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A Conceptualization and Operationalization of Process Visibility Capabilities

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Abstract. Lately, a trend towards real-time, process-centric Business Intelligence & Analytics on the operational level has emerged. Although there are various systems such as BAM, BPI or CEP that claim to deliver visibility for operational processes, the underlying capabilities remain vague. To close this research gap we present a conceptualization and operationalization for process visibility capabilities. We use the results of a literature analysis and expert interviews for the conceptualization of the respective capabilities. The operationalization is based on existing literature and refined in two academic feedback sessions as well as one card sorting procedure with experts from practice. Our results contribute to a better understanding which capabilities create process visibility and provide a basis for future research.

Keywords: Process Visibility, Business Intelligence & Analytics, Process Intelligence, Conceptualization, Operationalization.

1 Introduction

To meet growing business pressures firms increasingly employ Business Intelligence & Analytics (BI&A) – particularly for processes on the operational level. A multitude of concepts, methods and underlying software packages exist: They include Operational Business Intelligence [1], Business Process Intelligence [2], Business Activity Monitoring [3] or Complex Event Processing [4]. Process visibility captures the trend towards operational, process-centric decision support [5]. It labels the ability to access, analyze and share process information in an operational context [6].

Although the concept of process visibility is well-grounded in literature, it remains vague which underlying capabilities are important to make process information visible on the operational level [6]. A more thorough understanding can help to guide IT investments more effectively. For instance, software packages may be ranked along visibility capabilities to find the most fitting solution. In addition, the fit between process visibility capabilities and process visibility requirements may help organizations to prioritize IT investments [7]. As a basis, a deeper understanding of the technical IT capabilities that establish visibility for business processes is needed. This leads to the following research question:

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How can Process Visibility Capabilities be conceptualized and operationalized from an information technology perspective?

The remainder of the paper is structured as follows. First, process visibility and related research are described to create a common fundament for the conceptualization and operationalization of process visibility capabilities. Second, the research methodology is outlined. Third, the process visibility capabilities construct is conceptualized. Next, the operationalization from a technical IT perspective is introduced. The paper ends with a conclusion that includes limitations and areas for future research.

2 Conceptual Foundations

Process visibility describes the ability to share, access and analyze process information [6]. It includes "[…] information about process characteristics, performance and outputs […]" [8]. "The extent of Process Visibility depends on the degree to which process information is contextualized, relevant, trusted, timely, and integrated" [5]. It is targeted towards business users and independent from a concrete technology while capturing an explicit end-to-end focus on processes. Through the usage of measures, such as KPIs [9, 10], and analytical techniques [11] problems can be identified in a timely manner. This creates the opportunity to take proactive actions – especially if derived insights are easy to understand and directly usable [12]. Related literature from the area of supply chain management shows that increased visibility can improve operational performance [13] as well as flexibility, decision making and coordination [14] amongst others.

In the following we provide a more detailed description of process visibility along various dimensions that are adopted from existing literature [2, 7, 15, 16]: First, we define the *construct entity and property*. In line with supply chain visibility research [17], process visibility describes an outcome that can be evaluated along several information quality dimensions [5]. Accordingly, the differentiation between process visibility and the respective capabilities that create process visibility is important. Second, the *major process phase* can be described from a process lifecycle perspective: Process visibility is a phenomenon which is native to the monitoring phase of business processes and targeted towards the creation of end-to-end visibility during process execution [18]. Third, the *major decision support phase* can be defined. Process visibility constitutes the basis for decision making through the delivery of important process information. This understanding conforms to existing research, which considers process visibility as an antecedent for decision making [18]. Also in supply chain management visibility is seen as information that supports decision makers [19]. Fourth, the *process reach* of process visibility focuses on operational processes and encompasses both interorganizational and intraorganizational processes. Fifth, the *management level* of process visibility is characterized. Visibility is specifically relevant in an operational context [5] and suited for decision makers to monitor and support day-to-day processes. Sixth, as an operational concept the *range of users* is a broad. It is important for each process worker who handles specific process instances [18]. Seventh, similar to the concept of supply chain visibility, process visibility is not related to a certain *type of technology*. Thus, process visibility can be created by various IT infrastructures, such as service-oriented architectures (SOA), event-driven architectures, or a self-learning architectures [20]. Eighth, to characterize process visibility we also consider the *time relevance*. For the identification of problems during process execution, the timely availability of information is essential [5]. In the domain of BI, this is often referred to as “real-time” information availability. This separates process visibility from traditional BI which uses historical data from data warehouses [21]. Ninth, *information sources* refer to the origin of data used for the creation of process visibility. From a process perspective, information can origin from the process itself as well as from other sources, such as other related processes. Finally, the concept can be differentiated considering the *kind of information*. A traditional data warehouse is primarily based on structured data [22]. In contrast, both structured and unstructured data is useful for the creation of process visibility, as “[…] unstructured data provides valuable contextual information for more informed operational decision making” [22].

3 Research Methodology

The research methodology follows a five-step approach (Fig. 1) that is adopted from seminal literature in construct conceptualization and operationalization [15].

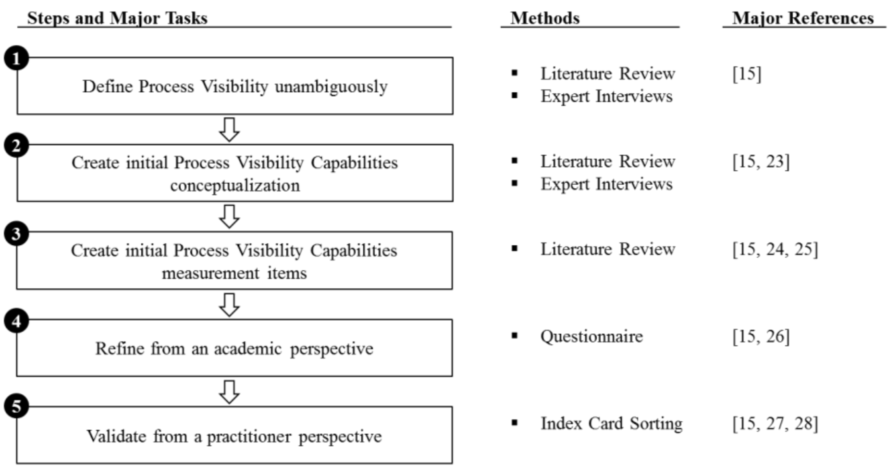

Fig. 1. High-level Illustration of the Research Methodology

In a first step the process visibility concept was defined unambiguously based on a systematic literature review (see previous section). In a second step a conceptualization of the process visibility capabilities construct was derived. The conceptualization is theoretically grounded in the Information Processing View (IPV) [29–31]. All working definitions of the construct were presented to academics to gather additional feedback. The collected input was then used to inform and refine the understanding of the construct. This procedure is appropriate, as especially in novel domains the construct and scale can evolve together [25]. Subsequently, in step three, an initial set of 26 measurement items were derived from academic literature to operationalize the construct. The items referred to technical capabilities and considered the process level as the unit of analysis. The measurement based on a 7-point Likert scale anchored from "strongly disagree" to "strongly agree". The measures were refined from an academic perspective in step four. To do so, questionnaires were distributed to academics, which instructed them to rate the suitability of the individual measurement items and to provide additional comments on the measures and the conceptualization. To improve the overall quality of the measurement items, two academic feedback rounds were conducted. Finally, in step five the refined measurement items were validated from a practitioner perspective. Six card sorting interviews [27, 28] were conducted with practitioners who work at a large software vendor. All results were analyzed to improve the measurement item quality.

4 Conceptualization of Process Visibility Capabilities

4.1 Theoretical Foundation

We choose the IPV as theoretical foundation for the conceptualization of process visibility capabilities. It describes information processing as "[…] the gathering of data, the transformation of data into information, and the communication and storage of information in the organization" [32]. The creation of visibility requires these information processing activities that are outlined in the IPV [33, 34]. Drawing from the IPV, this study interprets process visibility capabilities as an IT-based information processing mechanism. This is consistent with prior research, which views certain types of IT systems as information processing mechanisms [35]. Accordingly, process visibility capabilities describe the ability of IT to gather, analyze and disseminate process information (Table 1). Consequently, process visibility capabilities is defined as a multi-dimensional construct [15] consisting of three formative sub-dimensions. All three sub-dimensions are introduced in detail in the following subsections.

Table 1. Dimensions of Process Visibility Capabilities

Dimension	*Definition*
Process Information Gathering	The ability of information technologies to collect and integrate process information from various sources for a specific process.
Process Information Analysis	The ability of information technologies to systematically transform process information into meaningful knowledge.
Process Information Dissemination	The ability of information technologies to distribute meaningful process information to a broad range of process participants on the operational level in a usable format.

4.2 Process Information Gathering

Business processes can reach across multiple organizational units and across complete organizations [36]. Frequently, they are implemented across multiple systems. This generates various challenges for a unified end-to-end view on processes [18]. To create such visibility IT needs the ability to collect and "[…] integrate information from various sources and systems […]" [20]. With regard to the IPV data integration is seen as one mechanism to meet uncertainty [37]. Furthermore, the collection of the right information is seen as a prerequisite for effective information processing [31].

For the identification of root causes in processes, a high level of detail might be needed, which makes detailed information gathering important [8]. In addition, it might be necessary to collect information from sources which are external to the process. Thus, especially in dynamic, information-rich environments decision makers need timely and accurate information, which creates additional focus on the monitoring of external information to recognize changes in the environment [38]. In the process context, this is specifically relevant, if external data from other processes is needed for the process execution [39].

To meet the above mentioned challenges, process information gathering capabilities of IT are essential. In our context, information gathering refers to both information collection from internal as well as external sources. In summary, process information gathering is defined as the ability of information technologies to collect and integrate process information from various sources for a specific business process.

There are different technologies, which support the gathering of process information from various sources and systems. Key technologies include enterprise application integration technology [40] and sophisticated IT infrastructures, such as event-driven architectures or service-oriented architectures which provide a fundament for effective information collection [20]. A promising method to gather process information from various sources suggests the usage of non-intrusive techniques based on data traces created during process execution [18].

4.3 Process Information Analysis

The analysis of information is a critical task in information processing as it has the purpose "[…] to translate information into specific knowledge that can be used by managers and organizational members to achieve the purposes of the organization" [41]. From an IT perspective, analysis capabilities can be especially found in the area of BI&A. They enable the analysis of high volume data to derive vital information for decision making [42]. Through the creation of insights and the identification of opportunities [43, 44], those capabilities enable a shift from a reactive to a proactive responses to changes [45].

In the process visibility context, the time criticality of operational decision making has to be considered. Thus, sophisticated analytical tools, which require time consuming and labor intensive analysis, are often not suited for the operational level [46]. As a consequence, the IT systems should analyze process information in an almost automated way to derive information which is meaningful for business users. This can be achieved by embedding knowledge in IT artefacts [47], which is then used to transform data into information and lower value information into higher value information [48]. For instance, based on historical data, predictive models can be created through data mining and process mining techniques which are then used to predict the performance of running process instances [49].

The paper at hand considers process information analysis as part of process visibility capabilities. Process information analysis is defined as the ability of information technologies to systematically transform process data into meaningful process information. Transformation techniques include statistical and quantitative analysis as well as the usage of explanatory and predictive models [50]. Meaningful information is only created when the data is set in the right context [51]. Accordingly, data must be set in the process context through the analytical capabilities which are embedded in IT. KPIs about running processes are a typical example of meaningful process information, as they provide direct decision support [10]. In detail, there are two general types of metrics which can be differentiated in the process context [11]. Generic metrics, such as the cycle time, exist for all types of processes [11]. In contrast, user-defined metrics apply only to certain processes [11], but can be highly valuable.

There are various technologies and methods that support process information analysis. They range from basic descriptive techniques to advanced predictive and prescriptive capabilities (Davenport & Harris, 2007). Specifically relevant are key performance indicator managers, data mining tools and rule engines, which are often part of a BAM system [46]. Further, BPI tool suites can be used to analyze currently executed process instances in different ways [49]. CEP is another technology to derive valuable process information, as it has the ability to detect complex patterns in running processes [52].

4.4 Process Information Dissemination

"The best information will be wasted if it is not routed to the people in the organization who need it to perform their jobs" [8]. The concept of process information dissemination captures this aspect. On the organizational level, information dissemination generally refers to the exchange of information within an organization [53]. In the area of knowledge management, dissemination describes the distribution of information to persons who need it [54].

Applying those definitions to process visibility capabilities, process information dissemination refers to the ability of information technologies to distribute process information to a broad range of process participants on the operational level in a usable format. Based on an existing stakeholder definition [55] a process participant refers to any group or individual who can affect or is affected by the business process. Operational decision makers in a process may be one example in this regard. Process information dissemination should be role-specific, as information requirements can vary across job roles depending on the underlying contextual characteristics [56, 57]. This ensures that information is easily comprehensible to derive possible actions from it quickly [58]. Further, this aspect is central to reduce information overload [59, 60]. Additionally, it is beneficial to enable a fast analysis of the information by the recipient [59] with a consistent and comprehensible presentation format. From an IPV perspective, the presentation of information in a comprehensible and routine way reduces equivocality [61]. In addition to giving process participants basic access to process information, especially the time criticality on the operational level can make it necessary to push messages directly to the users in form of alerts [59]. For instance, in supply chain processes automatic alerts can be generated by IT when the inventory level reaches a certain threshold [62].

Technologies which support process information dissemination include but are not limited to dashboards, web portals and mobile applications [63]. If a process spans across multiple organizations, contemporary information exchange technologies such as internet electronic data interchange can be used [64]. In the area of finance, data exchange standards such as the eXtensible Business Reporting Language (XBRL) are already applied [65].

5 Operationalization of Process Visibility Capabilities

5.1 Item Generation and Academic Item Refinement

As a basis, an initial set of 26 measurement items was derived to operationalize the three sub-dimensions of the process visibility capabilities construct. In a first round, evaluation questionnaires were distributed to four academics with substantial experience in empirical research. To assure understandability and clearness of instructions, the questionnaire was constructed based on an existing questionnaire used in a scale development study in the business process domain [26]. The questionnaire provided respondents with an introduction into the research project and an explanation of major characteristics of process visibility. A working definition of the three process visibility capabilities dimensions was provided. Participants were asked to rate how well a given measurement item fits the overarching construct definition (from 1 – "fits extremely poorly" to 7 – "fits extremely well"). Further, they were asked to provide comments on ambiguous or unclear items and suggest further measurement items.

The results of the first evaluation round were analyzed. In line with previous research [26] a rank-ordered list with average ratings of the individual measurement items was used. Afterwards, all working definitions of the construct dimensions were refined. The wording of several items was revised based on the received comments.

A second evaluation round was conducted with the refined working definitions and measurement items. Questionnaires were administrated to four academics, two of whom had participated in the first round. The working definitions of the individual constructs received superior feedback than in round one. Furthermore, the mean rating of Process Information Gathering (PIG) related measurement items increased from 4.6 in round one to 6.2 in round two. The mean rating of Process Information Dissemination (PID) related measurement items increased from 4.4 to 5.6. Only for the Process Information Analysis (PIA) dimension, the rating declined from 5.1 to 4.6. As a result, the working definition and several measurement items were slightly refined following input from the participants.

5.2 Practitioner Item Validation

Following the academic refinement, the measurement items were evaluated from a practitioners' perspective using a card sorting technique. Six experts from a leading software vendor with long-year BPM experience and in the development of a process visibility related software product joined the card sorting. All participants received an introduction to the research project and the procedure. Additionally, a trial sort with examples from the automotive industry was conducted to familiarize the participants with the methodology [27]. Next, participants were asked to sort 26 randomly shuffled measurement items into the three construct categories of PIG, PIA and PID based on the formal construct definition which was provided. Within each construct category the items had to be ranked priority-wise. An category "other" was added for items, where respondents felt that the item did not fit in any category [27]. This identifies ambiguous items and delivers further input for the quality of the items.

In a first step a placement matrix (Table 2) was created from the sorting results of all participants [27, 66]. On average 85 percent of the items were placed into the intended category. Only three items were assigned to the dimension "other" indicating content validity for the overarching process visibility capabilities construct. The correct placement ratio was specifically high for the PIG items. High values in the off-diagonals between actual and target category can be an indicator for construct ambiguity, item ambiguity or a combination of both [27]. Ten items of the PIA construct were placed into the PID category and nine items of the PID construct were assigned to the PIA category. This indicates that only some items tap into the content domain of both, the PIA and PID construct. In addition, the interrater reliability of the sorting was evaluated by the average kappa [67] between each pair of sorters. A result of 0.64 indicates good reliability and is close to the recommended threshold of 0.65 [27].

Table 2. Results of the Card Sorting Procedure

	Actual Category				
Target Category	*PIG*	*PIA*	*PID*	*Other*	**Rate** (⌀ 85%)
PIG	**35**	1	0	0	97%
PIA	1	**49**	10	0	82%
PID	2	9	**46**	3	77%

The following tables provide an overview of the final measurement items and their evaluation in the practitioners' card sorting procedure (Table 3-5). The column "Correct Placement" shows the number of correct placements within the six card sorting sessions. The column "Normalized Priority" indicates the relative position an item received in a category. For instance, if an item was placed on the first position (i.e. it had the highest relevancy for a participant) within a specific category, it received rank one. For comparability the rating was normalized and the average for all participants was calculated. Finally, the column "SD" indicates the standard deviation. Items with three or less correct placements are sorted out for the final set of measurement items (see crossed out items in tables).

Table 3. Measurement Items for Process Information Gathering

Item Wording	*Correct Placement*	*Normalized Priority*	*SD*
IT enables us to capture granular (detailed) events in the entire process [68]	6	0.64	0.31
IT enables us to collect process information along the entire process in a timely manner [10]	6	0.58	0.43
IT enables us to gather process information from all steps (activities) in the process [49]	6	0.48	0.28
IT enables us to collect process information from the external process environment in a timely manner [41, 69]	6	0.36	0.40
IT enables us to collect granular (detailed) information about a processes' current status [68, 70]	6	0.35	0.27
IT enables us to integrate process information from a variety of data sources [20, 71]	5	0.29	0.29

Table 4. Measurement Items for Process Information Analysis

Item Wording	*Correct Placement*	*Normalized Priority*	*SD*
Our IT has the ability to aggregate process data into key performance indicators [20]	6	0.81	0.20
Process information, such as process-level key performance indicators, are continuously calculated by our IT systems [72]	6	0.74	0.09
Our IT has the ability to analyze process data to continuously measure process performance [73–75]	6	0.62	0.30
Based on preset levels (thresholds), IT can automatically detect deviations from process plans [76]	6	0.42	0.15
Based on process data, our IT has the ability to identify the state of multiple processes, contextualized by their relationships [70]	6	0.19	0.27
IT allows us to benchmark the performance of currently executed business processes [75]	5	0.35	0.29

Item Wording (cont'd)	*Correct Placement*	*Normalized Priority*	*SD*
IT enables us to predict final results of the business process during process execution [10]	5	0.22	0.17
Our IT offers extensive analytical capabilities to examine process information [77]	4	0.22	0.39
~~IT enables us to anticipate problems or opportunities in the process in a timely manner [41]~~	3	0.14	0.16
~~Before presentation, process information is filtered by IT to reduce information overload [41]~~	2	0.32	0.49
Crossed out items: Sorted out for the final set of items due to three or less correct placements			

Table 5. Measurement Items for Process Information Dissemination

Item Wording	*Correct Placement*	*Normalized Priority*	*SD*
Process information is distributed to process participants (e.g. operational decision makers) along the entire process [8]	6	0.62	0.38
IT can notify the concerned process participants regarding events that may require adjustments [76]	6	0.52	0.34
Using IT, process information is widely shared among process participants [78]	6	0.44	0.41
Process information is delivered to process participants through simple, understandable tools [79]	5	0.50	0.42
IT allows users to create personalized monitoring views, which let them see only the process information they want to see on the system [3]	5	0.49	0.31
Process information provided by IT often reaches relevant personnel timely enough to be of use [80, 81]	5	0.44	0.40
Through IT, process information, such as process performance metrics are presented to process participants [75]	5	0.35	0.25
~~IT displays process information in a readable, easily understandable format [82]~~	3	0.27	0.37

Item Wording (cont'd)	*Correct Placement*	*Normalized Priority*	*SD*
~~Processes and their outcomes are visualized in an easy and comprehensible format [10]~~	3	0.26	0.39
~~IT enables us to distribute process information along the process in a timely manner [83]~~	2	0.23	0.37
Crossed out items: Sorted out for the final set of items due to three or less correct placements			

6 Conclusion

This paper conceptualizes and operationalizes process visibility capabilities. Theoretically grounded in the IPV, we derive process information gathering, process information analysis, and process information dissemination as three sub-dimensions of process visibility capabilities. Afterwards, a carefully crafted operationalization procedure identified 21 measurement items. The procedure comprised the initial derivation of measurement items, two academic feedback rounds for refinement as well as a final card-sorting with industry experts.

There are specific limitations to this work. First, the initial generation of measurement items relied completely on academic literature. Although the basis in prior research assures high item quality, future endeavors can incorporate other techniques such as focus group interviews for the generation of measurement items. Second, the academic refinement cycles were conducted with personnel from one research group and the card sorting interviews were conducted with experts of one large software vendor. Consequently, the refinement results may be biased. Future research could include a more diverse group of academics. Furthermore, experts of other software vendors as well as users from deploying organizations could help to establish a more diversified setting. Third, future research could further advance the measurement items for process visibility capability. In this regard, it could be tested if a further breakdown of the sub-dimensions of process visibility capabilities is beneficial.

Several contributions of this paper can be highlighted. From a theoretical perspective, the conceptualization of process visibility capabilities establishes a common understanding of the underlying capabilities that are crucial for the creation of process visibility. In this regard, a clear and unifying concept for the trend towards operational, process-centric decision support has been derived. From a practical perspective, IT investments can be guided based on a clear understanding which capabilities are needed for the creation of process visibility. This paper identifies such relevant capabilities and provides measurement instruments for them. As suggested by [7], the comparison between current process visibility capabilities and corresponding process visibility requirements is useful to detect visibility gaps that benefit from appropriate investments. A web-based tool for this assessment will be available shortly. The tool incorporates previously derived measurement items in the evaluation. Practitioners can use it for an easy and convenient visibility assessment. The collected data will be synthesized towards a benchmark that shall provide further indications for practice.

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