Fall 10-16-2021

A proposed model for Process Mining Adoption: Using a Mixed-Methods Approach

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Abstract

Driven by digital transformation, Process Mining represents one of the biggest analytical trends in the Software-as-a-Service technology market, providing companies with transparency of their processes in place. As such, there has been little research about what are the factors that influence the decision of companies to adopt Process Mining in their organization. Hence, this study aims on developing a comprehensive research model that sheds light on the most decisive Process Mining adoption drivers among European firms. A Mixed-Method design was applied to ensure a tailored IT adoption model for Process Mining. Based on a qualitative pre-study with expert interviews as well as a thorough literature review about the IT adoption theories of TOE, DOI as well as OIPT we derived the most essential antecedents of Process Mining adoption and proposed to our knowledge the first Process Mining adoption research model on firm-level.

Keywords: Process Mining; Adoption; Mixed Methods

1. INTRODUCTION

Today´s digital transformation initiatives among firms strongly fuel the need for transparency of the processes in place in order to improve and orchestrate them consecutively (BearingPoint, 2019; Gartner, 2020). The technology Process Mining is exactly addressing these needs by enabling organizations to visualize their processes´ complexity (Reinkemeyer, 2020) and to rapidly analyze the retrieved data through process-oriented lenses (BearingPoint, 2019). Hence, it shouldn´t be surprising that the technology has recently seen an immense uptake of application among different industries (Ernst&Young, 2019) as well as a growing number of Process Mining vendors on the market (Gartner, 2020). The actual idea of Process Mining is to extract and use information from event data - that is stored and easily available in today´s information systems - to provide an evidence-based end-to-end view of an organization´s process landscape (Suriadi et al., 2017). Against that background, Process Mining is developing more and more towards being a crucial cornerstone for digital transformation initiatives (Gartner, 2020; Taulli, n.d.).

In hand with the rapidly evolving market, Process Mining also represents a growing academic research discipline, with a lately strong increase of publications, underlining its relevance further (Garcia et al., 2019). Previous research primarily explored different use cases and possible application areas (R'Bigui & Cho, 2017) of the three major Process Mining subdomains – discovery, conformance & enhancement (Garcia et al., 2019). Yet, there is a scarcity of Process Mining studies related to the overarching field of IS/IT adoption, which has been a major line of research over the past decade. Numerous theories and frameworks have been developed and explored (e.g. Liu et al., 2010; Oliveira & Martins, 2011) to understand the different drivers and characteristics of technologies and their influence on organizations. Regardless of IT adoption being a very thoughtfully researched topic, every technology has its unique properties and peculiarities correlating to different factors that influence its successful adoption (Wang et al., 2019). Hence, a research gap can be identified regarding the understanding of Process Mining adoption among firms and its main antecedents.

To fill this gap, the study on hand aims to develop a research model that sheds light on the following question: *What are the main factors that influence European firms in their decision to adopt Process Mining?* As the given study represents one of the first studies in that area, we will adopt a mixed-method approach and complement our literature review with a qualitative study to identify the particularly significant drivers for Process Mining through expert interviews. In doing so, this paper is organized as the following: Section two presents the literature review for Process Mining as well as three theories in the domain of IT adoption. Sect. 3 presents the qualitative study and introduces the model as well as the hypothesis; Sect. 4 its perspective implications; whereas Sect. 5 holds the conclusions and future work.

2. THEORETICAL BACKGROUND

2.1. The concept of Process Mining

Based on a long-lasting practice of organizations trying to improve process workflows and their outcomes, Process Mining emerged as a relatively new domain of study. The technology aims to learn about fundamental business processes by extracting and analyzing event data from transactional information systems (Van der Aalst, 2016; Van Der Aalst et al., 2012). The thereby attained transparency regarding the actual process behavior represents an opportunity for companies to leverage fact-based decision making and to define actionable items for enhancing their processes (Reinkemeyer, 2020). Therefore, Process Mining can be defined as technology to discover, monitor, and improve fundamental business processes based on event logs (Van Der Aalst et al., 2012).

Event data works as the foundation of Process Mining which is extracted as raw data from the underlying IT operating systems and is further turned into so called event logs (Van der Aalst, 2016). Each event log encompasses the essential process instance or case ID, the respective process steps and a time reference, commonly in the form of timestamps.

In the realm of Process Mining, three main strands can be delineated: Automated process discovery, conformance checking, and process enhancement (Van Der Aalst et al., 2012). With the help of the provided knowledge about the current processes' behavior and performance, organizations can employ Process Mining for process enhancement initiatives by deriving dedicated measures to improve their existing process landscape (Ly et al., 2015; Reinkemeyer, 2020).

The main body of previous Process Mining research focused on the technological aspects of the aforementioned Process Mining types and the respectively applied algorithms (see, e.g., Ailenei et al., 2012; Eggers & Hein, 2020) as well as the various application areas of Process Mining. Due to the focus on technological practices and challenges, a considerable gap exists regarding the socio-technical implications and organizational perspective concerning Process Mining application (Eggers & Hein, 2020). In that context, the prominent IS-related research domain of IT adoption is scarcely examined regarding Process Mining. To our best knowledge, only Ronny (2013) identified success factors for Process Mining implementation deduced from the literature of process modeling (Ronny et al., 2013) and Syed et al. (2020) recently published a study examining the adoption drivers of a dutch pension fund based in semi-structured interviews.

2.2. Technology Adoption

Over decades IT Adoption on firm level has been a highly relevant research strand, demonstrated by the numerous developed theories and explanatory frameworks (see e.g., Ain et al., 2019; Baig et al., 2019; Oliveira & Martins, 2011). The relevance is based on the underlying presumption that only a widely spread and utilized IT can have a significant effect on a firm's performance (Porter, 1985). Hence, it is essential to augment the understanding regarding IT adoption determinants (Bayo-Moriones & Lera-López, 2007; Liu et al., 2010; Oliveira & Martins, 2011), for which according to Oliveira (2011) it can be advisable to consider and merge multiple theories. After a comprehensive literature review, this study finds the DOI theory (E. Rogers, 1995), the OIPT theory (Galbraith, 1974; Tushman & Nadler, 1978) and the TOE (DePietro et al., 1990) framework to be relevant for explaining Process Mining adoption.

2.2.1. Technology – organization – environment (TOE) framework

Proposed in 1990, the TOE framework embodies a popular methodology in IT adoption research (DePietro et al., 1990). It outlines three contexts - technology, organization and environment - that seek to explain the adoption process of an IT innovation within an enterprise: (1) The technological context encompasses the current internal technologies in place as well as the available technologies external to the company; (2) The organizational context comprises significant characteristics of the firm, such as size, available resources and formal or informal communication processes among employees; lastly, (3) the environmental context depicts the ecosystem of the organization by containing the industry specific structure and dynamics, competitor behavior and governmental regulations (DePietro et al., 1990; Oliveira et al., 2014; Oliveira & Martins, 2011; Tornatzky et al., 1990). TOE allows a holistic illustration of the IT adaption phenomena and enables researchers to apply customized lenses on the given topic by including constructs tailored to the respective context and technology (Bose & Luo, 2011; Venkatesh & Bala, 2012). Gangwar, Date, and Raoot (2014) claim that every individual technology has due to its unique characteristic a specific set of factors driving its successful adoption. Thus, TOE has been used extensively in empirical studies for various types of IT adoption, such as Green IT (Thomas et al., 2016), Software-as-a-service (Martins et al., 2016), Big Data analytics (Maroufkhani et al., 2020), Business Intelligence (Ain et al., 2019; Puklavec et al., 2018) and Cloud computing (Gangwar et al., 2015; Oliveira et al., 2014).

TOE has also been combined commonly with other relevant theories (Martins et al., 2016; Oliveira et al., 2014; Zhu, Dong, et al., 2006), which is based on Oliveira´s (2011) initial suggestion to use and interrelate multiple theoretical models in order to attain a better understanding of the adoption phenomena.

2.2.2. Diffusion-of-Innovation (DOI) Theory

DOI theory (E. Rogers, 1995) has been widely used in IS research (Gangwar et al., 2014; Oliveira & Martins, 2011) to explain the diffusion of innovation within an organization by highlighting its technological characteristics as determinants of IT adoption. In that context, DOI defines five technological factors that impact the innovation adoption choice: relative advantage, compatibility, complexity, trialability, and observability (E. Rogers, 1995), whereas the latter two are only scarcely used among IT innovation studies (Chong et al., 2009). The broad empirical support of DOI´s technological factors makes it a valuable theory to integrate into the technological context of the TOE, and by doing so, increases the framework´s comprehensiveness and strengthen the ability to explain IT adoption (Hsu et al., 2006; Oliveira & Martins, 2011; Picoto et al., 2014). Accordingly, numerous studies followed the approach and used DOI and TOE in combination to explain the adoption of various technologies (Oliveira et al., 2014; Picoto et al., 2014; Zhu et al., 2006).

2.2.3. Organizational information processing theory (OIPT)

Organizational information processing theory, with its information processing view on organizations, manifests a meaningful approach in the area of organizational theory and has also found numerous applications beyond that (e.g., Atuahene-Gima & Li, 2004; Gales et al., 1992). OIPT comprises three key concepts – process information requirements, process information capability, and the corresponding fit implying respective firm performance (Galbraith, 1974; Tushman & Nadler, 1978). The theory´s underlying proposition suggests that a company requires an appropriate level of information, which promotes a manager´s decision-making, and ultimately leverages a firm´s performance (Galbraith, 1974; Tushman & Nadler, 1978). The subsequently extant Information Processing Requirements (IPRs) are therefore driven by the degree of uncertainty organizations are exposed to. The situation of increased volatility and uncertainty associated with an organization´s environment functions as a driver for companies to adopt - besides buffer control mechanisms - information processing capabilities such as information systems, to leverage the information flow, thereby supporting decision-making and combating uncertainty (Premkumar et al., 2005). OIPT has found only scarce application in adoption research so far.

3. MODEL DEVELOPMENT

Mixed-Method research (Venkatesh et al., 2013, 2016) embodies a methodology that combines the two strands of qualitative and quantitative methods and has been promoted by various researchers in the IS research context (Chiang, 2013; Côrte-Real et al., 2019; Venkatesh et al., 2012). By combining the two research approaches, the limitation related to either method alone can be overcome and thus enables drawing more substantive conclusions by addressing confirmatory and explanatory research questions simultaneously (Venkatesh et al., 2016). Considering the paucity of Process Mining adoption studies, a mixed-method approach is advisable for our study (Venkatesh et al., 2013). In virtue of our study´s research objective and research questions, we applied Venkatesh´s (2013) guidelines by stating the purpose of the study as "developmental", where "one strand provides hypotheses to be tested in the next one" (Venkatesh et al., 2013, p. 26). More specifically, we followed the sequential explorative mixed-method design that denotes a primarily explorative qualitative study which results are integrated into the subsequent confirmatory quantitative study (Venkatesh et al., 2016). However, the quantitative data collection and analysis is out of scope for this paper and will be part of a subsequent study instead. Concludingly, our qualitative study aimed to discover Process Mining adoption drivers through expert interviews (Phase 1), which served as the foundation together with the results of the literature review for the consequent hypothesis and research model development phase.

3.1. Qualitative study – in-depth interviews

Our primary qualitative study identified Process Mining adoption drivers, by conducting semi-structured in-depth interviews (Boyce & Associate, 2006; Myers, 1997) with experts in the realm of Process Mining. The sample of interviewees was selected by applying a purposeful sampling strategy (Flick, 2009), which enhances the generalizability of the results (Lyytinen & Rose, 2003). Therefore, we selected experts that represent perspectives from different actors in the Process Mining market. The number of interviews was determined by the principle of saturation, which is a commonly used approach for sample size definition in qualitative research and which we reached after 10 interviews (Nah et al., 2005; Vasileiou et al., 2018)

In the following phase of sequential qualitative-quantitative data analysis, we followed Zhang & Venkatesh´s (2017) approach to analyze the qualitative data. Therefore, we first examined the collected interview responses by identifying overarching themes among Process Mining benefits as well as its unique characteristics. Based on that, we structured and analyzed the exposed expert opinions according to factors that affect Process Mining adoption decisions. Subsequently, the retrieved results were correlated with extant constructs of the theories from literature, which were formerly proposed for this study (TOE, DOI, OIPT). Lastly, the constructs were prioritized and accordingly selected for the research model based on the number of mentions during the interviews.

Besides the well-known constructs within the IS research realm, we believe to have also identified two novel constructs with potentially high significance in the context of IT adoption: Time-to-value (the innovation bringing quantifiable value to the organization in a relatively short time span) & Digital Transformation maturity (an existent comprehensive digitalization initiative being a significant factor in the adoption decision).

3.2. Hypotheses

Hence, our proposed conceptual model emerged from Process Mining literature as well as from our conducted qualitative research. Ultimately, the TOE was selected as the overarching theoretical framework, with the technology as well as organizational context being represented by derived constructs from DOI and with the environmental context by constructs from OIPT. Furthermore, the from the expert interviews derived novel constructs - ‘time-to-value and ‘digital transformation maturity - were integrated into the model. The research model is illustrated in the following figure:

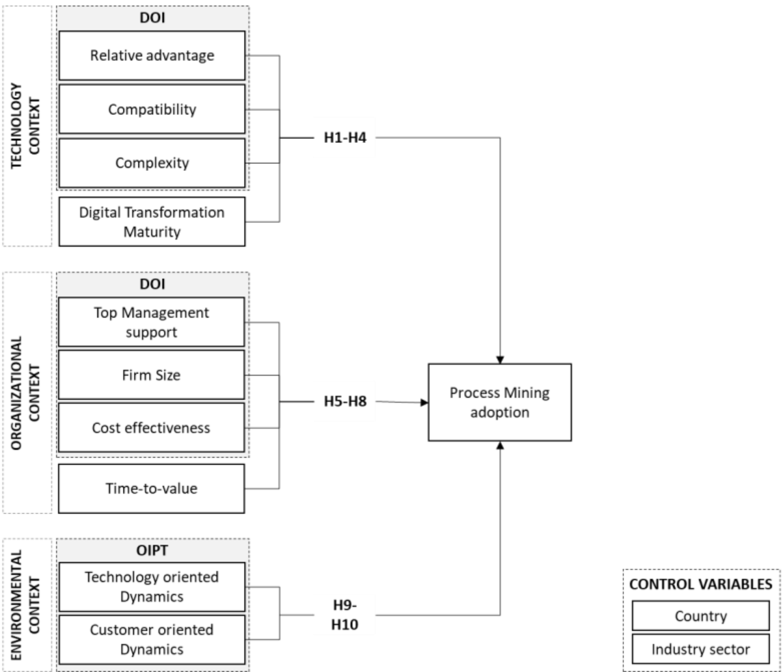

Figure 1 – The research model

Relative advantage

Within the technological context, relative advantage (Baker, 2012; Kapoor et al., 2015) describes the "*degree to which an innovation is perceived as being able to provide greater organizational benefit***"** (E. M. Rogers, 2010). Multiple studies (Li et al., 2011; Martins et al., 2016; Oliveira et al., 2014; Tsai et al., 2010) posit that the relative advantage by an IT innovation represents a significant motivator for firms to adopt it. As suggested by our qualitative study, we consider relative advantage as a latent variable in the context of Process Mining adoption due to its ability to provide process transparency as well as cost and process cycle-time cutting opportunities, which eventually influences a firm´s performance. Hence,

H1: Relative Advantage (RA) has a positive influence on PM Adoption (AD).

Compatibility

Compatibility encompasses the "*degree to which the innovation fits with the potential adopter's existing values, previous practices, and current needs*" (Roger 2003). It has been proven to be a substantial adoption driver for various technology innovations (AL-Shboul, 2019; Gangwar et al., 2015; Ruivo et al., 2012). Indicated by our qualitative studies, firms seem to consider Process Mining especially when they perceive it as an answer to their current pain points as well as compatible with their existing technical infrastructure and organizational data-driven culture in place. Thus,

H2: Compatibility (CP) has a positive influence on PM Adoption (AD).

Complexity

The complexity of an IT innovation can be defined as the supposed degree of difficulty to understand and use the respective technology (Sonnenwald et al., 2001). Equally, Rogers (2003) stated that if a new technology is perceived as easy to use, its probability to be implemented is enhanced. Hence, complexity was proven to be a crucial factor of adoption for various technologies (Gangwar et al., 2015; Lai et al., 2018; Martins et al., 2016). As suggested in our qualitative study, we consider complexity as a latent variable for Process Mining adoption, justified by the standard high extent of system customization that represents a considerable barrier for seamless Process Mining adoption. Therefore,

H3: Complexity (CX) has a negative influence on PM Adoption (AD).

Digital transformation maturity

Digital transformation maturity evaluates and describes the state of a technology-induced change within cooperation. According to Evans (2017), Digital transformation is based on four key pillars: strategy and vision, people and culture, process and governance as well as technology and capabilities. Process Mining can leverage and catalyze a company´s digitalization transformation initiative (e.g. a new ERP system or RPA deployment) by providing clear process transparency, which is required and decisive for a successful implementation of such technologies. Hence, we propose that a mature digital transformation initiative can have a considerable promoting impact on the decision of whether to adopt Process Mining. Hence,

H4: Digital transformation maturity (DTM) has a positive influence on PM Adoption (AD).

Top management support

Top Management support is defined as the degree to which managers understand and embrace the technological capabilities of a novel technology (Sanders, 2008). Multiple previous studies have concluded top management support to be one of the most determining factors within the Organization context to explain technology adoption (AL-Shboul, 2019; Chan & Chong, 2013; Cruz-Jesus et al., 2019). According to our qualitative study, top management support was also seen as fundamental due to the nature of Process Mining to affect end-to-end processes and therefore requires the allocation of resources and enterprise-wide decision power for process re-engineering initiatives. Thus,

H5: Top management support (TMS) has a positive influence on PM Adoption (AD).

Firm size

Firm size is another commonly studied organizational factor in the context of innovation adoption (AL-Shboul, 2019; G. Lee & Xia, 2006; Oliveira et al., 2014; Oliveira & Martins, 2010). Our qualitative study also strongly indicates that Process Mining requires a qualified technical workforce, which is more likely available in large organizations (E. Rogers, 1995). Furthermore, larger companies have more financial power and more data available to leverage the value of Process Mining. Consequently,

H6: Firm size (FS) has a positive influence on PM Adoption (AD).

Cost-effectiveness

The financial aspect of innovation uses to be a big restrictive factor to adoption (Premkumar & Roberts, 1999) and has been examined in various studies. (Chan & Chong, 2013; Y. Lee & Kozar, 2008; Y. Lee & Larsen, 2009). However, we follow Puklavec and Tiago´s (2018) approach on BI system adoption and consider cost as cost-effectiveness, meaning the positive deviation between the technology´s costs and its generated benefits. In accordance with our qualitative study, Process Mining tends to amortize its investment many times over and has an expected positive Return on Investment. Therefore,

H7: Cost-effectiveness (CF) has a positive influence on PM Adoption (AD).

Time-to-value

When considering an IT adoption, the value proposition of the respective IT guides the justification, funding as well as legitimization of the potential investment (Chatterjee et al., 2002). Accordingly, it plays an important role to be aware of whether this value proposition can be expected in a timely manner after the investment or not. Due to Process Mining´s capability to provide process transparency and actionable insights within a short time span after obtaining – especially relative to other technologies – we suppose the expected short time-to-value to have an influence on Process Mining adoption. Hence,

H8: Time-to-value (TTV) has a positive influence on PM Adoption (AD).

Technology oriented dynamics

Uncertainty emanating from a company´s environment can have diverse sources, one of them being the speed of technological development (Moser et al., 2017; Premkumar et al., 2005; Tushman & Nadler, 1978). These technology-oriented dynamics represent process information requirements for a company and thus demands capabilities to cope with (Moser et al., 2017). Process Mining enables organizations to enhance their information circulation and facilitates fact-based decision-making, which consequently supports coping with the present uncertainty (Premkumar et al., 2005). Thus,

H9: Technology Oriented Dynamics (TOD) has a positive influence on PM Adoption (AD).

Customer oriented dynamics

Following the same logical sequence as with technology-oriented dynamics, customer-oriented dynamics represent information processing requirements (Moser et al., 2017; Tushman & Nadler, 1978). They denote the pace of how quickly customer needs change in the respective company´s market environment (Moser et al., 2017). Process Mining offers, on the one hand, the analytical capability to track and analyze changes in customer preferences and customer journey, and on the other hand, it also fosters fact-based decision-making in the customer context. Therefore,

H10: Customer Oriented Dynamics (COD) has a positive influence on PM Adoption (AD).

Control variables

Control variables are necessary to explain potential data variation that is not explainable by ordinary variables. In our study, following previous studies in the context of IT adoption, we will use the industry sector, and country (Son & Benbasat, 2007).

4. PERSPECTIVE IMPLICATIONS

The study on hand makes important theoretical contribution to literature in the realm of IT adoption and Process Mining likewise. Firstly, our research provides to our knowledge the first theoretical model for Process Mining adoption on firm level and hence addresses the paucity of scientific research in that area. Within that context, we suggest two novel adoption driver variables that emerged from our expert interviews during our qualitative study. These variables, namely digital transformation maturity and time-to-value, have to our knowledge not seen any application in the scope of IT adoption and offer new perspectives to an IT adoption initiative. We believe that these variables have a huge potential to be decisive for any other technology adoption and therefore strongly suggest further empirical examination.

Secondly, by incorporating the 3 theories TOE, DOI and OIPT into one comprehensive Process Mining adoption model, we are proposing an unique model, that to the best of our knowledge, no previous study has proposed with these theories in such a way, which therefore underlines the contribution to the IT adoption literature.

Additionally, the study provides also important managerial implications for Process Mining users, vendors, and decision-makers alike as they are presented with a meaningful body of knowledge about the major drivers that conjunctly leverage the Process Mining adoption phenomena. Hence, they can use this knowledge and benefit from it during the next Process Mining adoption initiative, by being able to consider and address all relevant and decisive factors.

5. CONCLUSION AND FUTURE WORK

Based on a comprehensive literature review combined with qualitative expert interviews we developed a research model that sheds light on the factors contributing to the adoption of Process Mining among European firms. Furthermore, we proposed two variables that to our knowledge haven´t been used previously in the context of IT adoption, namely digital transformation maturity as well as time-to-value. Due to our exhaustive methodology, we are convinced that our model is custom-made to explain Process Mining adoption, represented by the supposition that it wouldn´t be as effective if applied to other technologies. We have established ten hypotheses that intend to explain the effect of relevant factors on the decision of organizations to adopt Process Mining. As future research, we suggest the model can be empirically tested and validated using partial least squares structural equation modeling (PLS-SEM).

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