Business Process Management: Integrated Data Perspective. A Framework and Research Agenda

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Abstract

Business Process Management (BPM) is confronted with rapidly growing data flows of various types. One established way to address the complexity caused by structured log flows produced by Information Systems (IS) is Process Mining (PM). However, in this approach, unstructured natural language data generated by humans remains uncovered. With the significant advances in Natural Language Processing (NLP), we observe the attention of BPM research and practice shifting towards this type of data. In the study, building on the Task Technology Fit Theory and Contingency Theory, we derive a framework that addresses relevant future research questions in the context of integrated process data perspective, including structured logs and unstructured natural language. The proposed framework considers traditional BPM logics and highlights BPM as a socio-technical discipline.

Keywords: Business Process Management, Natural Language, Log Data, Task Technology Fit, Contingency Theory

1. Introduction

Business Process Management (BPM) constantly undergoes various challenges triggered by internal and external factors. The most significant external factors can be digitalization and vigorous environmental changes, such as recent pandemics. Altered work conditions enforce changing communication channels and technologies to support operational and strategic needs. Remote work is becoming more popular, resulting in a substantial increase in data flows of various types. Notably, online communication triggers the massive generation of natural language mainly stored in a textual form.

In the context of BPM, Information Systems (IS) supporting the processes produce the structured data, i.e., logs, which are analyzed with Process Mining (PM) techniques used to discover processes and bottlenecks, check compliance, and propose process improvements [5]. However, unstructured natural language data massively produced during the process execution remains out of scope in this approach. BPM mainly deals with the quantitative analysis of key performance process dimensions of time, cost, or flexibility without considering textual data. While BPM researchers recognize Natural Language Processing (NLP) maturity and the lack of related research, the mainstream efforts are directed to NLP application in business process (BP) modeling support [1].

These efforts are justified by the fact that BP modeling is a rather labor-intensive and tedious task which becomes even impossible in the current dynamics and leads to BPM project failures [10]. Unquestionably, a BP model remains the primary source for process analysis and improvement. However, recent research shows that a synergetic combination of PM and NLP can provide immediate insights into the actual process execution based on which successful improvement occurs. For example, [27] demonstrate how the event log enrichment with comments resulted in implementing the bots to reduce the delays caused by waiting for information. [19] successfully leverage text analytics and PM to analyze the text from a process perspective, i.e., the flow of activities. This way, the authors minimize human labeling and allow for various process improvements, including training programs. In line with such approaches, emails, comments, chat communication can be used as an additional information source for process improvement.

In fact, though hard to estimate and verify, it is widely assumed that unstructured text accounts for over 80% of data in organizations [35]. This abundance can open new opportunities also for BPM. Hence, as we observe, some research in the intersection of PM and NLP has started to appear. Yet, it remains unclear how it affects and changes the nature of BPM, especially in a larger context of IS and the organizational environment, i.e., what other improvements or possible challenges can be expected.

In the study, we (i) inquire into the potential of integrated process data perspective, i.e., machine- (logs) and human- (natural language) generated data, and its possible positive effect on the BPM success factors and (ii) pose an overall research question of *how such integrated process data perspective can impact BPM research and practice.* This paper provides a framework and research agenda that can pave the way for innovative future studies and theory building. Moreover, we consider BPM as a socio-technical phenomenon, as we highlight the importance of both machine- and human-generated process data. This represents the growing integration of social and technical artifacts within the processes of today's work environments. Since the socio-technical standpoint implies an adaption of BPM settings, we build a multi-view understanding of BPM. The results provide researchers and managers with a structured overview of the possible research questions and success factors concerning (i) IS design, (ii) BPM as a discipline, and (iii) business environment. As a theoretical framing, we use two theories commonly known in the BPM context: (1) Task Technology Fit (TTF) Theory [25] and (2) Contingency Theory [20].

The rest of the paper is structured as follows. Section 2 provides a critical analysis of central BPM logics of a regular business context. In Section 3, we develop a framework that contributes to a deeper understanding of how the integrated process data perspective can impact BPM discipline, IT / IS, and business environment and highlight possible success factors. In Section 4, we summarize and synthesize our points.

2. Traditional BPM Logics and Their Problematization

The research and practice specify three dominant logics of BPM: (1) business processes (BPs) [13], (2) IT infrastructures to support the BPs [54], and (3) BP actors [12]. These three logics determine how process owners, employees, or other stakeholders analyze and (re-)design BPs.

Whereas a declared necessity for further research into the role of BPM in these contexts exists [50], the BPM dynamics in times of digitalization, rapid technological and economic changes have to be addressed. The questions regarding the suitability of prior logics for BPM theory and practice need to be reconsidered [10]. In the study, we critically review the three logics under the integrated process data perspective. In this context, we also note that any BP is carried out in socio-technical arrangements, i.e., under consideration of both machine- and human-generated data types.

Following Alvesson and Sandberg's problematization methodology for generating novel research questions [8], we identify and problematize assumptions following the mentioned three BPM logics. Using dialectical interrogation, we identify three central problematizations regarding traditional BPM that appear under the socio-technical integrated process data perspective.

2.1. Business Processes

BPs are defined as sequences of clearly understood activities that are to be modeled and remodeled when necessary [3]. The core of BPM consists of modeling work whereby the processes are captured, analyzed, designed, and redesigned, which makes up a prevailing research direction in BPM [37]. It follows that the dominant view in BP logic is modeling. Process-relevant textual data, such as process documentation and descriptions, are also mainly used for modeling support, as in the case of the automatic generation of process models and compliance checks [1].

At the same time, continuous developments bring many difficulties for process owners, consultants, and employees to keep updating BP models for all the processes [10]. Process update requests, in which multiple parties' interests need to be addressed, become difficult due to political, economic, and socio-technical reasons [50]. Hence, according to the new logic forced by fast-paced changes, the processes should be highly adaptive and easily configurable [34]. Although we agree with this perspective, much information and stakeholders make the operationalization of a highly adaptive and configurable process approach challenging. In practice, a high level of modeling abstraction, minimal reliance on process models, and more focus on agile work in terms of so-called "light touch" processes are observed [10]. Considering these two different approaches of rigorous and light touch process modeling, we problematize as follows:

P1: *Under conditions of agility, adaptability, and light touch process modeling, integrated machine- and human-generated data will allow process improvements bypassing constant creation and updates of BP models*.

2.2. IT Infrastructure

IT infrastructure is considered a true enabler of any BP. In the sense of the traditional BPM IT infrastructure logic, infrastructure is to be reengineered and aligned with the goals of the BP it supports [18]. As a rule, such efforts extend to larger IS contexts that connect departments, business units, and various stakeholders [33].

By and large, information processing is more advantageous when data of various types and volumes are gathered from different parts of the organization following BP goals, decreasing redundancy and increasing productivity. It is enabled by the assumption that process capabilities rely on information processing, and IT infrastructure is designed to realize the expected information flow [10]. Hence, the dominant view in the IT infrastructure logic is infrastructural alignment in conformity with BP goals.

While we agree with this view, we cannot neglect the effects of the rapid penetration of new data sources and technologies in the IT infrastructure. According to the traditional IT infrastructure logic, every time the IT infrastructure updates are made, they should be aligned with BP goals and vice versa. However, BP goals, same as models, are rigid to change. One possible way to address this problem found in practice is to build independent middleware solutions responsible for all change requests. For example, in the case of changing information processing requirements, an independent data aggregation platform could be an alternative to the constant updates and realignment of IT infrastructure [10]. This way, somewhat infrastructural flexibility can be provided. Considering these two approaches of infrastructural alignment and flexibility, we problematize as follows:

P2: *Under conditions that integrated machine- and human-generated data are becoming a relevant part of BPs, IT infrastructures should be naturally designed to fulfill these conditions.*

2.3. Process Actors

The first processes in the industrialization and factory automation context were designed under the logic that the work steps follow one another [16]. Accordingly, the traditional BP actors' logic relies on the procedural assumption that the actors should strictly follow the process steps in conformity with the rules. This assumption found mutual acceptance in BPM as it facilitates the creation of understandable models [12], making it easy to demonstrate process improvements [30]. In this respect, the provision of exact guidelines and rules on the BP execution is essential.

However, economic and environmental challenges considerably impact the roles and tasks, demanding changes according to the varying work conditions [66]. Dealing with existing employees, hiring new ones, outsourcing activities, employee turnover – all these factors demand certain flexibility in the process roles definition [14]. Moreover, other factors discussed in Subsection 2.1 that complicate keeping process models up-to-date make the procedural assumption of actors' logic problematic. As a response to these challenges, BPM researchers and practitioners' focus shifts towards so-called "mindful" actors capable of improvisations and adjustments to the changing work conditions and making their own decisions based on the collected information [10]. Considering the assumptions of procedural and mindful actors, we problematize as follows:

P3: *Under conditions of non-availability of up-to-date process models and process instructions, it is important to enhance actors' competencies and abilities with the process execution and decision support based on integrated machine- and human-generated data.*

To sum up, we discussed problematizations of the three BPM logics highlighting the integrated data perspective. Accordingly, both machine- and human-generated data play an important role in successfully adapting to the changing work conditions triggered by dynamic developments.

3. Framework Exploring Integrated Data Perspective in BPM

This section aims to build a framework to deeper understand the importance of the integrated data in the modern BPM, its elements, and associated success factors. In the latter, we aim to outline the expected benefits which the framework potentially enables. As a theoretical framing, we use the TTF and Contingency Theories.

The Contingency Theory affirms that organizational performance depends on the fit between an organization and contingencies such as technology, innovation, environmental change, size, culture [24]. In BPM, the Contingency Theory plays a significant role in shifting from the justification of BPM practices' value to understanding the contextual conditions under which they are effective [61].

The Contingency Theory gave rise to the principle of fit in IS, which has become increasingly important in assessing a technology's performance. As a result, the TTF Theory and model were introduced to emphasize the importance of a fit between technology and the individual task to maximize individual achievement. Some IS studies used both the Contingency and TTF Theories in the IS adoption, implying that a task and technology fit is important for IS performance [26].

Similarly, in BPM, the Contingency and TTF Theories are often considered together to reflect the fit between BPs and (i) business environment and (ii) technology correspondingly [65]. TTF concepts initially reflect that positive individual performance is facilitated by the IT capabilities matched to the user's tasks [26]. Extended to organizational context, TTF posits that positive organizational performance is facilitated by the IT capabilities matched to the BPs [33].

These two theories outline the main three elements in our framework, i.e., BPM, IT / IS, and business environment (see Fig. 1). Further, in each of the elements, we identify the relevant constituents. To understand the integrated data perspective in more detail, we propose considering the three framework elements and their constituents in the context of respective research questions.

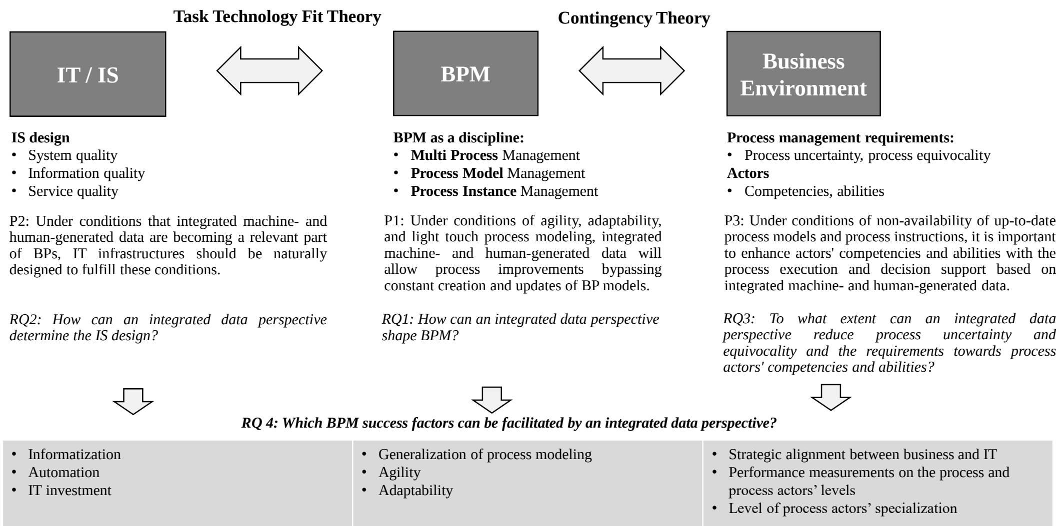

Fig. 1. Framework and research agenda of integrated process data perspective in BPM

First, we define the constituents of the BPM discipline. BPM encompasses a wide range of managerial activities related to BPs. Typically, one differentiates between three layers, i.e., Multi Process Management, Process Model Management, and Process Instance Management [46]. The first layer of Multi Process Management is associated with identifying the organization's major processes and their prioritization. The second layer of Process Model Management deals with managing a single process in a traditional BPM lifecycle, including process discovery, analysis, redesign, implementation, and controlling. The third layer of Process Instance Management is concerned about single enactments of a process, i.e., planning tasks of a process, executing, monitoring, and potentially adapting them to the current setting [1]. All three layers make use of BP models and log data. Hence, this observation proves the gap we focus on in this study: (i) the attention of BPM researchers and practitioners is directed towards structured machine-generated data and process modeling and (ii) the lack of integrated machine- and human-generated data perspective. In this context, we refer to P1 and formulate the first research question (RQ):

RQ1: *How can an integrated data perspective shape BPM?*

Second, we define the most important constituents of IT / IS. Due to the new challenges, experts are working to improve the functionality and quality of solutions [67]. The quality in IS design has been investigated as the function of the second-order structures, such as system, information, and service qualities [32]. System quality is described as the degree to which users believe that systems are enjoyable and straightforward to use, connect, and learn [52]. Information quality refers to the degree to which users view information as reliable, detailed, timely, structured, and up-to-date [28]. Service quality is described with reliability, assurance, tangibility, responsiveness, interactivity, empathy, and functionality [43]. In the study context, two viewpoints are noteworthy: (1) IS design should enable the capture of both machine- and human-generated data types, (2) IS design quality constituents should be partially obtainable (measurable) from the data captured in the IS usage. Hence, we refer to P2 and formulate the second RQ:

RQ2: *How can an integrated data perspective determine the IS design?*

Third, we define the most important constituents concerning a business environment. As a rule, processes reflect the environment where they are performed [44]. Hence, in the study, we summarize the environment's properties with the two process management requirements according to the Organizational Information Processing Theory [23]: (1) process uncertainty determined by the amount of information required to perform a process and (2) process equivocality defined by the ambiguity of interpretations, i.e., information quality [69]. These requirements differentiate one process from another and describe the contingencies typical for a given environment. In addition to process characteristics, people, i.e., process actors, make up another important constituent of a business environment. Hereby, we consider such actors' characteristics as competencies or abilities that differentiate one actor from another and lay the ground for successful performance [11]. Accordingly, we refer to P3 and formulate the third RQ:

RQ3: *To what extent can an integrated data perspective reduce process uncertainty and equivocality and the requirements towards process actors' competencies and abilities?*

As follows from Fig. 1, the fourth research question is devoted to the BPM success factors. In the study, we suggest revisiting this significant yet understudied topic in BPM to highlight and specify the framework's benefits. Today, organizations often use the term BPM as a trendy established concept rather than implement it. Not only is BPM resource-intensive, but it also reveals a large number of failed projects and programs [65]. In this respect, the knowledge on (critical) success factors gains importance. For BPM, somewhat similar and generic success factors are suggested, such as top management support, project management, communication, cooperation, and end-user training [33]. Success factors studied in the IS context, such as leadership and investment, are also applicable to BPM [45]. Here similarly, we detect a strong influence of the IT / IS on the BPM development. Hence, in the study, we urge to reconsider the BPM success factors under an integrated data perspective and formulate the fourth RQ:

RQ4: *Which BPM success factors can be facilitated by an integrated data perspective?*

Using existing established literature, we attempt to suggest and map the selected exemplary success factors according to the three framework elements (see Fig. 1).

In the following subsections addressing each of the RQs, we discuss the theoretical and practical research developments indicating potential research directions, implementation possibilities, and challenges.

3.1. Foundations for RQ1

In times of fast-paced changes of various nature, agility and adaptability become one of the main requirements for successful organizational functioning [31]. Under these conditions, BPM sets out to consider human-generated natural language to support the modeling activities. Referring to the already mentioned three layers of BPM, there is solid prior research in respect to (i) Multi Process Management, such as identifying the similarity [17], matching [68] and merging of process models [60], textual-based [39] and semantic [64] search and (ii) Process Model Management, such as a transformation of textual descriptions into process models [22] and vice versa [42], text annotations [62], multiple languages, semantic quality check [41], and compliance check [2].

However, all these cases are closely related to texts describing BP models or textual data inherent in BP models, such as labels. The research works considering an integrated perspective of structured logs and natural language generated in the processes have recently started to appear, suggesting process analysis and improvement approaches that bypass the laborious and resource-intensive process modeling work, see [19], [27] presented in the introduction section.

From an implementation viewpoint, further exploitation of PM algorithms' enrichment with various text analytics techniques can open new process improvement opportunities. Hereby, word ambiguity and semantics remain the main challenges, like (i) a correct match of the pronouns to the related nouns or several different expressions in text meaning the same thing and (ii) identification and correct match of activities' concurrency, iteration, and decision points described in text [1].

To sum up, it is essential to follow such research endeavors and discover the implications of how and to what extent an integrated data perspective can contribute to agility and adaptability in BPM.

3.2. Foundations for RQ2

The Big Data boom with economic and social transactions going online has generated new demands. The ability to understand the structure and content of the human speech has significantly increased the dimensionality of the available data sets. Such challenges lead to research on better IS design [6].

IS discipline relies on two complementary but different sciences: (1) behavioral science related to human or organizational behavior and (2) design science related to innovative IS artifacts [29]. Regarding the investigation of human behavior with respect to behavioral science, much research exists to analyze the synergies of IS design and natural language, i.e., NLP, in general [47] and in addressing specific challenges such as large-scale NLP [7], ethical design for NLP [36], building NLP pipelines [55, 56]. In BPM, one of the suggested research directions is the design of conversational systems based on semantic understanding, context resolution, and language generation that would guide process actors through the process [1].

Regarding the IS design and IT artifacts in BPM with respect to design science, one popular approach is the so-called Process-Aware IS (PAIS), executing operational processes based on the process models [4]. Additionally, much research is done on the specific IS design questions based on Process Mining (PM), for example, privacy and system design in the Internet of Things (IoT) [48], PM-enabled decision support systems (DSS) [21], PM-enabled design issues in healthcare [57], to name a few.

As can be concluded from above, IS design implementation technologies and challenges reveal both well-known generic and IT artifact- and domain-specific trends. For example, using natural language as a direct input for conceptual design, finding an appropriate mapping between sentences and objects in the database and operations [47], scalability of text processing and architectural challenges [7], the societal impact of data collection and usage [36], algorithmic and text representation choices in building NLP pipelines [55, 56] are well-known generic challenges related to NLP in the IS context. In the design of specific IT artifacts, we observe such challenges as user-friendly design, seamless navigation and viewing of BP models in PAIS [4], privacy concerns in IoT [48], implementing concrete task-level support in DSS supporting BPM projects [21], adapting the generic approaches to specific domains like healthcare [57].

Hence, in the unified view of IS artifact- and NLP-related challenges, IS solutions which (i) gather, store, and re-use both data types ensuring their quality, (ii) address IS architectural challenges ensuring system quality and this way (iii) increase service quality are relevant research directions.

3.3. Foundations for RQ3

Due to a rather broad definition of a business environment, we limit the scope to the process perspective and consider the business environment through the lens of the process management requirements, i.e., process uncertainty and equivocality, and process actors' competencies and abilities. Increasing the amount of information with an integrated data perspective may help decrease the uncertainty but is ineffective in high equivocality cases. Here, it is essential to assist process actors with various interpretation solutions [15].

Process uncertainty and equivocality have been widely addressed in PM [49], [51]. NLP techniques have also been used to solve these problems. However, the usage is mainly limited to process models, i.e., already mentioned process model semantic quality [41] and compliance check [2].

Concerning process actors, the PM approaches have recently started to explore the "social" aspects of the processes. For example, [63] examine PM from a socio-technical perspective by conceptualizing a PM-based approach to improve work conditions. Furthermore, mentioned in Section 3.1. [19] and [27] demonstrate synergetic usage of PM and NLP in the IT ticket processing scenario and customer service of a financial software company. Another new direction in supporting process actors with PM techniques is Robotic Process Mining aiming to detect those routine tasks that should be automated [38]. At the same time, NLP has been widely implemented in business to enrich process actors' abilities in dealing with large amounts of textual data [9].

The implementation possibilities and challenges of RQ3 are closely related to and can be derived from those of RQ1 and RQ2, for example, semantic considerations in automatic extraction of meaning from textual data [1], user-centricity [4], privacy [48], and ethics [36] in IS design.

To sum up, an integrated data perspective naturally enhances the amount of information, helping to reduce process uncertainty. Various PM- and NLP-based solutions processing, interpreting, and making this information useful are essential to deal with process equivocality. Moreover, an integrated data can empower the research on the "social" part of PM, better addressing process actors' needs and helping them adapt to the dynamic transformations in BPs.

3.4. Foundations for RQ4

Following the declared need for the research on success factors in BPM caused by a large number of BPM failures [65], we suggest that an integrated data perspective can be advantageous for realizing success factors. This helps us to outline related benefits. See Fig. 1 for our proposal exemplarily highlighting, but not limiting to, the success factors in each of the three framework elements of BPM, IT / IS, and business environment. Below, we discuss the success factors starting with the BPM discipline.

In BPM, the level of details with which processes should be modeled, or generalization of process modeling, is a well-known problem [53]. An integrated data perspective contributes to this first success factor allowing for light touch BP models. This view underpins the idea that processes can be modeled and organized on a high abstraction level to support agility and adaptability. This approach will reduce the human efforts needed for creating and updating the BP models, enable process analysis and improvements bypassing the laborious modeling activities, and eventually decrease BPM project failures.

In the second framework element, IT / IS, informatization is an established success factor to ensure adequate support from IT / IS [65]. We propose that an integrated data perspective will positively influence informatization while providing various information sources. Informatization is closely related to another success factor, automation, i.e., the use of IT to support or replace process actors in the execution of, as a rule, routine tasks [65]. Here, both data types, logs [38] and natural language [40], [59], appear to be useful in identifying task automation candidates. Finally, we believe that the benefits derived from an integrated process data usage in BPM can provide arguments and justify the third important success factor, i.e., IT investment. Hence, with respect to IT / IS success factors, the consideration of both data types increases the informatization level of the processes providing (more) data sources for adequate IT / IS support, automation projects, and IT investment acquisition.

In the third framework element, business environment, strategic alignment is considered one of the essential factors for reaching the long-term success of BPM programs [65]. Whereas the term strategic alignment includes many constituents, we propose that an integrated data perspective can facilitate the alignment of business and IT. Log data naturally contains information about IT functioning. The business information is likely to be captured in an unstructured textual form, as the most typical data type in organizations [35], [58], and can be used to gain valuable insights, as suggested in [59]. Similarly, an integrated view can be favorable for measuring the performance on the process and process actors' levels [60], [65]. Lastly, we propose that the trade-off between specialists and generalists can be better addressed through enhanced decision-making enabled by integrated data. Thus, the mentioned success factors are beneficial for organizational and employees' performance increase.

For future research, we suggest exploring in-depth the suggested success factors (and beyond) and the role of integrated data, specifically in case study settings.

4. Conclusions

The introduced framework and research agenda demonstrate the multi-view of BPM-related elements structured and justified based on the TTF and Contingency Theories. We focus on the three main elements: BPM as a discipline, IT / IS, and business environment, and their constituents. Next, we problematize the traditional BPM logics regarding BPs, IT infrastructure, and process actors and derive the RQs. Finally, we enrich each framework element with the success factors that an integrated data perspective can facilitate.

We suggest the framework as a guideline for prospective qualitative and quantitative studies based on a structured view of the RQs to investigate the potential of the machine- and human-generated process data in BPM. The framework implies elementary yet future challenges and opportunities. We emphasize the importance of the "social", i.e., "humanistic", aspects of BPM in times of increasing digitalization and convergence of organizational structure and digital infrastructure. Recognizing BPM as a socio-technical phenomenon, we aim to understand its synergetic effects on BPM as a discipline, IT / IS, and business environment expressed by the specified constituents. We consider the interweaving of PM and NLP as an essential determinant of BPM future research under the growing importance of natural language and NLP maturity.

To deeply exploit the potential of the integrated data perspective, we resume the discussion on BPM success factors. We set future research directions to understand how increasing integration of machine- and human-generated data can positively impact the establishment of BPM success factors.

For future research, through focused discussions, we suggest (i) critically reviewing the traditional BPM logics and studying (ii) how an integrated data perspective evolves in BPM in general and in particular, i.e., according to the proposed three framework elements and their constituents, and (iii) which benefits for the realization of success factors can be derived.

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