The Technological Maturity of Process Mining: An Exploration of the Status Quo in Top IS Journals

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Abstract

This paper reviews top IS journals to explore the status quo of process mining as a technology. We use a three-category classification scheme that emerged from synthesizing prior maturity models from an ERP and a business analytics context. The three categories string together the organizational and system-orientated perspective and add a focus on digital services. The tentative results from screening twenty-two top IS journals show that thus far publications within these journals have dedicated attention primarily to the first category, single systems. Cross-system or cross-organizational process mining is underrepresented as well as the analysis of services with non-digital components. However, the results also suggest that process mining is on the cusp of becoming a technology that allows new insights into consumer processes by supplying business operations with detailed information to tailor the customer experience.

1 Introduction

We all know the feeling. You have been traveling for hours, so when you finally arrive in a new city, you really do not want to spend too much time trying to figure out how you get to your next stop. A GPS navigation device helps you out.

Process mining refers to “the idea […] to discover, monitor and improve real processes (i.e., not assumed processes) by extracting knowledge from event logs readily available in today’s (information) systems” (van der Aalst 2011, 8). Similar to the observation at the beginning of the section, van der Aalst (2009) used the analogy of a navigation system a few years ago to point to the direction in which business process management should transform itself. He noted that process mining is a technology having the potential to create detailed process maps of the reality to serve different purposes just like a navigation system does.

Six years after, in this paper we aim to evaluate the status quo of the technology of process mining and its potentials. Prior reviews of the literature have tapped into other important aspects, such as algorithms (Tiwari et al. 2008; Yang and Su 2014) or tools (Turner et al. 2012). However, we note a gap in our field’s understanding with regards to process mining’s technological maturity, its application fields, and its link with service management. In this paper, we provide an overview of the progress of process mining as a technology. By analogy to similar technologies, we develop a categorization scheme to determine the progress that has been made so far and we point to interesting emerging research directions.

In 2007, van der Aalst et al. mentioned three limitations of process mining: first, its dependency on log files, second, the constraints of workflow management systems (WfMS) and third, the caveat of privacy issues. To determine the current status of the technology, it is also of critical importance to re-examine what progress has been made to overcome these three limitations.

The IEEE task force on process mining (van der Aalst et al. 2012) referred to a “digital universe” offering new opportunities. With more and more non-digital artifacts becoming equipped with sensors and internet access (Yoo 2010), the number of potential log files increases and therefore also the fields of application. Whereas streaming music via the internet is a digital service as it occurs entirely online, think of the delivery of a parcel as a service with non-digital components. Postman and customer interact upon delivery. While the interaction remains offline, it is supported by an IT system, in this case a barcode scanner.

Although business models become increasingly digital (Bharadwaj et al. 2013; Eaton et al. 2015), most services today are not yet completely digital but composites of different kinds of digital and non-digital services. For the purpose of this article, we define service broadly as “the application of specialized knowledge skills through deeds, processes, and performances for the benefit of customers” (Vargo and Lusch 2004, p. 2). For instance, a customer buying an article in a web shop (digital service) receives it by a dispatching service (non-digital). According to this view, services are situated on a *continuum* between completely non-digital and completely digital ones. In the latter case (digital services), the provider firm’s knowledge is fully packed into algorithms and machines and made available in real time.

One interesting observation in this line of thought is that sensors and internet-accessing (e.g. mobile) devices constitute an additional layer on top of even non-digital services that may be exploited by process mining techniques. Although van der Aalst already advocated for using process mining as a technique to analyze *services* (van der Aalst 2011), he narrowed his focus to *web services*, rather than a more holistic service understanding, including non-digital services.

To gain deeper insight into process mining as a technology, we focus on two research questions:

(1) How mature is process mining as a technology?
(2) How far is the exploration of non-digital services using process mining yet?

First, several years passed since process mining was introduced as a concept. Many tools with different techniques serving different purposes have been launched. We aim at giving fellow researchers a representative overview on previous work and possibilities of process mining. Second, prior work pointed to the limitation of the dependency on log files. However, this major concern does not necessarily limit process mining to digital processes. With the increasing digitalization of non-digital artifacts (Yoo 2010), the possibilities to log non-digital processes are equally increasing. Therefore, we aim to analyze the work in this specific field of application.

This paper proceeds as follows. In the next chapter, we introduce a categorization model by melding different streams of related research on IS maturity and business analytics. Subsequently, we present the literature review method on which the classification of the current status of process mining is based. Finally, we conclude and point to future research opportunities.

2 Process Mining as a Technology: A Classification Model

2.1 Conceptual Foundations

As stated above, the main purpose of the model is to define the current status of process mining. Drawing on the field of technology management, the concept of the technology S-curve is a centerpiece to define the maturity of a technology (Christensen 2009). It is based on the idea of technology life cycles (Burgelman et al. 2009), and named after the typical shape of its graphical representation of the performance of a technology in relation to its cumulative R&D investments. The technology trend curve concept is based on the technology S-curve concept and states that the development of a technology is influenced by the development of other technologies, which leads to a stage of growth model (see Figure 1). Nolan's (1973) stages-of-growth model of the evolution of data processing is a landmark reference in this field (Solli-Sæther and Gottschalk 2010). However, later work shows that the use of budgets as a basis for a stage theory of computer development in an organization is not recommendable (Lucas and Sutton 1977).

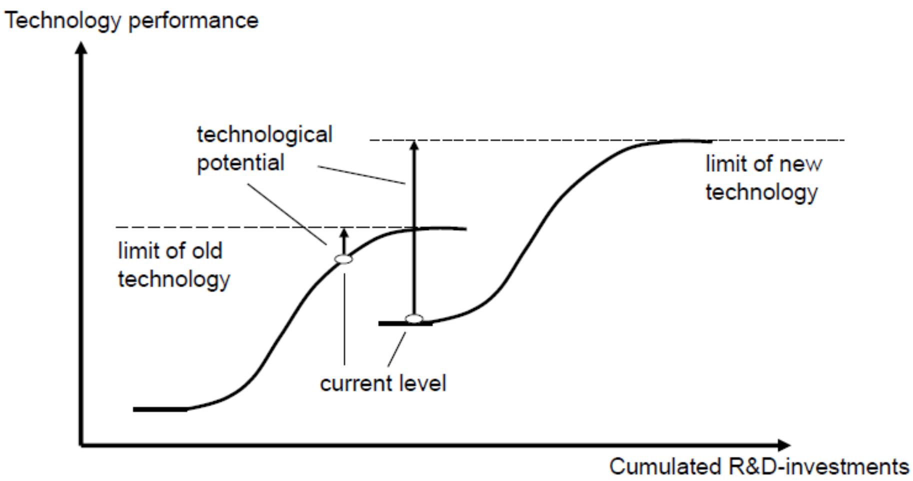

Figure 1. Principle of Technology Evolution (adapted from Baghai et al. 1999)

Thus, the model is supposed to be a stage model with a prescriptive character (Pöppelbuß and Röglinger 2011). It should support to distinguish between digital or non-digital services. Furthermore, the evolution stage of process mining shall be considered as a technology rather than a technique or application as Bruin and Rosemann (2005) argued elsewhere.

In IS research several models already exist as a base for maturity assessments (refer to Pöppelbuß et al. 2011 for an extended overview). But none of the discussed models matches the requirements in a perfect manner. Also, domain independent maturity models, such as the one by Krivograd and Fettke (2012), do not fit as they are too generic. Yet, one model that is closest to our problem domain is Holland and Light's (2001) ERP maturity model. We take it as our point of departure because process mining originated in an ERP context and as it captures the stages characterizing the introduction of a new technology in an organizational setting.

The first stage describes the beginning of an ERP introduction. Within this stage, the organization manages legacy systems. The second stage starts after the finished implementation of the ERP system. During this stage the initial scope of the ERP project is extended and other systems are adopted throughout the organization. The third stage extends the ERP transaction scope into high value processes that include so-called satellite systems, which support new functionality and capabilities in areas such as supply chain management.

This stage model was initially created for ERP systems. It reflects the technology S-curve concept with a stage growth approach similar to the one suggested by Nolan. Used by itself, however, it has limitations. When applied to process mining, it does not allow to distinguish between digital and non-digital use, nor does it have a prescriptive character, as necessary to support researchers and practitioners in detecting under-researched application fields.

Consequently, to build digital and non-digital use into our model, we turn to a similar model by Chen et al. (2012) that has been used to classify the development of the business intelligence and analysis (BI&A) field. Their model defines three stages describing the development of business intelligence and analytics. The first phase, called 1.0, covers various legacy systems through which companies collect and store data. The second phase (2.0) is characterized by the desire to understand the customer, particularly, companies will start tracking their users. The last phase (3.0) is characterized by the increasing number of digital devices. In addition to smartphones and tablets, other sensor-based Internet-enabled devices are also opening new opportunities.

Adding this newly emerging perspective to our model gives it a prescriptive character. In contrast to Holland and Light's approach, the model also touches upon non-digital services. While Holland and Light focus on single ERP installations (technique), Chen et al. (2012) adopt a broader view (application field). A technology is neither as restricted as a technique nor as broad as an application field. And indeed, process mining is in between: As a technology, process mining is supposed to become a technique in the BI&A field. It is deeply related to ERP as it mainly uses log files from ERP systems.

The first phase of both models focuses on a single, stand-alone system. Within the second phase further integration of systems is conducted. In the case of the ERP maturity model, this phase consists of the integration of other internal information systems. The BI&A model is more customer-oriented and includes executed source code on customers' devices. The common point is that, in this stage, more than one system is included. As it is important whether process mining is used within a company or in a cross-boundary system, the stricter definition of this stage is preferable. Due to the date of the model, the BI&A model offers a much more updated version of the last phase. Besides that the view of the ERP systems maturity model scope is very limited to the organization. The scope of the third phase of the BI&A model extends above computers and also includes other devices outside the organization. This view is necessary to underpin the thesis that the potential of process mining beyond organizational boundaries is still underexplored.

2.2 Classification Model

As deduced in the previous section, we suggest a classification model consisting of three categories. The first category is characterized by a **single source** system within one organization. The organization has full control over the information system. Access of users outside of the organization is possible (e.g., customer browsing through a Web server).

Within the second category, process mining is still executed within one organization but in a **cross-system** manner. The process mining model shows a process running on multiple systems and is based on (merged) log files from more than one system.

The last category is **cross-organizational** process mining. This category is characterized by the use of log files from information systems outside to the focal organization. An information system can be defined as outside of an organization when the organization has no administrative permission to access or modify the system. Process mining across such boundaries could be accomplished by the explicit supply of the log files of another organization or by the execution of an application on a device (e.g., tracing users with cookies).

Table 1 provides an overview of the identified categories. The matrix consists of two dimensions (system-oriented and organizational) and maps different approaches to process mining onto these dimensions. As a system is usually owned by one organization, we do not consider the combination of a single system across organizations. To determine the state of current approaches, we have so far put forward a two-dimensional classification scheme. In addition, to review our second main argument–the neglect of non-digital services by prior work–we also take into account the *types of services (digital or non-digital)* upon which the process is modeled.

		Organizational Perspective	
		Internal	**Cross-boundary**
System-oriented Perspective	**Single System**	*Single source*	-
	Multiple Systems	*Cross-system*	*Cross-organizational*

Table 1. Classification Model to Categorize Process Mining Approaches

3 Literature Review

3.1 Methodological Background

We turn to an *explorative* approach to classify the current accounts of process mining that have been reported in the literature according to their technological maturity. We chose a literature analysis (Cooper 1989) as the research method. The literature analysis and synthesis can be divided into three sequential steps (vom Brocke et al. 2009; Webster and Watson 2002):

1. Collection
2. Filtering
3. Evaluation

Within the initial step, a representative collection of process mining papers was collected. For this purpose, we chose the top 20 journals of the *AIS ranking* (http://aisnet.org/?JournalRankings) and added four dedicated expert journals that we expected to publish work on process mining (*BPMJ*, *Expert Systems with Appl.*, *Applied Soft Computing,* and *Information Systems*).

We selected these journals because we expected them to offer a broad range of different viewpoints and approaches to process mining. We excluded book sections and practitioners' case studies as we doubted that contributions published there would meet the high-quality standards of the selected journals with respect to methodological rigor and validity of the findings. Furthermore, we wanted to keep the analysis lean and to the point which also let us to exclude conference papers[1] as well as other more peripheral and practical journals.

IEEE Transactions and ACM Transaction were excluded from the list since they are a collection of different journals and the journals are ranked themselves. Nonetheless, the *IEEE Transaction on Software Engineering* is, as one of the top 20 journals, part of the considered journals. Thus, we started with a list of twenty-two top IS journals.

In the case of the *Sloan Management Review* the search was conducted for *Sloan Management Review* as well as for the successor *MIT Sloan Management Review*.

A full text search for "process mining" or "process-mining" without a temporal bracketing was executed in the databases EBSCOhost, Elsevier, Gale Cengage, IEEE Computer Society Digital Library, Palgrave and Wiley Online Library in May 2015. Due to the representative character of the review a full backward or forward search was not conducted (see limitations in section 5).

After all the papers have been collected, we assessed the relationship among each of them with our subject matter (process mining). Papers that did not mention the term "process mining" or "process-mining" within the text but just, for example, within the author's profile or the references were excluded, as well as those that were clearly distanced from process mining. Purely theoretical and conceptual papers without a practical element were left out, too.

Finally, the remaining papers (i.e. the presented application therein) were coded into the categories of the process mining maturity model. Due to the artificial nature of simulation works and therefore, an absence of unexpected challenges, papers evaluating their conceptual model with a simulation were classified as "single system". Additionally, we coded the type of service that the process supports as "digital" or "non-digital".

3.2 Results

Our first search step resulted in 148 papers from 14 journals (see Table 2). Most of them were published in *Exp. Syst. with Appl., Information Systems, Decision Support Systems,* and *BPMJ.*

Within the next step, we excluded papers in which process mining was mentioned only in the references (14), the authors' profile description (4) or in the outlook or papers that strongly dissociated from process mining. Fifteen of the results were lists with titles of scientific

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[1] While we acknowledge that our focus on these top IS journals is a limitation, we have chosen this approach as a starting point for three reasons. First, top-tier journals are a field's most quality-assured outlets (see for instance the mission statements of MISQ or ISR). Thus, focusing on these journals provides an opportunity to see what approaches have moved one step beyond the initial idea generation and prototyping phase; and thus have itself gained maturity. Second, starting at conference proceedings could tilt the analysis towards approaches that have actually never reached broader audiences. Thus, one may create a bias towards contributions within a very specialized target community. Third, as conference contributions often speak to very specialized audiences, in this case the process mining community, one may find tendencies towards pigeon-holing and sticking around dominant ideas without actually disseminating and challenging these ideas in and with broader communities (Corley and Gioia 2011; Weick 1996). In all, our argument is thus also on the advantages of our sample selection as an opportunity to go beyond process mining's impact beyond very specialized but broader communities in IS.

contributions, editorial notes or tables of content. Surprisingly in six papers, which came up when searching the databases, process mining has not even been mentioned at all.

Journal Name	Hits	Journal Name	Hits
ACM Trans. on Database Systems	0	*Information and Management*	0
AI Magazine	1	*Information Systems Research*	1
Artificial Intelligence	1	*Journal of Comp. and System Sciences*	0
Communications of the AIS	3	*Journal of Management IS*	0
Communications of the ACM	2	*Mgmt. Science*	0
Decision Sciences	0	*MIS Quarterly*	2
Decision Support Systems	30	*Sloan Mgmt. Review*	0
European Journal of IS	1	*Applied Soft Computing*	1
Harvard Business Review	0	*BPM Journal*	16
IEEE Software	4	*ESWA (Exp. Syst. with Appl.)*	41
IEEE Trans. on Software Eng.	5	*Information Systems*	40
Total			148

Table 2. Results of the Literature Search

In the next iteration all papers were checked if they consist of an empirical case study. Two papers could be classified as purely theoretical papers without any application part (Lombardi and Milano 2010; van der Aalst 2012). Figure 2 shows the remaining 68 papers and their distribution over time (complete list available upon request from the authors).

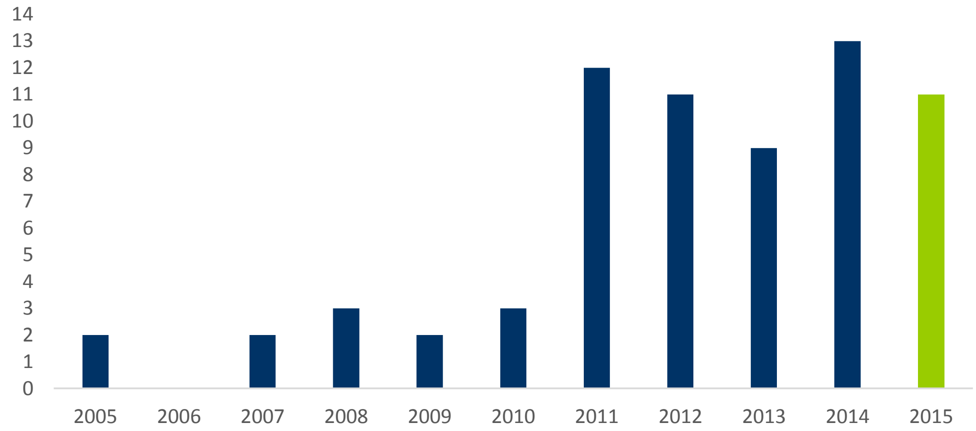

Figure 2. Chronological Overview

These papers were analyzed and classified using the maturity model. Early work was based mostly on event logs of a single ERP or workflow management systems (e.g. Ceglowski et al. 2005; van der Aalst 2006; Ciccio et al. 2015), and most contributions still do (see Figure 3).

Some other papers use a simulation to demonstrate the contribution (Ghattas et al. 2014; Ribarsky et al. 2014). Papers from the second category use different sourcing systems to demonstrate the application of standardized data exchange (e.g. Lau et al. 2009) or to track processes across or even outside of a single IT system (e.g. Wen et al. 2015). Three papers (Clae and Poels 2014; Engel and

Bose 2014; Zeng et al. 2013) that concern cross-organizational process mining were recently published. They focus on the possibility of mining processes across organizations using different methods. Very few papers focus on non-digital services. Zhou and Pirauthu's paper tracks the movements of patients using RFID technology (Zhou and Piramuthu 2010). Wen et al. (2015) demonstrate the use of pattern recognition within smart environments.

Figure 3 shows the result by category. On the y-axis we can see the category of the process mining approach from single systems up to cross-organizational ones. The x-axis of the diagram is the time axis, starting in 2004. The size of the bubble represents the number of published papers within this category and year. The bluish bubbles represent the paper concerning non-digital services. The green bubbles refer to papers concerning digital services.

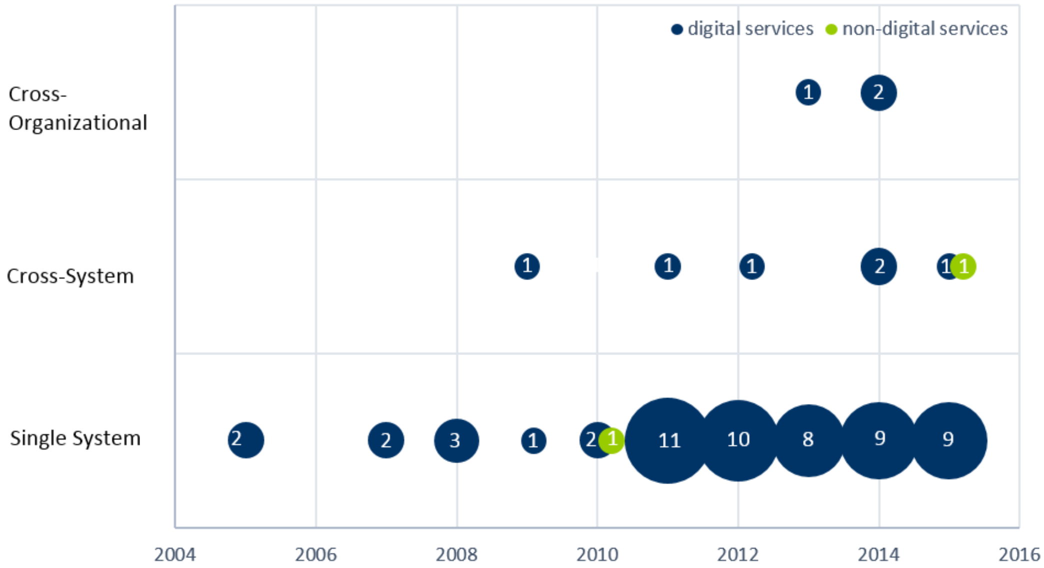

Figure 3. Results by Category

4 Discussion

The first result of the review is that process mining is still a niche topic. Except for *Decision Support Systems* all journals of the AIS top 20 basket have published less than five papers on the topic. In specialized journals, process mining is much more prominent. This fact indicates that the potential of process mining and its relevance for broader IS audiences has not yet been realized.

Although our analysis was explorative in nature, the results indicate that most papers focus on problems in a simple information system environment. Over 80% of the papers in scope belong to the first category. Also the increasing number of papers in total and especially in the first category show that its potential does not come close to being reached. Due to the different formats for storing log files it is difficult to use several tools in combination or to model processes across different information systems (Dongen et al. 2005). The first papers in the second and even the third category indicate that under certain conditions the focus can be extended and more complex scenarios can be modeled using process mining.

Usually processes are not limited onto one system but information travels across several systems. Therefore an end-to-end perspective is necessary (Maddern et al. 2013). The dependence of today's processes on information systems provides interesting opportunities for process mining. For example, redundant tasks in different information systems can be explored by modeling processes across several systems. Also dependencies become easier to spot because with classical process analysis methods the model always shows the reality of the source but not as it is. The more complex processes become, the greater the advantage of models generated by process mining. This result is consistent with the challenges that have been noted by the IEEE task force (van der Aalst 2012).

Besides the under-explored problems of process mining across several systems or organizations, process mining has hardly been tested in settings with non-digital services. Although Zhou and Piramuithu (2010) and Wen et al. (2015) have shown the applicability and use of process mining in this area, the field remains largely unexplored. These two examples can be seen as a call for service management researchers to use process mining to explore consumer processes. While not directly referring to “process mining”, further examples from related research areas such as service analytics (Fromm et al. 2012; Hottum et al. 2015) reinforce the urgency to advance process mining in interorganizational service contexts. Especially given that, with the service dominant logic (Vargo and Lusch 2004), consumer processes get more important and it becomes essential to know them.

As one example, within the field of mobility services process mining can offer a new dimension of knowledge about the consumer processes. With traditional analyzing methods a provider of a public transport system will usually just know the number of people getting in and out of a vehicle (Vincente et al. 2009) or their departure and arrival station (Lathia et al. 2010). Public Wifi, which is an increasingly available service of public transport providers, offers the opportunity to track and trace consumer through the system. As a result of such an analysis, the provider gets several important pieces of information about the consumer, like the exact route the consumer is using, his use of additional local service like a coffee shop and the locations the consumer is spending time to wait. This information can be used to improve the consumer experience.

Other services such as the flight of a passenger can be modeled, based on log files recorded at the booking portal, the check-in, security gate, boarding gate, etc. Such consumer process models offer several new insights and opportunities to increase not just the efficiency but also the effectiveness (Gersch et al. 2011; Vukšić et al. 2013). In particular, as a service provider cannot generate value by itself but only in cooperation with the consumer (Vargo and Lusch 2004). Therefore, a service provider needs to know and tailor the consumers’ processes. Customization of processes means that they become more flexible and as a result more complex. In turn this makes it difficult to analyze and manage the processes without process mining.

5 Summary and Outlook

This paper remarked that the technology of process mining is still in an early stage. We found that previous research has often focused on (too) simplified systems and sandbox scenarios. Yet, due to improvements of process mining techniques, first works began to explore more complex problems such as mining processes across systems or organizations or integrating sensor-based internet-enabled devices. Beyond determining the state-of-the-art in process mining, this paper aimed at pointing to possible paths that process mining research could pursue. Considering the results we have obtained, we call for (a) mining processes across systems and organizations as well as (b) applying process mining to non-digital services.

Zeng et al. (2013) have demonstrated the feasibility of cross-organizational process mining, yet, our results also show that such approaches are underrepresented. Due to the importance of an end-to-end view on processes, cross-system or even cross-organizational process mining offers great potentials. It allows a real-time process monitoring and analysis going beyond the oversimplified assumption that processes stay inside-the-box of one system. Similar to cross-organizational process mining, non-digital services have also been underrepresented. As discussed above, here lies a tremendous potential for research that investigates techniques to log non-digital processes and to use these techniques for different processes. As the Web 2.0 is considered a "gold mine for understanding customers' needs and identifying new business opportunities" (Chen et al. 2012), process mining has the potential to provide similar insights for not yet digital services.

Extending our work, a logical next step would be an exhaustive and less constrained review of the literature to identify further articles in specialized process mining outlets and conference proceedings (e.g. BPM, CAiSE, and PETRI NETS). More general, explorative and unforeseen insights may arise as process mining is a relatively young discipline and journal publication usually takes time. We, however, also pursued the objective to reflect what has made it to the fields' top IS journals to see how legitimate the field is itself from a broader IS perspective.

After all, our contribution was to show that techniques to use process mining in a cross-system or cross-organizational environment have yet to be designed to explore their potential. Additionally, we call for empirical demonstrations of process mining for non-digital services taking into account the increasing availability of sensor data and data produced by digital devices (e.g. GPS positions from mobile phones). We wish that with the increasing applicability, process mining will receive more attention from different disciplines, for example marketing, to gain new insights into the customer processes, and BI&A to calculate the costs and revenues in a more detailed way. And with that, process mining will hopefully also become more prominent in major IS journals.

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