs incorporate digitalization, usually focusing on quick and simple implementation to yield short-term benefits. The reasoning lies in the conflict between investments in a stable economy with a view toward the ongoing economic situation and increasing the competitive advantage through increased digital maturity.[81]

As early as 2015, BMWK initiated different programs to strengthen SMEs' competitiveness and digital transformation to support their position, as these are major German economic drivers[82] . A cornerstone of the strategy is setting up a national network of Mittelstand 4.0 centers of excellence to provide SMEs with information and specific support in digitalization free of charge, e.g., workshops, training sessions, and implementation support.[83].

SMEs come with specific characteristics distinct from larger organizations: organizational flexibility and quick adaptability, short decision paths in management, and close contact with clients characterize the daily business. Employees in key roles with long-standing work experience and expertise are their most valuable resources. Therefore, their role in the progressing digitalization is essential, even in increasing automation of processes and less human involvement.[84]

Following the COVID-19 pandemic, new business practices and digital channels have emerged as insecurity about quarantine and regulations have impacted daily face-to-face business. Profound changes have been observed briefly, along with implementing

[77]cf. Weber et al. 2020, p. 12.
[78]cf. Bitkom Research and Tata Consultancy Services 2016, p. 40.
[79]cf. Kykalová et al. 2018, pp. 27–28.
[80]cf. Hauri and Ricken 2021, p. 7.
[81]cf. Weber et al. 2020, p. 12.
[82]cf. German Federal Statistical Office 2019, p. 1.
[83]cf. BMWi 2019, pp. 4–5.
[84]cf. Müller et al. 2018, pp. 73–75.

digital technologies in the scope of quick-paced digital transformation. Prior to this, the slow pace has been associated with low business priority.[85] The challenges and opportunities of digitalization change with technological advancements, but the approach to digital transformation does not differ from pre-pandemic.

Moreover, the significance of the involvement of the entire organization and the stakeholders becomes apparent and steadily increases. The quick pace of changes is independent of previous status and experience in digital transformation. As it requires restructuring processes and a more agile organization, the requirements of complete preparation are relatively high. Reinforcing standardization and automation is necessary to optimize response capacity in an agile organization - and SMEs have fewer resources to face challenges in the transformation and dematerialization of tasks and services.[86]

2.3.2 Requirements and Challenges in Process Digitalization

The digital transformation of an organization is an ongoing change process. While the core digital transformation activities have remained identical, the transition faces dynamic challenges reflected in the modest progress of organizations in their digital transformation throughout the past years despite a wide range of support initiatives (cf. chapter 2.3.1).[87] Chhor et al. formulate fundamental requirements for a sustainable and successful process digitalization based on an extensive literature review and emphasize the necessity of agile approaches, employee participation, and management support along with ongoing change management to support a sustainable and successful digital transformation. The essential requirements comprise four dimensions[88]:

- **Culture:** This dimension revolves around the organizational culture and the role of employees in the organization. It represents the willingness and readiness of an organization to commit and participate in organizational change, the qualification of employees to support the transition process, and the required skills post-transition. Social collaboration across organizational divisions, e.g., employee participation and open communication, is significant throughout these stages.
- **Organization:** Organization structures and handles the cooperation within the organization in their day-to-day operations, like the internal organization

[85] cf. LaBerge et al. 2020, pp. 4–5.
[86] cf. Almeida et al. 2020, pp. 97–100.
[87] cf. Bitkom Research and Tata Consultancy Services 2020, pp. 40–41.
[88] cf. Chhor et al. 2021, pp. 627–628.

of workflows and the resources for inter-divisional cooperation aligned to digitalization objectives.

- **Resources:** Resources ensure the necessary support for change management. It covers frame conditions for digitalization initiatives, such as support from management, a diverse core team with digital competencies, efficient communication structures with the opportunity for employee participation, and technical capabilities and resources for operational activities.
- **Information system:** The information system represents the technical foundation for process digitalization and covers tasks from software selection, integration into present infrastructure, and the deployment process during change. In addition, it extends to considerations concerning data handling, processing, and usage concerning data security and privacy.

In an ideal setting, an organization considers and satisfies all dimensions mentioned above and thus ensures a smooth transition towards a larger share of digital processes. However, only some organizations display high maturity and fulfillment in all metrics. It is not necessary to equally satisfy the requirements in all dimensions before being deemed capable of digitalizing processes, though an established infrastructure will facilitate the transition immensely[89].

As previously discussed in section 2.3.1, larger organizations can initiate and commit to digitalization projects more than SMEs. Larger organizations benefit from their resources and involvement in supra-regional value chains with high requirements in digital business practices. An example is the high degree of process automation due to the scale of transactions and the usage of e-invoicing. Henceforth, it is no surprise that digitalization activities focus on digitalizing contact points between clients and suppliers, then modernizing the IT infrastructure and building digital competencies to exploit new technological advancements. On the other hand, the digitalization of internal processes ranks behind and refers to linking different divisions and reorganizing workflows[90].

As digitalization activities impact the organization, it also affects work practices and the pace of organizational changes. Therefore, organizational change management is essential to cope with the quicker pace and to consider the necessity of new skills and competencies, new forms of leadership, and organizational agility[91].

Modrak presents a comprehensive literature review about barriers to introducing

[89] cf. Zimmermann 2020, p. 9.
[90] cf. ibid., p. 11.
[91] cf. Kohnke 2017, p. 89.

digital technologies. The author identifies 19 barriers into six categories interlinking with sustainable and digital transformation requirements. The findings complement the requirements with the legal perspective of digitalization associated with present bureaucracy, restrictive laws, and regulations that represent a hurdle for quick-paced implementations. Furthermore, the author stresses the impact of a lack of standards and methodological approaches in digital technologies' implementation on its success. As a result, a high coordination effort and investment of time and money follow. The cases studied further highlight challenges attributed to the lack of cooperation among departments, the employees' resistance to change, and weak IT compatibility with the present infrastructure. Overall, the situation aggravates on account of not sufficiently qualified employees.[92]

Studies underline the challenge of employees to adapt to the changes in the wake of digitalization that hinders the development of required skills.[93] Training employees and acquiring young talents present a challenge. Especially in quick-paced digitalization efforts, an organization's inability to attract talent worsens. It poses a challenge to integrate digital talents into the core business while available digital skills are seldom leveraged across the organization. The know-how gravitates to the IT department, which tends to be loosely connected to core operations. It is more likely to observe isolated business areas in bottom-up digitalization initiatives misaligned with the overall business strategy. This circumstance wastes resources and impedes employees' motivation, as the lack of communication of business strategies and objectives will become clear. Rather, a proactive action on the management level as a model example will be necessary to involve employees, engage them to contribute, share awareness and concerns, and establish follow-up procedures.[94]

From a rational perspective, SMEs are worse off than larger organizations with lower budgets, fewer resources, and limited employee capacity and skills. Even considering the clear benefits of digitalization activities, investments may be risky. Low staffing leads to employees usually occupying multiple roles in the organization and working to the capacity to handle day-to-day business. Changes in the business environment and the organization due to digitalization activities can have a significant resource impact that aggravates employees' workload. Considering a usually poorly developed IT infrastructure and no dedicated organization department to keep overhead to a minimum, digitalization activities must justify the investment through an appropriate return on investments and the quick delivery of results. In the worst

[92]cf. Modrák and Šoltysová 2020, pp. 262–271.
[93]cf. Novikova n.d., p. 100.
[94]cf. Dahlander and Wallin 2018, pp. 1–2.

case, the lack of technologies and skills may impede the deployment of a business process management infrastructure.[95] However, in many industries, digital processes are a prerequisite to exploiting an organization's digital transformation to enable digital services and new business models.[96] Usually digital processes represents the first and most basic step[97].

On the other hand, SMEs' unique qualities exhibit clear benefits compared to larger organizations. As fewer people are involved in all organizational hierarchy levels and stages of a digitalization project, quick and adequate decision-making in an agile environment is possible, even in collaborative settings. The lack of staff requires employees to focus on critical capabilities in their business in a process-oriented manner. The involvement in a broad range of processes gives the individual a better overview across division boundaries than highly specialized employees in large organizations. Also, the regular and direct interaction with clients reinforces the setup of a process-oriented organization aligned with client needs. In this context, business process management remains essential for SMEs to scale their business and balance agility and standardization to succeed in a dynamic and competitive business environment. Standardization of core processes gives the structure essential to scale the business, and agility ensures customer orientation and focuses on value creation in a dynamic environment. Business process management builds upon this foundation and supports eliminating repetitive work and inefficiencies typically observed in small organizations.[98]. Nonetheless, deficits and hurdles in process digitalization remain that need to be addressed (cf. section 2.3.3).

2.3.3 Deficits and Need for Action

Assuming the satisfaction of essential requirements to execute digitalization projects (cf. section 2.3.2), the process manager will encounter more specific challenges in the practical execution of process digitalization. For example, ERP software propagation in organizations leads to a significant share of digitalized core processes as it is a readily available core module based on best practice examples in the respective industries. Hence, it is common only to observe minor deviations from this standard to tailor the business process to the individual needs of organizations[99]. Limited modifications in the core system may necessitate the procurement of standalone

[95] cf. Kirchmer 2017, pp. 169–171.
[96] cf. Legner et al. 2017, pp. 302–303.
[97] cf. Lichtblau et al. 2018, pp. 11–13.
[98] cf. Kirchmer 2017, pp. 172–175.
[99] cf. Chtioui 2009, pp. 153–154.

software solutions, as seen in the COVID-19 pandemic, and lead to a convoluted IT infrastructure with increasing media disruption and lagging organizational adaption.

These convoluted IT systems exhibit likewise complex organizational structures and impede effective communication and collaboration. Business growth features similar characteristics, for instance, in mergers and acquisitions[100]. This circumstance impedes efficient decision-making processes required for organizational and cultural changes. Few German enterprises denominated as hidden champions boast effective management through lean structures[101]. Hence, capturing the organization's characteristics and maturity level concerning the organizational and digital capabilities is essential.

In addition, the approach to process digitalization for process types other than core processes, especially support processes, becomes the object of interest. Support processes are essential and enable core processes in day-to-day business, but generally need more awareness in process digitalization. Accordingly, little information in process descriptions and metrics is readily available or does not correctly portray the as-is situation, inhibiting the initiation of process digitalization. The maturity of the process and its performance are either unknown or hard to gauge. It reflects the challenge of deriving a structured, methodological approach to define a starting point for an organization-wide digitalization of internal processes.

Once process data is available, data-driven modeling approaches can offset challenges in process evaluation and analysis to a certain degree by integrating and applying process mining types, namely process discovery (cf. section 2.2.3). It requires the data logged in event logs to be trustworthy and complete to reflect the factual process status properly.[102]. Based on pertinent data preprocessing to clean the event log, further considerations and analysis steps are essential to allow process mining application. Concept drift, an underlying process change reflected in the data set or the applicability of process algorithms, and the lack of sufficient data set size for recently digitalized processes are common challenges. Therefore, it is essential to develop methods to deal with and mitigate the impact of process analysis.

A common denominator that inhibits quick progress in process digitalization and the solution development to the deficits mentioned above is the essential skill proficiency in digital technologies combined with the domain knowledge specific

[100] cf. Gursch et al. 2013, pp. 74–75.
[101] cf. Simon 2009, pp. 235–237.
[102] cf. Aalst et al. 2012, p. 180.

to the respective process.[103] In SMEs, process optimization usually involves the process or quality manager. Therefore, the foundation for process digitalization is a business management process. The application of data-driven methods for process analysis should begin at a low level of required proficiency and requires easy interpretability while still enabling sizable benefits, given the unique situation of SMEs. Digitalization projects must ensure the anticipated benefits while keeping costs to a minimum.[104] Especially the latter point seldom holds as most know-how aggregates to software vendors and process consulting experts.[105]

2.4 Research Scope

The terminological delimitation of relevant terms introduces the research's object area and scope. It serves the purpose of delimitation and specifies the application domain of the thesis along with boundary conditions. It overlaps with the initial phases of research methodology based on Ulrich introduced in chapter 1.3.

Figure 2.10 depicts the heuristic frame for this thesis. The thesis focuses on the organizational-technical implementation between the conceptual and operational levels from a business process management perspective. The strategy-oriented phase is a prerequisite that represents the foundation for the business process implementation as a workflow. Hence, a minimum process maturity is apparent to ensure a sound and working workflow implementation within the organization's digitalization efforts. The workflow implementation alludes to semi-automation in handover tasks following a workflow's predetermined sequence of activities. As most core processes and their workflow represent a modification of standard ERP software modules, the process type in focus is support processes that have a significant role in securing business success but usually surmise a low-attention role.

Once digitalized, process optimization tends to focus on incremental improvements as radical changes are part of the digitalization process, not after that. Hence, the investigated process life cycle phases will be management and optimization, which require process data emerging from process execution and monitoring. The specific implementation of a digital process is not considered in the scope of research as it heavily depends on the individual situation of the organization. Instead, the focus will be on the process data generated through process executions in the information system, thus focusing on internal processes in the organization. As data analysis predominantly uses data about past events, analysis predominantly addresses the

[103] cf. Weber et al. 2020, pp. 58–71.
[104] cf. Zimmermann 2020, p. 11.
[105] cf. Reinkemeyer 2020a, p. 198.

perception and reaction, less the predictive and prevention perspective. Hence, operational support in process mining will have a minor role at most. Following this argumentation, outsourcing business processes will not be in focus either.

Nonetheless, while radical process optimization is not an objective, it will have a role in the data analysis to ensure proper application in the wake of concept drift. Process automation is predominant in robot process automation (RPA) and follows another objective compared to continuous optimization. It aligns with the idea of radical change due to necessities in system change and thus is not in focus.

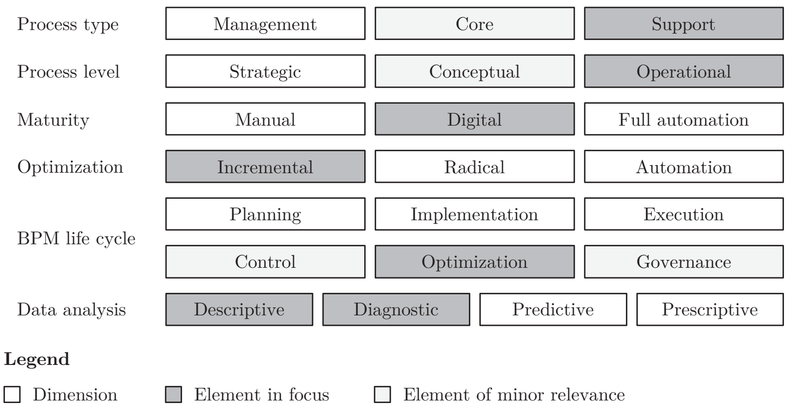


Figure 2.10: Research scope delimitation of the thesis

Outside the research scope of this thesis is the role of human factors. Here, it is assumed that only the process manager with domain knowledge and advanced expertise in process digitalization is the target group.

2.5 Objective and Tasks

The research questions frame the research objective and allow the enumeration of associated research tasks.

2.5.1 Research Questions

The research on the status quo of process digitalization shows significant progress over the past decade. Furthermore, advancements in data analytics, especially in process mining, allow the application of data-driven approaches to support process analysis. Therefore, a systematic approach to process digitalization and optimization is required to consider SMEs' specific situations to facilitate the deployment in broad industrial applications. This perspective requires a business management view to derive an appropriate starting point in process digitalization and demonstrate the added value by uncovering process insights. Hence, the primary research question of this thesis is:

RQ *How can a systematic approach to process optimization contribute to uncovering process insights for digital business processes?*

Prior to answering the primary research question, more aspects require thorough investigation. Based on the status of an organization and its business management structure, the initial question is which business processes to select as an anchor point to initiate an organization-wide digital transformation process and how to prioritize these. Many factors, for instance, the present process maturity, contribute to the decision-making. Thus, making a choice is not trivial. Therefore, the first underlying subordinate research question is:

SRQ1 *Which criteria support the decision-making of prioritizing business processes in digital transformation?*

Once the selected and digitalized process is in operation and generates exploitable process data, it is paramount to follow a systematic approach to gain insights into the process in data-driven process analysis. While the analysis exploits established methods of process data analysis, the deployment of methods follows a trial-and-error approach and is unsuitable for the target group of process managers with limited knowledge of data-driven analytical methods. Here, it is crucial to consider the balance between the generality and specificity of the approach to uncover valuable insights. The process-specific interpretation will remain within the responsibility of the process manager. Hence, the second underlying subordinate research question is:

SRQ2 *How can data-driven analytical methods be aggregated in a guided procedure model to facilitate process analysis and uncover process insights?*

As a common practice in business process management, process monitoring is continuous. The same applies to the envisioned process analysis that supports uncovering process insights to support the process manager in decision-making in process optimization. In cyclical approaches, it is essential to recognize underlying changes in the process data, thereby impacting process analysis. Questions arise on detecting and locating concept drift and gauging the implications for the analysis. Thus, the third underlying subordinate research question is:

SRQ3 *How can concept drift be considered in the cyclical process analysis?*

This thesis research follows the sequential order of the subordinate research question to answer the primary research question. Reviewing available digitalization quick checks and maturity models will establish the framework to help identify and prioritize business processes for organizations. Based on a digitalized business process, only recorded process data with little domain expertise is used to warrant generalization. Process data comprises the workflow model, process model, and event logs. A review of deployed models in different types of analysis will help structure and derive a reference procedure in process data analysis. Evaluating the impact of concept drift on the reference procedure will be further refined to accommodate its implications for the analysis and ensure its feasibility.

Individual sections in the thesis address and answer the research questions. The theoretical adaption based on the literature review will answer the first underlying research question. A guided reference model based on a literature review will elucidate solutions to the second underlying research question. Adapting the acquired reference model to mitigate implications due to concept drift will resolve the third research question. Chapter 6 will verify and validate the research results and process, and give insights into adopting the result in industrial applications. Finally, the primary research question will be answered based on the answers to the subordinate research questions.

2.5.2 Categorization of Research Tasks into BPM Life Cycle

Figure 2.11: Research question categorization in BPM life cycle

Describing the individual tasks in the procedure to digitalize and optimize processes facilitates categorizing research tasks to answer the primary research question. In addition, it is the foundation for developing methods to bridge the gaps in the underlying research questions. Figure 2.11 depicts the BPM life cycle that serves as the basis in the scope of research (cf. section 2.4). The reference helps match the subordinate research questions (cf. section 2.5) to the progress in consecutive phases of digital transformation.

The BPM life cycle phase in focus starts with process optimization realized by process digitalization (1), extending to the process organization and implementation phase. The research question associated with this step concerns the metrics in identifying and prioritizing the selected business process. Following the business process implementation as a digital process, its execution during the pilot and later in a day-to-day business generates the data for monitoring and controlling the process (2). The assumption here is a one-to-one transfer of a manual process into a digital process focusing on eliminating media disruptions. While this phase is not associated with research questions, it generates the data basis to answer the subsequent underlying research questions.

The primary focus on support processes implies that no performance indicators serve process control. Therefore, this phase assumes less significance in the thesis and is considered an integral part of process optimization. The optimization intends to exploit the recorded process data that raises the question of a standardized procedure given the frame conditions in the heuristic frame of the thesis. This outset coincides with the second research question. The requirements for this framework derive from the heuristic frame of the research and its formulated objective. The requirements act as criteria to collate established concepts and approaches on an abstract level to the requirements and assess the overlap. Based on this matching, a framework will be derived to structure the research tasks and the underlying research questions. The third research question addresses the concerns arising in a loop of process optimization, specifically how to deal with concept drift.

3 Process Maturity Assessment for Process Optimization

Building on the scientific fundamentals and the research's application domain (cf. chapter 2), the knowledge basis in this chapter introduces relevant research and practices to answer the first subordinate research question SRQ1 *Which criteria support the decision-making of prioritizing business processes in digital transformation?* The research focuses on assessing the process maturity level to gauge the most prominent potential and significant impact for an organization post-digitalization. After establishing the requirements to benchmark existing approaches (cf. sections 3.1 and 3.2), the most suitable one given the application scenario in the previous section will be selected (cf. section 3.3) and expanded if required (cf. section 3.4). Conclusively, the chapter ends with a summarizing assessment of the research question (cf. section 3.5).

3.1 Requirements for Process Maturity Assessment Model

The first step in prioritizing the process for digitalization is to estimate the potential and impact of improvements based on the status quo. A suitable approach is to deploy process maturity models as the foundation of process evaluation.[106] The initial assessment allows to formulate a target status post-implementation, estimate the expenses, and derive a roadmap with specific tasks to proceed with the implementation.[107] Refer to the ISO/IEC 33000 family for general information on terminology, principles, building elements and guides regarding process assessment[108]

The specific requirements for process maturity models deployed in the thesis originate from the identified gaps in the status quo of German organizations and the research objective (cf. section 2.3 and section 2.4), supplemented with further information and considerations:

- RQ1-R1 Business process maturity assessment
- RQ1-R2 Digital maturity assessment
- RQ1-R3 Optimization potential evaluation

[106]cf. Geers et al. 2010, p. 113.
[107]cf. Hanschke and Lorenz 2021, p. 278.
[108]cf. International Organization for Standardization and International Electrotechnical Commission 2015, p. 8.

- RQ1-R4 Process optimization prioritization
- RQ1-R5 Non-expert usability

The explanation of the list of requirements follows. The requirements serve as evaluation criteria to discuss the below process maturity models and their fit within the scope of this research. Each requirement discerns three levels of compliance. The degree of compliance to the respective criteria determines its level. Accordingly, the visual representation with Harvey Balls (none, partial, and full) gives a quick overview.

RQ1-R1 *Business process maturity assessment:* The assessment of a business process is multi-dimensional and distinguishes between process-specific and organization-wide business process management metrics. Standardized maturity levels offer objective assessment criteria and support a sharp distinction between the maturity levels of different processes. In addition, the metrics assessment must ensure transparency and reproducibility to support decision-making in their improvement based on facts properly.

- ○ **None:** The process maturity model assesses low-dimensional business process criteria on a process-specific or organization-wide level.
- ◑ **Partial:** The process maturity model assesses multi-dimensional business process criteria on a process-specific or organization-wide level.
- ● **Full:** The process maturity model assesses multi-dimensional business process criteria on a process-specific or organization-wide level. It introduces comprehensible metrics to discern between maturity levels by deploying a standard with objective evaluation criteria or defining a benchmark to compare the characteristics.

RQ1-R2 *Digital maturity assessment:* Digital maturity is a specific dimension required in the maturity level assessment to distinguish between non-digital processes, digital processes, and hybrid variants. Digital maturity refers to the degree of digital integration and process automation, allowing for a more sophisticated assessment. However, a digital and especially fully automated process does not necessarily correspond to the highest theoretical level of maturity, considering the potential of self-control in networked systems.[109] Given this research context, the latter characteristic of digital processes is negligent as it is more applicable to sentient production systems demonstrating artificial intelligence capabilities and autonomous control.

- ○ **None:** The process maturity model does not deploy metrics on a process-

[109]cf. Appelfeller and Feldmann 2018, pp. 20–24.

specific or organization-wide level to differentiate between non-digital processes, digital processes, and hybrid variants.

- ◑ **Partial:** The process maturity model deploys low-dimensional metrics on a process-specific or organization-wide level to differentiate between non-digital, digital, and hybrid variants.
- ● **Full:** The process maturity model deploys multi-dimensional metrics on a process-specific or organization-wide level to differentiate between non-digital, digital, and hybrid processes. Comprehensible metrics discern between maturity levels by deploying a standard with objective evaluation criteria or defining a benchmark to compare the characteristics.

RQ1-R3 *Optimization potential evaluation* A process maturity model not only assesses processes or the organization but also identifies areas for improvement on a process-specific or organization-wide level. The latter provides the foundation for working processes, e.g., employee training and connected information systems. The maturity metrics give insight into the identified gaps and their opportunities for improvement. The opportunities expand to direct or indirect recommendations based on best practices in case of predetermined standards or a benchmark. It guides a recommended sequence of activities if it addresses multiple optimizations within one domain.

- ○ **None:** The maturity model assesses metrics but does derive recommendations for action. It manifests in vaguely defined metrics or offers no objective guidance on indicators to determine the maturity level.
- ◑ **Partial:** The maturity model assessment provides insights on specific recommendations for action to progress the organization's or processes' maturity level. It is of negligible significance whether the recommendation is direct or indirect. Few maturity models offer checklists of items containing specifics to progress the maturity level. Others define a benchmark to compare the assessment metrics to a best practice.
- ● **Full:** The maturity model not only provides specific recommendations for action but also supports prioritizing and sequencing these to derive the best course of action, e.g., in the form of a roadmap. In addition, flexible criteria result in specific recommendations based on experience, individual weighting, and preferences (e.g., focus on low-hanging fruits or long-term benefits).

RQ1-R4 *Process optimization prioritization:* The maturity model assesses an organization's business processes on a holistic level, considering the organization's business process management and other contributing factors. If metrics address individual processes and metrics on an organization-wide level, the maturity levels follow suit accordingly and discern between the two perspectives. Hence, in conjunction with identified gaps and recommendations for action, an assessment of individual processes allows for ranking multiple processes and their prioritization order for digitalization.

- ○ **None:** The maturity model assesses business processes on an organizational level and does not differentiate or cluster processes into coherent segments.
- ◑ **Partial:** The maturity model differentiates between clusters of business processes structured by a common denominator. It is specific to the organization and can be a specific process type (e.g., core and support processes), organizational affiliation, or another criterion. The segmentation alludes that a ranking of maturity level across these clusters, either directly or indirectly, is possible.
- ● **Full:** The maturity model assesses business processes individually, differentiating maturity levels. Given the level of detail, flexible metrics allow prioritizing which business process to first digitalize to factor in an individual organization's characteristics.

RQ1-R5 *Non-expert usability:* A low inhibition barrier without needing external experts ensures the usability of the process maturity model for non-experts to gain insights into the process maturity and derive recommendations for action. In addition, the support extends to the prioritization of processes digitalization in line with the organization's strategy.

- ○ **None:** The maturity model only allows for external assessment by a team of assessors that have undergone special training due to the scale and complexity of the required knowledge.
- ◑ **Partial:** The maturity model allows for a self-assessment but only gives limited insights due to the model's complexity or requires additional training for domain experts before its application.
- ● **Full:** The maturity model allows for a self-assessment without supplementary training. It focuses on the assessment's practicability and the domain expertise's availability and experience. Hence, it may impede the depth of the assessment compared to a thorough assessment by trained assessors in favor of lower expenses and a quick initial assessment.

3.2 Process Maturity Models

Estimates gauge the number of process maturity models beyond 200[110]. This section focuses on a selection of models that demonstrate overlap with the defined criteria in section 3.1) and references most common maturity models, as suggested by Schmelzer et al.[111] and Hanschke et al.[112], also recently published maturity models (cf. section 3.2.1). Aside from conventional maturity models, the review includes models and frameworks descending from neighboring thematic fields enterprise architecture management (cf. section 3.2.2) and management practices (cf. section 3.2.3).

3.2.1 Business Process Maturity Models

The first model type is the maturity model focusing on business process management or business processes. The sequence of model introduction and brief evaluation regarding the defined criteria follows the chronological order of referenced papers and publications.

Rosemann et al. (2005): Business Process Management Maturity Model (BPM-MM)

Rosemann et al. propose a BPM maturity model based on the assumption that the identified factors contribute to process performance and business success. An increase in the maturity of these factors boosts success accordingly. These factors are categorized into six dimensions (strategic alignment, culture, people, governance, methods, and IT) and have different sub-characteristics that are assigned a maturity ranging from one to five. It does not focus on a specific process but on an organizational entity within an organization and builds upon the foundations of business process management.[113]

Figure 3.1 illustrates the underlying theoretical model. The assessment of stages follows the five maturity stages defined in *Capability Maturity Model* (CMM), the predecessor of *Capability Maturity Model Integration* (CMMI), and includes the scope, i.e., the perspective in the assessment. Aside from the organizational perspective, it includes the time of assessment to display changes during time frames. Each

[110]cf. Schmelzer and Sesselmann 2020, p. 476.
[111]cf. ibid., p. 477.
[112]cf. Hanschke and Lorenz 2021, p. 61.
[113]cf. Rosemann and Bruin 2005b, p. 5.
[114]own representation based on ibid., p. 6.

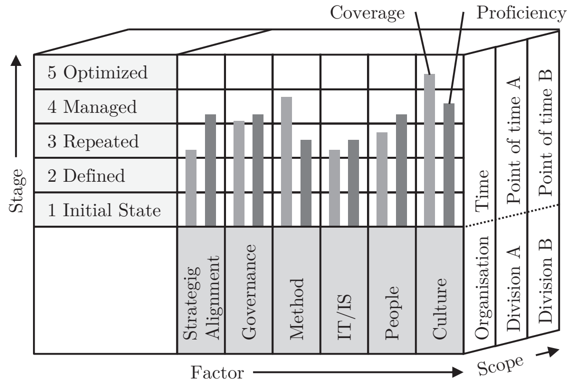


Figure 3.1: Business Process Management Maturity Model[114]

factor differentiates in the assessment between coverage and proficiency (broadness vs. specificity). A survey with 300 questions is the input for the assessment towards either dimension and maturity level but does not specify sub-dimensions yet.[115] More detailed information on the model is referenced in[116].

Evaluation: The BPM-MM covers the essential requirements to assess business process maturity and highlights the importance of digital maturity regarding the role of information systems. However, it lacks model details and more hands-on guidance on the application and derivation of optimization potentials. Since its release in 2005, more comprehensive models with subdimension information have emerged that increase transparency and non-expert usability.

Hammer (2007): Process and Enterprise Maturity Model (PEMM)

Hammer introduces the comprehensive framework *Process and Enterprise Maturity Model* (PEMM) to allow organizations to perform a self-assessment independent of their industry. The framework distinguishes between process enablers and enterprise capabilities that assess the maturity of the processes and the organization's readiness for change. It does not specify a best practice for a specific process but gives guidance toward a standard based on four statements for each criterion. For each statement, the assessor evaluates the degree of compliance with the statement and assigns a

[115] cf. Rosemann and Bruin 2005a, pp. 18–19.
[116] cf. ibid., pp. 6–19.

color code (traffic light system). Less compliance indicates hindrances to attaining a higher maturity degree.[117] Process enablers assess a single process based on five criteria (design, performers, owner, infrastructure, and metrics) with multiple subcriteria each. The organization's capabilities across the four dimensions of leadership, culture, expertise, and governance assess overarching criteria for high-performing processes that are equally valid for all processes and, therefore, their foundation.[118] Figure 3.2 depicts the framework structure. Refer to the authors' publication for further information and application examples.

Dimension		E-1	E-2	...	Assessment		
Leadership	Awareness	[Statement for this level]	...	...			
	Alignment	[Statement for this level]	...				
	...	...					
	...	...					
⋮	...	...					
	...	...					

Figure 3.2: Process and Enterprise Maturity Model framework[119]

Evaluation: The framework PEMM distinguishes between the assessment of individual processes and necessary, underlying capabilities provided by the organization. Pre-determined statements across multiple subcriteria allow non-experts with minimal previous knowledge to apply the framework in an initial assessment. As the statements for evaluation are independent of a specific process, these offer generalizability and easily highlight the gaps to increase maturity. A minor drawback is that it falls short when prioritizing processes and evaluating their digital maturity.

ISACA (2018): Capability Maturity Model Integration (CMMI)

The *Capability Maturity Model Integration* (CMMI) is an internationally renowned maturity model with a broad application area.[120]. The *International Information Systems Audit and Control Association* (ISACA) manages and continually develops CMMI. Its main goal is to improve the business performances of organizations and adapt software process improvement to changing business needs by evaluating the

[117] cf. Hammer 2007, pp. 4–10.
[118] cf. ibid., p. 3.
[119] own representation based on ibid., pp. 15–16.
[120] cf. Dumas et al. 2018, p. 490.

organizational capability and performance according to defined metrics. It addresses three views for process improvement in its appraisal process in its latest release: development, services, and supplier management.[121]

CMMI differs between capability and maturity appraisal ratings: the first allows continuous evaluation of individual process areas. The maturity level refers to a set of predefined process areas or even the organization as a whole.[122] CMMI defines four categories of process areas (project management, engineering, support, and process management) that incorporate 22 process areas in total. Capability metrics help targeted improvement in individual process areas based on specific or generic goals. For each goal, best practices serve as a support to achieve the goal. Specific goals and practices are individual to the process area, while generic goals and practices apply to all areas. For cross-department improvements in the organization, a maturity appraisal is more suitable.[123] Figure 3.3 depicts the corresponding CMMI levels for both capability and maturity.

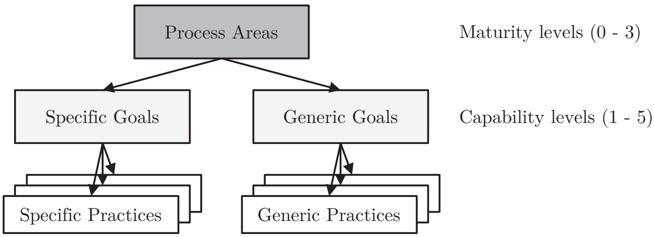


Figure 3.3: CMMI levels[124]

The appraisal method is known as the *Standard CMMI Appraisal Method for Process Improvement* (SCAMPI) and differentiates between classes A, B, and C, each with a different focus (institutionalization, deployment, and approach). A higher class sets more rigorous standards for detailed data collection, identification, and coverage of organizational units, while the lower classes relax these requirements. Accordingly, the expenses and insights increase with the appraisal class.[125]

[121] cf. Chaudhary and Chopra 2017, pp. 5–7.
[122] cf. ibid., p. 9.
[123] cf. ibid., pp. 15–28.
[124] own representation based on ibid., pp. 15–16.
[125] cf. Hayes et al. 2005, pp. 3–4.

Evaluation: The CMMI framework is the most widely used model for maturity assessment and often serves as the basis for newer models. However, while it offers a detailed approach and insights based on best practices collected with industry experts, limitations exist for non-experts due to the volume of information and types of appraisals and its approach to defining best practices. Furthermore, for each process area, it defines essential processes but does not specify the implementation per se[126]. Hence, the applicability to prioritize process digitalization is nonexistent.

OMG (2008): Business Process Maturity Model (BPMM-OMG)

The *Object Management Group* (OMG) expands CMMI with a stronger focus on the organizational perspective to develop a standardized approach to evaluating and improving enterprise systems.[127]. The *Business Process Maturity Model* intends to allow organizations to achieve organizational agility at a low cost by guiding and implementing business process foundations. The belief is that business processes reflect organizational weaknesses and thus represent a means for improvement.[128].

Hence, business process evaluation can determine an organization's capability to contribute to its organizational objectives and sustain its efforts. The objective of process improvement here is to achieve predictable states of organizational capability through organizational changes. Corresponding maturity levels describe the potentials in improvement structured along process areas.[129]. The model itself is not restricted to a specific domain and applies to both internal and external processes.[130].

A process area is a cluster of related and standardized practices structured along five threads across all maturity levels. Organizational process management and organizational support are two examples taken from a set of 30 described process areas. The process area thread for organizational process management links all associated management practices to initiate, sustain, direct, and improve the organization's process management. With increasing maturity, the scope of practices and their complexity grows accordingly. The requirements defined for the process areas of each maturity level must be satisfied (or are not applicable) to proceed with a higher

[126] cf. Dumas et al. 2018, p. 491.
[127] cf. Hogrebe and Nüttgens 2009, p. 18.
[128] cf. Object Management Group 2008, p. 3.
[129] cf. ibid., pp. 19–20.
[130] cf. ibid., p. 69.
[131] own representation based on ibid., p. 73.

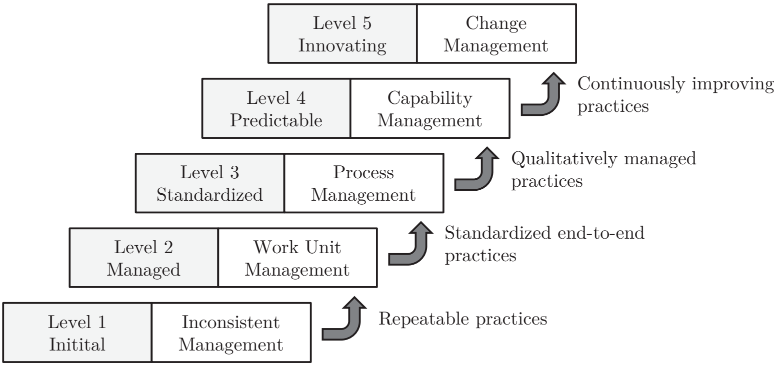


Figure 3.4: BPMM maturity levels[131]

maturity level. It constitutes best practices but does not impose restrictions regarding specific structures, e.g., on organizing and storing business process information. Thus, it neither stipulates which business processes an organization requires.[132] The BPMM-OMG documentation covers four appraisal types that range from a brief and high-level internal evaluation (starter appraisal) to a thorough investigation of all process areas and practice areas by an external appraisal team.[133] Refer to the documentation published by OMG for further information and guidance.[134]

Evaluation: Similar to CMMI, BPMM-OMG is generally applicable and defines process areas with best practices that serve as a benchmark for assessing and identifying gaps. Hence, it shares the identical drawback of not allowing one to prioritize an individual process for digitalization. On the other hand, BPMM-OMG is complex and requires expert knowledge to apply appropriately and derive practical insights. The deployment of BPMM-OMG requires individual modification to adapt to the organization's requirements prior to the application.[135].

Appelfeller et al. (2019): Digital Process Maturity (DPM)

Appelfeller et al.[136] introduce four different characteristics and respective maturity degrees for digital processes(cf. figure 3.5):

[132]cf. Object Management Group 2008, pp. 87–89.
[133]cf. ibid., pp. 5–6.
[134]cf. ibid., pp. 431–448.
[135]cf. Hogrebe and Nüttgens 2009, p. 24.
[136]cf. Appelfeller and Feldmann 2018, pp. 20–33.

- **Degree of digitalization:** The first characteristic of digital processes refers to the share of activities within a process that uses information systems in their execution. For example, paper-based activities with no information system support are analog processes, whereas processes with complete IT support and digital data are fully digital.
- **Degree of digital automation:** Digital automation refers to activities executed by an information system without manual human intervention. Automation requires processes to be digital, but not necessarily within a single information system. Non-automated activities can be digital or analog but share the commonality of manual execution.
- **Degree of digital integration:** Digitally integrated processes assume at least a partial process digitalization. Complete integration refers to process execution within one integrated information system with a shared database and does not necessitate the automation of activities. Full integration requires at least defined IT interfaces for data exchange in multiple information systems. Activities supported by different, non-networked information systems are considered isolated.
- **Degree of digital self-control:** Digital self-controlled and networked processes enable autonomous decision-making and self-control. It requires capabilities for reactivity, adaptability, and collaboration. Partial self-control requires complete digitalization, automation, and integration for the respective activities.

Comparing the respective share of activities that satisfy the respective characteristic to the quantity of all activities within a process yields the maturity degree. The author suggests a four-level maturity model for each characteristic, split into 25 % intervals each. Level one corresponds to the lowest, and level four to the highest degree of maturity. Refer to the authors' publication for further information and application examples.[138]

Evaluation: *Appelfeller et al.* present an approach that centers around distinct characteristics of digital processes. It assesses individual processes and breaks them down on a process step level. It gives much insight into the level of digital integration and automation per process step but does not distinguish between different levels of process digitalization for a single step: it either corresponds to

[137] own representation based on ibid., p. 21.
[138] cf. ibid., pp. 20–35.

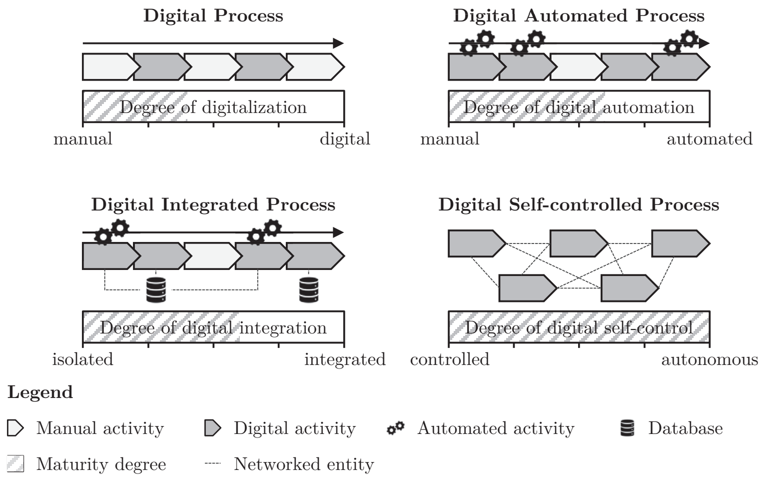


Figure 3.5: Digital Process Maturity[137]

the digital characteristic or not, thus not allowing intermediate characteristics. It focuses on the interrelation of process steps and highlights the gaps but completely neglects aspects of business process management and organizational capability.

Froger et al. (2019): Business Process Management Maturity Framework (BPM-MF)

Froger et al. develop a framework for business process management maturity that considers three perspectives: the BPM cycle, the fields (culture, business, and IT), and the abstraction level (data, jobs, and behavior). The consideration of the BPM cycle allows a differentiated assessment for organizations with further progress along the BPM cycle. Hence, it differentiates between designing, enacting, and maintaining processes. The business field axis covers culture and business-related structures such as the organization and the IT infrastructure.[139] The last axis abstraction level breaks down the granularity of improvements of data, jobs, and its sequencing represented as behavior.[140]

[139]cf. Froger et al. 2019, pp. 9–10.
[140]cf. ibid., p. 11.
[141]own representation based on ibid., p. 16.

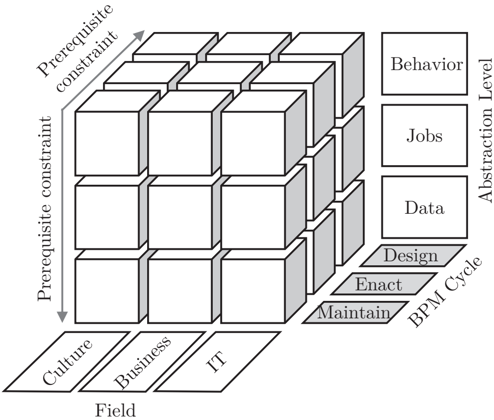


Figure 3.6: Non-linear Business Process Management Maturity Framework[141]

Figure 3.6 illustrates the non-linear framework. The division of the three-axis results in 27 cubes resulting from the interaction between the three axes.[142] The logic behind the axis dictates prerequisite constraints for the BPM cycle and the abstraction level. First, processes require their design before being enacted and maintained. Also, data as input realizes jobs, and their chaining result in behavior that results in an order for improvement. On the other hand, the other cubes in the field are independent. Hence, it does not dictate a specific way to improve maturity and allows modification tailored to an individual organization. Multiple approaches to increasing BPM maturity exist.[143] The author suggests defining the 27 cubes as prescriptive achievements that allow for overall assessment and tracking of individual processes along the framework.[144]

Evaluation: The framework follows a novel, non-linear approach as, contrary to most models, it does not suggest a specific sequence of activities to reach an overall higher BPM maturity. As this is its strength, it also is a disadvantage as it requires extensive expertise to comprehend the framework's application. The identified 27 achievements to follow are not detailed and do not offer much insight into how

[142]cf. ibid., p. 12.
[143]cf. ibid., pp. 15–16.
[144]cf. ibid., p. 24.

to improve the process. Due to its complexity and non-linear approach, setting a benchmark that reflects a good maturity level is hard. The assessment of an individual process requires the organization's assessment for a benchmark to issue an estimate, whether it is better or worse. Other vital factors for the organization's assessment are amiss, i.e., strategic alignment and staff expertise.

Bitkom (2020): Maturity Model Digital Business Processes (MM-DBP)

The task force *Digital Business Processes* of *Bitkom e.V.,* a German digital industry association representing more than 2,700 organizations in the digital economy[145], has developed a sector-independent maturity model to assess business processes with a focus on practical application. Both scientific advances and domain knowledge contribute to the creation of this handbook[146].

The authors differentiate four dimensions with three subdimensions, creating the assessment's foundation. The technology addresses technical aspects and evaluates the integration into the organization's IT infrastructure and its compatibility with other process dimensions. The dimension data covers data handling, including data collection, analysis, and usage. Quality covers the status of the process. In this sense, the process quality and aspects related to business management. The organization dimension represents organizational frame conditions related to the processes and contributes to their success, e.g., employee qualification and change management.[147]. Two statements represent operational criteria for each subdimension, and a scale from one to five corresponds to the fulfillment assessment (not digital to full digital). The weighted sum on each level gives a quick insight into its maturity. The assessment is intended for a single business process but is extendable to larger units, e.g., whole divisions. Additional documentation support process mapping and assessment visualization[148]

Evaluation: The maturity model assesses the business process and digital maturity considering select dimensions. The operationalization of criteria serves as hints towards the optimization potential evaluation as these also are the benchmark criteria. While its primary purpose is to assess individual processes, the maturity model is flexible enough to apply in division-wide business processes. A shortcoming in

[145]cf. Britze et al. 2020, p. 31.
[146]cf. ibid., p. 31.
[147]cf. ibid., pp. 8–9.
[148]cf. ibid., pp. 10–12.
[149]own representation based on ibid., p. 17.

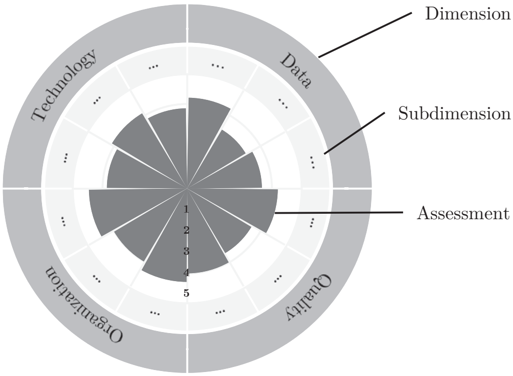


Figure 3.7: Maturity Model Digital Business Process[149]

the application is the lack of prioritization, as there is no information in evaluating multiple business processes. However, the practical usability is high as a low-threshold offering that is freely accessible and offers use cases.

Schmelzer et al. (2020): Process Maturity Model (PMM)

Schmelzer et al. introduce a process maturity model to assess individual business processes. It is not limited to a specific process type or domain and differentiates five maturity dimensions for assessment: process optimization, control, planning, responsibility, and definition. Contrary to its definition, a maturity level resembles an assessment dimension more than the maturity level, where a higher level requires the requirement satisfaction of lower levels. The weighting can either be equal or adapted to the organization's strategy.[150]

A checklist supports the assessment of each maturity level. Questions guide the process to estimate the degree of requirements' fulfillment, and its mean average percentage reflects the assessment for each maturity level.[152] The maximum score of

[150]cf. Schmelzer and Sesselmann 2020, pp. 496–497.
[151]own representation based on ibid., pp. 496–500.
[152]cf. ibid., pp. 847–850.

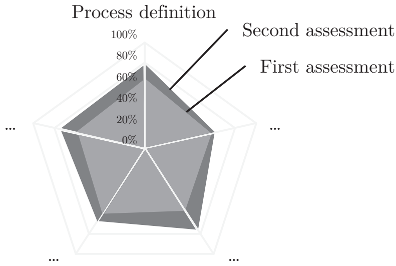


Figure 3.8: Process Maturity Model[151]

100 percent reflects the process quality and gives insight into action recommendations, especially when comparing multiple business processes. Multiple assessments show the progress over time.[153]

Evaluation: Schmelzer introduces a process maturity model applicable to all process types and intended for individual assessment. The model allows a comparison of processes but not necessarily a ranking for prioritization. In addition, it addresses specifics in business process maturity but neglects a more holistic view if there is an underlying issue with the business process management in the organization.

Szelagowski et al. (2021): Business Process Management Maturity Assessment (BPM-MA)

Szelagowski et al. introduce a framework for business process maturity assessment that differentiates between groups of processes on different levels with a varying set of assessment criteria based on the general BPM maturity level. Differentiating factors are, among others, the unpredictability and knowledge-intensity of processes[154] The intended application is embedding the maturity assessment in implementing BPM in the organization. The results of the assessment serve as the basis for following implementation steps based on objective data regarding benchmarking, recommendations for implementation, and the verification of selected methods[155]

[153]cf. Schmelzer and Sesselmann 2020, pp. 498–500.
[154]cf. Szelągowski and Berniak-Woźny 2021, pp. 188–189.
[155]cf. ibid., p. 186.
[156]own representation based on ibid., p. 189.

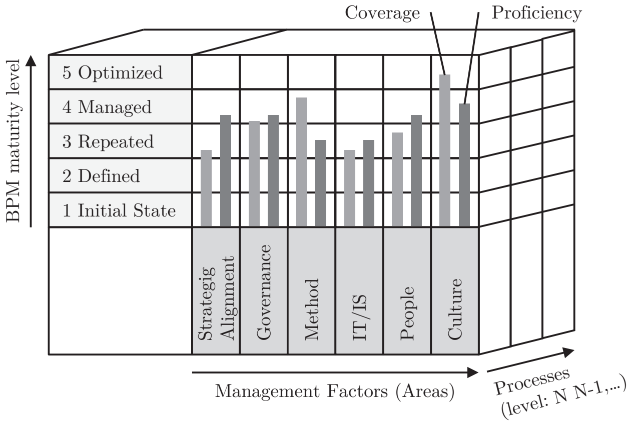


Figure 3.9: Business Process Management Maturity Assessment[156]

Figure 3.9 picks up six dimensions, so-called management factors, that constitute the assessment criteria (strategic alignment, governance, methods, ICT, people, and culture) and can incorporate subfactors. Each dimension has two indicators: coverage and proficiency, representing broadness and specificity. According to the standard definition of the five-scale BPM maturity levels following *CMMI* (cf. section 3.2.1), the assessment follows suit. Accordingly, for each process level, the assessment then requires evaluating a minimum of twelve criteria[157]

Evaluation: The *BPM-MM* builds upon the work of ROSEMANN (cf. section 3.2.1) and focuses on the process perspective from an end-to-end view in comparison to the previous organizational perspective. Although it incorporates a novel perspective, the underlying theoretical foundation remains unchanged and on a high level. Accordingly, it scores similarly in the evaluation.

3.2.2 Enterprise Architecture Framework

Enterprise architecture frameworks assume different functions depending on their interpretation. The context of this research mainly addresses the alignment of business and IT. It thus focuses on the designing and planning of IT capabilities to meet the business objectives.[158] Most frameworks that fall within this category

[157]cf. ibid., p. 189.
[158]cf. ARNOLD 2022, pp. 18–19.

not only define a standard but usually give guidance based on best practices and derive a maturity model for assessment. While it maintains a vital role in process digitalization, the strong IT perspective neglects the business process perspective that serves as its foundation. Hence, these frameworks assume a minor role in this chapter.

The most widely used enterprise architecture framework developed by the *Open Group* is *The Open Group Architecture Framework* (TOGAF). It has the objective of creating effective and efficient business operations to contribute to an organization's digital transformation[159]. In addition, it serves as the evaluation benchmark for enterprise architecture frameworks. Other widely-known frameworks are *Control Objectives for Information and Related Technologies* (COBIT) and *IT Infrastructure Library* (ITIL), which differ in their focus on IT architecture.

Evaluation: Similar to some process maturity models, enterprise architecture maturity models define a standard to benchmark processes and practices. However, as the focus is strictly on IT processes at most, it requires expert knowledge. It serves as information input to derive comprehensive assessment characteristics for the general assessment of digital process maturity, thus not allowing assessing or evaluating different processes to derive a prioritized order in digitalization.

3.2.3 Management Practices

Some models and frameworks benchmark an organization's performance excellence against their respective models or frameworks. Moreso than the previously introduced models, these allow for a comparison between different organizations through a third party that governs the framework and awards a prize for outstanding performances to model organizations. The most well-known ones are the *EFQM Global Award* based on the *EFQM Excellence Model* in Europe and the *Malcolm Baldrige National Quality Award* (MBNQA) based on the *Baldrige Excellence Framework* in the United States of America. Additionally, ISO 9004:2018 gives guidelines for enhancing the quality of an organization from a quality management perspective. Akin to the previous sections, this section introduces management practices and evaluates them according to the criteria in section 3.1.

EFQM Excellence Model

EQFM Excellence Model is a management framework developed by the *European Foundation for Quality Management* (EFQM) to support organizations in managing

[159]cf. The Open Group 2005, pp. 7–8.

change and improving performance. Figure 3.10 visualizes the framework with essential elements derived from Total Quality Management. In its latest version, it has incorporated sustainability in the framework[160].

Three dimensions structure the approach: direction, execution, and results. Within these dimensions, seven criteria assess the organization. Criterion seven in results, strategic and operational performance, addresses the operations and thus BPM of the organization. The RADAR logic (results, approaches, deployment, assessment, and refinement) in EFQM serves as the diagnostic tool to evaluate the status quo and opportunities for improvement. It breaks the seven criteria into tangible attributes with associated leading questions to differentiate their level. A self-assessment and assessment by a trained assessor team with RADAR scoring matrices of 1,000 points (20 % for the relevant criterion) are possible.[161]

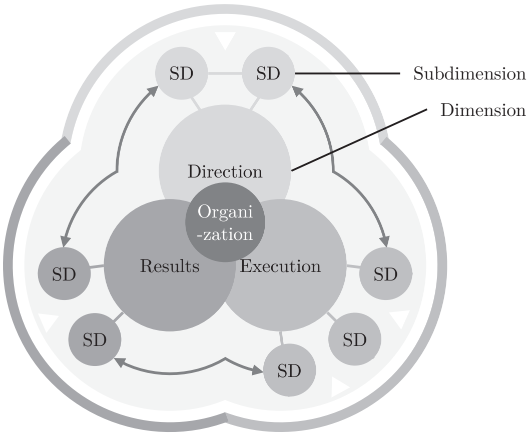


Figure 3.10: EFQM Excellence Model[162]

Evaluation: The *EFQM Excellence Model* evaluates the organization on a system level. Its newest version incorporates additional criteria on the organization level but only addresses relevant topics on the surface without the required depth. In

[160]cf. Institute or Total Quality Management 2019, p. 5.
[161]cf. ibid., pp. 27–33.
[162]own representation based on ibid., p. 4.

addition, while it allows for self-assessment, the RADAR scoring matrices do not differentiate between individual processes.

Baldrige Excellence Framework

Established by the *National Institute of Standards and Technology* (NIST) in America, the *Baldrige Excellence Framework* assesses an organization's performance from a system perspective. Figure 3.11 depicts the framework. It comprises core values, concepts, seven evaluation criteria, and scoring guidelines. The assessment differentiates business/non-profit, healthcare, and education industries. Like other frameworks, it serves to understand the organization's inner workings and assesses and identifies gaps to handle in multiple improvement cycles. The criteria cover leadership, strategy, customers, measurement, analysis and knowledge management, workforce, operations, and results.[163]

Different categories award point values to a total sum of 1,000 points. The relevant category operations occupies a relative importance of 85/1,000 points. It focuses on how an organization designs, manages, and improves key processes. While the other categories contribute to it, e.g., workforce and results, these are outside the focus. The assessment follows leading questions addressing work processes (process design, management, improvement, supply chain, and innovation management) and operational effectiveness (process efficiency and effectiveness, information system management, safety, and emergency preparedness).[164] Scoring guidelines give insights to scoring ranges.[165]

Evaluation: The *Baldrige Excellence Framework* focuses on evaluating the organization as a whole and only addresses business process management on a high level with low relevance. While it scores in BPM and addresses principal aspects, it per se does not assess maturity on a reference scale. Instead, it uses generic descriptions to assess individual dimensions into scoring ranges. Self-assessment also is possible. Also, it incorporates dimensions not generally applicable to all organizations. For example, concerning support processes, only one question addresses the issue of their determination and has identical relative weight to supply chain management, which is not equally essential to all organizations.

[163] cf. National Institute of Standards and Technology 2017, pp. i–iii.
[164] cf. ibid., pp. 23–25.
[165] cf. ibid., pp. 31–34.
[166] own representation based on National Institute of Standards and Technology 2021, p. 2.

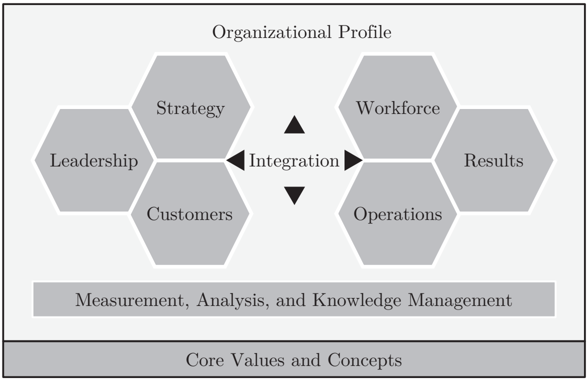


Figure 3.11: Baldrige Excellence Framework[166]

ISO 9004:2018

ISO 9004:2018 guides an organization to success through quality management. It builds upon the quality management principles provided in ISO 9000:2015 but focuses on the organization's ability for sustained success from the management level. It shares information on systematic improvements in overall performance through planning, implementation, analysis, evaluation, and improvement of an effective and efficient management system.[167] The norm provides a self-assessment tool in the appendix. Five maturity levels for 30 criteria related to subclauses in the document assess the overall organization. Level one refers to a base level, while level five corresponds to a best practice of a criterion.[168].

The relevant criteria reference subclause eight, which focuses on processes in the organization and the respective maturity scale[169]: process governance, determination, responsibility, and authority and management (alignment, maintenance, and improvement). Each level of maturity covers statements relevant to the subclause and requiring fulfillment to achieve a higher maturity level, e.g., statements for maturity level two are a subset of requirements for maturity level three.

[167]cf. Deutsches Institut für Normung e. V. 2018, p. 10.
[168]cf. ibid., pp. 55–56.
[169]cf. ibid., pp. 74–84.
[170]own representation based on ibid., p. 84.

	Maturity level		Conclusion	
	Lvl.	Item	Yes	Comment
Subclause 8.4: Managing processes	1	Processes improved in ad hoc manner.		
	2	[Requirement for this level]		
		...		
		...		
	...	...		
		...		

Figure 3.12: ISO 9004:2018 self-assessment[170]

Evaluation: ISO 9004:2018 provides a guideline for systematically improving the organization's performance. While it addresses relevant criteria to sustain and improve processes, processes digitalization only assumes a minor role within the organization's self-assessment as it targets the organization as a whole. Hence, it remains vague and generic and does not allow for assessing individual processes. Moreover, it is challenging for non-experts to comprehend the foundation for the self-assessment as it requires knowledge about related standards in the ISO 9000 family.

3.3 Interim Results for Process Maturity Models

Many process maturity models come with inconsistent naming, e.g., process improvement frameworks or maturity assessments, which refer to business process management and a method for assessing the present state to derive optimization potentials.[171]. Most do not distinguish between business process management maturity and process business process maturity, which inhibits their applicability for adopters[172]. Table 3.1 summarizes the assessment in a comprehensive overview. Most process maturity and digital maturity models are comparable in both specifications of maturity levels and evaluation dimensions[173].

Hence the review in the previous section focuses on the approaches with more distinct differences and widely referenced approaches. It is common for more recent maturity models to extract their foundations from previous models, e.g., the above-referenced model by Rosemann et al. that builds upon insights from Fisher[174].

[171]cf. Looy et al. 2017, p. 462.
[172]cf. Röglinger et al. 2012, p. 15.
[173]cf. Gökşen and Gökşen 2021, p. 5.
[174]cf. Fisher 2004, p. 1.

On the other hand, proprietary maturity models such as EDEN[175] without open access documentation, or maturity models tailored to specific industries such as the *Digital Maturity Model* (DMM) for telecommunications[176] or these tailored to the needs of specific companies such as the *Process Management Maturity Assessment* (PMMA)[177], are not considered.

Table 3.1: Literature review on process maturity assessment

	Literature	R1	R2	R3	R4	R5
Process Maturity Models	Rosemann et al. (2005): BPM-MM	◑	◑	◑	○	○
	Hammer (2007): PEMM	●	◑	◑	○	●
	ISACA (2008): CMMI	●	◑	◑	○	◑
	OMG (2008) BPMM-OMG	●	◑	●	○	●
	Appelfeller et al. (2019): DPM	◑	●	◑	◑	◑
	Froger et al. (2019): BPM-MF	◑	◑	◑	○	○
	Bitkom (2020): MM-DBP	●	●	●	◑	●
	Schmelzer et al. (2020): PMM	●	◑	●	◑	●
	Szelagowski et al. (2021): BPM-MA	◑	◑	◑	○	○
Enterprise Architecture Framework	TOG (2005): TOGAF	◑	◑	◑	○	○
Management Practices	ITMQ: EFQM-EM	◑	◑	◑	○	◑
	NIST: Baldrige-EF	◑	◑	◑	○	◑
	DIN: ISO 9004:2018	●	◑	◑	○	○

Legend
RQ1-R1 Business process maturity assessment
RQ1-R2 Digital maturity assessment
RQ1-R3 Optimization potential evaluation
RQ1-R4 Process optimization prioritization
RQ1-R5 Non-expert usability
The table omits RQ1- in the requirements' abbreviation to reduce visual clutter.

The overview of approaches in the research areas, process maturity model, enterprise architecture framework, and management practices cover the most relevant areas to the research. The evaluation of these approaches concerning the defined requirements (cf. section 3.1 yields similar results to a recent literature review, even regarding

[175]cf. Schmelzer and Sesselmann 2020, pp. 492–493.
[176]cf. Newman 2017, pp. 6–7.
[177]cf. Rohloff 2009, p. 11.

recent approaches such as the process management maturity model by Hermkens et al. in 2022[178]: most approaches do not sufficiently address process optimization prioritization. In contrast, it is more common to address the business process management within the organization and not assess specific processes[179]. While most approaches fare well in assessing business processes and digital maturity, few indicate which business processes to prioritize in an organization that wants to digitalize processes.

Among the reviewed approaches, the *Maturity Model for Digital Business Processes* released by Bitkom satisfies the postulated requirements. It is also among the few that give insights into process optimization prioritization by offering the opportunity to compare individual processes. Still, it does not fully satisfy the requirement as it lacks the tools for an iterative assessment of processes with low effort. The same conditions apply to the approaches by Appelfeller et al. (Digital Process Maturity) and Schmelzer et al. (Process Maturity Model). Henceforth, the maturity model developed by Bitkom is the foundation for its iterative improvement. Other high-scoring approaches offer supplementary information to offset identified shortcomings and incorporate individual assets.

3.4 Process Maturity Assessment Model Adaption

The suggested process maturity assessment model is a practical guideline to assess the maturity of individual business processes based on predetermined dimensions. The focus lies in process digitalization order prioritization. The assessors define the desired target process status before implementing necessary actions with the PDCA cycle.[180] Figure 3.13 visualizes the individual phases.

The *Digital strategy* and *Process screening* are prerequisites as formulated in section 2.4. An organization-wide digital strategy ensures the satisfaction of basic technical and organizational requirements to plan and implement digital processes. Hence, general business process management maturity is assumed as the foundation. This assumption comes with screening digital and especially non-digital processes, e.g., a process map in the knowledge management system or a pre-selection designated for pending digitalization efforts that serve as input for the subsequent phases. From a business process perspective, processes ought to be suitable for digitalization in terms of standardization and usage. The subsequent sections outline the specifics of succeeding phases, starting with *Process maturity assessment*. Given this research

[178] cf. Hermkens et al. 2022, pp. 82–83.
[179] cf. Kalinowski 2020, p. 34.
[180] cf. Appelfeller and Feldmann 2018, pp. 17–18.

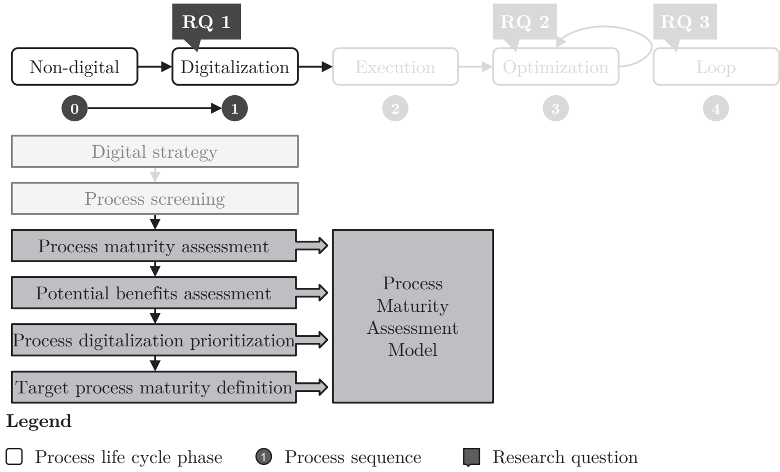


Figure 3.13: Process maturity assessment model phases

context, the self-control characteristic of digital processes is negligent as it is more applicable to sentient production systems demonstrating artificial intelligence capabilities and autonomous control.

3.4.1 Phase 1: Process Maturity Assessment

The four dimensions in the assessment correspond to the specification in the *Maturity Model for Digital Business Processes* by BITKOM: *Quality*, *Organization*, *Data* and *System*. Each dimension covers two or more subdimensions referencing two indicators that outline the essential criteria for assessing process maturity. Table 3.2 gives an overview of the maturity model assessment indicators.

As the model retains most of the content of MM-DBP, the portrayal focuses on modifications and extensions. Hence, the description of dimensions, subdimensions, and indicators remains brief to allow a comprehensive overview. To review detailed information regarding the underlying MM-DPP, refer to section 3.2.1 and the publication by BRITZE ET AL.[181]. The dimension's order reflects the approach to capturing a snapshot of the process according to increased process maturity.

- **Quality**: The dimension *Quality* assesses process maturity based on process quality. It does not necessitate and therefore neglects the digital process matu-

[181] cf. BRITZE et al. 2020, pp. 8–14.

Table 3.2: Process Maturity Assessment Model dimensions

Dimension	Subdimension	Indicator
Quality	Process definition	Process documentation Process responsibilities
	Process requirements	Compliance management Process risk management
	Process execution	Process stability Continuous process improvement*
Organization	Employee	Qualification Readiness for change
	Change management	Endeavor for acceptance increase Organizational culture*
	Digital strategy	Definition and critical reflection Open communication*
Data	Data properties	Digital data maturity Media disruption prevention
	Data requirements	Data quality Data security
System	Technology and integration	Digital technology maturity Digital integration maturity
	Tools and automation	Process visualization Digital automation maturity

* modifications in comparison to MM-DBP by Bitkom

rity. The subdimension *Process definition* addresses the process documentation and responsibilities and corresponds to well-defined and standardized processes. *Process requirements* predominantly cover compliance, e.g., privacy regulations and risk management specific to the individual process, that significantly impact business success if relevant. The quality in *Process execution* requires stability. Expanding the MM-DPB, continuous strife for process improvement is an integral part of securing high process quality during process execution[182].

- **Organization**: The dimension *Organization* assesses the maturity in the subdimensions of *Employee*, *Change management*, and *Digital strategy*. *Employees*

[182] cf. Schmelzer and Sesselmann 2020, pp. 494–495.

require skills and an open mind to embrace the changes accompanying digital transformation. *Change management* sets the boundaries for a structured change process and follows the *Digital strategy*. This model expands the latter two subdimensions, emphasizing organizational culture and encouraging communication and open-mindedness. These two subdimensions also represent items in the model that apply to the individual process and the organization.
- **Data**: The dimension *Data* reflects the digital maturity in organizations regarding *Data properties* and *Data requirements*. It addresses digital maturity in data collection, provision, and usage. Meanwhile, it defines high standards for data quality and security. In comparison to MM-DBP, fewer characteristics describe subdimensions and indicators.
- **System**: The dimension *System* address the subdimensions of *Technology and integration* and *Tools and automation*. The first focuses on digital technology and digital integration maturity. The latter focuses on deploying supportive tools in process management and digital automation maturity. It is content-wise identical to the MM-DBP but offers a rearrangement of indicators for a more compact visualization.

The maturity model applies to both SMEs and large organizations as research denotes little differences[183]. A group of assessors, usually process managers or experienced employees in managing positions, uses these indicators to assess the business process maturity on a five-digit scale (one: lowest maturity level, five: highest maturity level). The mean value for subdimension and dimension aggregates in a bottom-up calculation. To ensure transparency and reproducibility[184], each organization requires a benchmark for the scale of each indicator. It is possible by defining universal requirements for each score, e.g., based on technological advancements or specifying a benchmark process within the organization. The recommendation follows the latter to have a quick and low-inhibition assessment. Accordingly, it is best to have the same assessors assess the selected processes in subsequent assessments.

Regarding the scale in the assessment, minor deviations may persist owed to the indicators relating to digital maturity, namely *Digital technology maturity*, *Digital integration maturity*, and *Digital automation maturity*. Processes exhibiting a high structure with repetitive tasks facilitate automation and integration, whereas creative and collaborative tasks cannot achieve the same maturity level (cf. section 2.1.4). Accordingly, either the scale or assessment adapts to ensure comparability between

[183] cf. Ongena and Ravesteyn 2019, p. 142.
[184] cf. Felch and Asdecker 2020, p. 379.

processes. However, no modifications result in an identical score, possibly denoting similar maturity levels. Hence, the recommendation is to cap the maximum score according to the objective level of maturity and adapt the calculation of mean value accordingly to ensure equal weights of indicators.

Although the maturity model focuses on business process maturity, two indicators correspond primarily to business process management: subdimensions *Change management* and *Digital strategy*. The recommendation is to assume an identical assessment independent of the process because these address organizational structure and business culture fundamentals. Exceptions to this convention persist as processes may be associated with distinct divisions and their organizational management principles that result in individual assessment.

After concluding the process maturity assessment, an overview of business process maturity for selected processes emerges. The rank suggests a general approach, assuming the lowest process maturity yields the most significant benefit through digitalization.

3.4.2 Phase 2: Potential Benefits Assessment

The process maturity assessment yields a snapshot of the as-is process state, giving the first suggestion for the process prioritization order. The next step in the sequence foresees a potential benefits assessment for all processes according to selected criteria. In essence, it represents a multi-criteria problem that algorithms may quickly solve. For instance, HEIMES ET AL. suggest a data-based algorithm to solve this multi-objective combination optimization problem[185] that is very theoretical and complex for non-specialists to apply.

Hence, this thesis deploys a few transparent criteria derived from practical expertise and condenses them into six relevant criteria. The criteria reflect the project management triangle[186] or triple constraint associated with time (temporal savings), costs (financial savings and implementation costs), and quality of results (personal burden and process improvement). The process execution frequency represents a lever regarding the impact of constraints when comparing multiple processes:

- **Process execution frequency**: A high process execution frequency justifies the investment into process digitalization due to the scaleability of potential savings.

[185] cf. HEIMES et al. 2019, pp. 39–42.
[186] cf. ALAM and GÜHL 2016, p. 75.

- **Temporal savings potential**: Temporal savings refer to the time saved in each process execution.
- **Financial savings potential**: Financial savings refer to the costs saved in each process execution.
- **Personal burden**: The personal burden reflects the subjective perception of additional stress factors to execute the process. While it represents a soft factor, the contribution to improved morale is not negligible.
- **Process improvement potential**: Process digitalization yields quality improvements according to the scope of intended digitalization, e.g., through minimizing process interfaces and media breaks within a workflow.
- **Implementation costs (optional)**: Implementation costs represent optional criteria that reflect the costs for the factual implementation of process changes and measures incurred through change management.

Akin to the process maturity assessment, the assessors assess the potential benefits based on either an absolute reference or a benchmark process. The recommendation is to use past digitalization efforts as a reference, as an absolute reference requires excessive research and expense to determine for an individual organization. Each criterion scores on a five-digit scale (one: no significance, five: high significance) and is of equal weight. The total potential benefits score is the mathematical product of the criteria except for the optional *Implementation costs* that is an individual score. This approach facilitates differentiating similar total scores compared to calculating a mean value and allows for facilitated weighting of individual factors if required.

3.4.3 Phase 3: Process Digitalization Prioritization

There is no strict demarcation for the potential benefits assessment criteria. Accordingly, the criteria show overlaps and dependencies. Still, the total score helps prioritize process digitalization based on potential benefits but does not dictate the final order. Instead, all scores - the business process maturity, the potential benefits score, and the implementation costs - constitute the basis for the manual decision-making by decision-makers, usually the organization's management. In addition, this assessment requires considering external factors that can override the assessor's decision, e.g., a change in digital strategy by top management.

3.4.4 Phase 4: Process Maturity Target State Definition

After screening and filtering the processes in the process maturity and potential benefits assessment, few prioritized processes with a prioritized digitalization order remain. For these processes, it is essential to define the target state post-digitalization.

It serves as a guide and reference in digitalization, making the optimization potentials tangible and the results measurable. Figure 3.14 condenses the assessment in a comprehensive figure for quick visualization.

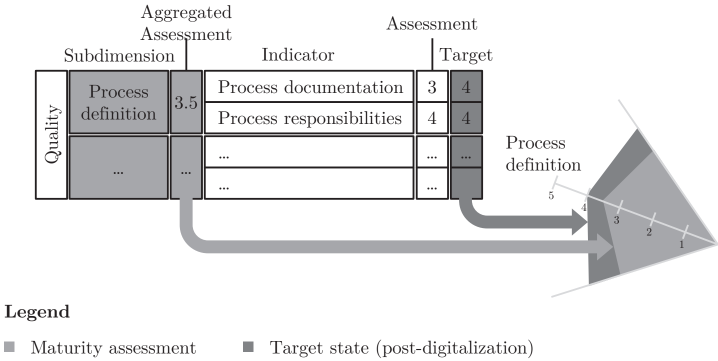


Figure 3.14: Process maturity target state for subdimension view

The process maturity assessment indicators touch upon various technical and organizational matters. Approaching these requires a cost-benefit analysis. Understanding that the objective is not to maximize all dimension's maturity levels is essential. Instead, it requires balancing the cost-benefit for an individual process and the possible positive impact of a change upon other processes. Strategy and budget are significant, and the responsibilities for defining the desired target state extend toward a greater circle of employees in the management.

3.5 Interim Conclusion to Sub Research Question SRQ1

Chapter 3 elaborates on a specific approach for process maturity assessment to support the decision-making of prioritizing business processes for digitalization, and thus answers the first underlying research question *RQ1 Which criteria support the decision-making of prioritizing business processes in digital transformation?*. Figure 3.15 displays its integration into the overall approach of this research.

The first two sections specify the requirements for the assessment (cf. section 3.1) and outline state of the art regarding a broad range of process maturity models developed in recent decades (cf. section 3.2). However, the majority exhibits a shortcoming regarding business process prioritization as most focus on the business process management level, not individual business processes. The maturity model

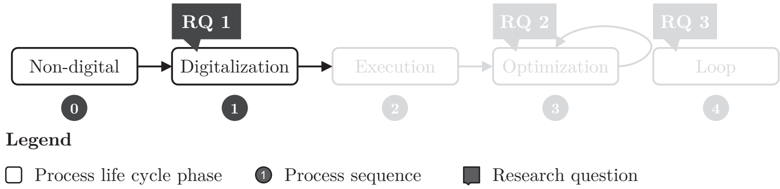


Figure 3.15: RQ1 interim results' integration in the overall thesis

developed by BITKOM serves as the foundation for a model adaption towards a general approach, as it best satisfies the formulated requirements (cf. section 3.3).

The application of the maturity model yields a maturity score that reflects the as-is process maturity regarding the dimensions *Quality*, *Organization*, *Data*, and *System*. A low maturity level represents a decisive factor in process optimization prioritization, aside from potential benefits assessment specific to individual processes. These factors aggregate into a few fundamental values that support digitalization prioritization but do not yield an automatically calculated ranking. The reason is to keep the flexibility to consider external circumstances that may override any such assessment. Assessors devise the target digital process definition and create the foundation to execute the process digitalization (cf. section 3.4). Hence, the modified process maturity assessment model improves the satisfaction of requirement *RQ1-R4 Process optimization prioritization* and answers sub research question *SRQ1*.

4 Continuous Process Optimization Cycle

Building on the scientific fundamentals and the research's application domain (cf. chapter 2), the knowledge basis in this chapter introduces relevant research in state of the art to answer the second sub research question *SRQ2 How can data-driven analytic methods be aggregated in a guided procedure model to facilitate process analysis and uncover process insights?*. The alluded reference model constitutes the research object that guides the individual phases of process data analysis to uncover process insights and thus derive process improvements. Its input is process data in the form of event logs and process models of a digital process. After establishing the requirements to benchmark existing process analysis approach (cf. sections 4.1 and 4.2), the most appropriate given the application scenario in the previous chapters will be selected (cf. section 4.3) and expanded if required (cf. section 4.4). Finally, the chapter concludes with a summary regarding the answer to the research question (cf. section 4.5).

4.1 Requirements for Process Optimization Procedure Model

The processes in contemplation for the process optimization procedure model comply with the boundary conditions in the research scope (cf. section 2.4), affecting the applicability of procedure models for process optimization. The focus lies on digital support processes undergoing initial process analysis with limited domain knowledge provided by business process management experts and business analysts. Accordingly, no specific key performance indicators are defined. Still, these processes traverse optimization approaches based on retrospective analysis detached from a specific triggering reason, constituting a data-driven approach. The objective is to generate a quick process diagnostics report that provides information about its status, which in the next step serves as input for process owners and managers to derive profound actions for improvement.

Before deciding on a general procedure model for process optimization, it is essential to establish further requirements in line with the scope of this thesis. The requirements originate from the identified gaps in status quo (cf. section 2.3) and the research objective and (cf. section 2.4), supplemented with challenges identified by the *IEEE Task Force on Process Mining*[187]:

[187]cf. Aalst et al. 2012, pp. 185–191.

- RQ2-R1 Continuous process optimization
- RQ2-R2 Systematic approach
- RQ2-R3 Knowledge transfer
- RQ2-R4 Process data utilization
- RQ2-R5 Concept drift handling

The explanation of the list of requirements follows. The requirements serve as evaluation criteria to discuss the below approaches to process optimization and their fit within the scope of this research. Each requirement discerns three levels of compliance. The degree of compliance to the respective criteria determines the level of compliance. Accordingly, the visual representation with Harvey Balls (none, partial, and full) gives a quick overview.

RQ2-R1 Continuous Process Optimization: The continuous and iterative improvement of business processes in organizations requires approaches considering a cyclical sequence of activities and suggests the infrastructure and resources to commit to this philosophy. It is contrary to project approaches characterized by their uniqueness.

- ○ **None:** The approach does not consider a cyclical and iterative application.
- ◑ **Partial:** The approach incorporates the cyclical and iterative sequence of activities on a high level without outlining specifics.
- ● **Full:** The approach incorporates the cyclical and iterative sequence of activities and reflects upon the implications of the overall approach along with a suggestion on how to minimize efforts in recurring iterations.

RQ2-R2 Systematic Approach: A systematic approach ensures comprehensibility and transparency regarding the approach and is the foundation for its reapplication in a cyclical sequence and the knowledge transfer to other processes. The methods and their application are comprehensible for each activity in the sequence.

- ○ **None:** The approach does not specify the activities or only describes them on a high level, impeding their replication by a third party.
- ◑ **Partial:** The approach embeds activities and methods in a structured manner but only partially describes the details in their application.
- ● **Full:** The approach embeds activities and methods in a structured manner. The description of their application is comprehensible, facilitating the replication of each activity.

RQ2-R3 Knowledge transfer: The overall approach, activities, and methods deployed in process optimization, especially regarding data analysis, are applicable independent of the process type. The emphasis lies in its general applicability without requiring specific domain expertise while ensuring the generation of process insights to optimize processes. Hence, a delicate balance between generalization and specificity is desirable.

- ○ **None:** The approach, activities, and methods are either too specific regarding a process or too general and thus vague. It is limited in its application to other processes and generates no or very few insights.
- ◑ **Partial:** The approach, activities, and methods partially apply to other processes. In principle, these contribute to generating insights but sometimes demonstrate limitations.
- ● **Full:** The approach, activities, and methods balance specificity and generalization. In principle, these apply to other processes and generate insights.

RQ2-R4 Process data utilization: In a data-driven approach to continuous process optimization, exploiting the available process data, e.g., event logs and process models, with appropriate techniques, is essential. Here, a particular focus is on process mining methods tailored to process analysis.

- ○ **None:** The approach either does not use process data or offers no specifics on the utilized data.
- ◑ **Partial:** The approach utilizes process data among other data in process analysis but fails to disclose specifics on pre-processing and utilization.
- ● **Full:** The approach uses processes data among other data in process analysis. The individual steps in data pre-processing and its utilization are comprehensible and replicable.

RQ2-R5 Concept drift handling: It is essential to consider concept drift during process analysis, especially in a cyclical approach, to ensure the validity of analysis results and minimize efforts. Therefore, it presumes a consideration of continuous process optimization in the approach. Internal or external factors can impact the process performance that its process data reflects. This change in process data may require modifications in the approach to process data analysis. Hence, it is integral to have the means to identify and derive measures to handle concept drift and ensure efficient and effective data analysis.

- ○ **None:** The approach does not consider means to handle concept drift.
- ◑ **Partial:** The approach partially considers means to handle concept drift and suggests integrating it into the analysis.
- ● **Full:** The approach integrates means to handle concept drift. Specific measures enable identifying concept drift and deriving appropriate means to

ensure cyclical analysis with decreased efforts in repeated application.

4.2 Process Optimization Approaches

The approaches for process optimization described after this subordinate the phase *Process Optimization* and elaborate a standardized procedure. The circular sequence in business process management on an operational level alludes to the fact that process optimization focuses on iterative improvement. Process restructuring and process re-engineering are not within the research scope. (cf. section 2.4).

For the same reason as above, general frameworks that target the overall organization and its structure to achieve business performance improvements exceed the scope of research. On the one hand, these include management paradigms such as *Total Quality Management* (TQM), *Lean Management*, *Zero Defects*, *EFQM Excellence Model*, *Quality Management Systems* specified by the ISO 9000 series, and *Theory of Constraints* (TOC). These share the commonality of deployment in manufacturing industries and a heavy focus on manufacturing processes. On the other hand, the line of thought applies to information technology architecture frameworks that go in tandem with digital processes. Essential representatives are *The Open Group Architecture Framework* (TOGAF), *Architecture of Integrated Information System* (ARIS), and *DevOps*. As process optimization assumes an existing digital process, information technology architecture that satisfies elementary requirements is a precondition (cf. section 2.3.2).

Specific methods and tools for process improvement that specify and assume subtasks of methodologies and improvement approaches are not further elucidated. These include, for example, *Makigami*, *Value Stream Mapping* (VSM), and *Total Cycle Time* (TCT). The same applies to general problem-solving approaches and techniques originating from ideation, for example, *Design Thinking*.

Two distinct backgrounds and perspectives differentiate the approaches to process optimization described in this thesis: conventional (cf. section 4.2.1) and data-driven approaches (cf. section 4.2.2). After the initial and brief introduction, comparing the formulated requirements (cf. section 4.1) evaluates their deployability in this research work and highlights benefits and shortcomings.

4.2.1 Conventional Approaches to Process Optimization

Process optimization constitutes an essential part of quality management in its process orientation and continuous optimization philosophy. However, while the approaches tend to generalize the viewpoint and provide a comprehensive set of methods and tools, they seldom integrate progressive data analytics methods. The brief introduction and evaluation instead serve the sake of completeness.

Kaizen

Kaizen is a systematic approach to business improvement based on the fundamental practice of continuous improvement. The core principle is identifying and reducing process waste through each employee's contribution, independent of their organizational role. The objective is steady and incremental process improvements that contribute to long-term success, contrary to re-engineering approaches reflected in innovative thrusts accompanied by large changes.[188]

The application of *Kaizen* in an organization is manifold. It extends and overlaps with neighboring fields such as TQM and *Lean Management.* For any optimization, the standard usually references the generic and cyclical procedure PDCA.[189] It constitutes the phases *Plan*, *Do*, *Check* and *Act*[190]:

- **Plan**: The initial phase covers the definition of objectives, the analysis of the current situation, and the derivation of necessary procedures to achieve the desired results.
- **Do**: The second phase involves implementing planned measures. Pilot studies assume the same functionality in complex projects.
- **Check**: Phase three extends to the monitoring and evaluating results. Comparing the objectives and the outcome shows the effectiveness of planned measures.
- **Act**: The implementation defines a new standard if there is no gap between the present and expected outcome. Otherwise, this phase introduces countermeasures and reboots the PDCA cycle.

A specific application of PDCA is *Improvement Kata*, which emphasizes the cyclical nature that subdivides an objective into smaller milestones. By iterating through the cycle, it is easier to achieve the initial objective through more loops.[191] Figure 4.1 visualizes interlinked PDCA cycles.

[188] cf. Schmitt and Pfeifer 2015, pp. 65–67.
[189] cf. ibid., pp. 65–66.
[190] cf. Neuhaus and Lennings 2008, p. 40.
[191] cf. Brandl et al. 2020, p. 840.
[192] own representation based on ibid., p. 840.

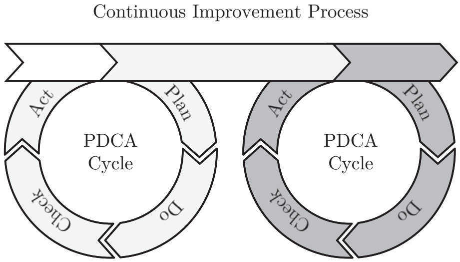


Figure 4.1: PDCA cycle in Kaizen[192]

Evaluation: *Kaizen* represents the foundational concept of a systematic approach for continuous optimization. The PDCA cycle as the central approach has minimal application as it requires adjacent systems, e.g., knowledge management systems, to cater to the formulated requirements. Moreover, as a standalone approach, it is too generic and fails to offer specific tools and methods for deployment in each phase.

Six Sigma

Six Sigma is a systematic and data-based approach that targets process improvements for existing processes by reducing variations in the process. Initial project planning before the launch of a *Six Sigma* project is essential to define the objectives and establish the project team in charge of its execution. The procedure follows the DMAIC cycle[193]:

- **Define**: The framing of boundary conditions, the definition of SMART objectives, and the delimitation of the improvement project scope represent the first tasks in DMAIC.
- **Measure**: Developing accountable key figures and recording relevant data helps capture the initial situation based on factual and reliable data.
- **Analyze**: Process and data analysis help identify underlying issues and core reasons for the observed process behavior.
- **Improve**: This phase covers the process from developing solutions proposals, evaluating alternative solutions, and implementation preparation to implementing the best solution.
- **Control**: The documentation and monitoring ensure a sustainable solution and allow for proactive action in case of deviations.

[193] cf. Elser et al. 2021, pp. 267–275.

Figure 4.2 visualizes the DMAIC cycle. Each phase provides a range of tools and methods. Recommendations for their utilization scenario based on established practices persist, but the usage is not mandatory. Rather, the appropriate selection and application lie with the project team's responsibility.[194] *Lean Six Sigma* is a variation of Six Sigma that incorporates additional tools and methods usually associated with Lean Management practices to reduce waste along the inspected process: e.g., *Value Stream Mapping* (VSM), *Theory of Constraints* (TOC), *5S*, and *Poka Yoke*. It follows the procedure specified above.[195]

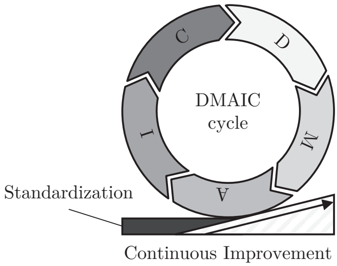


Figure 4.2: DMAIC cycle in Six Sigma[196]

Another application domain of the *Six Sigma* fundamentals is *Design For Six Sigma* (DFSS), focusing on engineering design for products and processes. It starts with developing processes or products to deliver the best realization of customer demands with recognizable value creation. Its approach is comparable but differs in provided methods and tools.[197]

Evaluation: *Six Sigma* focuses on process improvement projects and provides tools and methods embedded in a systematic approach for planning, execution, and monitoring. The DMAIC cycle is flexible and caters to all process types. Data analytics methods are integral to *Six Sigma* but do not specifically cater to process data. Although it incorporates a continuous approach, concept drift occupies a minor role due to the scope and uniqueness *Six Sigma* projects usually have.

[194] cf. Roenpage et al. 2007a, pp. 12–13.
[195] cf. ibid., pp. 13–14.
[196] own representation based on Elser et al. 2021, p. 277.
[197] cf. ibid., p. 276.

ISO/IEC TR 33014 - Information technology - Process assessment - Guide for process improvement

ISO/IEC TR 33014 constitutes a technical report for process improvement within the ISO/IEC 33001 - ISO/IEC 33099 standards. This reference guide covers strategic, tactical, and operational process improvement. The strategic and tactical levels provide the framework and environment to enable improvement projects mirrored on the operational level. Thus, the organizational framework enables process assessment and improvement.[198]

The process improvement on the operational level constitutes five phases that loop back to the strategic level of process improvement[199]:

- **Develop action plan:** This phase uses the process assessment results to identify improvement areas, define improvement objectives and targets, and derive an actionable plan.
- **Implement improvements:** The execution of the action plan covers the selection of the implementation strategy, the preparation and execution, and the monitoring of its progress along the execution.
- **Confirm improvements:** After completing the improvement project, the evaluation of results compared to planned objectives follows. This phase includes adopting appropriate practices and processes and the organizational culture change.
- **Sustain improvements:** Following the improvement confirmation, monitoring the institutionalization of improved processes and providing support in its wide adoption, e.g., in an organization-wide roll-out, reinforces sustainable improvements.
- **Monitor performance:** Subsequently, continuous monitoring ensures consistent performance and may initiate new process improvements.

Evaluation: ISO/IEC TR 33014 defines a standard to approach process optimization in an organization. It describes on a high level the required activities in each phase of a cyclical approach from a strategic to an operational level. However, it does not provide details on how to put each activity into practice, e.g., by suggesting methods or tools.

[198] cf. International Organization for Standardization and International Electrotechnical Commission 2013, pp. 3–5.
[199] cf. ibid., pp. 12–18.

4.2.2 Data-driven Approaches to Process Optimization

Data-driven approaches to process optimization depend primarily on recorded data and do not necessitate excessive domain knowledge regarding the matter at hand. Still, a designated environment analysis in the initial phases clarifies the framework conditions of the analysis, e.g., the specific analysis target, and explains metadata regarding the process to facilitate their application. The approaches originate from the data mining and process mining domain and see an increasing propagation in BPM.[200]

Chapman et al. (2000): Cross-Industry Standard Process for Data Mining (CRISP-DM)

The *Cross-Industry Standard Process for Data Mining* (CRISP-DM) is an application- and domain-neutral approach and the de facto standard procedure for data mining projects. The development has been financed with public resources by *European Union*.[201] It is the most common process model deployed for data analytics and thus chosen to represent other data mining approaches such as *Knowledge Discovery in Databases* (KDD) and SEMMA. Six phases describe the approach CRISP-DM with respective activities. The phases show interdependence, and it is possible to have loopbacks between individual phases[202]:

- **Business Understanding**: In the initial phase, clarifying the project objective and evaluating the initial situation is essential. Transferring to a data mining problem definition and creating a project plan supports achieving the objectives.
- **Data Understanding**: Presuming there is enough available data, this phase deals with the understanding of data. Task support familiarizing with the data and getting insights. Visualization and simple statistical methods help formulate initial hypotheses framed by learnings in business understanding and verify data quality.
- **Data Preparation**: Initial criteria defined by analytical targets, data quality, and technical limitations filter the raw data to extract relevant data. Data preparation tasks such as data cleansing do not necessarily follow a predetermined order and serve to increase the data quality. Further tasks extend

[200] cf. Aalst 2016, p. 44.
[201] cf. Wirth and Hipp 2000, pp. 1–2.
[202] cf. Chapman et al. 2000, pp. 13–34.
[203] own representation based on ibid., p. 13.

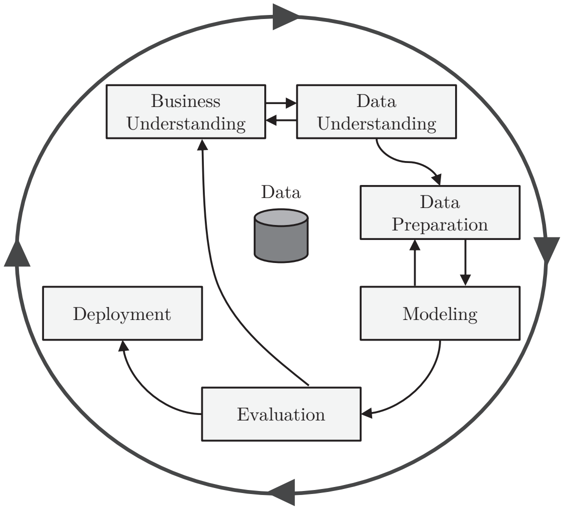


Figure 4.3: Cross-Industry Standard Process for Data Mining (CRISP-DM)[203]

to transforming data attributes, merging data sets, and modifying the data format to satisfy the requirements of deployed modeling tools.

- **Modeling**: Different modeling tools require different data preparation methods to cater to specific requirements. Test models serve to determine parameter settings before creating the target model. Multiple model creation and evaluation loops may be necessary to increase the model quality.
- **Evaluation**: A high-quality model from a technical perspective still requires evaluation and model interpretation in the application scenario. A critical reflection and comparison of the results with the business objective estimates the model maturity and determines the following steps for model handling.
- **Deployment**: Planning its deployment in industrial applications is essential after model creation. This phase covers integrating the model into existing systems, continuous monitoring, and model maintenance to ensure its validity. Finally, the project concludes with a report and evaluation.

Figure 4.3 depicts the activities in a circular procedure. In applying CRISP-DM, key questions guide each phase and cover the essential tasks. The outer circle indicates the possibility of iterating the procedure for further development. Refer to the description of Chapman et al. for guidance on using the procedure.[204]

Evaluation: CRISP-DM is the de facto standard procedure for data analytics, especially for data mining projects. However, from a business process perspective, continuous process optimization is not integral to CRISP-DM, nor does it cater specifically to process data analysis. Nevertheless, the approach is iterative, cyclical, and well-structured along the activities of each phase. However, it shows shortcomings regarding specific methods for each phase and does not disclose how to factor in concept drift.

Aalst (2016): Process Mining Framework (PMF)

The *Process Mining Framework* (PMF) introduced by Aalst demonstrates the capabilities of process mining with a dominant focus on distinct data types and model types. Data types refer to whether data belongs to a completed process (post-mortem) or an ongoing process (pre-mortem). Model types differentiate normative models (de jure model) and descriptive models (de facto model). It expands the previously introduced view on process mining types(cf. figure 2.9).[205] Figure 4.4 introduces the framework and its ten process mining techniques grouped into three types[206]:

- **Navigation:** *Exploring* processes at run-time (online) represent the foundation for *predicting* process flow and *recommending* most suitable actions to achieve a process target.
- **Auditing:** Event logs serve in audits to *detect* deviations (online) and *check* compliance in retro-perspective. Other techniques focus on the *comparison* of de facto and de jure models and to *promote* improvements to create a new de jure model.
- **Cartography:** The focus lies with post-morten data and de facto models. This type includes *discovering* and *enhancing* process models, and further on the *diagnosis* in terms of model-based analysis.

Evaluation: The *Process Mining Framework* does not originate from a business process improvement perspective but solely focuses on the analytical methods provided by process mining. The relation between the framework's event log and process model types provides insight into the data requirements for specific process

[204] cf. Chapman et al. 2000, pp. 35–68.
[205] cf. Aalst 2016, pp. 301–303.
[206] cf. ibid., pp. 303–305.
[207] own representation based on ibid., p. 302.

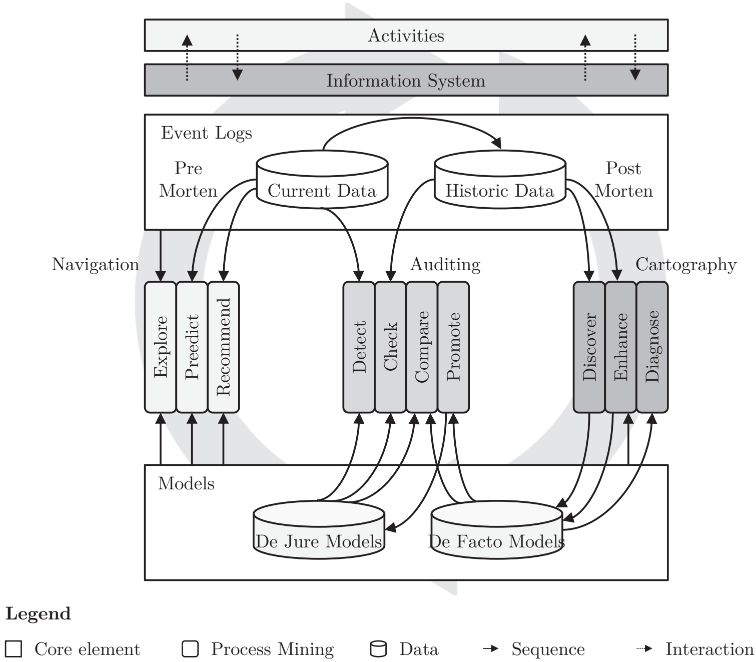


Figure 4.4: Process Mining Framework (PMF)[207]

mining techniques. However, it does not relay the iterative procedure designated in continuous improvement. Hence, handling concept drift does not occupy any thought in the framework.

Bozkaya et al. (2009): Process Diagnostics Method (PDM)

Process Diagnostics Method (PDM) is a methodology to quickly generate a broad overview of processes by deploying process mining techniques. It operates on the assumption that neither prior nor domain-specific knowledge is available and that the only source of information is event logs extracted from the information system.[208]. Six phases constitute the simplistic approach visualized in figure 4.5[209]:

[208] cf. Bozkaya et al. 2009, p. 22.
[209] cf. ibid., pp. 23–26.

- **Log Preparation:** After data extraction, the event log requires pre-processing to ensure a usable data format.
- **Log Inspection:** The inspection uncovers process statistics and underlying meta information. It allows the filtering of appropriate event logs for the subsequent deployment of process mining techniques.
- **Control Flow Analysis:** The control flow analysis generates a process model from the event log.
- **Performance Analysis:** With the aid of the mined process model, performance analysis uncovers insights into the temporal operation of processes and process variants.
- **Role Analysis:** The role analysis provides insight into the organizational process matters and allows distinguishing roles.
- **Transfer Results:** After concluding the analysis, composing the findings and verifying the interpretation is essential. Otherwise, the distinction between conforming and non-compliant behavior is not discernible without domain knowledge.

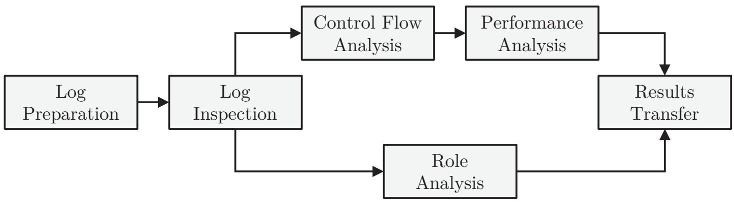


Figure 4.5: Process Diagnostics Method (PDM)[210]

Evaluation: PDM focuses on applying process mining techniques on event logs to generate insights into a process quickly. While it limits the number of applied techniques, its strength lies in the practicability of the concise approach without limiting itself to specific process types. On the other hand, it exhibits shortcomings in considering continuous process optimization and iterative application regarding concept drift handling.

Aalst (2016): L* Life Cycle Model (L* LCM)

The *L* Life Cycle Model* describes the life cycle of a process mining project focused on improving structured processes and providing operational support. The approach

[210] own representation based on ibid., p. 23.

incorporates the process mining activities identified in the *Process Mining Framework* (cf. section 4.2.2) and yields four possible improvement actions: redesign, adjust, intervene and support.[211] Figure 4.6 visualizes their interrelations in an integrated model that differentiates five essential phases, denominated as stages[212]:

- **Stage 0: Plan and justify:** The initial phase comprises project planning activities and the decision for the process mining project type (data-driven, question-driven, and goal-driven). Its selection impacts the deployed techniques in subsequent phases.
- **Stage 1: Extract:** The extraction extends beyond process data and includes domain expertise and other information. This phase may elaborate on questions and objectives depending on the project type.
- **Stage 2: Create control flow model and connect event log:** This phase aims to acquire a control flow model tightly interlaced with the event log. Multiple approaches yield feasible process models depending on the process and available data.
- **Stage 3: Create integrated process model:** Analyzing additional perspectives, e.g., organizational, time, or case perspective, yields more insights and enables initiating process improvements.
- **Stage 4: Operational Support:** The last phase requires pre-mortem data but can offer live operational support to process users, managers, or owners through advanced process mining techniques.

Evaluation: *L* Life Cycle Model* takes up the essence of the *Process Mining Framework* to incorporate it into a project methodology. Hence, it scores better in the evaluation in direct comparison, especially from the managerial perspective. The approach indirectly encourages iterative process improvements through operational support but fails to suggest solutions for concept drift.

Eck et al. (2015): Process Mining Project Methodology (PM^2)

The *Process Mining Project Methodology* PM^2 supports projects targeting process performance improvement and increasing compliance with rules and regulations. Research questions serve as the starting of the application that decomposes into performance and conformance findings, which act as an impetus for improvement suggestions. To achieve this goal, it deploys a wide range of tools and techniques

[211] cf. Aalst 2016, pp. 392–393.
[212] cf. ibid., pp. 393–397.
[213] own representation based on ibid., p. 394.

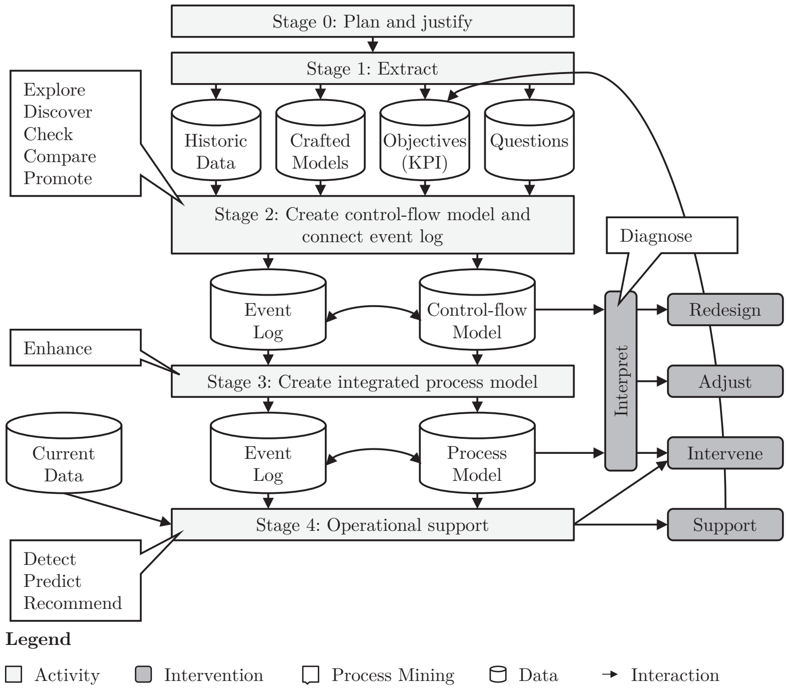


Figure 4.6: L* Life Cycle Model (L* LCM)[213]

depicted in figure 4.7 suitable for both structured and unstructured processes. Six phases relate to each other via exchanged objects that serve as either input or output, e.g., event logs and process models. Within this approach, multiple iterations of analysis phases are feasible to achieve the analysis objective.[214] A brief introduction to the phases follows[215]:

- **Planning:** The planning phase starts with selecting the business process to analyze, improve, and define the objective. Then, the setup of the multi-disciplinary project team executing the project follows.
- **Extraction:** The analysis objectives determine the data extraction and process data extraction scope. Additional shared process knowledge improves

[214]cf. Eck et al. 2015, pp. 298–299.
[215]cf. ibid., pp. 300–309.

the understanding of the process.

- **Data processing:** The data processing prepares the collected data for the mining and analysis phase. This activity includes creating specific data views, aggregating events to reduce complexity, enriching the event logs with more information, and filtering event logs.
- **Mining and Analysis:** This phase covers applying process mining techniques to gain insights into performance and conformance.
- **Evaluation:** The evaluation focuses on interpreting the findings, verifying them through comparison with the underlying data, and validating the interpretation with domain knowledge.
- **Process Improvement and Support:** The insights serve as input for deriving and implementing improvements through process modifications.

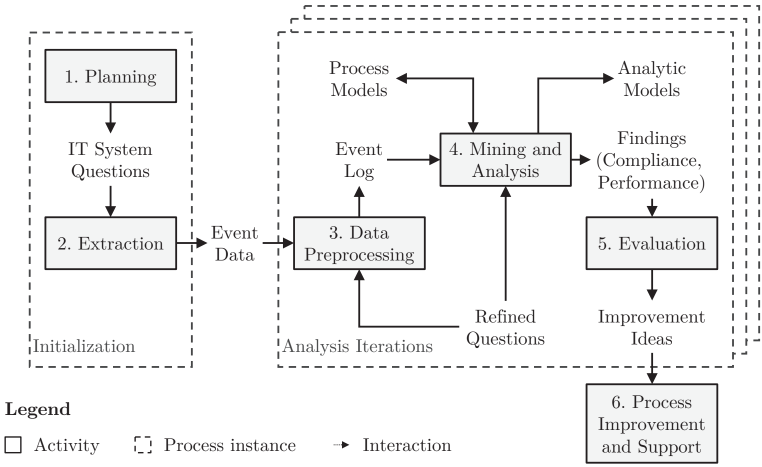


Figure 4.7: Process Mining Project Methodology (PM²)[216]

Evaluation: PM² is a specific approach for process mining projects targeting process performance improvements. It details in a structured manner the individual activities in each phase and references further information to facilitate its application. However, the shortcoming manifests in the limited integration of continuous process optimization from a business perspective. Hence, there also is a lack of consideration

[216]own representation based on Eck et al. 2015, p. 299.

for methods of handling concept drift.

Park et al. (2020): Framework for Action-oriented Process Mining (FAO-PM)

Park et al. introduce the *Framework for Action-oriented Process Mining* (FAO-PM) with the objective of better operational process management. In continuous process improvements, process mining techniques require the repetitive application not to limit its benefits to one-time reports but to enable the handling of novel issues. Hence, the framework focuses on online, operational support techniques in process mining capable of monitoring and analyzing processes in action.[217] The authors suggest the framework depicted in figure 4.8 to connect process insights with the automated execution of appropriate improvement actions.

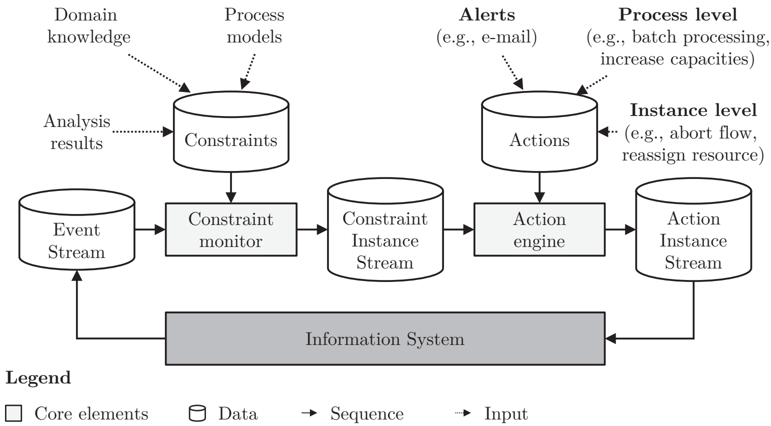


Figure 4.8: Framework for Action-oriented Process Mining (FAO-PM)[218]

The core elements are the *Constraint monitor* and the *Action engine*, embedded into a continuous control loop within the information system[219]:

- **Constraint monitor:** The event stream representing continuous live event data is the input to the *Constraint monitor*. The monitor revises violations

[217] cf. Park and Aalst 2020, pp. 206–207.
[218] own representation based on ibid., p. 207.
[219] cf. ibid., p. 207.

of defined constraints, e.g., via domain knowledge or analysis results, with dedicated diagnostic tools.

- **Action engine:** The *Action engine* assesses this resulting constraint instance stream for necessary intervention and generates appropriate actions to mitigate risks. The actions range from simple alerts to instance-level actions and can affect the process. Finally, the consequential action instance stream circulates and closes the cyclical framework.

Evaluation: FAO-PM seizes the opportunity to connect continuous process optimization and powerful operational process mining techniques to exploit the capability of process mining. However, despite the mention of use cases, the approach operates on the theoretical background, and neither is fully comprehensible nor transparent. Despite the theoretical capabilities, operational support, and applicability for concept drift handling, there is no information on its specific application in the presence of concept drift.

4.3 Interim Results for Process Optimization Approaches

Table 4.1 summarizes the process optimization approaches reviewed in this chapter, which belong to conventional or data-driven approaches. Conventional approaches have in common that they exhibit a vital business process orientation. Structured procedures provide tools and methods to analyze processes and derive measures for continuous process optimization. However, process data, e.g., event logs and process models, seldom seize any role in the analysis.

On the contrary, data-driven approaches fully exploit available process data, particularly those with roots in process mining. Notably, recent approaches such as L* LCM and PM^2 score highest against the background of formulated requirements. The latter represents a refinement of the prior one[220] and also integrates elements of PDM[221]. Hence, an increase in the overall satisfaction of requirements is comprehensible, even if the evaluation does not properly reflect subtle differences. Both approaches boast an edge in integrating business process management elements and data analysis and illustrate or reference specific tools and methods for implementation. Thus, both score highest in the assessment regarding the criteria. Although the most recent approach, FAO-PM, best portrays the embedding of continuous process optimization, it is the least mature among these in terms of process mining techniques and specificity for knowledge transfer.

[220] cf. Aalst 2016, p. 396.
[221] cf. Eck et al. 2015, pp. 297–298.

Table 4.1: Literature review on process optimization approaches

	Literature	R1	R2	R3	R4	R5
Conventional approaches	Kaizen	◑	◑	○	○	○
	Six Sigma	◑	●	●	○	○
	ISO 33014	◑	●	◑	○	○
Data-driven approaches*	Chapman et al. (2000): CRISP-DM	◑	●	◑	◑	○
	Aalst (2016): PMF	○	◑	◑	●	○
	Bozkaya et al. (2009): PDM	○	◑	●	●	○
	Aalst (2016): L* LCM	◑	●	●	●	○
	Eck et al. (2015): PM^2	◑	●	●	●	○
	Park et al. (2020): FAO-PM	◑	◑	◑	●	◑

* The chronological order is oriented towards the publication year of the approach and deviates from the referenced paper publication year indicated in brackets.
Legend
RQ2-R1 Continuous process optimization
RQ2-R2 Systematic approach
RQ2-R3 Knowledge transfer
RQ2-R4 Process data utilization
RQ2-R5 Concept drift handling
The table omits RQ2- in the requirements' abbreviation to reduce visual clutter.

None of the referenced approaches cater to the requirement *R5 Concept drift handling*. Concept drift is deferred in this chapter's discussion to facilitate the creation of the procedure model. Instead, chapter 5 discusses the implications for the procedure model through the third research question and demonstrates propositions to modify the procedure model to cater to the requirement adequately. On the same notion, neither approach fully satisfies *R1 Continuous process optimization*. Regarding the data-driven approaches, this circumstance relates to the outset of pursuing ad-hoc process analysis driven by objectives or questions in a project-like manner and, to a lesser extent, a repeated application with a certain degree of freedom in analysis contrary to a rigid, fully defined approach. This fact bears similarities to the process mining use cases defined by AALST[222].

Per the findings, the data-driven approaches L* LCM and PM^2 serve as the foundation to create a procedure model better tailored to the frame conditions and requirements (cf. section 4.1). As recent literature notes[223], current approaches

[222]cf. AALST 2016, p. 328.
[223]cf. AALST 2020, pp. 181–186.

can still benefit from more practicable guidelines to exploit the process mining domain's progress, particularly as core challenges remain and are not solved even in commercial solutions.

4.4 Process Optimization Procedure Model Adaption

Independent of the design and elaboration in the specific methodology or model, the activities in data analytics share commonalities on a meta-level. The general approach to process optimization follows the procedure in figure 4.9. PM^2 is the foundation of each phase specification. It exploits the findings in sections 4.4 and 4.3. The depicted structure also serves as the subdivision of subsequent subsections to elaborate the activities and deployed tools and methods (cf. sections 4.4.1 to 4.4.4).

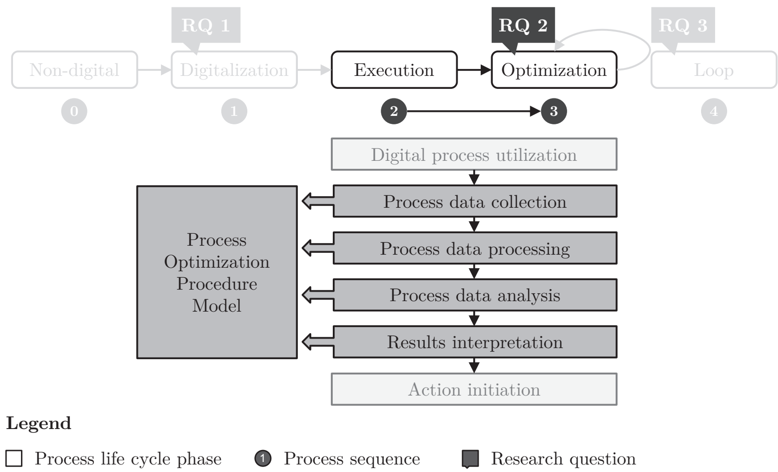


Figure 4.9: Process optimization procedure model phases

The procedure model's target user is the organization's process owner or manager. The allocation depends on the role definition but generally targets the person responsible for overseeing the process management and its improvement. This person accounts for the business process and surmises responsibilities to governance, and thus has a profound interest in the present condition of the digital process (cf. section 4.1). Generally, the procedure model's application domain is iterative deployment. Given the approach to postpone handling concept drift in this chapter (cf. section 4.3), the focus of the procedure model lies in its first application after process digitalization in a data-driven approach. Accordingly, the procedure model commences with the roll-out of the digital process and the conclusion of the first phase *Digital process utilization*. The concluding subsection 4.4.5 encapsulates the phases elaborated in sections 4.4.1 to 4.4.4) into the aggregated procedure model with a visual representation inspired by L* LCM.

Application Software

The conceptualization and verification of the procedure model require deploying application software. The below paragraphs outline two commonly used open-source software solutions in the process mining community, which find application in this research work for demonstration purposes, particularly in chapter 6. The assets lie in their accessibility, ease of use based on a no-code drag-and-drop interface and propagation in research.

The *Workflow Petri Net Designer* (WoPeD) provides an essential toolkit to create workflow models in the desired notation and allows conversion with standard notations such as BPMN. Its focus as an educational software lies in its application in research, and scientific publications cite its value.[224]It is available under the *Lesser GNU Public License* (LGPL) and hosted on *GitHub*[225].

ProM provides an extensible open-source framework for process mining that integrates process mining techniques as plugins. It is the leading process mining tool prevalent in academic research on process mining. Accordingly, it provides access to the newest developments and process mining algorithms.[226] The core framework is available under the *GNU Public License* (GPL) and hosted on *SourceForge*[227].

4.4.1 Phase 1: Process Data Collection

The outset of the procedure model application considers the business process to be digital and in use. Accordingly, the objective in the initial phase is the extraction of process data. Figure 4.10 displays the available and essential data sources for the subsequent phases that require extraction: event logs and process models. Unlike the referenced approaches in section 4.2.2, the working assumption is an existing

[224]cf. Freytag and Sänger 2014, pp. 31–34.
[225]The source code depository for WoPeD is accessible via the following link: https://github.com/woped/WoPeD
[226]cf. Aalst 2016, p. 331.
[227]The depository for and documentation of ProM are accessible via the following link: https://sourceforge.net/projects/prom/

workflow model. Aalst addresses core challenges in data extraction which this section discusses[228]: correlation, timestamps, snapshot, scoping and granularity.

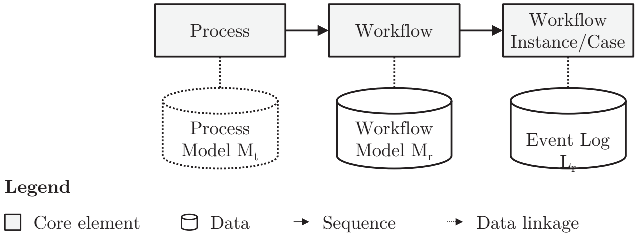


Figure 4.10: Process data collection

Process user activities in the digital process, hereafter also designated as workflows that represent its implementation in the information system, create digital traces systematically recorded in the event log with designated timestamps. The focus in process mining lies in transaction data. The specific data format and logging syntax are negligible in this phase. It is more vital to be structured in a database table and satisfy the minimal requirements for data content and precise semantics (cf. section 2.2.3) to be of use. If data sources originate from different software systems, the identifiers and timestamps support correlating different data sets to merge into one single source of truth.

Given that the first iteration of the procedure model occurs after process digitalization, all process data up until the extraction from the information system constitute the present data population for analysis. In theory, this captures the start event of all process instances. However, as a snapshot of a specific point in time, alluding to a precise enough resolution of time in minutes or seconds, it does not guarantee complete recordings of end-to-end process executions as the event log also comprises ongoing processes. The scope of data extraction hinges on the specific process, the workflow implementation, and the interfaces with other systems. Interesting process data addresses the foremost operational information with the focal point in knowledge transfer.

The process model, or, to be more precise, the workflow model, represents the technical implementation of the process in the information system during its initial production operation (cf. figure 2.4). Its granularity and level of detail hinge on many

[228]cf. Aalst 2016, pp. 142–144.

factors but are in the ballpark of the event log. In a well-defined setting, the process and workflow are identical. However, technical limitations, the specific type of activity, or other circumstantial influences usually inhibit the precise adoption in the workflow. A specific manifestation of this is the anticipation of all process sequences, including back loops in designated process steps, requiring special consideration. Hence, the workflow model inevitably visualizes more process variants than intended in a target process model without back loops. Furthermore, depending on the deployed application system, the extraction of this workflow model poses challenges as processible data formats rarely emerge. Most systems only offer a snapshot as image data that is inadequate for subsequent processing.

Scope Definition

The scope definition for the process optimization and the application of the procedure model originates from the initial motivation (cf. section 4.1) and targets a quick diagnostics report on the process under investigation. Brief information on the process status and insightful findings based on readily available process data support the following steps to derive appropriate actions in continuous process optimization for an organization.

Data Extraction

Confidentiality and data privacy occupy an increasingly vital role in data extraction. The event log reflects employees' activity and performance using the underlying digital processes. Merging data across different systems creates a data set with high personal information value. Accordingly, confidentiality and data privacy regulations surmise essential factors, e.g., limited access rights and data anonymization. While it represents a growing research sector, e.g., via group-based privacy preservation methods[229], data recorded in smaller organizations still allow concluding the identity of process users. While it is not within the scope of this research, data anonymization and blurring sensible data are prevalent to secure responsible data handling.

Concluding this phase, event log L_r and workflow model M_r are available, and data pre-processing can commence.

4.4.2 Phase 2: Process Data Processing

The process data collected in the initial phase requires varying degrees of effort for pre-processing depending on its quality and format. Below ensues the respective elaboration for event logs and workflow models. The focus lies in the procedural

[229] cf. Rafiei and Aalst 2021, pp. 1–20.

description and, to a lesser extent, its execution in an auxiliary software system. This phase usually occupies the most time in data analysis.

Workflow Model Processing

The efforts and the scope of activities for workflow model M_r processing depend on its data format. At best, no processing is necessary. However, recreating the workflow model in a machine-readable data format becomes vital if only image data is available. Usually, a representation in the Petri net notation is recommended for process mining techniques as it is the input format, which most process mining algorithms can process. On the other hand, if the workflow model conforms to another notation, usually *BPMN*, due to its user-friendliness and broad propagation, capable algorithms facilitate and automate the conversion (cf. section 2.1.2).

Independent of the workflow model M_r's creation method, activities described within the model must conform to the activities in the event log and exhibit distinctiveness. Generally, there are two options to realize the latter criterion. At best, the individual activities in the business process have unique names. An alternative is to use unique identifiers to enforce unequivocal identification to correlate events in the event log with the corresponding transition in the workflow model. The workflow model M_p arises from executing the required processing.

Based on this workflow model M_p, it is essential to derive a second workflow model M_t without loops. As previously described, the workflow model represents the digital process implementation, including loops to facilitate process execution. However, creating a model without loops facilitates performance analysis in the subsequent data analysis process as it represents the target process flow. Figure 4.11 illustrates the differences between workflow model variants M_p and M_t.

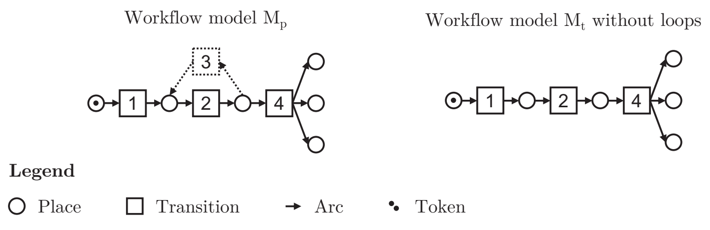


Figure 4.11: Workflow model and variant without loops

Event Log Processing

BOSE ET AL. discuss quality issues that can arise with the data recorded in event logs[230]: *missing*, *incorrect*, *inaccurate* and *irrelevant data*. In order to comprehend the implications of these seemingly identical quality issues and derive appropriate actions, it is necessary to examine the relationships between elements in the event log in more depth compared to the description in section 2.2.3. Figure 4.12 visualizes the relationship between event log elements and detailed data attributes for cases and events. The event log only records the event data attributes but comprises implicit information about the cases and enables inferring process insights. Data processing activities in this section primarily affect data attributes (data columns) except for data aggregation, whereas filtering activities concern events (data rows).

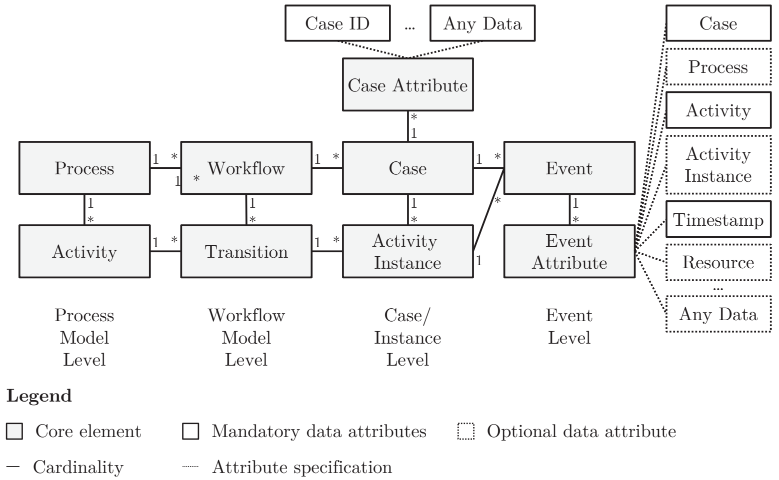


Figure 4.12: Event log class diagram[231]

The root causes of possible quality issues are manifold, depending on the deployed information system and observation tiers identified in the class diagram. However, the first three quality issues cause the most concerns, whereas *irrelevant data* is

[230]cf. BOSE et al. 2013, p. 128.
[231]own representation based on AALST 2016, pp. 145–147.

negligible and outlined below. So first, the elaboration addresses the quality issues along the observation tiers to evaluate their immediate impact on data processing.

On the process and workflow model levels, *missing*, *incorrect*, or *inaccurate data* do not pose any issue because the digital process should now be stable and in use considering the outset of the procedure model application. Hence, the workflow reflects the process description and usually comprises more detailed activities and information than the process description because it involves its execution. On the contrary, recording too much data is the case that instead occurs and concerns the issue of irrelevant data. Accordingly, *inaccurate data will* pose less of an issue as it concerns the scope of data extraction.

On the entity level comprising *Case*, *Activity Instance* and *Event*, the quality issues *missing* and *incorrect data* account for problems usually situated in the technical implementation. It does not preclude other root causes, such as human error, although it is unlikely given good process execution at the outset. The underlying issue of *missing* or *incorrect data* can manifest in either the data set, e.g., occurred events not reflected in the event log or fictitious events that have not occurred emerging in the event log. Detecting these issues is challenging as minimal domain expertise feeds into the procedure. Likewise, these quality issues may manifest on the level of the case or event attributes. AALST examines these occurrences in detail and derives a guideline for event logging from preventing their emergence from the get-go.[232] Counteractive measures to process event logs with quality issues in hindsight depending on the degree of deterioration and occurrence hence, requires case-specific handling.

As noted before, *irrelevant data* has the most negligible impact among the indicated quality issues as processing comprises data aggregation, cleansing, and filtering. Based on different information systems, event logs can output not anticipated data specific to the system that requires data structure analysis and inspection to determine its added value. This step can include aggregating activities from low-level to high-level events to minimize data volume and increase informational value. Beneficial data enriches the event log through correlation, e.g., by creating and appending additional data attributes, whereas redundant data is submitted to cleansing operations, e.g., deleting duplicate entries. It involves preserving machine-readable data points, e.g., date format according to ISO 8601, to express the timestamp in minute resolution while ensuring that other data attributes, such as the activity description, are human-readable. Reviewing the event log data

[232] cf. AALST 2016, pp. 149–153.

comprises understanding the data semantics, e.g., if multiple timestamps exist, the capability of assigning it to either activity start or end. These activities result in the creation of the processed event log L_p. Process mining software usually is capable of data conversion from commonly used database table formats such as *Comma-separated values* (CSV) to process mining specific formats such as *Extensible Event Stream* (XES) or *Mining Extensible Markup Language* (MXML)[233], for instance, the plugin *Convert CSV to XES* in ProM.

Event Log Filtering

Concluding data processing for event logs, the next step is filtering the log to create subsets L_c and L_o to facilitate the analysis. Fundamentally, the below procedure applies to all event logs and exploits the completion status of process instances. The cases with high information content are end-to-end cases that encase all activities from start to end, denominated L_c. The respective elements in the workflow model M_p help identify start and end activities. Cases that miss the start event, e.g., due to a delay in data logging, only give limited insights, particularly regarding performance metrics, and usually remain ignored. Despite this applying to ongoing cases in log L_o with a recorded start event, it is theoretically possible to create a forecast for the process in the sense of operational support. Accordingly, it is vital to retain these two event log subsets, L_c and L_o. Figure 4.13 visualizes this filter method.

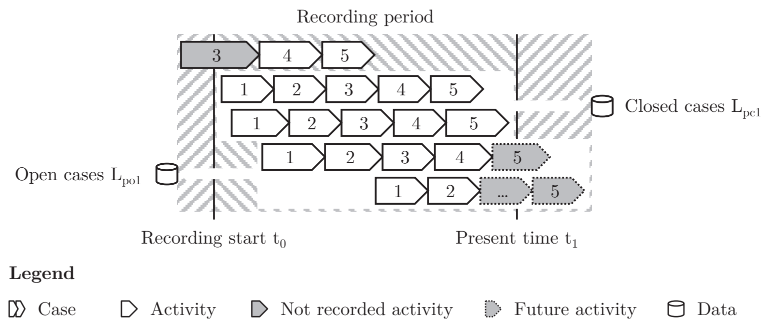


Figure 4.13: Event log subsets based on case completion status

Supplementary filtering methods comprise *slice and dice* (removal of events or cases based on attributes or statistics), *variance-based filtering* (segmentation of the log

[233]cf. ibid., p. 142.

through clustering), and *compliance-based filtering* (removal of events or cases based on defined rules).[234]

Processing Automation

After the initial setup and data structure evaluation, the deployment of automation for data processing is feasible and recommended. This step facilitates the iterative application of the procedure model and minimizes expenses for processing, assuming no underlying fundamental changes affect the event log recording and reflect in the process data, e.g., changes to syntax, over the observed time.

Concluding this phase, pre-processed process data is available. Therefore, this phase's outcome constitutes two event log subsets for completed and ongoing cases, denominated L_c and L_o respectively, and the complete workflow model M_c with a no-loops variant M_t, the target process model.

4.4.3 Phase 3: Process Data Analysis

The process data analysis exploits the processed data to give insights into the process's status and performance. The analysis comprises basic process diagnostics on meta-information and process perspectives in a data-driven approach. Alternative approaches in process mining pertain to question-driven or goal-driven analysis.[235] With the outset and general procedure model applicability in mind, this phase follows up with the retrospective analysis of control flow, case, organizational, and time perspective in partially sequential order (cf. section 2.2.3).

The upstream activity *Process diagnostics* serves to familiarize with the process prior to initiating control flow perspective analysis. The analysis of additional perspectives can occur concurrently and iteratively. The procedure model differs from PM^2, which structures the analysis according to process mining types. It resembles the approach of L*LCM[236] in creating a control flow model that integrates additional analysis perspectives (case, temporal, and organizational) into a comprehensive and integrated process model. However, the integrated model creation is integral to the subsequent phase *Results interpretation*.

[234]cf. Eck et al. 2015, pp. 302–303.
[235]cf. Aalst 2016, p. 394.
[236]cf. ibid., p. 396.

Process Diagnostics

Throughout the process data processing phase, getting a good grasp of the data structure is usual. It focuses on syntax and structure, whereas process diagnostics engages with the data content. This perspective aligns with conventional process optimization approaches such as *Six Sigma*. PM^2 is the only process mining approach that recognizes its value[237]. Bringing it forward in the analysis sequence facilitates familiarization with the process. Hence, a good recommendation is to visualize the cases in the event log L_p in a dot plot versus the time, plotting the case identifier on the Y-axis. The visual plot gives a rough overview of the business process condition. Additional information linked to design elements in the plot, e.g., deploying shape and color maps to include resources or identify common transitions, assists in increasing the informational value. Figure 4.14 visualizes this dot plot type.

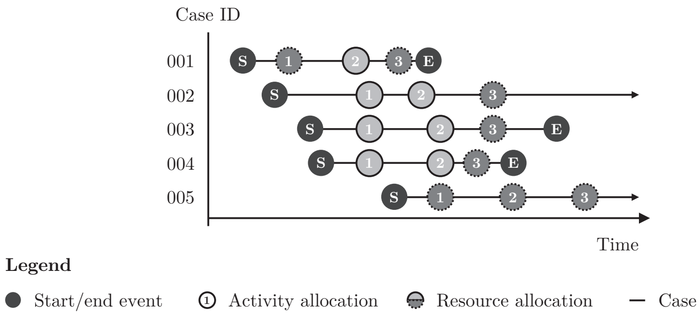


Figure 4.14: Event log dot plot

ProM provides the plugin *Dotted Chart* that facilitates creating a dot plot. The cases' start event arrangement supposedly orients towards a sloping curve with progressing time. Deviant behavior indicates underlying difficulties exceeding the iterative improvement approach or issues in data logging. However, this observed behavior does not apply to end events, as process cycle time varies across processes and variants. Conspicuous behavioral patterns or symptoms usually emerge in one way or another and remain a good starting point for the below analysis.

Process diagnostics incorporates process metrics that mainly belong to the specific analysis perspectives. Different entity levels, frequencies, distributions, and temporal and organizational information comprise essential process metrics. However, as

[237] cf. Eck et al. 2015, pp. 302–303.

outlined at the outset, these metrics focus on universally applicable ones, namely process performance indicators. The ProM plugin *Log Visualizer* computes and visualizes essential metrics based on entity frequencies. The elaboration of other indicators follows in the below sections. Good, high-level metrics with informational value accompanied by various granularity are, among other things[238]:

- **Throughput time:** The period with statistical characteristics required for executing a particular activity or complete cases.
- **Case variants:** The number of case variants for complete cases.
- **Transition (quantity):** The number of transitions in complete cases.
- **Loops (quantity):** The number of loops in completed cases.
- **Resource (diversity):** The number of unique resources in complete cases.

The conclusion of this phase yields essential status information about the business process. The scatter plot and process metrics contribute to quick insights with a manageable effort after setup.

Control Flow Perspective Analysis

The control flows analysis concerns the sequence of activities and contributes to familiarizing with executed transitions in the process history. Most process mining approaches, e.g., PDM and PM^2 stipulate creating a process model from the event log by deploying process discovery algorithms. Here, the creation is optional due to verified workflow models. Nonetheless, imagery supports creating comprehension of the factual process execution. For example, while the workflow model M_p describes all possible paths a process instance traverses, including loops, it does not provide any information on the most frequented paths. Two complementary methods with the same objective are available to counteract the lack of information: replay the event log L_p in the workflow model M_p, and compare a newly discovered workflow model M_d based on L_c with M_p.

Before executing any of the above methods, an upstream examination of process conformance regarding the control flow minimizes the possibility of fragmented cases. The event log filtering for complete cases concerns verifying case completion based on a start and end event but does not investigate the sequence of events. Conformance checking is another layer of compliance assurance that can detect divergent cases that do not follow defined and feasible process sequences, e.g., extra or skipped activities. Conformance algorithms deploy different measurement metrics but fundamentally compare the behavior of the event log and process model.

[238]cf. Bozkaya et al. 2009, p. 23.

Deviations per event in case inspection happen in either log or model and confer a penalty score, an arbitrarily defined value, to measure the degree of deviation[239]. The focal point to determine a conformance score is the model quality dimension fitness, which describes the degree to which a process model allows all observed behavior. Other quality dimensions are negligible, assuming the presence of a verified workflow model.[240] Figure 4.15 illustrates the particular conditions for the business process post-processing and its relations between event log, process model, and workflow.

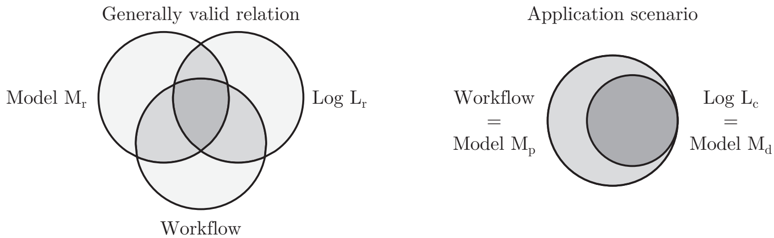


Figure 4.15: Relation between log, model, and workflow[241]

Literature does not agree on a universally good score, as multiple process models with divergent objectives co-exist and make the assessment use case and algorithm dependent. The broader application arises in process discovery to assess model quality, as few scenarios strive for full compliance due to competing objectives, among other shortcomings such as increasing model complexity.[242] *L*LCM* and *PM²* see conformance checking as an essential tool and outline general application scenarios but fail in disclosing practical added value in analysis. Instead, multi-perspective conformance checking catering to attributes exceeding control flow creates more value, e.g., concerning temporal and organizational data[243], but requires more domain expertise and manual data input for practical application.

Accordingly, conformance checking in conventional applications targeting compliance holds little value in the scope of this research, particularly considering the outset of

[239]cf. Aalst 2016, p. 188.
[240]cf. Mannhardt 2018, p. 54.
[241]own representation based on ibid., p. 55.
[242]cf. Weidlich 2020, pp. 203–206.
[243]cf. Mannhardt et al. 2016, p. 114.

limited domain expertise at this junction. Deviations are either positive or negative, applicable in a given scenario. Hence, it only provides valuable information in the presence of supplementary domain expertise to enable interpretation. Nonetheless, conformance analysis as a tool creates benefits at this stage. Stipulating a 100 % conformance accounts for zero logging errors as a verified workflow model M_p exists. Here, conformance only concerns the criterion fitness of the event log L_c. Comparing L_p may yield lower conformance scores, as algorithms can penalize missing events outside the observation period. Exemptions resulting in a lower score require removal from L_c to derive a new filtered event log L_{cp} and a per case analysis outlined in the below section. *ProM* provides the above conformance checking algorithm devised by Mannhardt et al. in multiple plugins, e.g. *Conformance Checking of DPN (XLog)* and *Multi-perspective Process Explorer - Fitness View*.

Regarding the preliminary conformance checking, the input L_c, or in case of necessary case removal L_{cp}, serves as input for both replay and process discovery. The information content is comparable, albeit their visual output differs. As the name implies, replay refers to the playback of events in the workflow model M_p. The time-lapse of this replay imposes an impression of the process flow and frequently traversed paths. Interactive implementations of replay algorithms in ProM best portray process flow, e.g., *Replay a Log on Petri Net for Conformance Analysis*.

With a view to the process discovery, the consequential process model M_d inevitably needs to be a subset of M_p, possibly with fewer transitions. The notion follows the process model rather than the workflow model, as its origin lies in the event log L_{cp}. The algorithm choice depends on the underlying business process. Laue et al. characterize the most frequently used process discovery algorithms with properties and application scenarios.[244] Considering the frame conditions, heuristic and inductive miner ensure the best modeling results while preserving maximum fitness and integrating statistical figures regarding frequencies in the model. ProM plugins are,e.g., *Interactive Data-Aware Heuristic Miner* and *Mine with Inductive Visual Miner*, respectively. Other algorithms like *Integer Linear Program (ILP)* miner require expertise for parameter configuration or prioritizing divergent quality dimensions. Superimposing the models M_d and M_p outlines the workflow model transitions not observed in real life. It serves as a potential impetus for process improvement suggestions.

Subsuming the activities in control flow analysis, it secures complete conformance between complete cases in the event log L_c (or L_{cp} in the case of discovered deviations)

[244]cf. Laue et al. 2020, pp. 252–267.

and the workflow model M_p. This activity improves the informative value of metrics derived in the below sections based on the event log L_c or L_{cp}, whichever is applicable in a given scenario. In addition, the ancillary methods of *replay* and *process discovery* contribute to identifying possibly dispensable activities as input for case perspective analysis to derive and initiate process improvement actions.

Case Perspective Analysis

The case perspective analysis pertains to all other perspectives, representing an entity level. Cases associate singular events with coherent process sequences through an identification number. The term traces is interchangeable with cases. At the outset, this section addresses process diagnostics and control flow related analysis and metrics and integrates the outlined time and organizational perspectives below. The input for case analysis is the processed event log L_p. The division to L_c and L_o increases the informational value to differentiate between retrospective analysis and hypothetical forecast. The analysis concerns the identification of case variants and frequencies. It is expected to aggregate similar process sequences based on the frequency and computes statistical values to asses these regarding temporal and organizational perspectives, e.g., cycle times, to uncover variant-specific behavior and peculiarities. Figure 4.16 constitutes a case perspective visualization for a complete event log solely based on completely conforming traces.

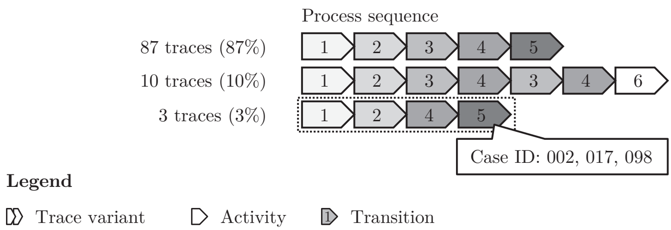


Figure 4.16: Case information in event logs

As mentioned above, it also integrates a performance assessment based on operational indicators. For example, comparing case variants provides insight into the shortest possible process sequences in transition numbers and the reverse for the longest. In addition, process loops during execution manifest characteristic behavior in event logs: the total number of transitions per case increases, and identical transitions exhibit repeated execution. Hence, the number of transitions exceeds the number of unique transitions. In accordance, it enables generally deducing valid performance indicators. Furthermore, it supports their interpretation of divergent cases identified earlier. Although the case analysis extends towards different perspectives, the ProM plugin *Explore Event Logs* aggregates the required functionality in an interactive environment.

Temporal Perspective Analysis

The informational value from a temporal perspective hinges on the granularity of timestamp recording associated with transitions. The event log records a transition at a specific point in time, the timestamp. Accordingly, two timestamps delineate the start and end of an activity. However, not all information systems record both timestamps. It is common to pertain to the end time if only one timestamp is available, but it is essential to ascertain which point in time it references in process execution, as it impacts the temporal analysis regarding the cycle time of traces and events.

Provided the log records starting and finishing times, breaking down activity throughput time to process and idle times are feasible. Figure 4.17 demonstrates the decomposition. It allows for an in-depth analysis, notably when including the organizational perspective. Time recording assists in identifying notably efficient activities and time-consuming performance bottlenecks. While single-activity timestamps are less conclusive due to impreciseness in the discerning process and idle times, it still creates added value by giving estimates. However, a detriment is that either the first or the last activity is not incorporated in this analysis because a single timestamp is insufficient for estimating the activity duration.

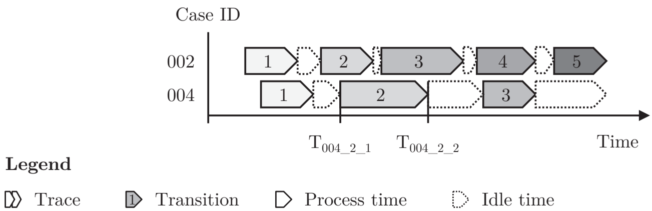


Figure 4.17: Temporal information in event logs

Calculating temporal metrics and their distribution per case variant, case, and event is straightforward based on timestamps. The statistical analysis gives insight into the performance and increases informational value by integrating the other perspectives. For example, in multi-dimensional conformance checking, time limits for executing tasks and task sequences become important metrics if defined. Few plugins for ProM already integrate the temporal perspective in *replay* and *process discovery* based on the complete event log L_c or L_cp. Examples are the plugins *Interactive Data-Aware Heuristic Miner* and *Mine with Inductive Visual Miner*.

Organizational Perspective Analysis

The organizational perspective analysis requires logging information about the person executing an event, denominating a resource in process mining. This analysis elucidates the cooperation and collaboration among people involved in process execution and requires the event log L_c or L_cp. Figure 4.18 features customary deployed visualization. To begin with, a role analysis[245] outlines which person typically assumes which tasks. The result feeds into aggregating people into groups occupying a similar role. Among these roles are specialists focusing on few activities and generalists capable of assuming responsibility for many tasks. The direct comparison with the organization structure provides helpful information regarding the allocation of responsibilities and their execution but also requires the consideration of data privacy.

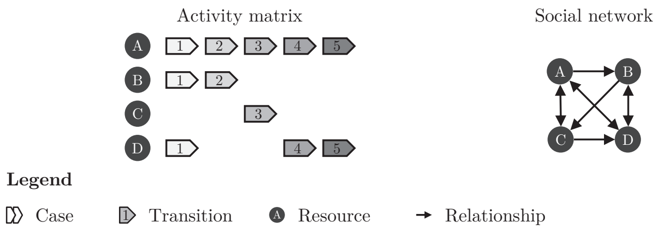


Figure 4.18: Organizational information in event logs

A sound analysis also extends to creating social networks that outline the relationship between people or in aggregated form between roles or groups. It examines, for instance, the handover of work and whether it represents a form of task delegation or a handover. In this sense, it expands previously introduced analysis from the organizational perspective. Different ProM plugins cover the individual analysis, e.g., *Mine for a Handover-of-Work Social Network*. Here, multi-dimensional conformance checking integrates the organizational perspective and can imply reviewing breaches of dual control principles in process sequences during approval processes or non-approved process executions. However, it requires domain expertise for a thorough

[245] cf. BOZKAYA et al. 2009, p. 23.

analysis and interpretation as people can occupy multiple roles within a single business process or if access management is not kept up-to-date.

4.4.4 Phase 4: Results Interpretation

Process diagnostics and perspective analyses uncover the process status based on essential metrics and informative graphics. The selected methods focus on a low inhibition threshold in usage but still display essential information to minimize information overload.

Process Model Visualization

An enhanced process model M_e, per process mining algorithms displays condensed information regarding the temporal perspective and frequencies. Supplementary information, e.g., regarding organizational matters, increase its informational value. Figure 4.19 displays an exemplary enhanced process model. It facilitates detecting process anomalies and assesses the process's health.

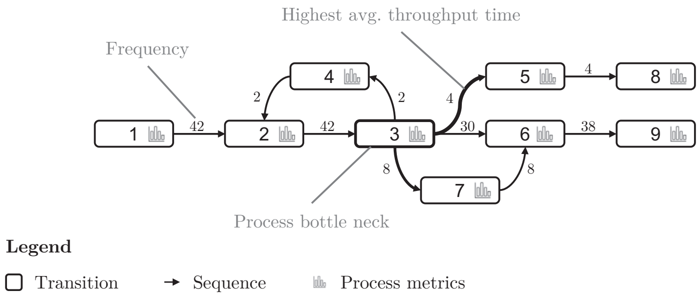


Figure 4.19: Additional analysis perspectives in an enhanced process model

Process Insights Generation

The data interpretation, especially regarding root causes for anomalies, hinges on the findings and can make the exploitation of process-relevant domain knowledge necessary in the next step. The procedure model stipulates the possibility of ancillary in-depth analyses if required, especially if a target- or question-oriented approach is present contrary to this data-driven approach to process mining.

The closure of this phase marks the beginning of the phase *Action initiation*. The decision-making on appropriate measures hinges on the analysis findings and process frame conditions. Hence, it is not feasible to deduce general statements or recommendations for action, as the decision requires domain knowledge that lacks modeling and model integration, which are outside the research scope. Generally, actions range from support, intervention, and adjustment to redesign as suggested in L* LCM.

4.4.5 Process Optimization Procedure Model

This section aggregates the content of the individual phases into an integrated procedure model for process optimization. Figure 4.20 displays the comprehensive model. It deploys essential visual elements akin to L* LCM to help outline core activities, data outputs, and cross-linking information exchange points to guide the process owner or manager with process optimization. Visualizing data flow across the procedure model phases helps indicate the specific data handling and binning in subordinate activities. The focus on data interdependency provides clarity on data requirements for each activity. With this, it establishes the foundation for the repeated application of the procedure model in continuous process optimization and its challenges that come along, in particular, concept drift (cf. section 5), starting with a digital process in use at the outset (*Phase 0: Digital Process Utilization*).

Phase 1: Process Data Collection addresses the necessary preparatory activities to extract relevant process data, event logs, and workflow models from the information system. Subsequent *Phase 2: Process Data Processing* comprises activities for data type-specific processing tasks and concludes with the setup of processing automation, anticipating the repeated application of the procedure model in continuous process improvement. Afterward, *Phase 3: Perspective Analyses* commences and deviates from the previously sequentially organized activities. The perspective analysis exploits initial insights from process diagnostics and control flow analysis that trigger case-specific responses. Accordingly, subsequent concurrent and iterative analysis is not uncommon. Finally, the procedure model concludes with the visualization of analytic results and process insights in *Phase 4: Results Interpretation*. It is the foundation to support the process owner or manager in deciding appropriate actions to improve the process in *Phase 5: Action Initiation*.

The case studies in section 6.3.2 expand on the tasks within each activity and reference ProM modules for implementation in a comprehensive and structured manner. The overview includes information on results, executed processing steps, and input and output data.

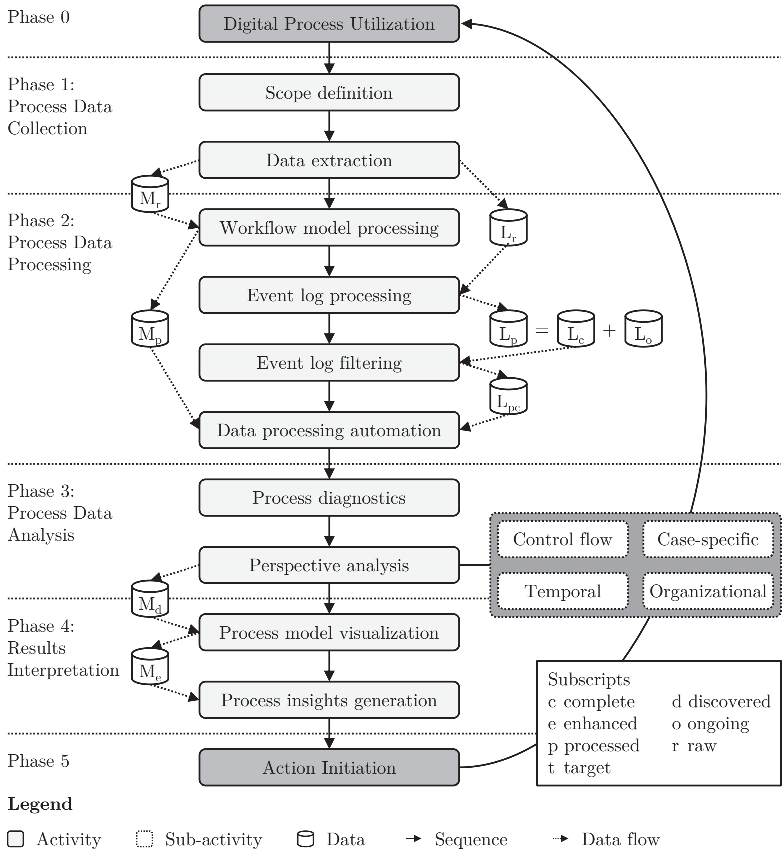


Figure 4.20: Procedure model for process optimization

4.5 Interim Conclusion to Sub Research Question SRQ2

This chapter introduces a process optimization procedure model that provides insight into process performance based on performance indicators. The process analysis exploits the availability of process data and minimizes the need for domain knowledge. It uses event logs linked to process execution and workflow models reflecting the implementation in the information system. Hence, the procedure model answers the research question *RQ2 How can data-driven analytic methods be aggregated in a guided procedure model to facilitate process analysis and uncover process insights?* Figure 4.21 displays the interim results of chapter four and its integration into the overall approach in this research.

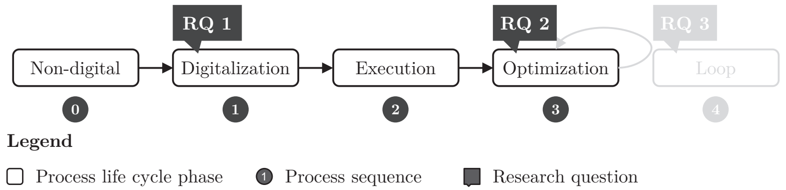


Figure 4.21: RQ2 interim results' integration in the overall thesis

The first section specifies the requirements for the procedure model (cf. section 4.1 and outlines state of art regarding conventional and data-driven approaches to process optimization (cf. section 4.2). Conventional approaches are proven and still in use but do not exploit available process data. Recent advances in process mining make it the prevailing approach in practical application. However, most approaches surmise a project approach instead of a continuous application (cf. section 4.3). Nonetheless, process mining approaches score best against the requirements and serve as a foundation for the revised procedure model.

The process optimization approach recycles essential elements of recent process mining approaches and expands them through the lateral integration of additional tools. It categorizes core activities in the phases *Process Data Collection*, *Process Data Processing*, *Process Data Analysis*, and *Analysis Results Interpretation*. An aggregated overview (cf. section 4.4) provides phase sequence, information flow, and interactions information. The procedure model application yields process insights and indicates the overall process status. Except for *RQ2-R5 Concept drift handling*, it addresses identified shortcomings and improves requirements satisfaction. Thus, it provides an adequate answer to sub research question *SRQ2*. The subsequent chapter takes up *RQ2-R5* within the scope of the third research question.

5 Concept Drift in Process Data Analysis

Based on the previous chapter's results, this chapter addresses the third sub research question *SRQ3 How can concept drift be considered in the cyclical process analysis?*. In essence, it refers to the repeated application of the devised procedure model (cf. section 4.4.5), the result constituting the answer to RQ2, and considerations regarding concept drift handling. After establishing the specific impact of concept drift on procedure model application and deriving requirements to benchmark existing approaches (cf. sections 5.1 and 5.2), the most appropriate one emerges through the selection process (cf. section 5.3). The previous procedure model requires modification and extension to integrate concept drift handling and thereby allows for accommodating its mediate challenges in repeated application in continuous process improvement (cf. section 5.4). This chapter concludes with assessing the research question satisfaction (cf. section 5.5).

5.1 Requirements for Concept Drift Analysis

In principle, the multiple and iterative application of the procedure model for continuous process optimization is feasible. Nevertheless, the practical application indicates otherwise by possibly redundant activities. Instead, exploiting knowledge from past process analysis contributes to minimizing expenditures and accelerating the process optimization cycle as analysis remains identical. However, as time progresses, process documentation and workflow models require upkeep as the underlying process may have changed to adapt to altered circumstances. Moreover, documentation is not inevitably reliable even in case of known changes, for instance, due to process intervention to remedy identified process bottlenecks.

The event log theoretically can record explicit changes in the workflow depending on the deployed information system and its logging capabilities but does not necessarily reflect or integrate multiple processes or workflow version changes. Accordingly, reusing process insights and models leads to examining the impact of concept drift on the previously described procedure model and its approach. Consequently, this section dismantles and specifies the previously deferred consideration of procedure model requirement *RQ2-R5 Concept drift*.

Concept drift assumes a change affects process behavior. The behavior change is temporary or permanent and can affect different process perspectives. The notion in this research aligns with Sato et al.[246] that presume temporary changes manifest as data outliers. The objective of continuous optimization aligns with eliminating negative, permanent behavioral changes and, thus, is the focal point. Early research of Bose et al. distinguishes four classes of concept drift relating to the introduction of change[247]:

- **Sudden drift:** A new process substitutes an old process at a specific point in time. As the previous process ceases, open cases transfer to a new workflow, their new state pending the specific implementation of the new process.
- **Recurring drift:** Processes shift between different, possibly multiple states, substituting each other. The recurring appearance is periodic with a temporal trigger, non-periodic with an event-specific trigger, or a combination of both.
- **Gradual drift:** The concurrent existence of old and new process variants characterizes a gradual drift. The old process slowly phases out until the new one fully substitutes it. Open cases remain in their respective workflow.
- **Incremental drift:** Incremental changes modify an existing process to a minor degree in iterative cycles. It represents a special form of sudden drift on a minor scale.

Figure 5.1 contributes to the understanding of different concept drift classes by visualizing the manifestation of concept drift at a specific point in time. Here, the principal focus is on process behavior from the control-flow perspective.

Recurring drifts surmise a minor role, as their handling succumbs to the specific case and usual processing time, pending the nature of the occurrence. This type of drift includes temporal patterns of recurring behavior observed in short terms as brief as daily and weekly, and longer-term seasonal patterns.[249] The same general principle applies to a gradual drift, where case-specific analysis will require adequately identifying the exact time a change occurs to follow up with data binning. However, there is not necessarily a specific time of change, as a gradual drift may refer to a period of process change between recurring seasonal patterns or one-time changes. Accordingly, sudden and incremental drift handling remains relevant to the application scenario. Previously described frame conditions and requirements persist in consideration of concept drift (cf. section 4.1). Hence, a repeated retrospective analysis comes with past results, whereas process-specific domain

[246] cf. Sato et al. 2021, p. 6.
[247] cf. Bose et al. 2011, pp. 394–395.
[248] own representation based on ibid., p. 395.
[249] cf. Aalst 2016, p. 318.

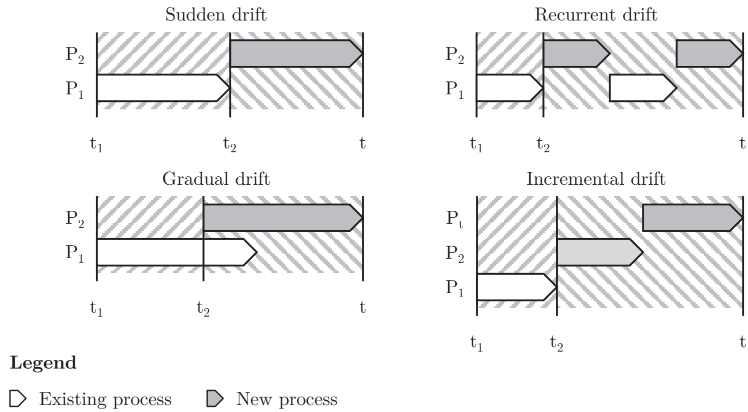


Figure 5.1: Manifestations of concept drifts in processes[248]

expertise is not integral to the model in the analysis but in the action initiation in process improvement.

According to Bose et al.[250], it is essential to denominate the emerging core challenges that require restatements as requirements: the fundamental challenge is to detect concept drift in the process, and more specifically its presence in the event log. This task includes allocating the period of the change, the so-called change point detection, and the localization of the concept drift in the process. Concept drift seizes different manifestations depending on its nature. Moreover, distinct perspectives and dimensions interact and impact each other concerning concept drift. Therefore, its characterization becomes essential to derive recommendations on process analysis modification or process modification to accommodate the changes but requires domain expertise that a concept drift analysis approach usually does not provide.

Meanwhile, some drifts are negligent in process optimization, as the concept drift may be neutral and not impact the process objective. Hence, the categorization into concept drift classes surmises a minor role in this context as the derivation of appropriate measures follows suit in a different activity. Lastly, change process discovery is negligible in this work as cyclical process analysis uncovers process evolution as consecutive concept drifts. Therefore, this chapter's requirements

[250]cf. Bose et al. 2014, pp. 154–155.

for solution development emerge from handling the specified core challenges. In addition, the same frame conditions for concept drift handling apply, for instance, the pragmatism regarding application software utilization and process data availability. With this, the derivation and further specification of requirements to resolve research question RQ3 based on *RQ2-R5 Concept drift* follow. It is essential to comprehend that the requirements refer to specific approaches to concept drift analysis, whereas *RQ2-R5* refers to its implementation in a more holistic approach, including the derivation of appropriate measures:

- RQ3-R1 Concept drift analysis
- RQ3-R2 Technology readiness
- RQ3-R3 Accessibility
- RQ3-R4 Simplicity

The explanation of the list of requirements follows. The requirements serve as evaluation criteria to discuss the below approaches to concept drift analysis and their fit within the scope of this research. Each requirement discerns three levels of compliance. The degree of compliance to the respective criteria determines the level of compliance. Accordingly, the visual representation with Harvey Balls (none, partial, and full) gives a quick overview.

RQ3-R1 Concept drift analysis: The prerequisite to handle concept drift is the capability of its identification based on available process data. The localization of concept drift implies its identification and relates to the temporal perspective of its appearance, also referred to as change point detection and the localization inside the process model.

- ○ **None:** The approach cannot identify concept drift.
- ◑ **Partial:** The approach can identify the emergence of concept drift.
- ● **Full:** The approach can identify and localize the emergence of concept drift for distinct perspectives.

RQ3-R2 Technology readiness: The technology readiness refers to the maturity of the provided concept drift analysis approach and its practical applicability. It can range from a theoretical concept to validation in a relevant application scenario.

- ○ **None:** The approach gives no insight concerning its technological readiness.
- ◑ **Partial:** The approach describes a sound theoretical concept with limited applicability or verification.
- ● **Full:** The approach describes a verified concept that shows practical applicability in a relevant application scenario.

RQ3-R3 Accessibility: This requirement refers to different perspectives of accessibility to the concept drift analysis approach. While high accessibility requires comprehensibility without extensive prior knowledge, its implementation in an open-access environment is equally essential and showcases the ease of use.

- ○ **None:** The approach is not easily accessible due to its high complexity and restricted access rights.
- ◑ **Partial:** The approach is comprehensible without excessive prior knowledge.
- ● **Full:** The approach is comprehensible without excessive prior knowledge and provided in an open-access environment.

RQ3-R4 Simplicity: The simplicity correlates to the expenditure required to implement the approach. While it shares commonalities with technology readiness and accessibility, it warrants an individual requirement due to the intended integration of the concept drift analysis into the cyclical process improvement. Complex approaches with concatenated pre-processing and limited transferability impede quick analysis cycles, even if a high technology readiness and easy accessibility persist.

- ○ **None:** The approach requires diverging pre-processing with limited transferability in the cyclical application.
- ◑ **Partial:** The approach requires little pre-processing and boasts limited transferability in the cyclical application.
- ● **Full:** The approach requires very little or no pre-processing.

5.2 Approaches for Concept Drift Analysis

Handling concept drifts in process mining shares similarities to the challenge it poses in data mining. Machine learning models in supervised learning contexts, such as classification tasks, aim to explain the relationship between input data and target variables. However, dynamic environments affect the model's capability to forecast the target variable over time precisely, thus giving birth to the concept of supervised online learning for data streams.[251] While the effects of concept drift visualized in figure 5.1 are unequivocally applicable, the underlying relation between input data and target variable differs. Data mining target variables are categorial or continuous values, whereas, in process mining, the target variable is process models with complex structures and inherent attributes like concurrency, choice, and loops. Hence, the applicability of data mining approaches without modifications to handle concept drift in process mining is limited.[252]

[251] cf. Jadhav and Jadhav 2018, p. 1.
[252] cf. Sato et al. 2021, p. 3.

Most approaches for concept drift handling in process mining adopt a means of feature extraction and a similarity comparison algorithm to compare different data clusters. While most approaches focus on the control-flow perspective to extract suitable features, recent approaches introduce more flexibility towards the consideration of resource and time drifts[253]. The deployment of so-called sliding windows to compare process behavior between two periods stems from the first considerations formulated in the process mining manifesto[254]. A systematic literature review conducted by Sato et al. in 2021 picks up on the requirements formulated in section 5.1 and categorizes the reviewed literature into distinct approaches.[255] Referenced papers and identified categories serve as the foundation for this review.

5.2.1 Change Detection

Change detection represents the most basic approach in concept drift handling as its capabilities limit it to the detection that a change has occurred. However, these do not specify the change point and only report a drift's observation. The general principle is to convert traces in the event log to an abstract representation or extract specific characteristics and compare these to other traces in a specific temporal interval. Approaches differ in feature extraction to identify a change. For instance, by deploying the sliding windows technique, the change detection algorithm *ADaptive WINdows* (ADWIN) proposed by Bifet et al.[256], the interval size becomes adaptive to the needs. The authors Carmona et al.[257] and Hassani[258] propose methods based on ADWIN for change detection in process mining event logs.

Impedovo et al. present a *Pattern-Based Change Detector* (PBCD) that extends the functionality of detecting changes by appending high-level characterization, whether a new or old process sequence exhibits the change[259]. Other approaches exploit the relationship between activities to infer a relation matrix to gauge similarity between process models[260]. Contrary, Liu et al.[261] and Stertz et al.[262] exploit more accessible process model-related metrics precision and fitness respectively.

[253] cf. Brockhoff et al. 2020, p. 33.
[254] cf. Aalst et al. 2012, p. 187.
[255] cf. Sato et al. 2021, p. 13.
[256] cf. Bifet and Gavaldà 2007, p. 2.
[257] cf. Carmona and Gavaldà 2012, p. 94.
[258] cf. Hassani 2019, p. 233.
[259] cf. Impedovo et al. 2020, p. 462.
[260] cf. Zheng et al. 2017, pp. 528–529.
[261] cf. Liu et al. 2018, p. 108.
[262] cf. Stertz and Rinderle-Ma 2018, p. 322.

Evaluation: Change detection is only capable of identifying changes within an event log without the capability to specify the location or time. However, the technology is mature and exhibits verification and validation with actual process data. In addition, the specific implementation using sliding windows requires domain expertise and expenditure in data pre-processing to extract relevant characteristics, while the probable insight is modest. Hence, comprehensive metrics such as process model precision and fitness are more suitable given the application scenario.

5.2.2 Change Point Detection

Bose et al. outline the challenges relevant to change point detection algorithms: capturing the characteristics of traces and the time a change occurs.[263] In comparison to change detection, the characterization metrics for change point detection may differ, as the feature requires the inference to a specific case or point in time.[264] *Pruned Exact Linear Time* (PELT) constitutes a method developed by Killick et al.[265] to detect change points by minimizing cost functions dependent on the possible number and location of change points.

From a holistic perspective, statistical hypothesis testing, cost functions, and trace clustering are equally capable of change point detection. Nonetheless, recent literature favors cost-based techniques in implementing concept drift detection. For instance, Yeshenko et al.Yeshchenko et al.[266] and Adams et al.[267] deploy variants of PELT to process multivariate time series that represent features to describe trace characteristics.

Evaluation: Change point detection gives insight into the time a concept drift surfaces. Depending on the specific implementation, it can provide localization and drift classification information. The most common approaches derive from data mining applications and exhibit advanced maturity. This circumstance speaks for its accessibility, albeit it requires expertise to comprehend and implement.

5.2.3 Statistical Hypothesis Testing

Most approaches deploy a variant of statistical hypothesis testing to detect concept drift, determine change points and localization, and characterize the concept drift class. The algorithm choice determines the complexity and potential insight into

[263]cf. Bose et al. 2014, pp. 159–161.
[264]cf. Adams et al. 2021, p. 408.
[265]cf. Killick et al. 2012, pp. 8–13.
[266]cf. Yeshchenko et al. 2022, p. 3058.
[267]cf. Adams et al. 2021, p. 412.

the concept drift. The overall procedure to apply hypothesis testing aligns with the other approaches but is more generalizable: define data to compare, pre-process relevant data, extract features, and apply a suitable statistical test pending feature and its distribution[268]. Usually, there is no a-priori information on distribution. Hence, non-parametric statistical hypothesis tests are prevalent.

Seeliger et al.[269] describe a method that exploits changes in graph metrics extracted from discovered processes as the variable for a statistical G-Test to detect the presence of concept drift. In the next step, this approach allows localizing the drift in the process model. Maaradji et al.[270] describe an automated method to detect sudden and gradual concept drifts from execution traces. Using a Chi-Square Test on the run, the agglomeration of direct follows relations determines the similarity of two periods and thus identifies sudden drifts. Gradual drift detection builds upon this detection method and appends an additional period in the analysis to track a gradual change from initial process behavior via a transition period to new behavior. Ostovar et al.[271] propose an automated method to characterize concept drifts after detecting the change point. The underlying idea is to discover two process models, before and after the drift, and explain the transformation based on minimizing cost functions for process model edits.

Evaluation: Statistical hypothesis testing, usually in combination with other approaches, covers all relevant aspects of concept drift analysis. The fundamentals are proven statistical tests deployed in other fields of research. Some references indicate an automated approach, but these require specific boundary conditions or expertise in setup and application in conjunction with feature extraction. In addition, the more holistic approaches require multiple pre-processing steps and data sampling to use statistical tests.

5.2.4 Trace Clustering

Trace clustering focuses on clusters of traces that share similar behavior. Cluster composition implicitly stores time information through the included traces. Usually, monitoring begins by considering a grace period to determine a default behavior. A change in cluster composition afterward corresponds to a behavior change, a concept drift. Overall, approaches to trace clustering differ in feature definition, clustering

[268]cf. Sato et al. 2021, pp. 13–18.
[269]cf. Seeliger et al. 2017, pp. 2–3.
[270]cf. Maaradji et al. 2017, pp. 2143–2145.
[271]cf. Ostovar et al. 2020, pp. 2–3.

approach, consideration of time in the clustering, and algorithm output[272]. An early approach by ACCORSI ET AL. uses distance matrices to describe the distance between activities as a measure for clustering similar trace clusters[273]. ZELLNER ET AL.[274] approach trace clustering from the opposite side via outlier identification and aggregation based on *Local Outlier Factor* (LOF)[275].

MORA ET AL.[276] integrate trace clustering into a toolkit based on the *Concept-Drift in Event Stream Framework* (CDESF) by JUNIOR ET AL.[277]. The approach computes graph distance metrics between direct activity succession in a trace and a reference model graph, clusters these with density-based algorithm *DenStream*[278], and outputs deviations identified as concept drifts. The integrated model update functionality enables keeping track of multiple process changes. *Local Complete-based Drift Detection* (LCDD) by LIN ET AL.[279] follows a similar approach despite not focusing on clustering traces but differs in the feature definition that checks for local completeness.

Evaluation: Concept drift detection via trace clustering can classify concept drift and, in some cases, pending on the means of clustering and optional visualization, localize and describe the specific change and change point. While the approaches are accessible and tested in experimental settings, they require setup and user expertise.

5.2.5 Trend Detection

Previously introduced concept drift detection approaches primarily focus on control flow and process sequences. Instead, trend detection concerns concept drift in the temporal perspective in which the considered feature is time.[280] RICHTER ET AL.[281] introduce a dynamic trend detection method *Tesseract* focusing on the temporal perspective of concept drifts based on completion times. It resembles temporal anomaly detection approaches but does not focus on singular events and outliers typical in these scenarios. Instead, the temporal pattern changes on the process level conform to the understanding of trends in this method. In addition, the authors

[272]cf. SATO et al. 2021, pp. 18–19.
[273]cf. ACCORSI and STOCKER 2012, pp. 155–160.
[274]cf. ZELLNER et al. 2021, pp. 210–212.
[275]cf. BREUNIG et al. 2000, pp. 95–99.
[276]cf. MORA et al. 2020, pp. 48–49.
[277]cf. JUNIOR et al. 2018, pp. 320–323.
[278]cf. CAO et al. n.d., pp. 4–6.
[279]cf. LIN et al. 2022, pp. 2090–2091.
[280]cf. SATO et al. 2021, p. 25.
[281]cf. RICHTER and SEIDL 2019, pp. 266–267.

deploy an indicator based on the *SigniTrend* approach by SCHUBERT ET AL.[282] to describe a distance metric to determine significant deviations that translate into sudden and incremental drifts.

Evaluation: Trend detection offers insight into concept drift in the temporal perspective of activities. It complements a control-flow perspective analysis but requires domain expertise for interpretation. Otherwise, the other requirements conform to the peculiarity of drift detection approaches.

5.2.6 Visual Analysis

The visual analysis integrates the process expert and collateral domain expertise into the analysis process to interpret findings regarding concept drift. It relies on techniques similar to the other approaches as the foundation of change point detection, for instance, sliding windows to extract trace features, construct visual representations, and facilitate interpretation through visual inspection. Approaches differ in the specifics of each phase. YESHCHENKO ET AL.[283] focus on declarative process modeling[284] to extract *Declare* constraints, and their confidence as trace cluster characteristics and thereby identify concept drifts in control-flow perspective. The authors deploy drift maps to visualize process change over time and drift charts for visual drift classification. It also boasts the capability to visualize the change in the process model.

The approach by BROCKHOFF ET AL.[285] deploys *Earth's Mover Distance* (EMD)[286] as the distance metric. EMD enables control flow and temporal drift detection in a visual representation but offers limited insight into the actual process changes. Other approaches deploy visual analysis on process model metrics derived from the event log[287] or clustered similarity matrices[288] regarding their change in time to detect potential drifts. RICHTER ET AL.[289] propose a trace clustering approach to visualize a high-level process structure in which emerging or vanishing structures correspond to concept drift.

Evaluation: Visual analysis employs methods presented in previous concept drift analysis approaches. The visual interpretation increases accessibility to the approach

[282] cf. SCHUBERT et al. 2014, p. 873.
[283] cf. YESHCHENKO et al. 2022, pp. 3056–3059.
[284] cf. AALST et al. 2009, pp. 102–105.
[285] cf. BROCKHOFF et al. 2020, pp. 35–37.
[286] cf. RUBNER et al. 1998, p. 61.
[287] cf. KURNIATI et al. 2019, pp. 597–598.
[288] cf. HOMPES et al. 2017, pp. 60–65.
[289] cf. RICHTER et al. 2021, pp. 221–224.

but requires additional pre-processing. Different approaches to visual analysis come with trade-offs in either facilitated drift analysis and classification or the integration of temporal drift analysis.

5.3 Interim Results for Concept Drift Analysis Approaches

Table 5.1 summarizes the interim results regarding concept drift analysis approaches that utilize the literature review by SATO ET AL.[290] as the primary source for references. All concept drift handling approaches referenced in section 5.2 satisfy the minimum requirement of detecting concept drifts. However, increasing analytic insights through concept drift point detection, localization, and categorization of drifts requires advanced comprehensive skills, expertise, and additional expenses in data pre-processing.

Table 5.1: Literature review on concept drift analysis approaches

Concept Drift Analysis Categorization	R1	R2	R3	R4
Change Detection	◑	●	●	●
Change Point Detection	◑	●	◑	◑
Statistical Hypothesis Testing	●	●	◑	◑
Trace Clustering	●	◑	◑	◑
Trend Detection	◑	●	●	◑
Visual Analysis	◑	◑	◑	◑

Legend
RQ3-R1 Concept drift analysis
RQ3-R2 Technology readiness
RQ3-R3 Accessibility
RQ3-R4 Simplicity
The table omits "RQ3ïn the requirements' abbreviation to reduce visual clutter.

A challenge in the research manifests in the comparability of different approaches because there is no universally accepted metric to evaluate the precision and accuracy of the underlying theoretical fundamentals.[291] Even considering well-scoring approaches with the most insight into concept drift analysis, the transferability and applicability in the context of this research remain to be examined due to different boundary conditions.

Looking back at the introductory section and subordinate research question *RQ3*,

[290]cf. SATO et al. 2021, pp. 8–10.
[291]cf. ibid., pp. 22–23.

the pivotal focal point is handling concept drift in cyclical analysis, not which approach produces the most insights in concept drift analysis. Overall, continuous process improvement remains in the foreground. Concept drift analysis constitutes a supporting activity that can trigger expert intervention(cf. section 4.4.5) depending on the scope of the identified concept drift. Consequently, the integration into the process optimization procedure model prioritizes accessibility and simplicity over profound concept drift insights in the analysis's initial consideration of concept drift. This circumstance leads to the preference for change detection approaches that exploit existing process metrics, for instance, conformity with a given workflow model, as it provides sufficient information about the presence of concept drifts with minimum effort. It is of particular interest because the iterative application of the process optimization procedure model aspires to minimize overall expenditure by reusing available process data, notably the workflow model.

5.4 Concept Drift Handling Integration into Procedure Model

Concept drift handling constitutes activities to adequately consider concept drift in cyclical process optimization within the procedure model. Section 5.4.1 discusses essential activities and suggests suitable approaches based on the previous review in sections 5.2 and 5.3. The drift analysis necessitates modifications to the process optimization procedure model that exceeds appending an additional phase. Pending interim analysis results, subsequent activities vary and lead to different access points to enable the procedure loop. However, the realization of these activities manifests in an updated and refined process optimization procedure model outlined in section 5.4.2.

5.4.1 Phase 5: Concept Drift Analysis

Figure 5.2 visualizes necessary activities in the phase *Concept Drift Analysis* to realize concept drift handling. The phase comprises, among other things, process data binning, concept drift detection, and more specific analyses rooted in the absence or presence of concept drift. As a result, the figure deviates in its representation from the figures 3.13 and 4.9 that only describe phases that account for linked sequential activities. The activities in *Concept Drift Analysis* do not follow a sequential order. Instead, the logical link depends on the absence or presence of the concept drift and its specific characteristics.

The baseline for concept drift handling is a preceding process optimization based on the procedure model. Per transacted process analysis, process insights and, in particular, process models, such as the workflow and process models, are available.

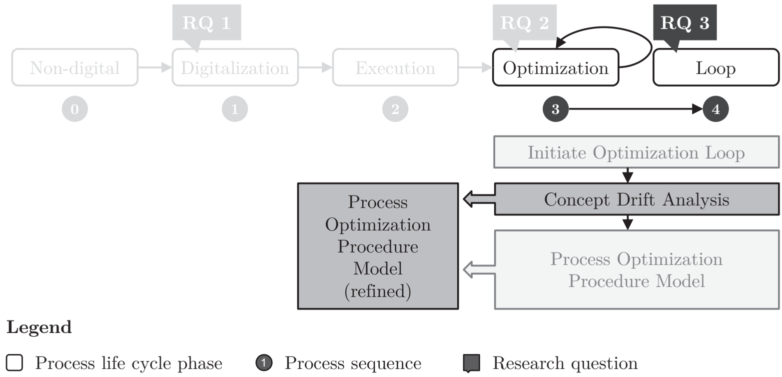


Figure 5.2: Concept drift handling model phases

Moreover, the pending drift analysis results are decisive for the access point to the procedure model, which realizes its looping functionality in the cyclical application.

Process Data Binning

Concept drift handling presumes data extraction and automated data processing as a preparatory step. Accordingly, *Process Data Binning* includes these activities. It intersects with the activities outlined in section 4.4.2, supplemented with complementary data screening operations, especially regarding event log processing. Hence, figure 5.3 emphasizes the scenario of cycling the procedure model for process optimization and the implications for data screening and data binning. The critical task is to segment the data and differentiate between past completed cases, newly completed cases, and ongoing cases. This action creates data sets L_{c2} and L_{o2} representing completed and ongoing cases, respectively, based on present time t_2.

Concept Drift Detection

Concept drift detection exploits the available process models and event logs, for instance, M_p and L_{c2}, to examine whether concept drifts have occurred since the last log extraction on t_1. In order to check the extent of reusable process data, particularly process models, drift detection on control-flow supersedes time perspective as the initial analysis. Nonetheless, the initial assumption, the null hypothesis, for both perspectives presumes the absence of concept drift.

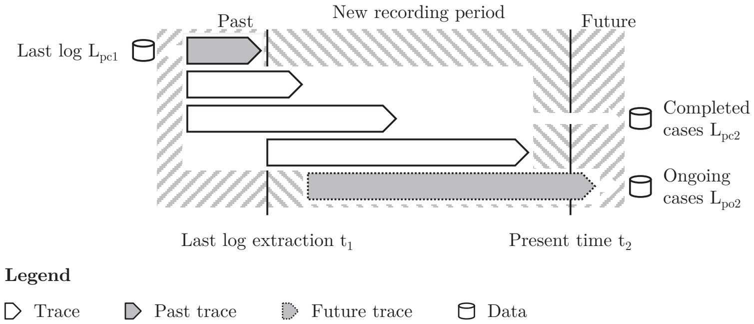


Figure 5.3: Event log subsets for new data extraction

About the change detection approach by Stertz et al.[292], conformance checking assumes the task of high-level concept drift detection for control-flow perspective. The input is the processed workflow model M_p, and the event log L_{c2} with completed cases since the last analysis. As previously outlined in the control flow perspective analysis, ProM plugins *Conformance Checking of DPN (XLog)* and *Multi-perspective Process Explorer - Fitness View* are suitable for this task. There is no need for deeper analysis because the procedure forks pending the calculated fitness. Therefore, full conformance with the workflow model is tantamount to the absence of deviations in the control flow, whereas a divergence points towards either erroneous data or concept drift.

Surmising the complete fitness of L_{c2} to M_p, examining concept drift in temporal perspective is the succeeding activity. The trend detection method requires little expenditure for a quick check. Moreover, the sensitivity in the configuration of the detection method differentiates a temporal drift from trends and outliers. However, there is little insight into non-conforming interim analysis results as a control-flow drift likely affects processing and waiting times, thus limiting the informational value of temporal concept drift detection.

Process Monitoring

The process reverts to a stable phase after a brief adaption phase once the initial process improvement concludes. Given proper and continuous process monitoring through process performance indicators, additional analyses become dispensable.

[292] cf. Stertz and Rinderle-Ma 2018, p. 322.

Nonetheless, for completeness, *Process Monitoring* condenses activities to check a process without anomalies regarding concept drifts. The reason for this is the trigger to initiate a cyclical run of the process optimization procedure model, for instance, the introduction of process improvement measures.

In the absence of concept drift in control-flow and temporal perspective, the cyclical process analysis skips to the phase *Process Data Analysis* and uses *Process Diagnostics* as the access point to the procedure model. While significant changes are unlikely due to the absence of concept drift, the update and comparison of process metrics compared to the previous period remain of interest to possibly uncover underlying positive or negative trends based on L_{c2}. These metrics complement the performance indicators habitually recorded and monitored in a process performance overview. Hence, the process analysis turns into process monitoring. The same applies to the perspective analysis, in which control-flow and temporal perspective are negligible due to the previous analysis in the scope of concept drift detection.

The residual activities in the phase remain identical to the previous process optimization cycle. However, the analysis of other perspectives can uncover outliers in cases or changes in the organizational cooperation that remain interesting objects of investigation to ensure continuous optimization but behave inconspicuously in concept drift detection. The subsequent phases *Results Interpretation* and *Action Inititation* secure the derivation and implementation of vital actions.

Control Flow Drift Analysis

Concept drift in the control flow implies significant changes to the process that require more comprehensive analysis. Following the procedure of concept drift analysis, the following activities comprise the localization and classification of the drift to understand its root cause and, in the next step, the impact on the process execution. With the primary focus on control flow and the probable requirement of an updated workflow model, deploying model-centered concept drift analysis approaches is plausible.

These activities incorporate surveying the process metrics to determine whether the concept drift is a positive or negative change to process performance. If the analysis necessitates a new workflow model due to profound concept drift, the procedure connects to the phase *Process Data Processing* to close the procedure loop. Otherwise, it skips to the phase *Process Data Analysis* as the access point to extract information based on the new event log L_{c2}.

Temporal Drift Analysis

The necessary tasks in the *Temporal Drift Analysis* are identical to the tasks in the scope of *Temporal Perspective Analysis* in phase *Process Data Analysis*. The access point to the initial procedure model depends on the sensitivity of the temporal drift detection method and its specific characteristics. The decisive factor is the temporal drift manifestation in either process activity or case level. The perspective analyses (cf. section 4.4.3) describe the activities that follow suit.

5.4.2 Procedure Model Refinement

This section integrates the phase *Concept Drift Analysis* into the process optimization procedure model visualized in figure 4.20. It connects *Phase 0: Digital Process Utilization* and *Phase 5: Action Initiation* with a diverging subset of activities to enable concept drift handling. However, the new phase is not as demarcated as visualized in the procedure model. This circumstance differs from previously defined phases for two reasons: divergent logical linking of activities and reuse of present activities.

The new activities fork, pending interim analysis results, mainly depending on the specific drift characteristics and needed information(cf. section 5.4.1). For instance, the absence of concept drift leads to omitting control flow and temporal drift analysis. Still, the procedure model indicates optional sequential order to retain a simple overall representation. Moreover, the activity *Process Monitoring* does not occupy its element in the figure, as it only aggregates and intermingles activities present in the other phases.

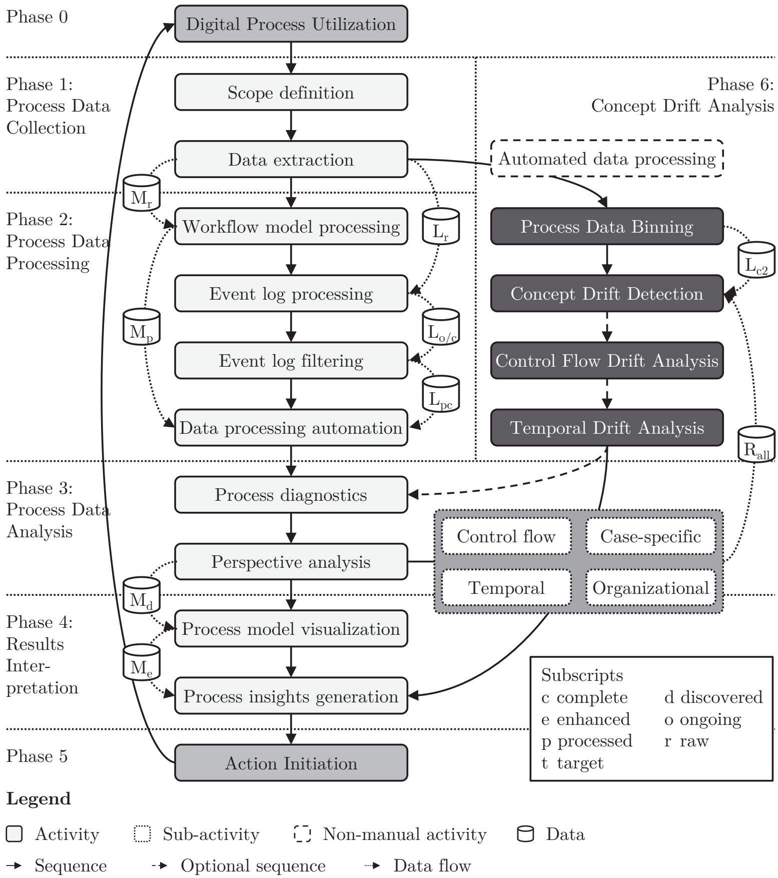


Figure 5.4: Refined procedure model for process optimization

5.5 Interim Conclusion to Sub Research Question SRQ3

Chapter 5 reflects upon the impact of concept drift in the iterative application of the process optimization procedure model that leads to research question *RQ3 How can concept drift be considered in the cyclical process analysis?*. Figure 5.5 visualizes its relevance with a view to the overall approach of this research.

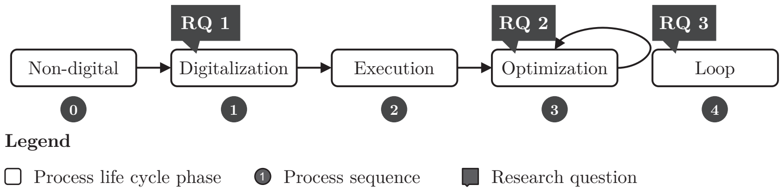


Figure 5.5: RQ3 interim results' integration in the overall thesis

The initial section revisits the requirement *RQ2-R5 Concept Drift* conferred to this chapter and details the scope and impact of concept drift for a repeated application of the process optimization procedure model. About the approach in the previous chapters, complementing requirements secure the procedure model refinement to incorporate concept drift handling (cf. section 4.1). On this basis, the literature review showcases a variety of activities in concept drift analysis with varying scope and associated expenses (cf. section 5.2). Finally, after reflecting on the overall role of concept drift analysis in the procedure model, interim results suggest a primary focus on change detection as an adequate compromise between potential process insights and necessary expenditure (cf. section 5.3).

Nonetheless, the other activities within concept drift analysis remain essential to comprehensive process analysis. Section 5.4 discusses the scope of relevant activities in detail and expounds on the way of integrating these in the new phase *Concept Drift Analysis* it to the procedure model, creating a refined version visualized in figure 5.4. The new phase substitutes a previously simple backward arrow to constitute the cyclical nature of the procedure. As a result, the refined procedure acquires the capability of considering concept drift in the process optimization and satisfies subordinate research question *SRQ3*.

6 Verification and Validation

The previous three chapters constitute the approach and interim results to optimize processes iteratively. The theoretical foundations from the literature review in related works support each of the sub-research questions SRQ1, SRQ2, and SRQ3 to create the solution central to this research. At this point, the theoretical procedure model requires evaluation in practical application to prove its validity and utility. Therefore, this chapter handles the verification and validation in the context of the research methodology to evaluate the research results. After the exposition of the approach to verification and validation (cf. section 6.1), the verification and validation in modeling and implementation (cf. section 6.2), and in case of studies (cf. section 6.3) follows.

6.1 Scope of Verification and Validation

The foundation to *Verification and Validation* (V&V) is the comprehension of both terms and the application of associated methods to the research object. ISO 9000 denotes verification as the result of providing objective evidence to confirm requirements' satisfaction[293]. Validation corresponds to the confirmation that requirements specific to the intended use or application are satisfied[294]. Hence, V&V refers to methods to confirm requirements satisfaction and usability regarding the intended purpose. The requirements result from the decomposition of the leading research question into sub-research questions (cf. section 2.5.1) and associated requirements engineering for solution concept development (cf. section 3.1, 4.1 and 5.1), whereas the intended application originates from use cases for validation.

It is essential to understand that a full verification and validation from theoretical model creation to its application is not feasible. A broad array of key determinants and boundary conditions, along with their complex relations and interactions, lead to exponentially growing expenditure in testing. Regarding the limited availability of resources, the focus shifts to prioritizing verification and validation for the model purpose to eliminate failures and increase credibility.[295] Sound and comprehensible assumptions and frame conditions create the basis to decide on credibility as the

[293]cf. Deutsches Institut für Normung e. V. 2015b, p. 49.
[294]cf. ibid., p. 50.
[295]cf. Robinson 2004, pp. 213–214.

criterion for model validity.[296] The assessment of credibility is by necessity tentative and context-dependent[297], as the validation centers around the result in the specified use case.[298].

Figure 6.1 visualizes this thesis' results, the *Process Maturity Assessment Model* as the solution to SRQ1, and the refined *Process Optimization Procedure Model* as the cumulative solution to SRQ2 and SRQ3. Hence, V&V consists of two sections to assess the respective partial results. V&V techniques constitute informal, static, dynamic, and formal techniques with an inherently varying degree of subjectivity[299]. Balci[300] and Rabe et al.[301] provide detailed information on a variety of techniques. The suitability of techniques depends on factors such as model type, available data, and expertise. No technique guarantees an error-free model, but a careful selection and combination of different techniques minimizes erroneous activities during model development and implementation and increases overall model credibility[302].

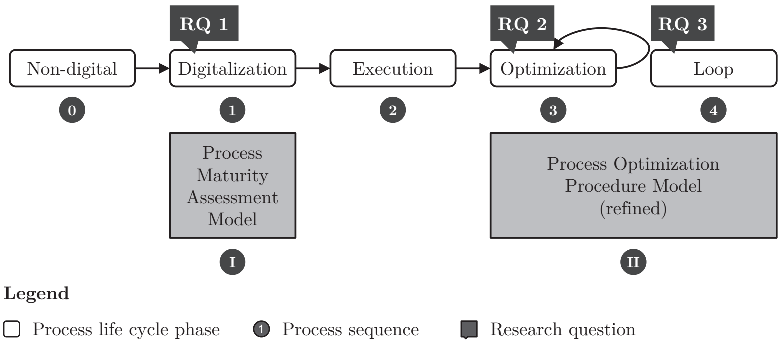


Figure 6.1: Verification and validation of theoretical models

The solutions to this thesis constitute procedure models whose structure deviates from simulation models. Accordingly, the model types limit the scope of suitable V&V techniques. A combination of informal, static, and dynamic V&V techniques aim at minimizing errors during model development and implementation and in

[296]cf. Rabe et al. 2008, pp. 1–2.
[297]cf. Gelfert 2019, pp. 258–259.
[298]cf. Liu and Yang 2019, pp. 590–592.
[299]cf. Balci 1998, pp. 354–355.
[300]cf. ibid., pp. 335–396.
[301]cf. Rabe et al. 2008, pp. 93–116.
[302]cf. ibid., pp. 93–94.

case studies. Table 6.1 summarizes deployed V&V techniques.

Table 6.1: V&V techniques applied in this thesis

V&V Technique*	V&V Type	V&V Category	Development and Implementation	Case Study
Data Analysis	V&V	Static	II	
Desk Checking	V&V	Informal	I&II	
Execution Testing	V&V	Dynamic		I&II
Face Validation	V&V	Informal	I&II	
Field Testing	Validation	Dynamic		I&II
Interface Analysis	V&V	Static	I	
Interface Testing	Validation	Dynamic		I
Traceablity Assessment	Verification	Static	I&II	

*The V&V techniques are sorted in alphabetical order.

6.2 Verification and Validation in Model Development and Implementation

Model development and implementation constitute the first stage in verification and validation. Here, static and informal V&V techniques ensure the minimization of possible errors. From the initial activities, desk checking ensures correctness, completeness, consistency, and unambiguity of the developed *Model I* and *Model II*, which originate from related work in literature (cf. section 3.3, 4.3 and 5.3). The research activities coincide with collaboration with a team of researchers and users in the research project ProMiDigit (funding code: 01IS20035), funded by the German Federal Ministry of Education and Research (BMBF).

Model I and *Model II* share the same applied V&V techniques face validation and traceability assessment in model development and implementation (cf. table 6.1), but differ to a minor degree in the latter stage regarding data analysis and interface analysis caused by differences in modeling. While *Model I* targets the assessment and prioritization of business processes for digitalization based on sequential activities within one environment. *Model II* constitutes a procedure model with iterative and optional order of activities, including forks with different interfaces. Independent of the differences, both models traverse multiple iterations of face validation and modifications with the above-specified team to inhibit conceptual errors in modeling and implementation. The traceability assessment surmises verification and satisfying specified requirements in modeling and implementation. Table 6.2) compiles the results specified in the respective chapters (cf. section 3.5, 4.5 and 5.5). The introductory first section of these chapters outlines the respective description of requirements (cf. section 3.1, 4.1 and 5.1).

Table 6.2: Traceability assessment for model development and implementation

	Requirement	Model characteristic
Model I	RQ1-R1 Business process maturity assessment	Specified in assessment indicators (e.g. *Quality* dimension)
	RQ1-R2 Digital maturity assessment	Specified in assessment indicators (e.g. *Data* dimension)
	RQ1-R3 Optimization potential evaluation	Specific evaluation criteria (e.g. triple constraint)
	RQ1-R4 Process optimization prioritization	Prioritization suggestion with the possibility of manual override
	RQ1-R5 Non-expert usability	Individual modification possible (e.g. assessment scale)
Model II	RQ2-R1 Continuous process optimization	Cyclic process optimization procedure
	RQ2-R2 Systematic approach	Procedure with phases
	RQ2-R3 Knowledge transfer	Insights generation from process data
	RQ2-R4 Process data utilization	Utilization of process data
	RQ2-R5 Concept drift handling	Drift handling measures in procedure
	RQ3-R1 Concept drift analysis	Drift detection and analysis tools
	RQ3-R2 Technology readiness	Validated software modules
	RQ3-R3 Accessibility	Open-access software modules
	RQ3-R4 Simplicity	Reutilization of past analysis results

Data analysis for *Model II* addresses data processing among the first activities in the procedure model and the interfaces between phases and individual modules. Specific data structures in the implementation stipulate tailored handling (cf. section 4.4.2). The application of the procedure model, particular modules, hinges on interim analysis results and represents more a toolbox than a prescribed order (cf. section 4.4.3). Nonetheless, utilizing readily available software modules in

ProM facilitates the interface between individual modules (cf. section 4.4). On the contrary, *Model I* only handles manual data input in a mock-up application that undergoes user interface analysis within face validation to ensure comprehensibility and usability.

6.3 Verification and Validation in Case Studies

The second stage in the verification and validation process proceeds with two case studies. The case studies and underlying data originate from the research project ProMiDigit (funding code: 01IS20035) to demonstrate model application under tangible framework conditions. The data provided by industrial partners remains original, except for anonymizing employee names to ensure data privacy. This action limits the analysis of process resources to a minor degree but is not expected to impact the findings related to verifying and validating these research results.

The verification and validation in case studies differentiate between the process maturity assessment (cf. section 6.3.1) and the process optimization (cf. section6.3.2) after digitalization. The following sections emphasize the first case study to increase comprehensibility and complement the findings with a recap or conspicuous features of the second case study. The activities correspond to the phases and activities in the model descriptions. Figure 6.2 displays the numbering of the case studies allocated to the same organization respectively: *Case Study 1* referring to a security system supplier, and *Case Study 2* to a logistics service provider. The organizations have their status as SME and the long-term use of a management system software with agile no code process digitalization capabilities in common.

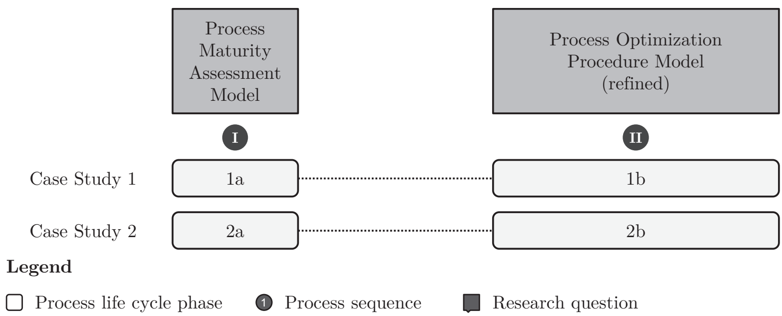


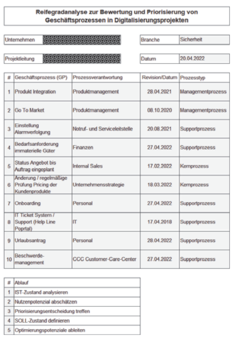
Figure 6.2: Overview of case studies

6.3.1 Process Maturity Assessment Model

Implementing the process maturity assessment model in a mock-up application serves as the foundation for the validation and contains information on its utilization. Section 3.4 comprises further information and details on the process maturity assessment model. The users, surmising roles in quality and process management with expertise in the respective domain, receive the mock-up and instructions for execution and field testing. The target is to assess business processes in the organization to identify a prioritization order for digital transition. Following assessment model execution, interviews provide insight into actual application.

Case Study 1a: Security system supplier

Subordinate to the organization's digital strategy, screening uncovers ten business processes to traverse the maturity assessment. This selection comprises processes subject to planned or recently concluded digitalization efforts, categorized into management processes (e.g., *product integration* and *go-to-market process*), core processes (e.g., *sales process from tender to scheduling* and *product pricing*) and support processes (e.g., *employee onboarding* and *customer complaint management*). The commonality of selected processes is their status of being targeted for improvement before the planned validation in the case study. The assessors constitute two employees with good comprehension and overview of all business processes in the organization: the head of quality management and the operative process manager.



Reifegradanalyse zur Bewertung und Priorisierung von Geschäftsprozessen in Digitalisierungsprojekten

Unternehmen	[redacted]	Branche	Sicherheit
Projektleitung	[redacted]	Datum	20.04.2022

#	Geschäftsprozess (GP)	Prozessverantwortung	Revision/Datum	Prozesstyp
1	Produkt Integration	Produktmanagement	28.04.2021	Managementprozess
2	Go To Market	Produktmanagement	08.10.2020	Managementprozess
3	Einstellung Alarmverfolgung	Notruf- und Serviceleitstelle	20.08.2021	Supportprozess
4	Bedarfsanforderung immaterielle Güter	Finanzen	27.04.2022	Supportprozess
5	Status Angebot bis Auftrag eingeplant	Internal Sales	17.02.2022	Kernprozess
6	Änderung / regelmäßige Prüfung Pricing der Kundenprodukte	Unternehmensstrategie	18.03.2022	Kernprozess
7	Onboarding	Personal	27.04.2022	Supportprozess
8	IT Ticket System / Support (Help Line Poprtal)	IT	17.04.2018	Supportprozess
9	Urlaubsantrag	Personal	28.04.2022	Supportprozess
10	Beschwerde-management	CCC Customer-Care-Center	27.04.2022	Supportprozess

#	Ablauf
1	IST-Zustand analysieren
2	Nutzenpotenzial abschätzen
3	Priorisierungsentscheidung treffen
4	SOLL-Zustand definieren
5	Optimierungspotenziale ableiten

Figure 6.3: Case Study 1a: Process overview

Process maturity assessment

The assessors conduct the process maturity assessment for each process one after the other, which yields an average score for each business process. Business processes that have recently undergone digital transition score, as expected, best: *application to request for time off* (4.5/5.0) and *IT ticketing system* (4.15/5.0). The business processes with the lowest maturity, ranked according to their score, are *product pricing* (2.47/5.0), *customer complaint management* (2.7/5.0) and *employee on-boarding* (2.5/5.0). It is plausible that no process realizes the highest (5.0) or lowest (1.0) score. It shows the organization's capability for process management, which is partially reflected in the company-wide indicators of the *Organization* dimension and the awareness of the present state.

Bewertungsskala		
trifft überhaupt nicht zu	nicht digital	1
trifft eher nicht zu	überwiegend nicht digital	2
trifft teilweise zu	teilweise digital	3
trifft eher zu	überwiegend digital	4
trifft vollumfänglich zu	vollumfänglich digital	5

			Digitale Reifegradbewertung											
			Qualität						Organisation					
			Prozess -definition		Prozess-anforderungen		Prozess-ausführung		Mensch		Change Management		Digitalisierungs-strategie	
Absteigende Priorität	#	Geschäftsprozess (GP)	Prozessdokumentation	Prozessverantwortung und -beteiligung	Compliancemanagement	Prozessrisikomanagement	Prozessstabilität	Kontinuierliche Prozessverbesserungen	Qualifikation	Bereitschaft für Veränderungen	Bestreben zur Akzeptanzsteigerung	Unternehmenskultur	Definition und kritische Reflexion	Offene Kommunikation ins Unternehmen
5	1	Produkt Integration	4	3	2	1	2	2	3	3	4	3	3	4
4	2	Go To Market	4	3	2	2	1	2	2	3	4	3	3	4
7	3	Einstellung Alarmverfolgung	4	3	2	1	2	2	5	4	4	3	3	4
8	4	Bedarfsanforderung immaterielle Güter	4	3	1	1	2	2	5	4	4	3	3	4
5	5	Status Angebot bis Auftrag eingeplant	2	2	1	1	2	2	4	2	4	3	3	4
1	6	Änderung / regelmäßige Prüfung Pricing der Kundenprodukte	1	1	1	1	1	1	4	4	4	3	3	4
3	7	Onboarding	2	3	2	1	1	1	4	2	4	3	3	4
9	8	IT Ticket System / Support (Help Line Poprtal)	5	4	4	3	4	2	5	4	4	3	3	4
10	9	Urlaubsantrag	5	5	5	5	5	3	5	3	4	3	3	4
2	10	Beschwerdemanagement	1	2	2	2	2	2	3	4	4	3	3	4

		Digitale Reifegradbewertung											Potenzialschätzung						Kosten-schätzung
		Daten / Informationen				System													
		Daten-eigenschaften		Daten-anforderungen		Technologie und Integration		Prozesstool und Automatisierung											
#	Geschäftsprozess (GP)	Digitalisierungsgrad der Daten / Informationen	Vermeidung von Medienbrüchen	Datenqualität	Datensicherheit	Digitalisierungsgrad der Technologien	Integrationsgrad	Prozessvisualisierung	Automatisierungsgrad (Maximal möglich, 1-5)	Automatisierungsgrad (Erreichte Bewertung)	Automatisierungsgrad (Gewichtete Bewertung)	Digitalisierungsgrad des Prozesses	Prozessdurchlauf (Häufigkeit) (1 - 5)	Zeitliches Einsparpotenzial pro Durchlauf (1 - 5)	Finanzielles Einsparpotenzial pro Durchlauf (1 - 5)	Leidensdruck im Unternehmen (1 - 5)	Erzielbare Qualitätsverbesserung (1 - 5)	Gesamtnutzenwert	Implementierungskosten (optional) (1 - 5)
1	Produkt Integration	4	2	3	5	4	2	3	3	3	5	3.10	3	4	3	5	5	900	
2	Go To Market	3	1	2	5	4	2	1	3	2	3.33	2.72	3	4	3	5	5	900	
3	Einstellung Alarmverfolgung	4	4	4	5	3	2	2	3	2	3.33	3.22	5	5	5	3	5	1875	
4	Bedarfsanforderung immaterielle Güter	4	4	4	5	4	2	3	3	2	3.33	3.27	5	3	3	3	5	675	
5	Status Angebot bis Auftrag eingeplant	4	3	3	4	4	4	3	3	2	3.33	2.92	5	5	3	5	5	1875	
6	Änderung / regelmäßige Prüfung Pricing der Kundenprodukte	2	2	3	4	2	2	3	3	2	3.33	2.47	2	4	4	4	4	512	
7	Onboarding	3	2	2	4	3	2	3	2	2	5	2.70	4	5	5	5	5	2500	
8	IT Ticket System / Support (Help Line Poprtal)	5	5	3	5	5	5	5	5	5	5	4.15	5	1	5	5	1	125	
9	Urlaubsantrag	5	5	5	5	5	5	5	5	5	5	4.50	5	1	1	1	1	5	
10	Beschwerdemanagement	1	1	2	4	2	2	1	1	1	5	2.50	3	5	5	4	5	1500	

Figure 6.4: Case Study 1a: Process maturity assessment

Potential benefits assessment

The potential benefits assessment follows the same setting. The mathematical product of the ratings yields the score for the potential benefits and creates a new ranking, complementing the ranking by maturity. A higher score represents the highest perceived value in the digital transition. The choice of the mathematical product as an alternative to the mean value simplifies the distinction between similar scores. It better portrays the impact of individual factors: the *application to request for time off* is among the most utilized processes with the highest recorded maturity in this assessment and scores the worst in potential benefits assessment. Most promising potential have *employee onboarding* (2,500/3,125), *sales process from tender to scheduling* (1,875/3,125) and *cance alarm tracing*(1,875/3,125).

The ranking is more conclusive than the specific scores, as the distance between ratings is not equidistant. However, the specific score is insightful in the case of a direct comparison between two business processes to compare the assessment. The optional factor costs remain excluded due to the difficulty of cost estimation. Notably, it hinges on the expected state of the business process post-digitalization and general conditions like the capabilities of the present workflow management system.

Process digitalization prioritization

Process maturity and potential benefits assessment are input for the process digitalization prioritization. The assessments suggest *onboarding* as the favored business process under digital transition. Nevertheless, the finalized ranking for process digitalization diverges from the suggestion with *product integration* ranking first. Outside factors, e.g., digital strategy for business development, may stipulate strategic benefits in diverging from the suggested order or consider success factors such as change management and the organization's culture. The assessment model enables modification to consider these factors and only serves as additional input for decision-making.

Digitale Reifegradanalyse				Nutzenpotenzial-schätzung	Kostenschätzung	Finale Priorisierung		
Absteigende Priorität	Digitalisierungs-grad	#	Geschäftsprozess (GP)	Gesamtnutzenwert	Kosten (optional)	Absteigende Priorität	#	Geschäftsprozesse (GP)
1	2.47	6	Änderung / regelmäßige Prüfung Pricing der Kundenprodukte	512	0	1	1	Produktintegration
2	2.50	10	Beschwerdemanagement	1500	0	2	3	Einstellung Alarmverfolgung
3	2.70	7	Onboarding	2500	0	3	2	Go to Market
4	2.72	2	Go To Market	900	0			
5	2.92	5	Status Angebot bis Auftrag eingeplant	1875	0			
6	3.10	1	Produkt Integration	900	0			
7	3.22	3	Einstellung Alarmverfolgung	1875	0			
8	3.27	4	Bedarfsanforderung immaterielle Güter	675	0			
9	4.15	8	IT Ticket System / Support (Help Line Poprtal)	125	0			
10	4.50	9	Urlaubsantrag	5	0			

Figure 6.5: Case Study 1a: Process digitalization prioritization

Target process maturity definition

The definition of a target process maturity is an optional activity regarding the assessment model validation but creates added value in supporting the planning and execution of the digital transformation. Figure 6.6 depicts the visualization for the first-ranked business process. The average target score is 4.55, within the range of present maximum scores regarding other processes (*application to request time off*: 4.5/5.0). Furthermore, it gives realistic expectations for the results considering triple constraints and other factors. Again, present digital business processes serve as a benchmark to define the target maturity.

Resume

Applying the process maturity assessment model in the case study reveals its practicability and added value for the organization. The experts emphasize its

Geschäftsprozess	Produkt Integration

Darstellung der Indikatoren

Dimension	Subdimension	Indikatoren	IST-Zustand	SOLL-Zustand
Qualität	Prozessdefinition	Prozessdokumentation	4	4
		Prozessverantwortung und -beteiligung	3	5
	Prozessanforderungen	Compliancemanagement	2	4
		Prozessrisikomanagement	1	5
	Prozessausführung	Prozessstabilität	2	4
		Kontinuierliche Prozessverbesserungen	2	4
Organisation	Mensch	Qualifikation	3	4
		Bereitschaft für Veränderungen	3	4
	Change Management	Bestreben zut Akzeptanzsteigerung	4	4
		Unternehmenskultur	3	3
	Digitalisierungsstrategie	Definition und kritische Reflexion	3	4
		Offene Kommunikation ins Unternehmen	4	4
Daten / Informationen	Dateneigenschaften	Digitalisierungsgrad der Daten / Informationen	4	4
		Medienbrüche (Vermeidung)	2	4
	Datenanforderungen	Datenqualität	3	4
		Datensicherheit	5	5
System	Technologie und Integration	Digitalisierungsgrad der Technologien	4	4
		Integrationsgrad	2	4
	Prozesstool und Automatisierung	Prozessvisualisierung	3	4
		Automatisierungsgrad	5	5
Digitaler Reifegrad			3.10	4.15

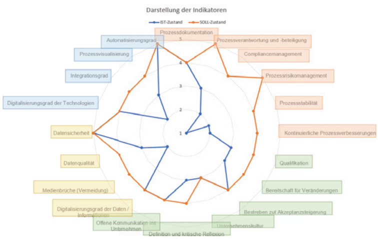


Figure 6.6: Case Study 1a: Target process state visualization

support in structuring the approach and preparing a sound foundation for decision-making that leaves users flexible, e.g., in the definition of assessment scales and the final ranking for digitalization order. The assessment with two users in this case study demonstrates the need within an organization to modulate the assessment ranges, preferably to a reference process, to ensure a common understanding of assessment levels. Otherwise, the experts perceive an Excel tool as self-explanatory and comprehensible without structured guidance. Restricting modifications to the implementation with a simple interface design except for filling in the assessment, supported by the deployment of a widely known software, contributes to the ease of usage and simplifies the interaction.

Case Study 2a: Logistics service provider

At the outset, the frame conditions are similar: the process screening under the umbrella of digital business strategy generates a list of nine business processes for the process maturity assessment with diverse maturity degrees. The list comprises core processes (e.g., *route planning* for disposition and *order collection*) and support processes (e.g., *employee onboarding* and *request for time off*). In particular, concerning support processes, similar processes emerge in process screening across two organizations in two independent assessments. Despite deviating process names, the activities within share commonalities. The assessor for the logistics service provider assumes a dual role as head of logistics and quality management representative.

Process maturity assessment

The approach is identical to the other case study and yields no surprising insights. The score span is narrower (3.15 to 3.95) but hinges on the present state of process maturity and a diverging definition of the rating scale. Recently transitioned processes *employee onboarding* and *employee offboarding* score the highest (3.95/5.0),

Reifegradanalyse zur Bewertung und Priorisierung von Geschäftsprozessen in Digitalisierungsprojekten

Unternehmen	[redacted]	Branche	Transportwesen
Projektleitung	[redacted]	Datum	26.04.2022

#	Geschäftsprozess (GP)	Prozessverantwortung	Revision/Datum	Prozesstyp
1	Eintritt MA	Personalstelle	16.11.2021	Supportprozess
2	Austritt MA	Personalstelle	16.11.2021	Supportprozess
3	Tourenplanung	Disposition	06.09.2021	Kernprozess
4	Auftragserfassung	Kundenservice	24.08.2021	Kernprozess
5	Abweichungen	Kundenservice	21.03.2022	Kernprozess
6	Urlaubsplanung	Personalstelle	14.09.2021	Supportprozess
7	Abliefernachweise Fahrer	Fahrer/Rechnungswesen	17.01.2022	Supportprozess
8	Abholnachweise Lager	Lagerverwaltung	08.04.2022	Supportprozess
9	Rechnungserstellung	Rechnungswesen	10.08.2021	Supportprozess
10				

#	Ablauf
1	IST-Zustand analysieren
2	Nutzenpotenzial abschätzen
3	Priorisierungsentscheidung treffen
4	SOLL-Zustand definieren
5	Optimierungspotenziale ableiten

Figure 6.7: Case Study 2a: Process overview

whereas *request for time off* (3.15/5.0) and *warehouse collection recipe* (3.15/5.0) score lowest.

Bewertungsskala		
trifft überhaupt nicht zu	nicht digital	1
trifft eher nicht zu	überwiegend nicht digital	2
trifft teilweise zu	teilweise digital	3
trifft eher zu	überwiegend digital	4
trifft vollumfänglich zu	vollumfänglich digital	5

			Digitale Reifegradbewertung											
			Qualität						Organisation					
			Prozess -definition		Prozess-anforderungen		Prozess-ausführung		Mensch		Change Management		Digitalisierungs-strategie	
Absteigende Priorität	#	Geschäftsprozess (GP)	Prozessdokumentation	Prozessverantwortung und -beteiligung	Compliancemanagement	Prozessrisikomanagement	Prozessstabilität	Kontinuierliche Prozessverbesserungen	Qualifikation	Bereitschaft für Veränderungen	Bestreben zur Akzeptanzsteigerung	Unternehmenskultur	Definition und kritische Reflexion	Offene Kommunikation ins Unternehmen
9	1	Eintritt MA	4	4	4	3	4	4	4	4	4	4	4	3
8	2	Austritt MA	4	4	4	3	4	4	4	4	4	4	4	3
7	3	Tourenplanung	2	5	4	4	4	4	4	3	4	4	4	3
6	4	Auftragserfassung	3	5	4	4	3	4	4	4	4	4	4	3
4	5	Abweichungen	3	3	3	4	3	4	4	4	4	4	4	3
2	6	Urlaubsplanung	3	3	4	4	4	4	4	4	4	4	4	3
3	7	Abliefernachweise Fahrer	3	4	4	4	4	3	4	4	4	4	4	3
1	8	Abholnachweise Lager	3	4	4	4	3	3	4	4	4	4	4	3
5	9	Rechnungserstellung	4	4	4	4	4	3	4	4	4	4	4	3

		Digitale Reifegradbewertung											Potenzialschätzung						Kosten-schätzung
		Daten / Informationen				System													
		Daten-eigenschaften		Daten-anforderungen		Technologie und Integration		Prozesstool und Automatisierung											
#	Geschäftsprozess (GP)	Digitalisierungsgrad der Daten / Informationen	Vermeidung von Medienbrüchen	Datenqualität	Datensicherheit	Digitalisierungsgrad der Technologien	Integrationsgrad	Prozessvisualisierung	Automatisierungsgrad (Maximal möglich, 1-5)	Automatisierungsgrad (Erreichte Bewertung)	Automatisierungsgrad (Gewichtete Bewertung)	Digitalisierungsgrad des Prozesses	Prozessdurchlauf (Häufigkeit) (1 - 5)	Zeitliches Einsparpotenzial pro Durchlauf (1 - 5)	Finanzielles Einsparpotenzial pro Durchlauf (1 - 5)	Leidensdruck im Unternehmen (1 - 5)	Erzielbare Qualitätsverbesserung (1 - 5)	Gesamtnutzenwert	Implementierungskosten (optional) (1 - 5)
1	Eintritt MA	4	4	4	4	4	4	4	3	3	5	3.95	3	4	3	4	4	576	
2	Austritt MA	4	4	4	4	4	4	4	3	3	5	3.95	3	4	3	4	4	576	
3	Tourenplanung	4	4	4	4	4	4	3	2	2	5	3.85	5	5	5	5	5	3125	
4	Auftragserfassung	3	3	3	4	3	3	3	5	3	3	3.55	5	5	5	5	5	3125	
5	Abweichungen	3	3	4	4	3	3	3	5	3	3	3.45	4	4	5	5	5	2000	
6	Urlaubsplanung	2	3	2	4	2	2	2	5	1	1	3.15	5	5	5	3	5	1875	
7	Abliefernachweise Fahrer	2	2	4	4	2	4	3	5	3	3	3.45	5	5	5	3	5	1875	
8	Abholnachweise Lager	2	2	4	4	2	2	2	5	1	1	3.15	5	5	5	5	5	3125	
9	Rechnungserstellung	3	4	4	4	3	2	3	5	1	1	3.50	5	4	4	3	5	1200	

Figure 6.8: Case Study 2a: Process maturity assessment

Potential benefits assessment

As before, the processes with the highest maturity, *employee onboarding* and *employee offboarding*, exhibit the most negligible potential benefits in digitalization (576/3,125). The business processes *route planning*, *order collection*, and *warehouse collection recipe* feature the maximum potential benefits in the assessment (3,125/3,125). Here again, a different utilization of the scoring range in comparison to *Case Study 1a* arises.

Process digitalization prioritization

The primary candidate for process digitalization is *warehouse collection recipe*, which comes with the lowest maturity score (3.15/5.0) and the highest optimization potential (3,125/3,125). In this case, the decision coincides with the results of the maturity assessment model due to the absence of external influencing factors.

Digitale Reifegradanalyse				Nutzenpotenzial-schätzung	Kostenschätzung	Finale Priorisierung		
Absteigende Priorität	Digitalisierungs-grad	#	Geschäftsprozess (GP)	Gesamtnutzenwert	Kosten (optional)	Absteigende Priorität	#	Geschäftsprozesse (GP)
1	3.15	8	Abholnachweise Lager	3125	0	1	8	Abholnachweise Lager
2	3.15	6	Urlaubsplanung	1875	0	2	7	Abliefernachweise Fahrer
3	3.45	7	Abliefernachweise Fahrer	1875	0	3	4	Auftragserfassung
4	3.45	5	Abweichungen	2000	0			
5	3.50	9	Rechnungserstellung	1200	0			
6	3.55	4	Auftragserfassung	3125	0			
7	3.85	3	Tourenplanung	3125	0			
8	3.95	2	Austritt MA	576	0			
9	3.95	1	Eintritt MA	576	0			

Figure 6.9: Case Study 2a: Process digitalization prioritization

Target process maturity definition

The average target process maturity for *warehouse collection recipe* exceeds the assessment of other processes from process screening. While it appears ambitious, a closer view reveals the present low assessment *System* dimension, mainly addressing its potential in system integration and automation.

Geschäftsprozess	Abholnachweise Lager

Darstellung der Indikatoren

Dimension	Subdimension	Indikatoren	IST-Zustand	SOLL-Zustand
Qualität	Prozessdefinition	Prozessdokumentation	3	4
		Prozessverantwortung und -beteiligung	4	5
	Prozessanforderungen	Compliancemanagement	4	4
		Prozessrisikomanagement	4	3
	Prozessausführung	Prozessstabilität	3	4
		Kontinuierliche Prozessverbesserungen	3	4
Organisation	Mensch	Qualifikation	4	3
		Bereitschaft für Veränderungen	4	4
	Change Management	Bestreben zut Akzeptanzsteigerung	4	4
		Unternehmenskultur	4	4
	Digitalisierungsstrategie	Definition und kritische Reflexion	4	3
		Offene Kommunikation ins Unternehmen	3	3
Daten / Informationen	Dateneigenschaften	Digitalisierungsgrad der Daten / Informationen	2	4
		Medienbrüche (Vermeidung)	2	4
	Datenanforderungen	Datenqualität	4	5
		Datensicherheit	4	4
System	Technologie und Integration	Digitalisierungsgrad der Technologien	2	4
		Integrationsgrad	2	4
	Prozesstool und Automatisierung	Prozessvisualisierung	2	5
		Automatisierungsgrad	1	3
Digitaler Reifegrad			3.15	3.90

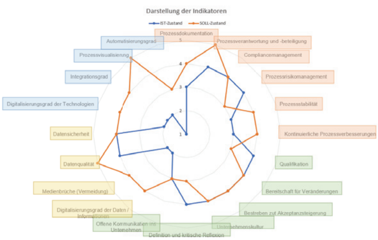


Figure 6.10: Case Study 2a: Target process state visualization

Resume

The findings coincide with *Case Study 1a* and emphasize the necessity of flexible scales, as the user indicates. In addition, the Excel implementation of the maturity assessment is perceived as intuitive and straightforward, and the supplementary explanation of dimensions, along with hints, provides a good reference for the assessment.

The verification and validation in the two case studies in direct comparison reveal in a greater scope the challenges of comparability of maturity levels between different organizations, even when referring to similar business processes. The definition of uniform scales across organizations is theoretically possible but impedes practicability and continuous reassessment due to technological advances and environmental conditions, e.g., new legal requirements concerning data privacy.

6.3.2 Process Optimization Procedure Model

Akin to the process maturity assessment model, implementing the refined process optimization procedure model that integrates concept drift handling in a mock-up application supports its verification and validation in practical application in two case studies. Section 3.4 and 5.4 entail more information on the procedure model. As a process expert with expertise in process mining, the author applies the procedure model in the use cases. The execution and field testing occur with a team of process experts, reviewing interim results and discussing process insights and interpretations.

As in the previous case study, the team integrates the respective organization's experts surmising quality and process management roles to cover organization-specific circumstances and domain expertise. The expertise primarily feeds into interpreting process analysis results to emphasize the procedure model's generalization capability. Here, the overall objective is to minimize failures in the procedure model and increase its credibility to uncover process insights that can serve as a foundation for continuous process improvement. The case studies comprise a twofold procedure model application to demonstrate its applicability for repeated use in two succeeding periods.

The case studies follow the individual activities described in the phases of the procedure model. Based on the organizations deploying the same agile management system software *Q.wiki* for process documentation and workflow management[303], specifics on initial activities in both case studies share a high degree of concordance. Accordingly, the case study description for *Case Study 1b* comprises more details, whereas *Case Study 2b* focuses on deviations and peculiarities to keep matters concise. The case study structure follows the activity described in the refined procedure model (cf. figure 5.4).

Case Study 1b: Security system supplier

The process selection for digital transformation in the security system supplier is subject to the decision of the management team and the overall digital strategy outside of the assessment conducted in *Case Study 1a*. The process *investment request* has traversed the procedure from non-digital to digital process under the leadership of their process management experts. Multiple iterations of modifications

[303]Information on Q.wiki is accessible via the following link: https://www.modell-aachen.de/en/interactive-management-software-qwiki

and minor improvements precede the go-live of the process that handles the entirety of internal procurement above a specified sum in a multistage inspection and approval process for goods and services. Figure 6.11) portrays the essential activities in a simplified process model. This digital process, along with its documentation and recorded process data, is the key process under investigation in *Case Study 1b*.

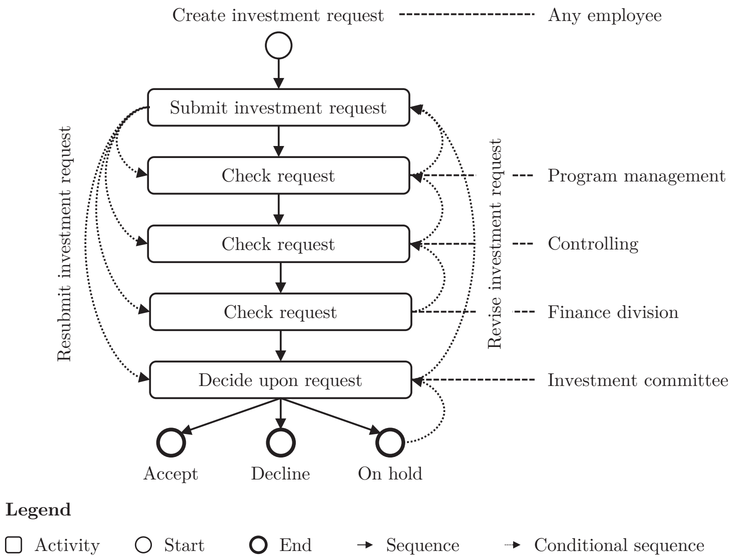


Figure 6.11: Case Study 1b: Investment request

Scope definition

The scope definition in the case study stems from the intended verification and validation in execution and field testing. Beyond that, the application within the case study benefits the security system supplier in ensuring continuous process optimization for the digital processes *investment request*. This approach reflects the first profound process analysis after process digitalization. Hence, the analysis generates insights into the process that previously have not been available or transparent due to the lack of data and process performance indicators. The second application of the procedure model reveals conceivable process changes over a more extended period and displays the utility and added value of the procedure model.

Data extraction

The security systems supplier uses an on-premise version of the management system software. Based on the organization's data security and privacy regulations, only selected IT personnel can access the database to extract the process event log. Hence, the experts extract and provide the event log L_r as a .txt file, whereas the data regarding the process description is organization-wide accessible in the knowledge management system. The specific workflow implementation via the no-code process configurator is only available as an image file and a tabular description due to the absence of export options, denoting the present status of M_r.

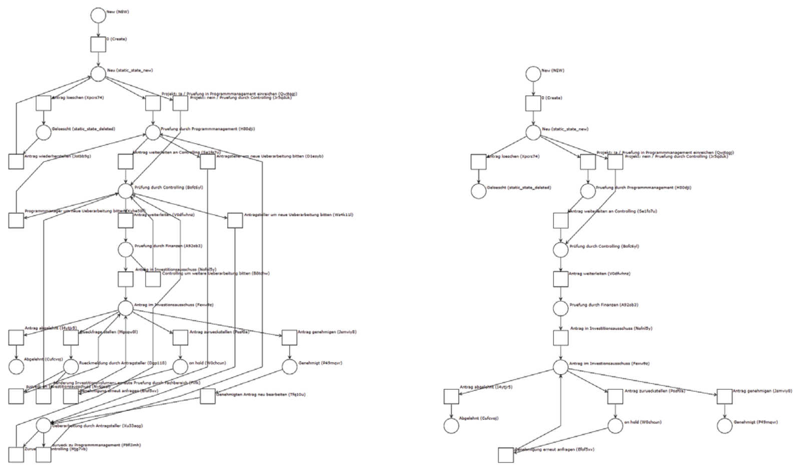
Workflow model processing

The workflow model, M_r, is an image file that requires manual recreation in a machine-readable data format in WoPeD for further processing. Following the formal representation in the management system software that deploys transitions and status to describe the workflow, the Petri net notation constitutes the notation for the workflow model in Petri net markup language .pnml. The workflow model mirrors the workflow implementation in the system and shares the same designation for the transitions and status as the event log. It exploits readily available identifiers deployed in the management system software to ensure the unambiguity of transitions, allowing one to deduce both statuses linked to the transition. This procedure creates the processed workflow model M_p portrayed in figure 6.12. The variant on the right sight of the figure features the workflow without any loops. The workflow implementation requires these loops to allow backlinks and revising inputs necessary to execute the workflow.

Event log processing

The extracted event log uses an individual format that requires transformation to CSV and XES for facilitated data manipulation. After the conversion, filtering of irrelevant data occurs. Apart from workflow transitions and essential information describing changes between process states, the event log records sub-activities and user interactions with the workflow, e.g., viewing, modifying, or saving a current activity instance. This information surmises a minor role and is optional for process data analysis. Figure 6.13 depicts the raw data in the event log and its data structure post-processing. After event log processing, only essential information remains in the event log L_p: timestamp, resource, transition, and case ID.

- *Timestamp:* The timestamp records the conclusion of a transition. Hence, the first recorded transition in a case reflects the completion of the first activity, thus impeding the calculation of its throughput time. However, the event log



(a) Workflow **(b) Process (no loops)**

Figure 6.12: Case Study 1b: Workflow and process model

indirectly discloses the start time of a case that coincides with the creation of the first record of the specific case ID, enabling time logging until its completion and, therefore, outlining the throughput time.

- *Resource:* The resource represents the organization's employee executing the management system transition. It only includes the anonymized names but no information on their acting role in the organization.
- *Transition:* The transition comprises information on the activity name and its unique identifier. This denomination prevents confusion between similarly or identically denominated activities within the exact workflow implementation and across others in the management system software.
- *Case ID:* The case identifier is an ascending number associated with a specific workflow implementation. It connects multiple activities to a typical trace, in this process, an investment request with the exact case ID.

Event log filtering

The processed event log L_p comprises all transitions in the observation period. Although it is the first holistic analysis after implementing the workflow, the recording does not necessarily coincide with the start of data recording. Hence, it is possible for open cases without a recorded start or end to occupy a share of the

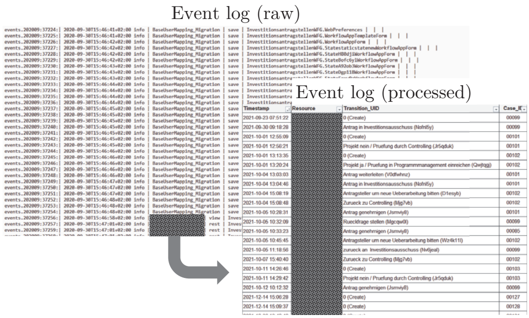


Figure 6.13: Case Study 1b: Event log processing

event log that requires filtering. Only closed cases allow for determining process performance indicators in the following steps. Concluding this step, it yields the event logs L_c and L_o. Process analysis focuses on the first data set, whereas the second can support process insights generation in a later phase.

Execution and field testing extends to a second application of the procedure model to examine the repeated application. As a result, partitioning the event log L_c in two similarly sized subsets creates the database for both iterations. Figure 6.14 displays the allocation of traces to the respective data subsets L_{c1} and L_{c2}, respectively for period p_1 and p_2.

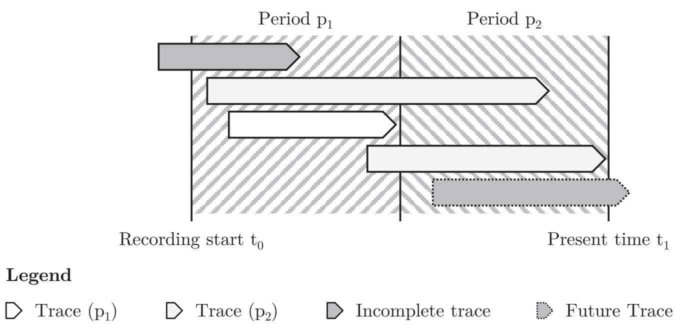


Figure 6.14: Case Study 1b: Event log partitioning

Processing automation

This activity surmises the automation of manual activities performed in *Event log processing* using macros to perform the described standard text processing techniques. Assuming identical data structure in data extraction, hard coding the processing activities constitutes an alternative feasible and quick solution. Hence, a Python script assumes the task of processing automation in this context.

Process diagnostics

The process data analysis focuses on period p_1 but incorporates insights on the second period where it is feasible and does not obstruct interim results presentation. Hence, the event log dot plot in figure 6.15, generated with the ProM plugin *Dotted Chart* showcases all traces in periods p_1 and p_2. The process metrics in table 6.3 complements the previous figure to give a brief overview of the process *investment request*.

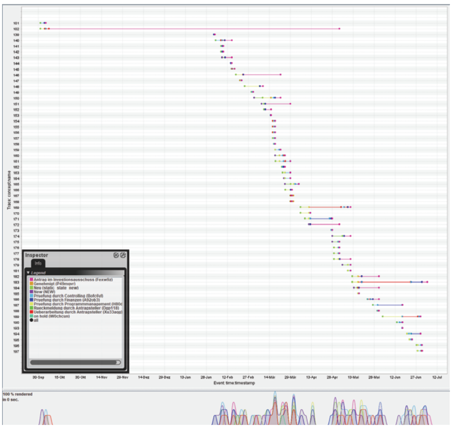


Figure 6.15: Case Study 1b: Dot plot

The dot plot indicates an outlier trace with an above-average duration. Also, a period without logged event data is striking, probably tracing back to flawed recording as the case numbers skip by a large margin in this specific period from 102 to 169. Apart from this, the traces are inconspicuous in the recorded period between 01.10.2021 and 05.07.2022, with an average throughput time of more than 19 days. In total, 20 employees are involved in 58 recorded investment requests, excluding any open traces.

Table 6.3: Case Study 1b: Process metrics

	p1	p2	p1+p2
Period	01.10.2021-04.04.2022	01.10.2021-05.07.2022	01.10.2021-05.07.2022
Throughput time (mean)	5d 21h 42m	19d 3h 20m	12d 01h 34m
Closed traces	31	27	58
Open traces	1	8	8
Variants	11	13	20
Transitions	216	189	405
Resources	15	17	20 (incl. open: 22)

The ensuing process data analysis addresses the first period p_1, except for specific references to deviations.

Control-flow perspective analysis

Event log filtering and processing ensures only completed traces in the event log. The completion criterion is the presence and recording of any possible configuration of known start and end transitions in the event log. As a result, the control flow perspective analysis anticipates a high degree of conformity between the event log L_{c1} and the workflow model M_p. Conformity refers here to the ability of the workflow model to replay the event log without encountering any issues. Assuming no process modifications, the workflow model M_p constitutes the digital process implementation and thus covers all observed transitions logged in L_{c1}. The plugin *Check Compliance Using Conformance Checking (All Best Matching)* supports this analysis by confirming the presence of only synchronous movements between the event log and the model. Hence, all observed behavior in the event log conforms to the workflow implementation. Figure 6.16 provides a glimpse of the presentation of the result.

Case perspective analysis

The process metrics refer to 11 observed variants a trace follows with an average of 6.97 (standard deviation 1.8) transitions each. Cross-referencing the traces with the workflow model W_p, two possible shortest paths for a trace are determined by the second transition. These shortest traces have either five (*variant 1*) or six transitions (*variant 2*) as visualized in figure 6.17 and share the same last transitions. These traces correspond to 16 of 31 observed traces that follow the shortest possible paths, denoting the presence of process loops without examining the background at this

Figure 6.16: Case Study 1b: Control flow analysis

analysis stage. The overall distribution of traces that follow the respective shortest path exhibits an almost equal distribution with 8/15 for *variant 1* and 8/16 for *variant 2*.

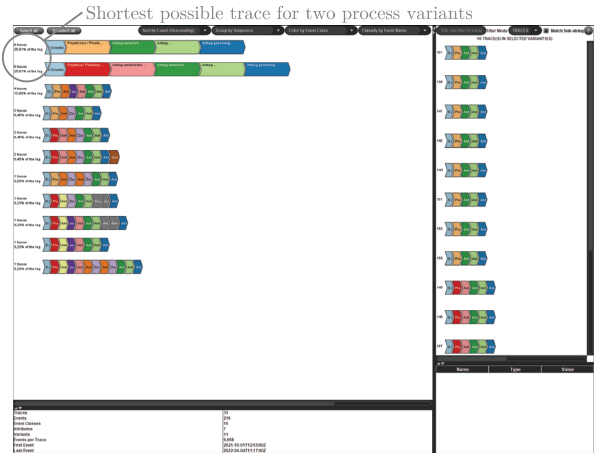


Figure 6.17: Case Study 1b: Event log

For most traces, the last transition is the process sink that translates into the decision regarding the investment request, except for two traces that allow for a loop back into the decision process. This circumstance impacts the functionality of the workflow model in the context of the process mining modules. The workflow allows for revocation of a decision that reflects realistic circumstances, e.g., *revise approved investment request* (Tfq10u), but contradicts the definition of processes in

Petri net notation that expect a process sink, an irreversible process sequence.

Temporal perspective analysis

As the timestamp recording in the event log refers to completing a process step characterized by a transition, it is impossible to differentiate between processing and waiting times. Hence, the time always refers to the sum of processing and waiting time between two transitions.

The process metrics condenses the throughput time without differentiating between the two process variants of the second transition (*project: yes [..]*)(Qwjtqgj); *project: no [..]* (Jr5qduk)) in the workflow to an average throughput time of 5d 21h 42m. *Variant 1* requires on average 3d 14h 52m, whereas *variant 2* requires 7d 22h 17m. Considering the difference in the average number of transitions between the two variants (*variant 1*: 6.33; *variant 2*: 7.56 transition), the reasoning is evident. More transitions relate to more process interfaces and involved personnel.

Due to the high variance in traces, a per-event perspective is less conclusive and requires the differentiation per trace variant and the consideration of its frequency. The frequency is vital to differentiate typical traces from outliers. Usually, transitions with the shortest and longest duration are of interest: the first refers to either efficient or superfluous processes, whereas the latter offers the most potential for optimization.

Regarding the temporal perspective, figure 6.18 shows two observations of interest. The first observation (top) refers to the second transition that differentiates between *variant 1* and *variant 2*. On average, not only does variant 2 have more transitions, but the distinguishing second transition also requires, on average, more than 21 hours longer, which accounts for 40% of the average difference in total throughput time. The second observation (bottom) traces a difference in throughput time in the decision regarding the investment request with the investment committee following the transition *forward investment request to investment committee* (Nofnl5y), that also happens to precede the outlier event with the longest throughput time of more than 26 days *postpone investment request* (Posf0a)). Closer examination hints that the investment committee does not decide on all investment requests when they convene a meeting. Hence, it most likely is no peculiarity but hinges upon input provided by the process experts.

Organizational perspective analysis

The resource information in the event log allows insights into the employees executing the transitions. While the log offers no information on the employee's specific role

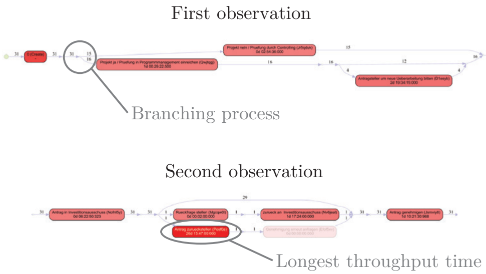


Figure 6.18: Case Study 1b: Temporal perspective

in the organization, it is possible to associate specific transitions across traces with employees and thereby assume part of their role in the organization. The dot plot in figure 6.19 is a variant of figure 6.15 with a focus on the resources. The figure shows that only a few employees execute specific transitions indicated by the same colors, e.g., the states *audit by controlling* (Bofc6vl) and *audit by accounting* (A92ob3). In contrast, almost all recorded employees create an investment request (e.g., transition *new* (static_state_new)).

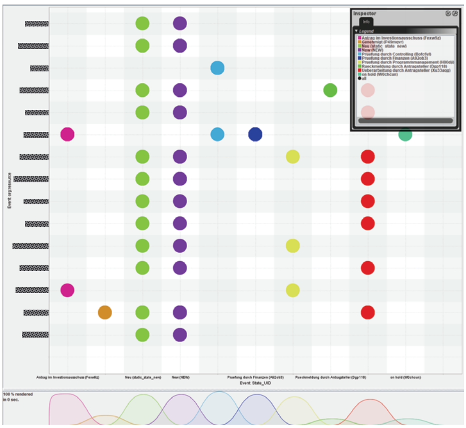
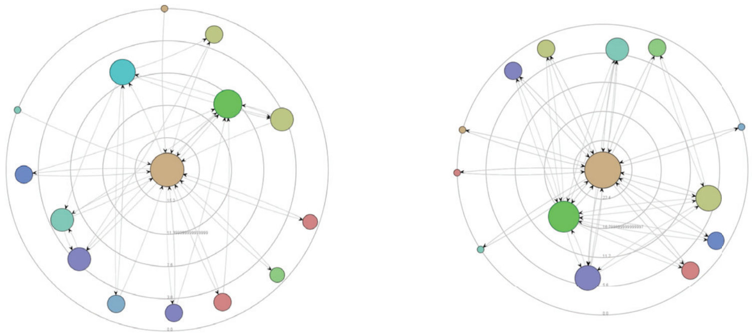


Figure 6.19: Case Study 1b: Dot plot (resource)

A social network increases the comprehension for collaboration across all traces for the process *investment request*. Perspectives like handover tasks and working together within a trace create transparency and offer insight into possible conflicts, e.g., employees handing over tasks to themselves. Usually, this case occurs for successive, interdependent activities to display work progress. In a setting of decision-making and approval processes, it may hint towards unconformity. For the process *invest request*, the social network for the handover task visualized in figure 6.20 shows no anomalies. Instead, it points towards essential employees within the process that handle specific tasks, which aligns with the findings in the alternate dot plot (cf. figure 6.19).



(a) Handover **(b) Collaboration**

Figure 6.20: Case Study 1b: Social network for handover and collaboration

Process model visualization

Process discovery and model enhancement originating from the event log L_{pc1} provide a comprehensive overview of the process status. The use of the module *Interactive visual miner* with standard settings yields the process model M_d, which serves as input in the module *Multi-perspective Process Explorer* to create the enhanced process model in figure 6.21.

The enhanced model comprises all observed traces in the event log L_{pc1} and thereby represents a share of all possible paths in the workflow. It enriches the model with information on transition frequency marked by an increasingly darker hue and the related throughput time. An increasing thickness of the edge between two transitions characterizes the transitions with the longest throughput time for the transition *postpone investment request* (Posf0a) and aligns with the earlier temporal analysis.

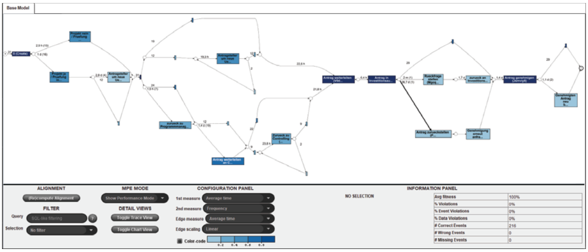


Figure 6.21: Case Study 1b: Enhanced process model

Process insights generation

The process analysis uncovers two trace variants representing the most traversed and shortest possible path. Hence, diverging completed trace variants that amount to a total of 15 out of 31 traces in the period p_1 suggest the presence of a type of waste based solely on process execution, e.g., insufficient information that requires a process loop to supplement vital information to the invest request status progress. The most frequent transition, separate from the trace variant, is *appeal applicant to revise the investment request* (Wz4k11l). This transition follows investment request investigation by the controlling division and represents an initial step for deeper investigation for process optimization. Two traces even demonstrate a second cycle through the very same loop, indicating potential improvements to the process. The second most frequent trace is the transition *appeal applicant to revise the investment request* (D1esyb), that shares the same name, but differentiated by its transition ID. It constitutes the revision of the project investment request and follows examination by the program management. The traces associated with these two transitions become points of interest to derive potential measures for improvement.

The traces with particular long throughput times are, as anticipated, outliers. The overall throughput time is not notably conspicuous, as expert input categorizes it within the estimations. The investment committee usually convenes once a week for discussion but may not decide all present requests. Coincidentally, a canceled or postponed meeting impacts all open investment requests and their throughput time. Hence, monitoring the temporal perspective remains vigilant to spot premature changes.

Interim resume

The first application of the process optimization procedure model yields actionable insights with the potential for process improvement and few supplementary expert inputs. Consulting the organization's experts happens in the final activity to accurately interpret the findings and demonstrate the added value of the procedure model.

Concluding the first procedure model application, the second application follows with particular regard towards concept drift analysis, considering period p_2.

Process data binning

The activity *Process data binning* is redundant in this case study, as the initial processing and filtering surmises the principal task of data segmentation to create data set L_{pc2}, aggregating completed cases in the period p_2 for the second procedure model application.

Concept drift detection

The initial quick check for the presence of concept drift concerns the usage of the module *Check Compliance Using Conformance Checking (All Best Matching)* to examine the replay of L_{pc2} on the workflow model M_p. While one trace appears to be an outlier with a skipped event, all remaining cases demonstrate synchronous moves between log and model, thus confirming overall conformance based on control flow.

Control flow drift analysis

Nonetheless, compliance of L_{pc2} and the workflow model still accommodates the possibility of control flow deviation between the periods. Accordingly, the conformance checking in figure 6.23 with M_d covers this scenario.

Most traces show synchronous moves between the log and the model. The transitions that include *tau* in their name originate from the model discovery algorithm to create M_d. Additional transitions in traces not covered by the discovered model generally handle process cycles previously not observed in period p_1, thereby contributing to the overall increase of trace variants. Figure 6.23 localizes the above-addressed deviations.

A single outlier trace that shows unexpected behavior in the sudden rejection of an investment request, even though the workflow does not stipulate the possibility, constitutes an exemption clause requiring profound analysis. Apart from this striking feature, the second conformance checking remains uneventful. Instead, the temporal perspective analysis gains importance concerning developing the throughput time facing these additional process cycles.

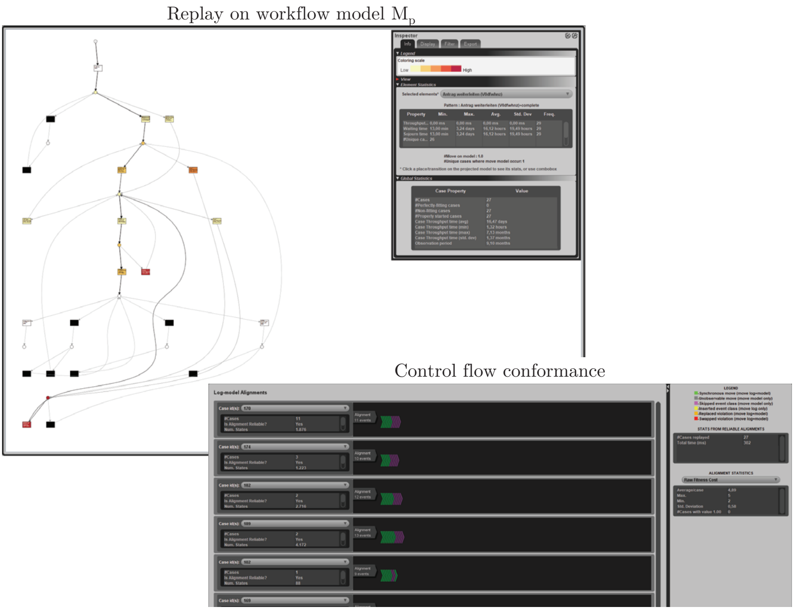


Figure 6.22: Case Study 1b: Concept drift detection (log vs. workflow)

Temporal drift analysis

While the data is lacking to conduct profound statistical analysis, comparing process metrics between the two periods is informative regarding initial presumptions concerning temporal drifts. The distinction follows the identified process variants 1 and 2. However, the drift detection in control flow drift analysis remains inconspicuous. Hence, the assumption of persisting process variants in the second period remains.

Table 6.4 gives an overview regarding the process metrics across the two consecutive periods and process variants. The box plot visualizing throughput for the four identified groups' permutations of period and process variants hints towards a non-normal distribution with few outliers. Statistical analysis in Minitab supports the assumption.

Figure 6.24 summarizes the essential findings in a cohesive figure. The probability plot to check for normal distribution confirms this assumption with a p-value <0.005, rejecting the null hypothesis (H_0 = normal distribution). The limited data impedes

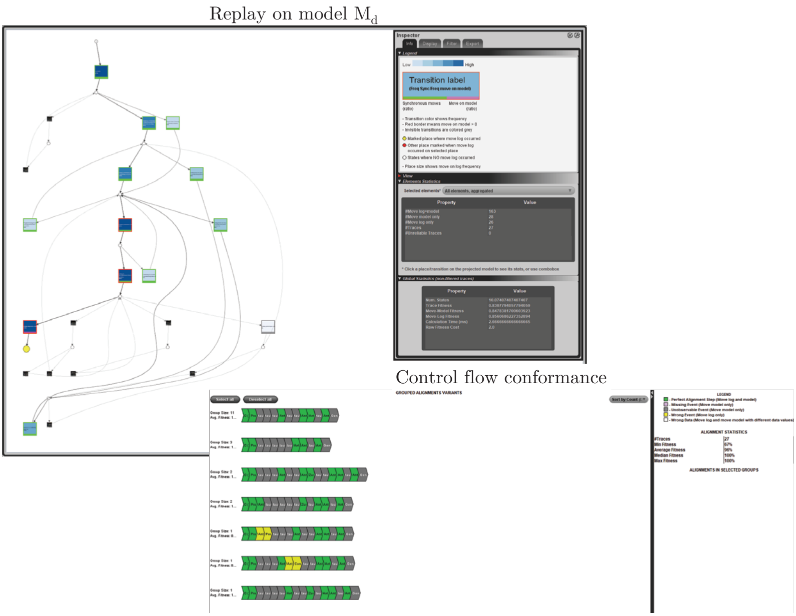
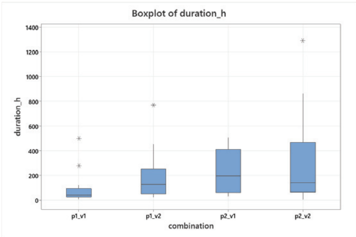


Figure 6.23: Case Study 1b: Concept drift localization

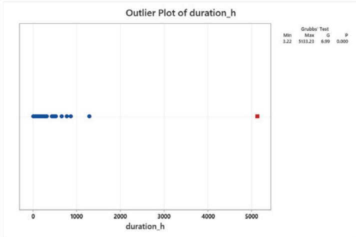
Table 6.4: Case Study 1b: Temporal drift analysis

	p_1		p_2	
Period	01.10.2021-04.04.2022		01.10.2021-05.07.2022	
Variant	Variant 1	Variant 2	Variant 1	Variant 2
Throughput time (mean)	3d 17h 52m	7d 22h 17m	9d 12h 25m	12d 03h 44m
Closed traces	15	16	5	21
Open traces			5	3
Variants	4	7	3	9
Transitions	95	121	31	151
Resources	12	9	9	13

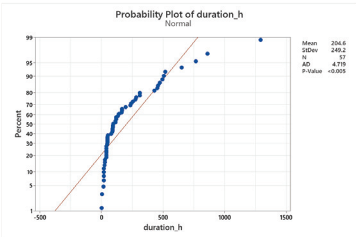
the closer determination of each group's distribution. Still, hypothesis testing provides insight regarding the comparability of the groups with median throughput time as a metric. Considering the unknown distribution, the mood median test provides information on whether the median differs among them.



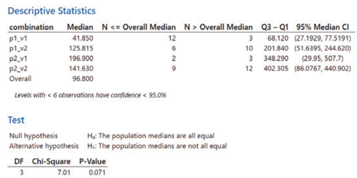
(a) Boxplot of duration



(b) Outlier plot



(c) Probability plot



Descriptive Statistics

combination	Median	N <= Overall Median	N > Overall Median	Q3 – Q1	95% Median CI
p1_v1	41.850	12	3	68.120	(27.1929, 77.5191)
p1_v2	125.815	6	10	201.840	(51.6395, 244.620)
p2_v1	196.900	2	3	348.290	(29.95, 507.7)
p2_v2	141.630	9	12	402.305	(86.0767, 440.902)
Overall	96.800				

Levels with < 6 observations have confidence < 95.0%

Test

Null hypothesis H_0: The population medians are all equal
Alternative hypothesis H_1: The population medians are not all equal

DF	Chi-Square	P-Value
3	7.01	0.071

(d) Descriptive statistics

Figure 6.24: Case Study 1b: Process metrics and statistical testing

Figure 6.24 visualizes the execution of statistical testing. The p-value below alpha leads to rejection of the null hypotheses, meaning the median of groups is statistically significantly different among groups. This circumstance warrants a more profound analysis and supervision of the following traces in the future. While there is a statistical significance, there is little recorded data to base it on and derive a premature action.

Resume

Applying the procedure model creates process insights previously not evident to the process manager with little expert input towards the end of the procedure. The actionable insights regarding the process *investment request* cover loops that accrue additional throughput time. Concept drift analysis supports this insight based on hypothesis testing of statistically significant median throughput time change. However, more data will allow for more reliable analysis.

Case Study 2b: Logistics service provider

The digital strategy of the logistics service provider envisages the digital transformation of internal processes, commencing with the process *employee onboarding*. The process covers all activities following the hiring process after the employment contract signing. The previously non-digital process has undergone a digital transformation in conjunction with multiple iterations of minor modifications and improvements under the guidance of an internal expert team preceding the go-live. In case study 2b, the *employee onboarding*, along with its documentation and recorded process data, is the process under investigation. Figure 6.25 visualizes the essential activities in the process.

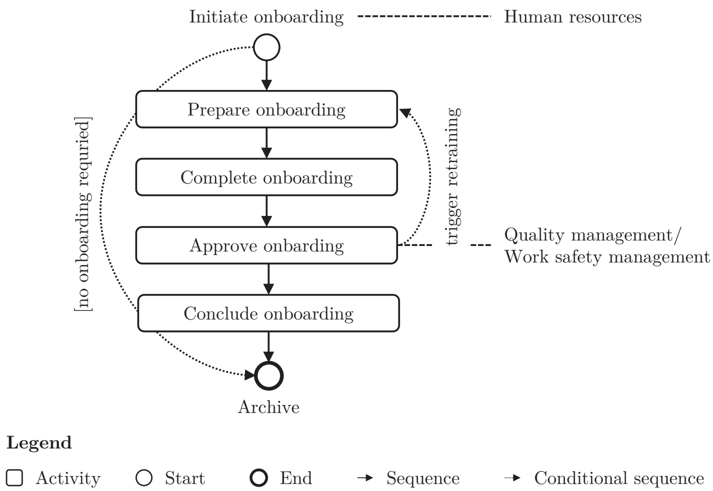


Figure 6.25: Case Study 2b: Employee onboarding

Scope definition

In principle, the scope definition of the logistics service provider corresponds to the security system supplier in case study 1b with particular emphasis on the process under investigation *employee onboarding*.

Data extraction

The logistics service provider deploys a cloud version of the agile management system software, which facilitates data access and extraction for selected IT personnel to ensure data security and privacy. Nonetheless, the process coincides with the approach in case study 1b.

Event log processing

The cloud version of the agile management system affects the type of extracted data to a minor degree, but otherwise, especially after processing, the event log exhibits the same structure as in case study 1b. For this process, the case ID refers to the onboarding process for a specific employee. This activity yields the processed event log L_p.

Event log filtering

Close inspection of the event log in event log processing and filtering completed cases reveals a low count of cases. Nonetheless, the subdivision of the event log tracks the approach of the first case study to split the event log according to periods of comparable size, producing L_{pc1} and L_pc2. As L_{pc1} only contains a single trace, the analysis only offers few insights into the process and, instead, will focus on L_{pc2}.

Workflow model processing

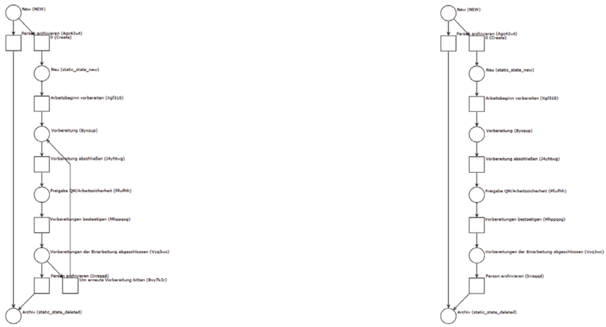
Creating the workflow model in the .pnml format corresponds to the actions in case study 1b. This procedure yields the workflow model M_p and an alternate version without any loops, as portrayed in figure 6.26 on the left and the right, respectively. It represents the workflow implementation of period L_{pc2}.

Processing automation

The event log structure is identical to the log in an on-premise version of the management system software. Hence, minor modifications facilitate the reutilization of the Python script deployed in *Case Study 1b*.

Process diagnostics

The event log processing anticipates at least one outlier due to the sparse event log in the period p_1. The dot plot visualization of the event log L_cp in figure 6.27 supports this anticipation by showcasing a period without logged event data in between the two periods p_1 and p_2 that requires a deeper analysis.



(a) **Workflow** (b) **Process (no loops)**

Figure 6.26: Case Study 2b: Workflow and process model

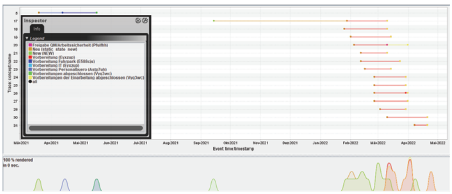


Figure 6.27: Case Study 2b: Dot plot

The same applies to an evident outlier with a conspicuously long duration in the recorded period between 19.03.2021 and 10.03.2022. This period comprises 15 completed onboarding processes and 14 ongoing onboarding processes not considered in the process metrics in table 6.5.

Control flow perspective analysis

The onboarding process is relatively simple, with few branching processes. Figure 6.28 constitutes the results of conformance checking between event log L_{pc2} and the workflow model M_p, which outlines a single process variant with synchronous movements constituting 100% conformity in replay.

Case perspective analysis

The examination of the event logs is inconspicuous. The workflow suggests possible deviations, but completed traces in L_{pc2} comprise no observed process variants.

Table 6.5: Case Study 2b: Process metrics

	p1	p2	p1+p2
Period	19.03.2021-17.05.2022	14.09.2021-10.03.2022	19.03.2021-10.03.2022
Throughput time (mean)	59d 02h 41m	44d 11h 28m	44d 11h 28m
Closed traces	1	14	14
Open traces	0	13	13
Variants	1	1	2
Transitions	7	70	77
Resources	1	2	2 (incl. open: 2)

Figure 6.28: Case Study 2b: Control flow analysis

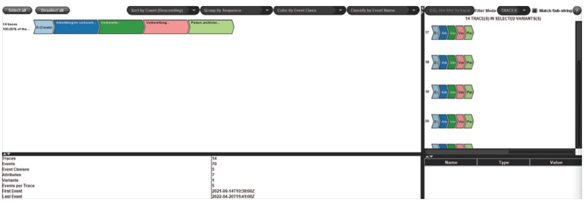


Figure 6.29: Case Study 2b: Event log

When considering the event log L_{pc}, a variant shares few similarities and comprises distinct transitions. This circumstance implies a concept drift between the two periods, requiring deeper examination in the scope of the second procedure model application.

Temporal perspective analysis

The temporal analysis remains uneventful regarding traces, as all traces in L_{pc2} share the same transitions. A comparison of variants between the two periods creates little value due to the sparse quantity of recorded, completed traces in L_{pc1}. As a result, the investigation into individual transitions gains increasing value. Figure 6.30 outlines the throughput time for each transition. Notably, and understandably, *complete onboarding* (J4yhtwg) demands on average the largest share of throughput time in the process with on average more than 33 days or almost 75% of the total throughput time. Most sub-activities comprising necessary onboarding activities are pooled in this transition, which checks and examines their completion.

Figure 6.30: Case Study 2b: Temporal perspective peculiarities

Organizational perspective analysis

The brief process overview (cf. figure 6.25) and the process metrics (cf. table 6.5) refer to only two employees involved in the onboarding process. The dot plot of resources in figure 6.31 shows the distribution of tasks among the divisions of human resources, quality management, and work security management. At present, one employee surmises the latter two roles.

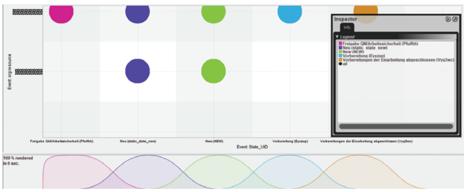


Figure 6.31: Case Study 2b: Dot plot (resource)

With the support of the social network showcased in figure 6.32 regarding the handover of tasks, it is also possible to deduce the roles and a share of responsibilities of the employees in the divisions: the employee in human resources initiates the onboarding and associated tasks, whereas the employee fulfilling the role in quality management and work safety management reviews their completion.

Process model visualization

Figure 6.33 outlines the enhanced process model originating from event log L_{pc2}. It contains information regarding the average throughput time and the frequency. As

(a) **Handover** (b) **Collaboration**

Figure 6.32: Case Study 2b: Social network for handover and collaboration

only one trace variant exists, all traces exhibit the same procedure. It condenses the essential findings from the process analysis and remains inconspicuous.

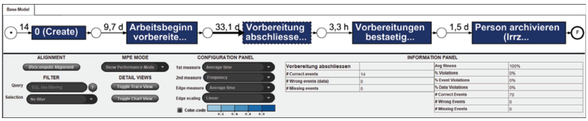


Figure 6.33: Case Study 2b: Enhanced process model

Process insights generation

The process analysis results do not evince conspicuous behavior except for the differences between the event logs in period p_1 and p_2. Supplementing the discovery of this deviation with the organization's experts confirms a stark process change between the two event logs. This circumstance and the sparse amount of completed employee onboardings owed to the organization's economic situation limits the generation of profound insights specific to the process *onboarding*.

While the data shows very few involved employees in the onboarding process, supplementary expert information remits sub-activities that constitute the specific onboarding training to the new employee's role. This circumstance suggests activities outside the workflow that are not logged automatically but require manual recording. Hence, a means to increase informational value in the analysis is to integrate the training into the software management system, if applicable, or ensure another means of data sharing to omit manual logging.

Interim results

The first application of the process optimization procedure model yields process insights with the potential for process improvement. Supplementary expert input from the organization's experts in process insights generation helps interpret the findings. It supports the formulated hypotheses as a result of process data analyses and demonstrates the added value of the procedure model.

At this point, the validation in the use case stipulates a second application to demonstrate concept drift handling and its implications for applying the above methods and techniques. While the sparse event log does not allow a compelling results interpretation for the as-is process status, it is possible to perform a backward-oriented analysis to evaluate the methods associated with concept drift analysis.

Process data binning

Process data extraction, processing, and binning are redundant to this case study, as the initial processing and filtering segments the data into the event logs L_{pc1} and L_{pc2}, whereas the latter serves as input for the examination of concept drift handling.

Concept drift detection

The replay of L_{pc1} on the workflow model M_p in the module *Conformance Checking of DPN* shows the presence of asynchronous moves between the log and workflow model, alluding to the detection of concept drift. The alignment statistics support this observation with an average fitness of 57%. Comparing L_{pc1} with M_d yields, as expected, the same results. The previous conformance analysis in the first application of the procedure model already confirms the traces associated with L_{pc2} to be a part of M_d, which by itself is a segment of M_p.

Control flow drift analysis

Subsequently, after confirming the presence of concept drift, the localization of the drift regarding control flow follows. The foundation to determine the deviations is the comparison of log and model movements. Synchronous movements allude to synchronization points in the trace that have persisted through the changes between the two periods p_1 and p_2. The presence of only a single deviating trace variant simplifies the reconstruction of the previous workflow and, accordingly, the localization of the drift in the control flow perspective.

The more profound investigation of the deviations evinces two change points, as seen in figure 6.35. It shows additional log moves in between synchronous moves, denoting additional transitions *prepare vehicle fleet onboarding* (Ucu2ac) and *prepare IT onboarding* (Dpelfws) in the past workflow. The second change point follows the synchronous move regarding the transition *complete preparations* (Jj4htwg). The trace in L_{pc1} contains an almost identically named transition *complete preparations* (Mhppqog), whereas the present workflow M_p indicates the transition *confirm preparations* (Mhppqog). As both transitions retain their unique model identifier

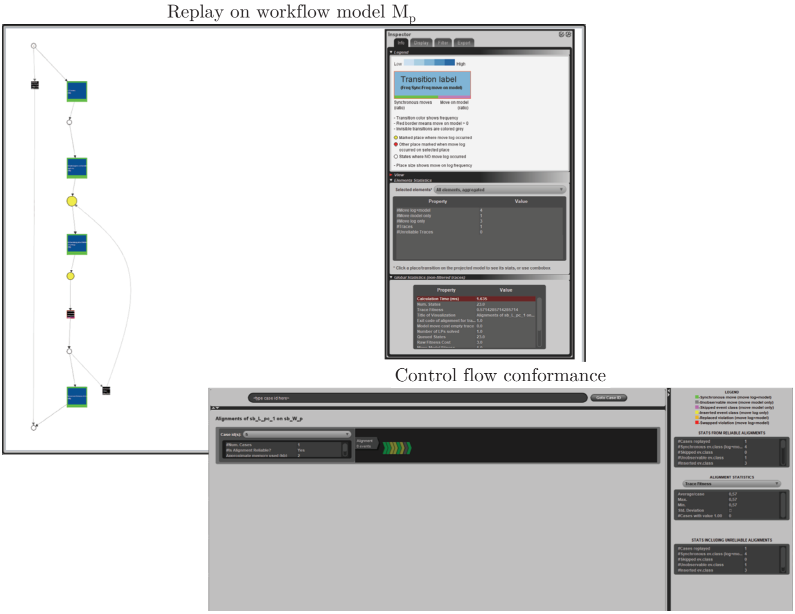


Figure 6.34: Case Study 2b: Concept drift detection

Mhppqog, it most likely is a redefinition of the specific transition. This interpretation supports the existence of two seemingly identical activities. Concluding the trace, the last transition represents a synchronous move to archive the onboarding file.

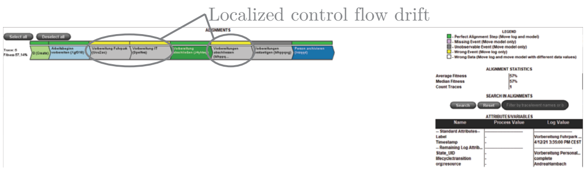


Figure 6.35: Case Study 2b: Concept drift localization

Temporal drift analysis

Examining the temporal perspective is not expedient, as a change in control flow usually impacts the comparison of throughput times between the logs. In addition,

L_{pc1} offers only a single data point that may be an outlier. Hence, concluding entails low credibility. Still, looking at the changes, the total throughput time, and the number of recorded transitions decrease (cf. table 6.5), that generally is a reasonable conclusion.

Process insights generation (II)

The concept drift analysis results support the initial hypothesis of concept drift based on the analysis of present process data. The input from the organization's process experts aligns with the findings. As the findings pertain to period p_1, there are no immediate conclusions from concept drift analysis to derive recommendations for process optimization. Instead, the process insights originating from analyzing L_{pc2} have more informational value and suggest a more integrative approach to include onboarding training information in the workflow instead of using it merely for documentation.

Resume

The procedure model creates recommendations for process improvement based on the inclusion of more process data and automated information logging. The findings regarding the employee onboarding process evince no direct added value, as there are no striking peculiarities or anomalies. While the lack of process data affects the contextual concept drift analysis, the procedure verifies a recorded concept drift, supported by the process expert's insights and knowledge of workflow changes after the process go-live.

6.4 Interim Conclusion to Verification and Validation

The case studies investigate the behavior of the process maturity assessment model and the process optimization procedure model in two different scenarios. While the organizations in both scenarios deploy the same management system software solution, the diverse environment offers insight into correct model behavior. Disparities manifest in the distinct organization of business processes, reflected in the roles associated with process management and the organization's integration and interaction level. Even though sparsely available process data restricts the scope of actionable findings, the involved experts attribute insightful findings in field testing with actual process data. Notably, the findings in the analysis meet their anticipation of process status and provide a sound basis to conclude and derive suitable actions for process improvement.

The examined processes *investment request* and *employee onboarding* are, while specific in implementation to the organization, comparatively generic processes easily encounterable in any organization. The process maturity assessment model requires no guidance from external experts to deploy transparently and comprehensibly while uncovering valuable insights. This circumstance supports the generalization of the applicability in a broader context. The postponement of expert involvement towards the end of the process optimization procedure model, especially regarding the proper interpretation of findings, supports this notion.

7 Conclusion and Critical Discussion

The previous chapter handles verifying and validating the developed models that represent the top research results. Suitable techniques assess the model development and implementation and its application in case studies. The results serve as input to draw a comprehensive conclusion regarding the research question *RQ How can a systematic approach to process optimization contribute to uncovering process insights for digital business processes?* (cf. section 7.1). The critical discussion dissects and debates possible shortcomings identified in the case studies (cf. section 7.2).

7.1 Conclusion to Research Question RQ

The chapters preceding the verification and validation handle the resolution of the subordinate research questions SRQ1, SRQ2, and SRQ3 (respectively cf. section 3.5, 4.5 and 5.5), refraining from answering the remaining principal research question:

RQ How can a systematic approach to process optimization contribute to uncovering process insights for digital business processes?

The approach to answering this research question follows the phases of business processes in the BPM life cycle, originating from non-digital processes, transitioning to digital processes, and undergoing cyclic process optimization (cf. section 2.5). The application of the developed models for process maturity assessment and process optimization procedure in two diverse case studies account for the fundamental applicability in realistic application scenarios within the life cycle view of business processes in field testing.

The process maturity assessment supports the transition of non-digital processes to digital processes by providing a systematic approach to evaluate and assess the suitability of processes for digitalization, considering their potential impact. The case studies in section 6.3.1 exhibit the contributions to sound and comprehensible prioritization of processes and emphasize its impact. According to the experts, customizable ranges for assessment criteria accommodate the individual organization's interpretation of maturity and cover the essential criteria necessary for a quick yet insightful assessment. In particular, appreciation of the intuitive and straightforward utilization without needing training or guidance highlights its benefits. Positive evaluation of experts extends to the internal deployment of the process maturity assessment model for future strategic decisions within each organization's digital strategy. Comparing the approach to other existing ones, the opportunity to rank assessed processes according to additional assessment metrics represents a distinctive and favorable feature.

The execution of digital processes yields the process data that serves as the foundation for the iterative execution of the process optimization procedure model. Section 6.3.2 covers the case studies that examine the execution and field testing of the model. Despite partial sparse data availability, the case studies demonstrate the capability of the procedure to systematically analyze and uncover process insights previously inconspicuous to the process experts. While the specific added value depends on the process and recording process data, i.e., the degree of integration and level of detail, it creates insightful leads for process optimization without the necessity of detailed domain expertise in the analysis. Furthermore, unlike other existing approaches, especially in process mining, its added value is considering business process management. Incorporating concept drift handling in iterative procedure application reflects the cyclic nature of business process management.

Overall, the verification and validation in the case studies demonstrate the developed models' requirements satisfaction as summarized in table 7.1. Table 6.2 provides supplementary information on the specific model characteristics concerning the requirements.

Following this line of argumentation, the research results evince a systematic approach to process optimization of digital processes, commencing with the decision on process prioritization for the digital transition, culminating in its implementation and continuous improvement. Hence, the conclusion supports a positive assessment of the research question in showing a feasible approach to process optimization and does not warrant refuting it at this stage.

Table 7.1: Assessment of thesis approach regarding requirement fulfillment

	Requirement	Related model development and V&V section	Chhor (2023)
Model I	RQ1-R1 Business process maturity assessment	3.4.1, 6.2 and 6.3.1	●
	RQ1-R2 Digital maturity assessment	3.4.2, 6.2 and 6.3.1	●
	RQ1-R3 Optimization potential evaluation	3.4.3, 6.2 and 6.3.1	●
	RQ1-R4 Process optimization prioritization	3.4.4, 6.2 and 6.3.1	●
	RQ1-R5 Non-expert usability	3.4, 6.2 and 6.3.1	●
Model II	RQ2-R1 Continuous process optimization	4.4, 6.2 and 6.3.2	●
	RQ2-R2 Systematic approach	4.4, 6.2 and 6.3.2	●
	RQ2-R3 Knowledge transfer	4.4, 6.2 and 6.3.2	●
	RQ2-R4 Process data utilization	4.4, 6.2 and 6.3.2	●
	RQ2-R5 Concept drift handling	5.4.2, 6.2 and 6.3.2	●
	RQ3-R1 Concept drift analysis	5.4.1, 6.2 and 6.3.2	●
	RQ3-R2 Technology readiness	5.4, 6.2 and 6.3.2	●
	RQ3-R3 Accessibility	5.4, 6.2 and 6.3.2	●
	RQ3-R4 Simplicity	5.4, 6.2 and 6.3.2	●

7.2 Critical Discussion

The conclusion to the research question remains optimistic against the background of the applied verification and validation techniques. Nevertheless, the model application in the case studies and the exchange with respective experts in different scenarios of verification and validation reveals limitations and, consequently, aspects with potential for further improvement. The findings relate to specific scenarios and conditions outlined in the respective sections. Hence, applied verification and validation techniques do not claim to encompass completeness in analysis. Nevertheless, essential aspects traverse critical discussion to outline potential links as an impetus for future research and mainly originate from the feedback of the expert team.

The process maturity assessment model references and adopts features of existing models, particularly concerning the dimensions and subdimensions for process maturity assessment, that encounter the approval of the expert team. However, instancing the assumption of approximately equal assessment of organization-centric subdimensions change management and digital strategy deviate. Examples comprise a post-merger situation for organizations that do not exhibit aligned organizational structures, deviating perceptions, and handling of organizational changes associated with different organizational divisions.

A direct comparison between the case studies demonstrates deviating assessments of maturity levels for most criteria across organizations. It does not pose an issue per se but limits the comparability across distinct organizations. Defining universal maturity levels is possible for specific industries but requires tremendous research and expertise to identify particularities and agree on standardized levels. A more substantial aspect of criticism in this regard addresses the experts who conduct the assessment. A team of experts ensures a more balanced and less subjective assessment in determining each level but aggravates a quick assessment. In this context, an expert suggests decreasing the range of maturity levels from five to four to force assessors to a more positive or negative assessment instead of allowing for a neutral option.

The verification and validation of the process optimization procedure model in the case studies, along with the research results, emphasizes the overall added value of the procedure. The decision to minimize the required expert or domain expertise about the specific process and focus on procedural process data increases the generalization in the application and the scope of potential users. However, it carries the detriment of a high quantity of necessary analyses before any interpretation of results. Knowledgeable process experts with experience in the examined process can decrease the necessary time for analysis by omitting select phases due to ex-ante knowledge, i.e., attributed to the simplicity of the process. Skipping entire phases in the initial procedure application is not intended to ensure a systematic and comprehensible approach, though it can prove beneficial to relax this condition considering the number of existing business processes in an organization.

A further aspect picks upon the sparse available data, particularly in the second case study. Although the procedure utilization supports the demonstration in field testing and is not unusable in the view of any expert, the added value for the examined process *employee onbarding* is limited. Here, including additional data streams, e.g., contextual data referencing individual cases, facilitates exposing the added value of deploying this procedure model. Furthermore, the extension of field testing towards other processes, possibly to organizations outside the ecosphere of the deployed management system software, can further validate the procedure model in deviating scenarios and conditions.

8 Summary and Outlook

The concluding chapter gives a comprehensive summary of the approach to the research deficit regarding continuous process optimization and the potential in process mining to overcome this gap, leading towards the principal research question and the decomposition and resolution in subordinate research questions (cf. section 8.1). After exhibiting the research results, the following section discusses the outlook on affiliated research topics to expand the potential impact originating from this research (cf. section 8.2).

8.1 Summary

Digital processes are the backbone of organizations' digital transformation and their quest to expand their business models to remain competitive in the ever-changing market conditions. While core processes offer a high digital maturity, processes that do not directly contribute to the value stream, mainly categorized as support processes, experience less attention in organizations' digital strategy but do not necessarily surmise a less essential role. Daily execution characterizes some of these processes and can profoundly affect an organization's productivity. For example, a quick and thorough employee onboarding minimizes mistakes and decreases the time until a new employee is self-reliant. In contrast, a transparent investment request process can contribute to a better working environment through transparent and comprehensible handling of employee suggestions for improvement.

This research embraces the role of overlooked business processes and deals with the identified gap in the digital transformation of non-digital to digital processes by providing a systematic and structured approach. It addresses two concerns regarding the process maturity assessment to identify and prioritize business processes for digitalization and to secure their continuous improvement by exploiting readily available procedural process data in cyclic process analysis. This approach leads to the principal research question structuring the approach to this topic.

RQ How can a systematic approach to process optimization contribute to uncovering process insights for digital business processes?

Structured literature provides insights into the shortcomings of existing maturity assessment approaches, particularly regarding the often overlooked step of prioritizing non-digital processes for digitalization based on potential merits. The first developed model addresses this gap formulated as the first subordinate research question and expands existing models that already satisfy most formulated requirements.

The second identified gap drives subordinate research questions, culminating in a cyclic procedure model for process optimization. The procedure respects existing and established approaches originating from process mining and expands the phases to include business process management aspects in its first application that represents the second subordinate research question. The third subordinate research question handles the requirements owed to repeated procedure application manifesting in the philosophy of continuous improvement. Hence, it modifies the derived procedure to handle unexpected concept drifts due to ever-changing operation conditions that affect business processes.

The verification and validation of the developed models in case studies prove both models' functionality and added value, further supported by feedback from a team of experts involved in developing, implementing, and testing the models in the case studies. The findings support a positive response to the research question and suggest a means to a systematic approach to process optimization in the form of the developed assessment and procedure model. Still, the critical discussion offers valuable insight into potential improvements discussed in section 8.2.

8.2 Outlook

All case studies showcase the application of the developed models in specific scenarios. While the approach to process maturity assessment leans on pre-existing assessment approaches, particularly considering the assessment dimensions and subdimensions, model utilization requires a larger sample to prove broad applicability across distinct industries and to accommodate unique organizational structures. The assessment of this criterion expands to the process optimization procedure model, which exhibits sparse process data associated with limited process utilization outside the organizations' sphere of influence.

An approach that seizes the shortcomings of a few data is to expand the scope of process data analysis to process data post-mortem and integrate additional and continuous data streams. Data stream processing potentially boosts the overall contribution of the analysis by reducing the period from data extraction to securing insights from data analysis and increasing analytical insights through the integration of supplementary process data that go beyond procedural data like process performance indicators. However, considering process inherent and contextual data associated with specific traces and cases comes with increased technical requirements, personal expenses, and domain expertise. This potential development aligns with the aspiration of research in process mining to offer operational support to users, as referenced by Aalst[304]. An example is to give live recommendations in process execution based on historical process data or other learnings, thus intervening in process execution and transforming reactive and retrospective into proactive action. It still poses many challenges that date back a few years, summarized by Aalst et al. in the process mining manifesto[305] and other works[306], but concurrently mirrors the most significant potential in process mining.

The third consideration extends towards the correlation of derived actionable insights in process analysis, the execution of actions, and the observation and evaluation of associated effects in the cause-effect analysis as suggested by Adams[307]. Deploying a closed feedback loop supports the creation of medium-term learnings to distinguish suitable courses of action in comparable scenarios, thereby creating a recommendation system or assistant system to support lasting process improvements. It succumbs to challenging conditional requirements, as the observation of performance change requires a period to take effect, e.g., if it involves the training of employees or addresses fundamental organizational changes. Even then, the derivation of specific cause-effect relationships is challenging due to the quantity of influencing factors to consider in these scenarios.

[304]cf. Aalst 2016, pp. 305–307.
[305]cf. Aalst et al. 2012, pp. 184–191.
[306]cf. Aalst 2020, pp. 1181–196.
[307]cf. Adams et al. 2021, pp. 2–3.

Bibliography

AALST, W. M. P. van der, PESIC, M., and SCHONENBERG, H. Declarative workflows: Balancing between flexibility and support. In: Computer Science - Research and Development 23.2 (2009), pp. 99–113. DOI: 10.1007/s00450-009-0057-9 (cit. on p. 118).

AALST, Wil van der et al. Process Mining Manifesto. In: Business Process Management Workshops. BPM 2011. Ed. by F. DANIEL, K. BARKAOUI, and S. DUSTDAR. Lecture Notes in Business Information Processing 99. Springer Berlin Heidelberg, 2012, pp. 169–194. ISBN: 978-3-642-28108-2. DOI: 10.1007/978-3-642-28108-2_19 (cit. on pp. 21, 22, 24, 31, 69, 114, 171).

AALST, Wil M. P. van der. Academic View: Development of the Process Mining Discipline. In: Process Mining in Action. Ed. by Lars REINKEMEYER. Springer International Publishing, 2020, pp. 181–196. DOI: 10.1007/978-3-030-40172-6 (cit. on pp. 87, 171).

– Making Work Flow: On the Application of Petri Nets to Business Process Management. In: Application and Theory of Petri Nets 2002. Ed. by Javier ESPARZA and Charles LAKOS. Springer Berlin Heidelberg, 2002, pp. 1–22. DOI: 10.1007/3-540-48068-4_1 (cit. on p. 11).

– Process Mining. Data Science in Action. Springer Berlin Heidelberg, 2016. DOI: 10.1007/978-3-662-49851-4 (cit. on pp. 21, 24, 25, 77, 79, 82, 86, 87, 89, 90, 93–96, 99, 110, 171).

AALST, Wil M. P. van der, WEIJTERS, T., and MARUSTER, L. Workflow mining: discovering process models from event logs. In: IEEE Transactions on Knowledge and Data Engineering 16.9 (2004), pp. 1128–1142. DOI: 10.1109/TKDE.2004.47 (cit. on p. 24).

ACCORSI, Rafael and STOCKER, Thomas. Discovering Workflow Changes with Time-Based Trace Clustering. In: Lecture Notes in Business Information Processing. Ed. by K. ABERER, E. DAMIANI, and T. DILLON. Vol. 116. LNBIP. Springer Berlin Heidelberg, 2012, pp. 154–168. DOI: 10.1007/978-3-642-34044-4_9 (cit. on p. 117).

ADAMS, Jan Niklas, ZELST, Sebastiaan J. van, QUACK, Lara, HAUSMANN, Kathrin, AALST, Wil M. P. van der, and ROSE, Thomas. A Framework for Explainable Concept Drift Detection in Process Mining. In: Business Process Management. Ed. by Artem POLYVYANYY, Moe Thandar WYNN, Amy Van LOOY, and Manfred

Reichert. arXiv, 2021, pp. 400–416. doi: 10.48550/ARXIV.2105.13155 (cit. on pp. 115, 171).

Aguilar-Savén, Ruth Sara. Business process modelling: Review and framework. In: International Journal of Production Economics 90.2 (2004), pp. 129–149. doi: 10.1016/s0925-5273(03)00102-6 (cit. on p. 9).

Aken, Joan Ernst van. Management Research as a Design Science: Articulating the Research Products of Mode 2 Knowledge Production in Management. In: British Journal of Management 16.1 (2005), pp. 19–36. doi: 10.1111/j.1467-8551.2005.00437.x (cit. on p. 3).

Alam, M. Daud and Gühl, Uwe F. Project-Management in Practice. In: Springer Berlin Heidelberg, 2016. doi: 10.1007/978-3-662-52944-7 (cit. on p. 64).

Almeida, Fernando, Santos, Jose Duarte, and Monteiro, Jose Augusto. The Challenges and Opportunities in the Digitalization of Companies in a Post-COVID-19 World. In: IEEE Engineering Management Review 48.3 (2020), pp. 97–103. doi: 10.1109/emr.2020.3013206 (cit. on pp. 2, 27).

Appelfeller, Wieland and Feldmann, Carsten. Die digitale Transformation des Unternehmens. Springer Berlin Heidelberg, 2018. doi: 10.1007/978-3-662-54061-9 (cit. on pp. 2, 24, 38, 46, 47, 60).

Arnold, Ingo. Enterprise Architecture Function. Springer International Publishing, 2022. doi: 10.1007/978-3-030-84589-6 (cit. on p. 53).

Balci, Osman. Verfification, Validation and Testing. In: Handbook of Simulation: Principles, Methodology, Advances, Applications, and Practice. Ed. by Jerry Banks. 1998, pp. 335–396 (cit. on p. 128).

Becker, Jörg, Kugeler, Martin, and Rosemann, Michael, eds. Prozessmanagement. Springer Berlin Heidelberg, 2012. doi: 10.1007/978-3-642-33844-1.

Becker, Jörg, Mathas, Christoph, and Winkelmann, Axel. Geschäftsprozessmanagement. Springer Berlin Heidelberg, 2009. doi: 10.1007/978-3-540-85155-4 (cit. on p. 18).

Bifet, Albert and Gavaldà, Ricard. Learning from Time-Changing Data with Adaptive Windowing. In: Proceedings of the 2007 SIAM International Conference on Data Mining. Society for Industrial and Applied Mathematics, 2007. doi: 10.1137/1.9781611972771.42 (cit. on p. 114).

Bitkom Research and Tata Consultancy Services. Die zwei Gesichter der Digitalisierung. Bitkom Research and Tata Consultancy Services, 2016 (cit. on p. 26).

– Germany is Learning AI. Bitkom Research and Tata Consultancy Services, 2020 (cit. on p. 27).

BMWi. SMEs Digital Strategies for the Digital Transformation. Bundesministerium für Wirtschaft und Energie (BMWi), 2019 (cit. on p. 26).

Bose, R. P. Jagadeesh Chandra, Aalst, Wil M. P. van der, Zliobaite, Indre, and Pechenizkiy, Mykola. Dealing With Concept Drifts in Process Mining. In: IEEE Transactions on Neural Networks and Learning Systems 25.1 (2014), pp. 154–171. doi: 10.1109/tnnls.2013.2278313 (cit. on pp. 111, 115).

Bose, R. P. Jagadeesh Chandra, Aalst, Wil M. P. van der, Žliobaitė, Indrė, and Pechenizkiy, Mykola. Handling Concept Drift in Process Mining. In: Notes on Numerical Fluid Mechanics and Multidisciplinary Design. Ed. by H. Mouratidis and C. Rolland. Vol. 6741. LNCS. Springer International Publishing, 2011, pp. 391–405. doi: 10.1007/978-3-642-21640-4_30 (cit. on p. 110).

Bose, R. P. Jagadeesh Chandra, Mans, Ronny S., and Aalst, Wil M. P. van der. Wanna improve process mining results? In: 2013 IEEE Symposium on Computational Intelligence and Data Mining (CIDM). IEEE, 2013. doi: 10.1109/cidm.2013.6597227 (cit. on pp. 23, 93).

Bozkaya, Melike, Gabriels, Joost, and Werf, Jan Martijn van der. Process Diagnostics: A Method Based on Process Mining. In: 2009 International Conference on Information, Process, and Knowledge Management. IEEE, 2009. doi: 10.1109/eknow.2009.29 (cit. on pp. 80, 81, 98, 103).

Brandl, Felix J., Ridolfi, Kevin S., and Reinhart, Gunther. Can we Adopt the Toyota Kata for the (Re-)Design of Business Processes in the Complex Environment of a Manufacturing Company? In: Procedia CIRP 93 (2020), pp. 838–843. doi: 10.1016/j.procir.2020.03.086 (cit. on p. 73).

Breunig, Markus M., Kriegel, Hans-Peter, Ng, Raymond T., and Sander, Jörg. LOF: Identifying Density-Based Local Outliers. In: ACM SIGMOD Record 29.2 (2000), pp. 93–104. doi: 10.1145/335191.335388 (cit. on p. 117).

Britze, Nils et al. Leitfaden zum Reifegradmodell Digitale Geschäftsprozesse. 2020 (cit. on pp. 50, 61).

Brocke, Jan vom, Fay, Maria, Böhm, Martin, and Haltenhof, Volker. Creating a Market Analytics Tool that Marketers LOVE to Use: A Case of Digital Transformation at Beiersdorf. In: Shaping the Digital Enterprise. Ed. by Gerhard Oswald and Michael Kleinemeier. Springer International Publishing, 2017, pp. 197–217. doi: 10.1007/978-3-319-40967-2_10 (cit. on p. 20).

Brockhoff, Tobias, Uysal, Merih Seran, and Aalst, Wil M. P. van der. Time-aware Concept Drift Detection Using the Earth Mover's Distance. In: 2020 2nd International Conference on Process Mining (ICPM). IEEE, 2020. doi: 10.1109/icpm49681.2020.00016 (cit. on pp. 114, 118).

Cao, Feng, Estert, Martin, Qian, Weining, and Zhou, Aoying. Density-Based Clustering over an Evolving Data Stream with Noise. In: Proceedings of the 2006 SIAM International Conference on Data Mining. Society for Industrial and Applied Mathematics. doi: 10.1137/1.9781611972764.29 (cit. on p. 117).

Carmona, Josep and Gavaldà, Ricard. Online Techniques for Dealing with Concept Drift in Process Mining. In: Advances in Intelligent Data Analysis XI. Ed. by J. Hollmén, F. Klawonn, and A. Tucker. Vol. 7619. LNCS. Springer Berlin Heidelberg, 2012, pp. 90–102. doi: 10.1007/978-3-642-34156-4_10 (cit. on p. 114).

Chamoni, Peter and Gluchowski, Peter. Business Analytics - State of the Art. In: Controlling & Management Review 4 (2017), pp. 8–17 (cit. on pp. 19, 20).

Chapman, Peter, Clinton, Janet, Kerber, Randy, Khabaza, Tom, Reinartz, Thomas P., Shearer, Colin, and Wirth, Richard. CRISP-DM 1.0: Step-by-step data mining guide. The CRISP-DM consortium, 2000 (cit. on pp. 77, 79).

Chaudhary, Mukund and Chopra, Abhishek. CMMI for Development. Apress, 2017. doi: 10.1007/978-1-4842-2529-5 (cit. on p. 44).

Chhor, Jimmy, Westermann, Pia, and Schmitt, Robert H. Nachhaltige Prozessdigitalisierung für KMU. In: Zeitschrift für wirtschaftlichen Fabrikbetrieb 116.9 (2021), pp. 627–631. doi: 10.1515/zwf-2021-0141 (cit. on p. 27).

Chtioui, Tawhid. Understanding the Impact of ERP Standardizationon Business Process Performance. In: International Journal of Business 14.2 (2009), pp. 152–162 (cit. on p. 30).

Dahlander, Linus and Wallin, Martin. The Barriers to Recruiting and Employing Digital Talent. 2018. url: https://hbr.org/2018/07/the-barriers-to-recruiting-and-employing-digital-talent (visited on 04/03/2022) (cit. on p. 29).

Deutsches Institut für Normung e. V., ed. DIN EN ISO 9001:2015 - Qualitätsmanagementsysteme – Anforderungen. Beuth Verlag, 2015. doi: 10.31030/2325651 (cit. on p. 8).

– ed. DIN EN ISO 9004:2018 - Qualitätsmanagement - Qualität einer Organisation - Anleitung zum Erreichen nachhaltigen Erfolgs. 2018 (cit. on p. 57).

– ed. DIN ISO 9000:2015 - Qualitätsmanagementsysteme – Grundlagen und Begriffe. Beuth Verlag, 2015. doi: 10.31030/2325650 (cit. on p. 127).

DG Connect. Digital Economy and Society Index (DESI) 2021. European Commission, 2021 (cit. on p. 25).

Dinov, Ivo D. Data Science and Predictive Analytics. Springer International Publishing, 2023. doi: 10.1007/978-3-031-17483-4 (cit. on p. 20).

DOMBROWSKI, Uwe, GRUNDEI, Jens, MELCHER, Paul R., and SCHMIDTCHEN, Kai. Prozessorganisation in deutschen Unternehmen. In: zfo (Zeitschrift Führung und Organisation) 84.1 (2015), pp. 63–69. ISSN: 0722-7485 (cit. on p. 1).

DOMBROWSKI, Uwe and HENNINGSEN, Nadja. Systems of objectives in a VUCA world within the Lean Enterprise. In: 2019 International Symposium on Systems Engineering (ISSE). IEEE, 2019. DOI: 10.1109/isse46696.2019.8984468 (cit. on p. 1).

DUMAS, Marlon, ROSA, Marcello La, MENDLING, Jan, and REIJERS, Hajo A. Fundamentals of Business Process Management. Springer Berlin Heidelberg, 2018. DOI: 10.1007/978-3-662-56509-4 (cit. on pp. 19, 43, 45).

ECK, Maikel L. van, LU, Xixi, LEEMANS, Sander J. J., and AALST, Wil M. P. van der. PM2: A Process Mining Project Methodology. In: Advanced Information Systems Engineering. Ed. by Jelena ZDRAVKOVIC, Marite KIRIKOVA, and Paul JOHANNESSON. Springer International Publishing, 2015, pp. 297–313. DOI: 10.1007/978-3-319-19069-3 (cit. on pp. 83, 84, 86, 96, 97).

ELLIOTT, Timo. Predictive Is the Next Step in Analytics Maturity? It's More Complicated than That! SAP. 2018. URL: https://blogs.sap.com/2018/04/19/predictive-is-the-next-step-in-analytics-maturity-its-more-complicated-than-that/ (visited on 06/04/2021) (cit. on p. 20).

ELSER, Hannes, WANGEROW, Kai, NGO, Quoc Hao, and SCHMITT, Robert. Six Sigma. In: Masing Handbuch Qualitätsmanagement. Ed. by Tilo PFEIFER and Robert SCHMITT. Carl Hanser Verlag, 2021, pp. 261–289. ISBN: 9783446434318 (cit. on pp. 74, 75).

FELCH, Vanessa and ASDECKER, Björn. Quo Vadis, Business Process Maturity Model? Learning from the Past to Envision the Future. In: Lecture Notes in Computer Science. Ed. by Dirk FAHLAND, Chiara GHIDINI, Jörg BECKER, and Marlon DUMAS. Springer International Publishing, 2020, pp. 368–383. DOI: 10.1007/978-3-030-58666-9_21 (cit. on p. 63).

FISHER, David M. The Business Process Maturity ModelA Practical Approach for Identifying Opportunities forOptimization. In: BPTrends (2004), pp. 1–7 (cit. on p. 58).

FLEISCHMANN, Albert, OPPL, Stefan, SCHMIDT, Werner, and STARY, Christian. Ganzheitliche Digitalisierung von Prozessen. Springer Fachmedien Wiesbaden, 2018. DOI: 10.1007/978-3-658-22648-0 (cit. on pp. 7, 8, 11, 16).

FREYTAG, Thomas and SÄNGER, Martin. WoPeD - An Educational Tool for Workflow Nets. In: Proceedings of the BPM Demo Sessions 2014. Ed. by Lior LIMONAD and Barbara WEBER. 2014 (cit. on p. 89).

FROGER, Manon, BÉNABEN, Frederick, TRUPTIL, Sébastien, and BOISSEL-DALLIER, Nicolas. A non-linear business process management maturity framework to apprehend future challenges. In: International Journal of Information Management 49 (2019), pp. 290–300. DOI: 10.1016/j.ijinfomgt.2019.05.013 (cit. on pp. 48, 49).

GADATSCH, Andreas. Geschäftsprozesse analysieren und optimieren. Springer Fachmedien Wiesbaden, 2015. DOI: 10.1007/978-3-658-09110-1 (cit. on pp. 7, 9, 12).

– Grundkurs Geschäftsprozess-Management. Springer Fachmedien Wiesbaden, 2020. DOI: 10.1007/978-3-658-27812-0 (cit. on pp. 10, 16, 17).

GEERS, Dennis, LANDGRAF, Katja, and JOCHEM, Roland. Welchen Beitrag leisten Reifegradmodelle bei der Qualitätsbewertung von Prozessen? In: Was kostet Qualität? Wirtschaftlichkeit von Qualität ermitteln. Ed. by Roland JOCHEM. Carl Hanser Verlag, 2010, pp. 113–142 (cit. on p. 37).

GEHRING, Hermann and GADATSCH, Andreas. Ein Rahmenkonzept für die Modellierung von Geschäftsprozessen und Workflows. Fachbereich Wirtschaftswissenschaft der FernUniversität Haagen, 1999 (cit. on p. 13).

GELFERT, Axel. Assessing the Credibility of Conceptual Models. In: Simulation Foundations, Methods and Applications. Springer International Publishing, 2019, pp. 249–269. DOI: 10.1007/978-3-319-70766-2_10 (cit. on p. 128).

GERMAN FEDERAL STATISTICAL OFFICE. Shares of small and medium-sized enterprises in selected variables, 2019. 2019 (cit. on p. 26).

GÖKŞEN, Haluk and GÖKŞEN, Yılmaz. A Review of Maturity Models Perspective of Level and Dimension. In: The 7th International Management Information Systems Conference. MDPI, 2021. DOI: 10.3390/proceedings2021074002 (cit. on p. 58).

GURSCH, Jennifer, SCHULZ, Christopher, and SEIZ, Sandra. Management von IT-Wissen bei Mergers & Acquisitions: Ein Blick in die Praxis. In: Wirtschaftsinformatik & Management 5.2 (Feb. 2013), pp. 72–79. DOI: 10.1365/s35764-013-0281-8 (cit. on p. 31).

HAMMER, Michael. The Process Audit. In: Harvard Business Review (2007) (cit. on p. 43).

HANSCHKE, Inge and LORENZ, Rainer. Strategisches Prozessmanagement - einfach und effektiv. Hanser Fachbuchverlag, 2021. 304 pp. ISBN: 3446465715 (cit. on pp. 37, 41).

HASSANI, Marwan. Concept Drift Detection Of Event Streams Using An Adaptive Window. In: ECMS 2019 Proceedings edited by Mauro Iacono, Francesco Palmieri, Marco Gribaudo, Massimo Ficco. ECMS, 2019, pp. 230–239. DOI: 10.7148/2019-0230 (cit. on p. 114).

Hauri, Philip and Ricken, Boris. Umfrage Digitalstrategie. f. 2021 (cit. on p. 26).

Hayes, William, Miluk, Eugene E., Ming, Lisa, and Glover, Margaret. Handbook for Conducting Standard CMMI Appraisal Method for Process Improvement (SCAMPI) B and C Appraisals. 2005. doi: 10.1184/R1/6574073.V1 (cit. on p. 44).

Heimes, Heiner, Kampker, Achim, Bührer, Ulrich, Schroth, Paul, and Krotil, Stefan. Prioritizing Digitalization Use Cases during Early Development Phases of Large Scale Manufacturing Systems. In: Procedia Manufacturing 28 (2019), pp. 37–42. doi: 10.1016/j.promfg.2018.12.007 (cit. on p. 64).

Helmold, Marc and Samara, Warda. Progress in Performance Management. Springer International Publishing, 2019. doi: 10.1007/978-3-030-20534-8 (cit. on p. 16).

Hermkens, Freek, Buuren, Tom van, and Kort, Sebastiaan. A model for attaining business process maturity. In: International Journal of Social Sciences and Management Review 05.02 (2022), pp. 77–87. doi: 10.37602/ijssmr.2022.5206 (cit. on p. 60).

Hilgers, Dennis. Performance Management. Gabler Verlag, May 15, 2008. 364 pp. isbn: 3834909327 (cit. on p. 16).

Hirzel, Matthias. Erfolgsfaktor Prozessmanagement. In: Prozessmanagement in der Praxis. Ed. by Matthias Hirzel, Ulrich Geiser, and Ingo Gaida. Gabler Verlag, 2013, pp. 1–12. doi: 10.1007/978-3-8349-4577-8 (cit. on p. 2).

Hirzel, Matthias, Geiser, Ulrich, and Gaida, Ingo, eds. Prozessmanagement in der Praxis. Gabler Verlag, 2013. doi: 10.1007/978-3-8349-4577-8 (cit. on p. 1).

Hogrebe, Frank and Nüttgens, Markus. Business Process Maturity Model (BPMM): Konzeption, Anwendung und Nutzenpotenziale. In: HMD Praxis der Wirtschaftsinformatik 46.2 (2009), pp. 17–25. doi: 10.1007/bf03340339 (cit. on pp. 45, 46).

Hompes, B. F. A., Buijs, J. C. A. M., Aalst, Wil M. P. van der, Dixit, P. M., and Buurman, J. Detecting Changes in Process Behavior Using Comparative Case Clustering. In: Lecture Notes in Business Information Processing. Vol. 244. LNBIP. Springer International Publishing, 2017, pp. 54–75. doi: 10.1007/978-3-319-53435-0_3 (cit. on p. 118).

Impedovo, Angelo, Mignone, Paolo, Loglisci, Corrado, and Ceci, Michelangelo. Simultaneous Process Drift Detection and Characterization with Pattern-Based Change Detectors. In: Discovery Science. Vol. 12323. LNAI. Springer International Publishing, 2020, pp. 451–467. doi: 10.1007/978-3-030-61527-7_30 (cit. on p. 114).

Institute or Total Quality Management. The EFQM Model. 2019 (cit. on p. 55).

International Organization for Standardization and International Electrotechnical Commission, eds. ISO/IEC 33001:2015 - Information technology - Process assessment - Concepts and terminology. 2015 (cit. on p. 37).

– eds. ISO/IEC TR 30014:2013 - Information technology - Process assessment - Guide for process improvement. 2013 (cit. on p. 76).

Jadhav, Aditee and Jadhav, Nikhil. Learning Using Concept Drifts: An Overview. In: 2018 Fourth International Conference on Computing Communication Control and Automation (ICCUBEA). IEEE, 2018. doi: 10.1109/iccubea.2018.8697732 (cit. on p. 113).

Junior, Sylvio Barbon, Tavares, Gabriel Marques, Costa, Victor G. Turrisi da, Ceravolo, Paolo, and Damiani, Ernesto. A Framework for Human-in-the-loop Monitoring of Concept-drift Detection in Event Log Stream. In: Companion of the The Web Conference 2018 on The Web Conference 2018 - WWW '18. ACM Press, 2018. doi: 10.1145/3184558.3186343 (cit. on p. 117).

Kahl, Timo and Zimmer, Frank. Kontextspezifische Visualisierung von Prozesskennzahlen. In: Geschäftsprozesse. Ed. by Thomas Barton, Christian Müller, and Christian Seel. Springer Fachmedien Wiesbaden, 2017, pp. 75–97. doi: 10.1007/978-3-658-17297-8 (cit. on pp. 16, 17).

Kalenkova, Anna A., Aalst, Wil M. P. van der, Lomazova, Irina A., and Rubin, Vladimir A. Process mining using BPMN: relating event logs and process models. In: Software & Systems Modeling 16.4 (2015), pp. 1019–1048. doi: 10.1007/s10270-015-0502-0 (cit. on p. 11).

Kalinowski, T. Bartosz. Business Process Maturity Models Research: A Systematic Literature Review. In: The International Journal of Management Science and Business Administration 7.1 (2020), pp. 29–35. doi: 10.18775/ijmsba.1849-5664-5419.2014.71.1003 (cit. on p. 60).

Killick, R., Fearnhead, P., and Eckley, I. A. Optimal Detection of Changepoints With a Linear Computational Cost. In: Journal of the American Statistical Association 107.500 (2012), pp. 1590–1598. doi: 10.1080/01621459.2012.737745 (cit. on p. 115).

Kirchmer, Mathias. High Performance Through Business Process Management. Springer International Publishing, 2017. doi: 10.1007/978-3-319-51259-4 (cit. on pp. 16, 30).

Koch, Susanne. Einführung in das Management von Geschäftsprozessen. Springer Berlin Heidelberg, 2015. doi: 10.1007/978-3-662-44450-4 (cit. on p. 2).

KOHNKE, Oliver. It's Not Just About Technology: The People Side of Digitization. In: Shaping the Digital Enterprise. Ed. by Gerhard OSWALD and Michael KLEINEMEIER. Springer International Publishing, 2017, pp. 69–91. DOI: 10.1007/978-3-319-40967-2 (cit. on p. 28).

KOSSAK, Felix, ILLIBAUER, Christa, GEIST, Verena, KUBOVY, Jan, NATSCHLÄGER, Christine, ZIEBERMAYR, Thomas, KOPETZKY, Theodorich, FREUDENTHALER, Bernhard, and SCHEWE, Klaus-Dieter. A Rigorous Semantics for BPMN 2.0 Process Diagrams. Springer International Publishing, 2014. DOI: 10.1007/978-3-319-09931-6 (cit. on p. 11).

KURNIATI, Angelina Prima, MCINERNEY, Ciarán, ZUCKER, Kieran, HALL, Geoff, HOGG, David, and JOHNSON, Owen. A Multi-level Approach for Identifying Process Change in Cancer Pathways. In: Business Process Management Workshops. Vol. 362. LNBIP. Springer International Publishing, 2019, pp. 595–607. DOI: 10.1007/978-3-030-37453-2_48 (cit. on p. 118).

KÜTZ, Martin. Kennzahlen in der IT Werkzeuge für Controlling und Management. dpunkt.verlag GmbH, 2009. ISBN: 9783898647038 (cit. on p. 17).

KYKALOVÁ, Denisa, BRUCKER-KLEY, Elke, and NÄPFLIN, Simon. Ergebnisse der Umfrage: «Status quo: Kundennutzen durch digitale Transformation?» In: Kundennutzen durch digitale Transformation. Ed. by Elke BRUCKER-KLEY, Denisa KYKALOVÁ, and Thomas KELLER. Springer Berlin Heidelberg, 2018, pp. 21–44. DOI: 10.1007/978-3-662-55707-5_2 (cit. on p. 26).

LABERGE, Laura, O'TOOLE, Clayton, SCHNEIDER, Jeremy, and SMAJE, Kate. How COVID-19 has pushed companies over the technology tipping point - and transformed business forever. McKinsey & Compnay, 2020 (cit. on p. 27).

LAUE, Ralf. Prozess-Optimierung. In: Prozessmanagement und Process-Mining. Ed. by Ralf LAUE, Agnes KOSCHMIDER, and Dirk FAHLAND. de Gruyter Oldenbourg, 2020, pp. 81–100. ISBN: 978-3-11-050016-5 (cit. on p. 16).

LAUE, Ralf, KOSCHMIDER, Agnes, and FAHLAND, Dirk, eds. Prozessmanagement und Process-Mining. de Gruyter Oldenbourg, 2020. 306 pp. ISBN: 978-3-11-050016-5 (cit. on pp. 23, 100).

LEGNER, Christine, EYMANN, Torsten, HESS, Thomas, MATT, Christian, BÖHMANN, Tilo, DREWS, Paul, MÄDCHE, Alexander, URBACH, Nils, and AHLEMANN, Frederik. Digitalization: Opportunity and Challenge for the Business and Information Systems Engineering Community. In: Business Information Systems Engineering 59.4 (July 2017), pp. 301–308. DOI: 10.1007/s12599-017-0484-2 (cit. on p. 30).

Lichtblau, Karl, Schleiermacher, Thomas, Goecke, Henry, and Schützdeller, Peter. Digitalisierung der KMU in Deutschland. IW Consult, DATAlovers, and beDirect, 2018 (cit. on p. 30).

Lin, Leilei, Wen, Lijie, Lin, Li, Pei, Jisheng, and Yang, Hedong. LCDD: Detecting Business Process Drifts Based on Local Completeness. In: IEEE Transactions on Services Computing 15.4 (2022), pp. 2086–2099. doi: 10.1109/tsc.2020.3032787 (cit. on p. 117).

Liu, Fei and Yang, Ming. The Management of Simulation Validation. In: Simulation Foundations, Methods and Applications. Springer International Publishing, 2019, pp. 587–606. doi: 10.1007/978-3-319-70766-2_24 (cit. on p. 128).

Liu, Na, Huang, Jiwei, and Cui, Lizhen. A Framework for Online Process Concept Drift Detection from Event Streams. In: 2018 IEEE International Conference on Services Computing (SCC). IEEE, 2018. doi: 10.1109/scc.2018.00021 (cit. on p. 114).

Looy, Amy, Poels, Geert, and Snoeck, Monique. Evaluating Business Process Maturity Models. In: Journal of the Association for Information Systems 18.6 (June 2017), pp. 461–486. doi: 10.17705/1jais.00460 (cit. on p. 58).

Lunau, Stephan, ed. Six Sigma +Lean Toolset. 2007.

Maaradji, Abderrahmane, Dumas, Marlon, Rosa, Marcello La, and Ostovar, Alireza. Detecting Sudden and Gradual Drifts in Business Processes from Execution Traces. In: IEEE Transactions on Knowledge and Data Engineering 29.10 (2017), pp. 2140–2154. doi: 10.1109/tkde.2017.2720601 (cit. on p. 116).

Mannhardt, Felix. Multi-perspective Process Mining. Tech. rep. TU Eindhoven, 2018 (cit. on p. 99).

Mannhardt, Felix, Leoni, Massimiliano de, Reijers, Hajo A., and Aalst, Wil M. P. van der. Measuring the Precision of Multi-perspective Process Models. In: Business Process Management Workshops. Springer International Publishing, 2016, pp. 113–125. doi: 10.1007/978-3-319-42887-1_10 (cit. on p. 99).

McCarthy, Richard V., McCarthy, Mary M., Ceccucci, Wendy, and Halawi, Leila. Applying Predictive Analytics. Springer International Publishing, 2019. doi: 10.1007/978-3-030-14038-0 (cit. on p. 19).

Modrák, Vladimír and Šoltysová, Zuzana. Development of an Organizational Maturity Model in Terms of MassCustomization. In: Industry 4.0 for SMEs. Ed. by Dominik T. Matt, Vladimír Modrák, and Helmut Zsifkovits. Springer International Publishing, 2020, pp. 215–250. doi: 10.1007/978-3-030-25425-4 (cit. on p. 29).

Mora, Davide, Ceravolo, Paolo, Damiani, Ernesto, and Tavares, Gabriel Marques. The CDESF Toolkit: An Introduction. In: Proceedings of the ICPM

Doctoral Consortium and Tool Demonstration Track 2020. 2020, pp. 47–50 (cit. on p. 117).

Mühlen, Michael zur and Hansmann, Holger. Workflowmanagement. In: Prozessmanagement. Ed. by Jörg Becker, Martin Kugeler, and Michael Rosemann. Springer Berlin Heidelberg, 2012, pp. 367–400. doi: 10.1007/978-3-642-33844-1 (cit. on p. 14).

Müller, Egon, Tawalbeh, Mandy, and Hopf, Hendrik. Reifegradbestimmung als Vorstufe der Industrie 4.0-Strategieentwicklung. In: KMU 4.0 - digitale Transformation in kleinen und mittelständischen Unternehmen. Ed. by Dominik Matt. GITO mbH Verlag, 2018, pp. 71–92. isbn: 9783955452674 (cit. on p. 26).

Nalbach, Oliver, Linn, Christian, Derouet, Maximilian, and Werth, Dirk. Predictive Quality: Towards a New Understanding of Quality Assurance Using Machine Learning Tools. In: Business Information Systems. Ed. by Witold Abramowicz and Adrian Paschke. Springer International Publishing, 2018, pp. 30–42. doi: 10.1007/978-3-319-93931-5_3 (cit. on p. 20).

National Institute of Standards and Technology. Baldrige Exellence Builder. 2021 (cit. on p. 56).

– Baldrige Exellence Framework. National Institute of Standards and Technology, 2017 (cit. on p. 56).

Neuhaus, Ralf and Lennings, Frank. Regelkreise für Produktionssysteme. In: Produktionssysteme Aufbau – Umsetzung – betriebliche Lösungen. Ed. by Institut für angewandte Arbeitswissenschaft e.V. 2008, pp. 37–47. isbn: 978-3-89172-465-1 (cit. on p. 73).

Newman, Mark. Digital Maturity and Model (DMM). 2017 (cit. on p. 59).

Novikova, Irina Viktorovna. Digitisation: A New Form of Precarity or New Opportunities? In: Digitisation and Precarisation. Ed. by Vyacheslav Bobkov and Peter Herrmann. Springer Fachmedien Wiesbaden, pp. 89–104. doi: 10.1007/978-3-658-26384-3 (cit. on p. 29).

Object Management Group. Business Process Modeling Notation (BPMN), Version 1.0. 2008 (cit. on pp. 45, 46).

Ongena, Guido and Ravesteyn, Pascal. Business process management maturity and performance. In: Business Process Management Journal 26.1 (June 2019), pp. 132–149. doi: 10.1108/bpmj-08-2018-0224 (cit. on p. 63).

Ostovar, Alireza, Leemans, Sander J. J., and Rosa, Marcello La. Robust Drift Characterization from Event Streams of Business Processes. In: ACM Transactions on Knowledge Discovery from Data 14.3 (2020), pp. 1–57. doi: 10.1145/3375398 (cit. on p. 116).

OSWALD, Gerhard and KLEINEMEIER, Michael, eds. Shaping the Digital Enterprise. Springer International Publishing, 2017. DOI: 10.1007/978-3-319-40967-2.

PARK, Gyunam and AALST, Wil M. P. van der. A General Framework for Action-Oriented Process Mining. In: Business Process Management Workshops. Ed. by Adela DEL, Río ORTEGA, Henrik LEOPOLD, Flávia MARIA, and SANTORO. Springer International Publishing, 2020, pp. 206–218. DOI: 10.1007/978-3-030-66498-5_16 (cit. on p. 85).

RABE, Markus, SPIECKERMANN, Sven, and WENZEL, Sigrid. Verifikation und Validierung Für Die Simulation in Produktion und Logistik Vorgehensmodelle und Techniken. Vorgehensmodelle und Techniken. Springer London, Limited, 2008. ISBN: 9783540352822 (cit. on p. 128).

RAFIEI, Majid and AALST, Wil M. P. van der. Group-based privacy preservation techniques for process mining. In: Data & Knowledge Engineering 134.101908 (2021), pp. 1–21. DOI: 10.1016/j.datak.2021.101908 (cit. on p. 91).

REINKEMEYER, Lars. Business View: Towards a Digital Enabled Organization. In: Process Mining in Action. Ed. by Lars REINKEMEYER. Springer International Publishing, 2020, pp. 197–206. DOI: 10.1007/978-3-030-40172-6 (cit. on p. 32).

– ed. Process Mining in Action. Springer International Publishing, 2020. DOI: 10.1007/978-3-030-40172-6.

RICHTER, Florian, MALDONADO, Andrea, ZELLNER, Ludwig, and SEIDL, Thomas. OTOSO: Online Trace Ordering for Structural Overviews. In: Lecture Notes in Business Information Processing. Vol. 406. LNBIP. Springer International Publishing, 2021, pp. 218–229. DOI: 10.1007/978-3-030-72693-5_17 (cit. on p. 118).

RICHTER, Florian and SEIDL, Thomas. Looking into the TESSERACT: Time-drifts in event streams using series of evolving rolling averages of completion times. In: Information Systems 84 (2019), pp. 265–282. DOI: 10.1016/j.is.2018.11.003 (cit. on p. 117).

ROBINSON, Stewart. Simulation: The Practice of Model Developmentand Use. John Wiley & Sons, Ltd, 2004, p. 316. ISBN: 0470847727 (cit. on p. 127).

ROENPAGE, Oliin, STAUDTER, Christian, MERAN, Renata, and JOHN, Alexander. Erfolgsfaktor Qualität. In: Six Sigma +Lean Toolset. Ed. by Stephan LUNAU. 2007, pp. 7–17 (cit. on p. 75).

– Prozessfähigkeitsrechnung. In: Six Sigma +Lean Toolset. Ed. by Stephan LUNAU. 2007 (cit. on p. 2).

RÖGLINGER, Maximilian, PÖPPELBUSS, Jens, and BECKER, Jörg. Maturity models in business process management. In: Business Process Management Journal 18.2 (2 2012), pp. 328–346. DOI: 10.1108/14637151211225225 (cit. on p. 58).

ROHLOFF, Michael. Process Management Maturity Assessment. In: Proceedings of the Fifteenth Americas Conference on Information Systems AMCIS 2009. 2009 (cit. on p. 59).

ROSEMANN, Michael and BRUIN, Tonia de. Application of a Holistic Model for Determining BPM Maturity. In: BPTrends (2005), pp. 1–21 (cit. on p. 42).

– Towards a Business Process Management Maturity Model. In: ECIS 2005 Proceedings of the Thirteenth European Conference on Information Systems. 2005 (cit. on p. 41).

ROSEMANN, Michael, SCHWEGMANN, Ansgar, and DELFMANN, Patrick. Vorbereitung der Prozessmodellierung. In: Prozessmanagement. Ed. by Jörg BECKER, Martin KUGELER, and Michael ROSEMANN. Springer Berlin Heidelberg, 2012, pp. 47–112. DOI: 10.1007/978-3-642-33844-1 (cit. on pp. 10, 11).

ROZINAT, A. and AALST, Wil M. P. van der. Conformance checking of processes based on monitoring real behavior. In: Information Systems 33.1 (2008), pp. 64–95. DOI: 10.1016/j.is.2007.07.001 (cit. on p. 24).

RUBNER, Y., TOMASI, C., and GUIBAS, L.J. A metric for distributions with applications to image databases. In: Sixth International Conference on Computer Vision (IEEE Cat. No.98CH36271). Narosa Publishing House, 1998. DOI: 10.1109/iccv.1998.710701 (cit. on p. 118).

RÜEGG-STÜRM, Johannes and GRAND, Simon. Das St. Galler Management-Modell : Management in einer komplexen Welt. Management in einer komplexen Welt. 2nd ed. Haupt Verlag, 2020. ISBN: 9783838554990 (cit. on pp. 1, 8).

SATO, Denise Maria Vecino, FREITAS, Sheila Cristiana De, BARDDAL, Jean Paul, and SCALABRIN, Edson Emilio. A Survey on Concept Drift in Process Mining. In: ACM Computing Surveys 54.9 (2021), pp. 1–38. DOI: 10.1145/3472752 (cit. on pp. 110, 113, 114, 116, 117, 119).

SCHEER, August-Wilhelm. Unternehmung 4.0. Springer Fachmedien Wiesbaden, 2020. DOI: 10.1007/978-3-658-27694-2 (cit. on p. 19).

SCHMELZER, Hermann J. and SESSELMANN, Wolfgang. Geschäftsprozessmanagement in der Praxis. Hanser Fachbuchverlag, 2020. ISBN: 3446446257 (cit. on pp. 13, 14, 16, 17, 41, 51, 52, 59, 62).

SCHMITT, Robert and PFEIFER, Tilo. Qualitätsmanagement. Strategien – Methoden – Techniken. 5th ed. Hanser Fachbuchverlag, 2015. ISBN: 3446434321 (cit. on p. 73).

SCHUBERT, Erich, WEILER, Michael, and KRIEGEL, Hans-Peter. SigniTrend: Scalable Detection of Emerging Topics in Textual Streams by Hashed Significance Thresholds. In: Proceedings of the 20th ACM SIGKDD international conference on Knowledge discovery and data mining. ACM, 2014. DOI: 10.1145/2623330.2623740 (cit. on p. 118).

Schuh, Günther, Anderl, Reiner, Dumitrescu, Roman, Krüger, Antonio, and Hompel, Michael ten. Managing the Digital Transformation of Companies. In: Industrie 4.0 Maturity Index – UPDATE 2020. Ed. by Günther Schuh, Reiner Anderl, Roman Dumitrescu, Antonio Krüger, and Michael ten Hompel. Springer, 2020 (cit. on p. 1).

Seeliger, Alexander, Nolle, Timo, and Mühlhäuser, Max. Detecting Concept Drift in Processes using Graph Metrics on Process Graphs. In: Proceedings of the 9th Conference on Subject-oriented Business Process Management. ACM, 2017, pp. 1–10. doi: https://doi.org/10.1145/3040565.3040566 (cit. on p. 116).

Shah, Mohak. Big Data and the Internet of Things. In: Studies in Big Data. Ed. by Nathalie Japkowicz and Jerzy Stefanowski. Springer International Publishing, Dec. 2015, pp. 207–237. doi: 10.1007/978-3-319-26989-4_9 (cit. on p. 20).

Simon, Hermann. Hidden Champions of the Twenty-First Century. Springer New York, 2009. doi: 10.1007/978-0-387-98147-5 (cit. on p. 31).

Stertz, Florian and Rinderle-Ma, Stefanie. Process Histories - Detecting and Representing Concept Drifts Based on Event Streams. In: Lecture Notes in Computer Science. Ed. by Hervé Panetto, Christophe Debruyne, Henderik A. Proper, Claudio Agostino Ardagna, Dumitru Roman, and Robert Meersman. Vol. 11229. LNCS. Springer International Publishing, 2018, pp. 318–335. doi: 10.1007/978-3-030-02610-3_18 (cit. on pp. 114, 122).

Szelągowski, Marek and Berniak-Woźny, Justyna. How to improve the assessment of BPM maturity in the era of digital transformation. In: Information Systems and e-Business Management 20.1 (Dec. 2021), pp. 171–198. doi: 10.1007/s10257-021-00549-w (cit. on pp. 52, 53).

The Open Group. The TOGAF® Standard, Version 9.2. The Open Group, 2005 (cit. on p. 54).

Ulrich, Hans. Die Betriebswirtschaftslehre als anwendungsorientierte Sozialwissenschaft. In: Die Führung des Betriebes. Manfred N. Geist and Richard Köhler, 1981, pp. 1–25 (cit. on p. 3).

Weber, Tobias, Bertschek, Irene, Ohnemus, Jörg, and Ebert, Martin. Monitoring-Report Wirtschaft DIGITAL 2018. Bundesministerium für Wirtschaft und Energie (BMWi), 2020 (cit. on pp. 26, 32).

Weidlich, Matthias. Abweichungsanalyse/Conformance-Checking. In: Prozessmanagement und Process-Mining. Ed. by Ralf Laue, Agnes Koschmider, and Dirk Fahland. de Gruyter Oldenbourg, 2020, pp. 199–234. isbn: 978-3-11-050016-5 (cit. on p. 99).

Weinreich, Uwe. Lean Digitization. Springer Berlin Heidelberg, 2016. doi: 10.1007/978-3-662-50502-1 (cit. on p. 1).

Weske, Mathias. Business Process Management. Springer Berlin Heidelberg, 2019. doi: 10.1007/978-3-662-59432-2 (cit. on pp. 10, 16).

Wirth, Rüdiger and Hipp, Jochen. CRISP-DM: Towards a Standard Process Model for Data Mining. In: Proceedings of the Fourth International Conference on the Practical Application of Knowledge Discovery and Data Mining. Practical Application Company, 2000, pp. 29–39 (cit. on p. 77).

Wittpahl, Volker. Neuer Umgang mit digitalen Daten. In: Digitalisierung. Ed. by Volker Wittpahl. Springer Berlin Heidelberg, 2017, pp. 10–59. doi: 10.1007/978-3-662-52854-9_1 (cit. on p. 18).

Yeshchenko, Anton, Ciccio, Claudio Di, Mendling, Jan, and Polyvyanyy, Artem. Visual Drift Detection for Event Sequence Data of Business Processes. In: IEEE Transactions on Visualization and Computer Graphics 28.8 (2022), pp. 3050–3068. doi: 10.1109/tvcg.2021.3050071 (cit. on pp. 115, 118).

Zellner, Ludwig, Richter, Florian, Sontheim, Janina, Maldonado, Andrea, and Seidl, Thomas. Concept Drift Detection on Streaming Data with Dynamic Outlier Aggregation. In: Lecture Notes in Business Information Processing. Vol. 406. LNBIP. Springer International Publishing, 2021, pp. 206–217. doi: 10.1007/978-3-030-72693-5_16 (cit. on p. 117).

Zheng, Canbin, Wen, Lijie, and Wang, Jianmin. Detecting Process Concept Drifts from Event Logs. In: On the Move to Meaningful Internet Systems. OTM 2017 Conferences. Vol. I. Part. Springer International Publishing, 2017, pp. 524–542. doi: 10.1007/978-3-319-69462-7_33 (cit. on p. 114).

Zimmermann, Volker. KfW Digitalisierungsbericht Mittelstand 2020. KfW Bankengruppe, 2020 (cit. on pp. 28, 32).

A Annex

A.1 Supervised Student Theses and Projects

Within the framework of this research carried out by the author, which is described in this thesis and other research publications, student theses and projects, in particular the research project ProMiDigit (funding code: 01IS20035) have been intensively supervised in terms of methodology and content concerning the development of the research topic, problem definition, objectives, research questions, methodology, and approach. The supervision took place at the Chair for Production Metrology and Quality Management of the Laboratory for Machine Tools WZL of RWTH Aachen University. Table A.1 lists the supervised student theses in alphabetical order. The student theses are closely related to the author's research activities. The present research work partially incorporates the findings and results of these papers.

Table A.1: Overview of supervised student theses

Student	Thesis title	Contribution	Year
Cornelißen, Simone	Process Mining mittels No-Code-Digitalisierung: Eine Moeglichkeit zur Prozessoptimierung fuer kleine und mittlere Unternehmen (KMU)	Chapter 4	2021
Kroeppel, Fabian	Entwicklung eines Vorgehens zur Verbesserung von No-Code-digitalisierten Prozessen mittels Process Mining	Chapter 4	2021
Le, Khung Phuoc	Framework to Handle Concept Drift in Data-driven Process Model Enhancement	Chapter 5	2022
Khajehi-Mahabadi, Kushan	Entwicklung und Validierung eines Vorgehensmodells zur Prozessverbesserung No-Code digitalisierter Prozesse mittels Process Mining	Chapter 4	2022
Oezcan, Mehmet	Potentialanalyse für die Prozessdigitalisierung	Chapter 3	2022
Vogt, Thomas	Entwicklung eines Vorgehens zur Konformitaetspruefung von No-Code-digitalisierten Prozessen durch Process Mining	Chapter 4	2022

A.2 Case Study Workflow Models

The process data in the case studies originate from German SMEs from the research project ProMiDigit (funding code: 01IS20035). Hence, most data is only available in German. For ease of reading and understanding, the verification and validation in chapter 6 uses the English translation, particularly for the workflow transitions. The workflow states and transitions for both case studies share the same ID as the original German description and are linked in the overview in tables A.2 and A.3.

Table A.2: Case Study 1b: Workflow states and transitions

ID	Original description	Translation
States		
A92ob3	Pruefung durch Finanzen	audit by accounting
Bofc6yl	Pruefung durch Controlling	audit by controlling
Cufcvoj	Abgelehnt	rejected
Dgp118	Rueckmeldung durch Antragsteller	feedback from applicant
Fexw9z	Antrag im Investionsausschuss	request in investment committee meeting
H80dji	Pruefung durch Programmmanagement	audit by program management
NEW	New	new
P49mqvr	Genehmigt	approved
static_state_deleted	Geloescht	deleted
static_state_new	Neu	new
W0chcun	on hold	on hold
Xu33aqg	Ueberarbeitung durch Antragsteller	revision by applicant
Transitions		
B8tchw	Controlling um weitere Ueberarbeitung bitten	appeal controlling to revise the investment request
Create	0	0
D1esyb	Antragsteller um neue Ueberarbeitung bitten	appeal applicant to revise the investment request

to be continued on the next page

Table A.2: Case Study 1b: Workflow states and transitions (continuation)

ID	Original description	Translation
Efof5xv	Genehmigung erneut anfragen	resubmit approval request
F9fl3mh	Zurueck zu Programmmanagement	return to program management
Fvlk	Aenderung Investitionsvolumen: erneute Pruefung durch Fachbereich	investment budget change: reaudit by department
I4ytjr5	Antrag abgelehnt	reject request
Jotbb9g	Antrag wiederherstellen	recover request
Jr5qduk	Projekt: nein / Pruefung durch Controlling	project: no / audit by controlling
Jsmviy8	Antrag genehmigen	approve request
Kyhe58f	Programmmanager um neue Ueberarbeitung bitten	appeal program management to revise the investment request
Mgcqw0l	Rueckfrage stellen	submit question
Mjg7vb	Zurueck zu Controlling	return to controlling
Nofnl5y	Antrag in Investitionsausschuss	forward investment request to investment committee
Nv6jeal	Zurueck an Investitionsausschuss	return to investment committee
Posf0a	Antrag zurueckstellen	postpone investment request
Qwjtqgj	Projekt: ja / Pruefung in Programmmanagement einreichen	project: yes / audit by program management
Se1fo7u	Antrag weiterleiten an Controlling	forward investment request to controlling
Tfq10u	Genehmigten Antrag neu bearbeiten	revise approved investment request
V0dfwhnz	Antrag weiterleiten	forward investment request

to be continued on the next page

Table A.2: Case Study 1b: Workflow states and transitions (continuation)

ID	Original description	Translation
Wz4k11l	Antragsteller um neue Ueberarbeitung bitten	appeal applicant to revise the investment request
Xpcrs74	Antrag loeschen	delete request

*outdated entry, non-existent in newest workflow version

Table A.3: Case Study 2b: Workflow states and transitions

ID	Original description	Translation
States		
A4uz7se*	Einarbeitung Dispo	disposition training
Astp7uh*	Vorbereitung Personalbuero	HR training
E588cjs*	Vorbereitung Fuhrpark	vehicle fleet training
Eyxzup	Vorbereitung	preparation
Jw2cx3*	Einarbeitung BBVV	BBVV training
L5dp0u*	Vorbereitung IT II	IT preparation II
Msm7moc*	Einarbeitung Lager	warehouse training
NEW	New	new
Pfuifhh	Freigabe QM/Arbeitssicherheit	QM/occupational safety approval
Q3netkb*	Einarbeitung abgeschlossen	complete onboarding
static_state_deleted	Archiv	archive
static_state_new	Neu	new
Vyq3wc	Vorbereitungen der Einarbeitung abgeschlossen	complete onboarding preparations
Wcdv7ic*	Einarbeitung	onboarding
Transitions		
Agc43wt	Person archivieren	archive file
Bvy7k2r	Um erneute Vorbereitung bitten	appeal to review preparation

to be continued on the next page

Table A.3: Case Study 2b: Workflow states and transitions (continuation)

ID	Original description	Translation
Create	0	0
Dpelfws*	Vorbereitung IT	IT onboarding preparation
I6ge286*	Dispo einarbeiten	train disposition staff
Irrzqqd	Person archivieren	archive file
J4yhtwg	Vorbereitung abschließen	complete preparations
Jg3jq2g*	Lagerist einarbeiten	train warehouse staff
Krkwk1p*	Einarbeitung abschließen	complete onboarding
Lbxf4lq*	Einarbeiten starten	initiate onboarding
M2i9m99*	Mitarbeiter einarbeiten	train employee
Mhppqog	Vorbereitungen bestaetigen	confirm preparations
Mhppqog*	Vorbereitungen abschließen	complete preparations
N4n4o8k*	Person archivieren	archive file
Sany3qg*	Einarbeitung abschließen	complete onboarding
Tn6ouq*	Einarbeitung abgeschlossen	complete onboarding
Ts5xwb5*	Einarbeitung abschließen	complete onboarding
Ty7nv9c*	Aufgabengebiet IT	IT area of responsibility
Ucu2ac*	Vorbereitung Fuhrpark	prepare vehicle fleet onboarding
Wokz3ig*	BBVV einarbeiten	train BBVV
Xgf318	Arbeitsbeginn vorbereiten	prepare onbarding

*outdated entry, non-existent in newest workflow version

A.3 Case Study ProM Modules

Table A.4 provides an overview of suggested ProM modules to handle the foreseen activity in the respective phase. It represents a suggestion of an appropriate tool to execute the intended tasks. The focus lies on demonstrating a proof-of-concept rather than the most suitable course of action considering a specific data set. Accordingly, the interpretation of analytic findings hinges on manual interpretation supported by domain expertise. Hence, substitutions may outperform the suggested ProM module considering changing frame conditions. The module descriptions provide further information concerning referenced scientific publications and algorithmic implementation in ProM.

Table A.4: Case Study: ProM modules

Module	Description	Phase
Conformance Checking of DPN (XLog)	Check fitness of process model and event log	3, 5
Convert CSV to XES	Convert CSV file to OpeXES XLog	1, 5
Dotted Chart	Visualize cases versus time in dot chart	1, 5
Explore Event Logs	Analyze the event log regarding variety and occurrences	3, 5
Interactive Data-Aware Heuristic Miner	Analyze multiple perspectives in an interactive environment	3, 5
Log Inspection	Visualize cases	2, 5
Log Summary	Visualize cases with statistical characteristics	2, 5
Log Visualizer	Visualize cases	2, 5
Mine for a Handover-of-Work Social Network	Analyze the collaboration of people independent of activity allocation	3, 5
Mine with Inductive Visual Miner	Analyze multiple perspectives in an interactive environment	3, 5
Multi-perspective Process Explorer - Fitness View	Check fitness of process model and event log	3, 5
Replay a Log on Petri Net for Conformance Analysis	Replay the event log in a process model	3, 5

*corresponding procedure model phase
1 Process Data Collection
2 Process Data Processing
3 Process Data Analysis
4 Analysis Results Interpretation
5 Concept Drift Analysis