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Unstructured Business Processes Improvement using Process Mining Techniques

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Executing loosely structured processes generate unstructured behaviours. Thus, an Unstructured Business Process (UBP) still has more issues that are difficult to be analysed and to be understood due to its complexity and variability. Moreover, the need of an instantiate response is clearly appeared in operational systems. Therefore, it is required to study related challenges that can be acquired during the transition from the structured BP to the unstructured one. In this context, process mining plays a dominant role to understand business process complexity using event data resulted from business process execution. Mainly, this paper treats three challenges related to unstructured BPs. The first challenge is how to support UBPs at runtime using process mining techniques. The second challenge is how to manage UBP variability taking into consideration variant conditions. The third challenge is how to adapt dynamically UBPs according to the company business rules and conditions.

Keywords: Process mining; business process improvement; complexity; variability; dynamicity; auto-defined business process; ad-hoc business process

I. INTRODUCTION

Process Mining (PM) is a relatively new field incorporating techniques for the discovery, monitoring, and enhancement of real processes by extracting knowledge from the information system event logs. Indeed, PM bridges two different fields: Process Science and Data Science (Van der Aalst, 2016a).

Process Science is a broad area of process modelling (Kumar *et al.,* 2022), analysis, and optimisation. It incorporates Stochastics (analysis of random processes, using Markov chains, queuing networks, and simulation), Optimisation (finding the best possible process implementation by applying mathematical optimisation techniques), Operations Management & Research (designing and controlling production processes from management and mathematical modelling perspectives), Business Process Management (methods and techniques for the modelling, execution, and enhancement of processes). Business Process Improvement (for instance, Six Sigma techniques and Business Process Re-engineering), Process Automation & Workflow Management (tools and methods for BP processive execution, including routing and resource allocation), Formal Methods & Concurrency Theory (analysis of process behaviours, using Petri nets, finite state machines, and other formal models).

Data Science incorporates all aspects of data analysis, and includes Statistics, Algorithms (providing efficient data processing), Data Mining (methods revealing unsuspected relationships in data sets), Machine Learning (techniques for giving computers capabilities to learn without being explicitly programmed), Predictive Analysis (methods predicting future trends), Databases (techniques for storing data), Distributed Systems (infrastructure for data analysis), Visualisation & Visual Analytics, Business Models & Marketing (techniques for turning data into real value), Behavioural/Social Science (methods for human behaviour analysis), Privacy, Security, Law & Ethics (principles protecting individuals from "bad" data science practices).

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PM is defined by three categories (Van der Aalst *et al.,* 2012): (i) process discovery, (ii) conformance checking, and (iii) enhancement. Discovery: An automatic process modelling methodology that takes event logs as input and produces a BP model as output. Conformance: compares the newly discovered process model with the existing process model. The purpose is to detect deviations and identify bottlenecks. Enhancement: focuses on improving or extending the existing process model using the information recorded in event logs.

PM uses mainly events logs to represent process models. In this context, PM can analyse BP structures. Business Processes with complex structure are incomprehensible, unreadable, and can be emerged because of human intervention during the BP execution. Indeed, unstructured processes (knowledge intensive) are loosely defined and rely on access to readily available knowledge. The problematic is how to obtain a simplified and improved representation of UBP (Lamghari *et al.,* 2021) using process mining techniques. The existence of structured processes (data-intensive) within the unstructured ones make process mining usable for both systems: data-intensive & knowledge intensive. The early style of data-intensive (BPM) defined processes as the core of the system. This style lets the data-flow through control flows as process instances. This means the process is primary and normally static. In contrast, knowledge-intensive places data in the centre which is able to support the surrounding processes to make decisions whenever necessary. The data is considered as a primary. In most cases, processes may not be fully predefined, knowledge workers have to define them on the fly depending on the situation. All in all, SBP contains predefined process routes, on the other hand, with UBP the case itself is the main focus.

Therefore, UBP still have more issues that are difficult to be analysed and hard to be understood due to its complexity and variability. Moreover, it is required to provide instantiate response in a dynamic manner to these unstructured BPs. In section 2, we present existing works, related to those 3 issues, in the process mining context: complexity, variability and dynamicity. Section 3 deals with three issues related to unstructured BPs. Indeed, we propose three approaches to resolve the complexity, the variability and the dynamicity challenges that can be acquired with unstructured BPs. The proposed approaches use process mining techniques. The tackled challenges are presented in the following order: First, the complexity concerns the possibility of supporting, at runtime, complex BPs by predicting and recommending actions. Second, the variability consists of managing BPs according to users' objectives. Third, the dynamicity introduces the concept of adaptability during the BP execution. Section 4 summarises the paper and introduces future research.

II. STATE OF THE ART

UBPs still have more issues that are difficult to be analysed and hard to be understood due to its complexity and variability. Moreover, it is required to provide instantiate response in a dynamic manner to these unstructured BPs. In the following paragraphs, we present existing works, related to those 3 issues, in the process mining context: complexity, variability and dynamicity.

To identify publications addressing these issues, we investigated three platforms: SCOPUS database, Process Mining Wiki and Google scholar. SCOPUS is the largest database of peer-reviewed literature. Process Mining Wiki is a publication platform that promotes research on the topic of process mining and contains publications only on process mining. Moreover, to not miss any paper, we also explored Google Scholar which allows a wide range of academic literature.

A. Complexity

In the last decade, many scientific studies have been defined to deal with the process mining issues. More specifically, approaches and techniques that allow reducing the complexity of unstructured BPs to a simplified representation. Through this sub-section, we illustrate the still encountered issues related to process mining applied to UBPs. In this context, the main challenge is how to deal with the event logs complexity at runtime (Lamghari *et al.,* 2019).

Process mining has difficulties to handle complex event logs properly. Fortunately, it is generally agreed that decomposing processes is the best technique to deal with the complexity challenge. The technique decomposes process mining problems into many smaller semi-problems that can be solved in short time (Kalenkova *et al.,* 2014). In the literature, many ways to partition process mining problems exist. However, these approaches of decomposition are not consistent among studies: some authors used the divide-and-conquer approach (Van der Aalst *et al.,* 2013), some used the Single-Entry Single-Exit technique (Munoz-Gama *et al.,* 2014), others used the notion of process cubes (Van der Aalst, 2013), the four conflicting quality dimensions, especially in conformance checking decomposition (Irshad *et al.,* 2015), some studies answer to issues related to computation and visualisation (Verbeek & Van der Aalst, 2016) and others have based their decomposition on clustering (Munoz-Gama *et al.,* 2013).

Moreover, each study for process mining decomposition has some limitations and need to be investigated in further works. The most relevant problem is choosing the appropriate algorithm to mine the composed event logs provided from an original complex event log. The structuring techniques are based on the following of four previous studies (Polyvyanyy *et. al.,* 2014; Polato *et. al.,* 2014; Oulsnam, 1987; Artem *et al.,* 2010). The first two approaches treat only unstructured acyclic rigid fragments with parallelism. The second two approaches deal only with rigid fragments without parallelism (exclusive gateways). This gap requires a hybrid approach that combines between the two aforementioned rigid fragments categories. To do so, the recent approach of Augusto *et al.* (2018b) is applied (Augusto *et al.,* 2018b). This later represents a discover-and-structure method for generating a SBP from event logs. This method builds upon the hypothesis: instead of attempting to discover a block-structured process model directly, higher-quality process models can be obtained by discovering abstracted representation of an UBP, then transforming it to a structured one in a best-effort manner. This approach aims at discovering a SBP by operating into the following structuring techniques:

1. Gateways structuring (repair unstructured gateways' representation)
2. Clones' removal (remove from the process model repeated activities and by necessity actions) and;
3. Soundness repair (verify soundness of the obtained process model). The approach uses the bpmn as a process model representation language.

Indeed, executing loosely structured processes generate unstructured behaviours at runtime. They are difficult to be analysed and hard to be understood, due to its complex structure. Besides, it is required to treat this complexity problem during the application of the operational support actions. In this context, several approaches have been developed. Since Process Mining Manifesto released at the end of 2011 (Van der Aalst *et al.,* 2011), we focus on research papers published from the beginning of 2012 year: Nakatumba *et al.* (2012) develop a concrete implementation of operational support meta-model, based on the work-flow system and the ProM framework (Nakatumba *et al.,* 2012). This meta-model treats four types of queries: simple queries, compare queries, predict queries, and recommend queries. Folino *et al.* (2018) propose a global approach that learn discovered behaviours to predict the classes of visible and invisible traces (Folino *et al.,* 2018). The discovered signature patterns allow the distinction between various classes of behaviour and by necessity related business conditions. Conforti *et al.* (2013) suggests a method that predicts process risks by applying decision trees to the logs of previous process executions, taking into account multi-perspectives of process mining like: process data, used resources, task durations, and contextual information (Conforti *et al.,* 2013). To do so, the proposed method helps the process participants to make risk-informed decisions. Likewise, De Leoni and Van der Aalst *et al.* (2014) explore an approach that forecasts the remaining processing time and recommend activities to reduce risks (De Leoni & Van der Aalst *et al.,* 2014). Hompes *et al.* (2015) illustrate a method that can prevent the undesirable behaviour from occurring in next executions (Hompes *et al.,* 2015). This is done based on the Markov Cluster (MCL) algorithm with the ability to detect changes of a process according to the selected perspectives. Van der Aalst and Dees (2016) present framework for predicting dynamic behaviour from event logs (Van der Aalst & Dees, 2016). It is capable of correlating and clustering dynamic behaviour. The framework allows the prediction of the executor of a certain activity, the remaining time to the end of the process instance, the next activities to work on, and the outcome of the executions of process instances. Mehdiyev *et al.* (2017) demonstrate a multi–stage deep learning approach for BP event prediction that aims at predicting the next BP event, considering the execution of log data from the previously completed process instances (Mehdiyev *et al.,* 2017). This is done to predict the BP events, to initiate timely interventions for undesired deviations from the desired workflow. Folino *et al.* (2018) propose a framework for detecting and analysing, at runtime, BP deviances, which leverages both a novel incremental approach to the discovery of an ensemble–based deviance detection model (Folino *et al.,* 2018). Moreover, Lin *et al.* (2019) establish a method that addresses the problem aiming at learning the impact of past events on the future events using deep learning methods (Lin *et al.,* 2019). It is a deep predictive model for multi–attribute Event Sequence. On one hand, all the cited papers reported on the application of process mining for operational support, do not use the orchestration of the whole existing process mining activities (Discover, Explore, Check, Compare, Promote, Diagnose, Enhance, Detect, Predict and Recommend). On the other hand, some of them only generate operational support to structured BPs.

The ability to know in advance the trend of running process instances, with respect to different features, such as the expected completion time, would allow business managers to timely counteract to undesired situations, in order to prevent losses. Therefore, there is a need for an operational support approach that bridges the gap between complexity and operational support actions (detection violations, predicting events and recommending actions).

B. Variability

There Business process variability is defined as the mechanism that permits users to perform their research according to their objectives in diverse ways. Indeed, different behaviours can be produced. Even users with the same objective may follow different paths and stand different sub-processes denoted as personalised/customisable BPs that vary in terms of structure, objective, and result. This puts forward the difficulty of obtaining and studying user's behaviours (Van der Aalst *et. al.,* 2009; El faquih *et al.,* 2014). Here, we denote the variant concept that may refer to the activity variant or the process model variant. Moreover, the variation point defines a crucial element (i.e., a node or a sequence flow) of the customisable process model that can be customised via model transformations. Accordingly, the customisable process model encapsulates customisation decisions between process variants that need to be made either at design-time or runtime. Customisable process models capture a family of process model variants in a way that the individual variants can be derived via transformations, e.g., adding or deleting fragments.

Therefore, the difficulty of representing some BPs type emerges from their variability concept (Athukorala *et al.,* 2016). This later change according to different contexts and requirement. Even though managing process variability is a non-trivial task because it requires specific standards, methods, and technologies, it still involves many parameters that are not always formally defined. For example, designing the reference process model, which represent the commonalities from the process family, is a challenge, as well as the necessary adjustments to configure a specific process variant. Thus, each BP variation is applicable to a different situation that affects specified customisation criteria in a different way. Such criteria may include high-level qualities or non-functional goals e.g., such as key performance indicators (KPIs) or operational constraints that prescribe patterns to decide which BP must be followed. In this context, two main definitions can be acquired (Van der Aalst *et. al.,* 2009; Detro *et. al.,* 2017; La rosa *et al.,* 2017):

- Variability by restriction starts with a customisable process model that contains all behaviour of all process variants. Customisation is achieved by restricting the behaviour of the customisable process model. For example, activities may be skipped or blocked during customisation. In this setting, one can think of the customisable process model as the union or Least Common Multiple (LCM) of all process variants. Customisable process models of this type are sometimes called as configurable process models.
- Variability by extension takes the opposite starting point. The customisable process model does not contain all possible behaviour, instead it represents the most common behaviour or the behaviour that is shared by most process variants. At customisation time, the model's behaviour needs to be extended to serve a particular situation. For example, one may need to insert new activities in order to create a dedicated variant. In this setting, one can think of a customisable process model as

the intersection of all process variants under consideration.

In this regard, process mining algorithms can be used to mine BP variability (variant details) in order to manage and decide the suitable path to execute.

C. Dynamicity

The concept of dynamicity defines the process that can change some BP activities during runtime under various conditions, which are emerged from real-time variables. It can be adapted according to internal or external environment changes. In this context, we focus on Ad-hoc processes that are characterised by a non-defined workflows design. Indeed, the control-flow between activities cannot be modelled in advance but can simply occur during runtime. Here, users must be able to decide what to do and when. They must also be able to assign work, as sub-process, to other people and create interactions among various users. This puts forward the difficulty of treating dynamically Ad-hoc processes.

The dynamicity can also be nominated, in such research, as the flexibility by design concept (Schonenberg *et al.,* 2008). However, our objective is to obtain a dynamic Ad-hoc BP. Indeed, we focus on research that combine between: 1) process mining techniques and Ad-hoc BP. 2) dynamicity and Ad-hoc BP and 3) dynamicity and process mining techniques. To this end, we present a brief literature review of those papers. Dustdar *et al.* (2005) proposed a tool for mining Ad-hoc processes has been demonstrated (Dustdar *et al.,* 2005). Here, the ambiguity concerns the definition of sub-processes with different guiding conditions. Besides, the adaptive process does not respect possible external changes. In previous study, the authors present two case studies in healthcare domain, especially into the emergency department (Duma *et. al.,* 2018; Duma *et al.,* 2020). Here, the process discovery technique illustrates possible processes that can do a patient in the emergency department. These cases must be generalised into a clear approach. Kiedrowicz (2017) presents an approach dealing with dynamicity into Ad-hoc BP using a pre and post sections to subsequently execute actions, based on the set of process goal (Kiedrowicz, 2017). In this study, process mining did not match in the Ad-hoc BP definition. Additionally, Jain *et al.* (2017) discussed the context changes (external and internal) and conditions that could influence the BP dynamicity (Jain *et al.,* 2017). Some works as Vasilecas *et al.* (2016) treat only the internal context, others do not predefine the automated BP activities and others do not discuss about changes of the context of activities (external to internal Ad-hoc process environment) (Vasilecas *et al.,* 2016). Further, Zhu *et al.* (2014) demonstrate just external changes (Zhu *et al.,* 2014). In spite of above, BP dynamicity Adams *et al.* (2010) is treated as agility, adaptability, and flexibility, where internal changes have been taken into consideration (Adams *et al.,* 2010).

According to the aforementioned studies, we observe that few researchers take up the study of the combination between: Dynamicity, Ad-hoc BP, Process mining techniques, external and internal changes of the BP environment or conditions related to Ad-hoc BP. To this end, we must treat dynamicity into Ad-hoc BP, using process mining techniques and taking into consideration runtime changes.

D. Synthesis

In this section, we have discussed recent approaches that predict, structure, manage variability and dynamicity for unstructured BPs. This is tackled related to the process mining field. First, we have illustrated approaches that treat event logs complexity. At this stage, it is important to explore structured sub-processes into the unstructured ones. Second, we have discussed the challenge of operational support that can be acquired with complex process models. For instance, it is required to predict the remaining time dimension to execute future activities during the BP execution. Third, we have defined the variability challenge where we have shown over related issues that must be resolved. Fourth, we have discussed the dynamicity challenge and the necessity to predefine processes to select the suitable adaptive sub-process.

III. OUR UNSTRUCTURED BUSINESS PROCESS IMPROVEMENT APPROACHES

During the BP execution, a BP can be changed from simple (understandable and readable) to complex structure (incomprehensible and unreadable). This transition may be daily caused by human knowledge intervention, to correct

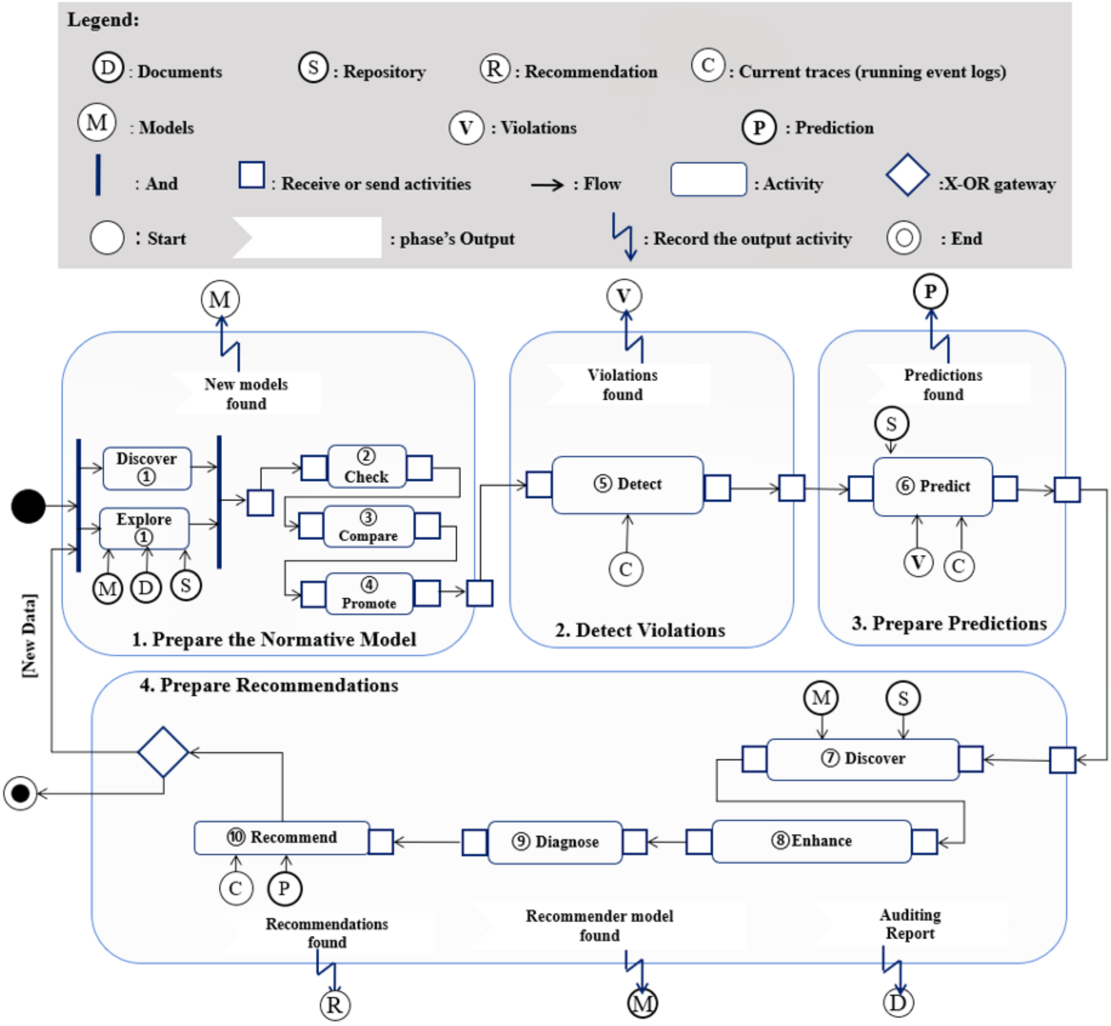

Figure 1. An overview of our operational support approach

violations that occur in a BP and that can prevent its progress. Here, a set of dramatical scenarios can be acquired and new challenges related to the BP improvement and structure can be defined. First, we propose an approach to treat the complexity of UBPs at runtime. Second, we define an approach that manages the variability challenge in order to decide which path should be chosen during the BP execution, Third, we present an approach that tackles the dynamicity challenge to execute in a dynamic manner UBPs according to the company business rules and conditions. These approaches are respectively validated in these publications (Lamghari *et. al.,* 2020; Lamghari *et. al.,* 2021; Lamghari *et al.,* 2022).

A. Operational Support Approach

The complex structure of unstructured BPs emerges the difficulty of predicting actions during the BP execution. This requires the use of other process mining techniques. In this sense, we cite the recent refined process mining framework. This framework extends process mining types into three categories with ten activities, which are: Navigation (Discovery, Enhance and Diagnosis), Auditing (Detect, Check, compare and Promote) and Cartography (Explore, Predict and Recommend). These activities link current and historic data to the de jure model (a normative model that specifies how things should be done or handled) and the de facto model (a control-flow model that represents the order in which process model activities must be executed).

However, the most challenging task is how current situations benefit from historic data. To this purpose, operational support systems have been defined to learn from existing structured models, normative ones, historic and current or running data. Thus, the use of the Detect, the Predict and the Recommend activities is mandatory. Also, the appearance of the predictive (aims at predicting an outcome that can influence next events) and the recommender models (aims at defining the "preference" that can be attributed to an activity or a resource) is crucial. These two models are considered as inference ones. Here, operational support approaches perform well with SBP, while they still a challenging task for UBP. In this respect, the still encountered issues related to the UBP operational support application. Buijis *et al.* (2012) presents briefly how the process mining activities re-organisation can provide operational support for UBP, based on the structured BP version, i.e., reducing the UBP complexity (Buijis *et al.,* 2012). This operation necessitates the intervention of other process mining activities as Diagnosis, Check, Promote, etc. Hence, the order of process mining activities stills a questionable task.

To this end, our approach objective is to establish an operational support approach that deals with UBP, i.e., detects violations, predicts events and recommends actions for unstructured BPs at runtime. So, we suggest combining, in a specific order, the ten activities of the refined process mining framework.

Tackling the analysis of UBP through the orchestration of existing process mining activities, by necessity techniques, brings new knowledge to the research field in terms of producing a complete approach that can treat the complexity problematic. Indeed, we detail our UBP operational support approach phases (see Figure 1).

- To achieve the UBP operational support objective, we require the existence of a SBP, an initial normative model (INM) and a refined or final normative model.
- To obtain the SBP of an UBP (de facto model), we apply the simplification algorithm combined with the structuring techniques (Augusto *et al.,* 2018a). Here, we select heuristics miner algorithm for the discover à activity. In parallel, to define the initial normative model, we explore ① Documentations and recorded models.
- To obtain the refined normative model (nominated as the de jure), it is required to use an audit approach by proceeding through these activities (check ②, compare ③ and promote ④). At this stage, we use the SBP and the INM.
- After obtaining the refined normative model and the SBP, we can detect violations (detect ⑤). This allows predicting events (predict ⑥) using the predictive model. We can also recommend ⑩ actions relatively to the obtained diagnosis information (discover ⑦, enhance ⑧ and diagnose ⑨) and the recommender model.

In our approach, we denote de facto model as an UBP before applying structuring techniques and as a SBP after the structuring step. As well as we denote a refined normative model as a de jure model or a final model. In this regard, we can present our approach into the following four phases (see Figure 1): We start by the phase of preparing the normative model using five activities: Discover, Explore, Check, Compare and Promote. This phase's output is a refined normative model. Then, we proceed to the second phase that aims at detecting violations using the Detect activity. According to the revealed violation and historic data, we can predict events in the third phase. Last, we use diagnosis information, to generate a recommender model and acquiring suitable recommendation using the Discover, the Enhance, the Diagnosis and the Recommend activities.

B. Managing self-defined BP Variability

The contribution presented in this sub-section is about mining self-defined BPs (Lamghari *et al.,* 2022). Indeed, a suitable technique for representing users' behaviour in their information seeking processes is required. In this sense, process mining seems to be an interesting option to deal with. Also, managing self-defined BP variability is essential (Configurable Process Model). Furthermore, it is important to handle semantic content (Ontologies based on semantic reasoning) to recommend one process in the case of variation points (Figure 2).

- Configurable process model (cpm): appeared with the objective of integrating different process variants into one model (Gottschalk *et al.,* 2007).

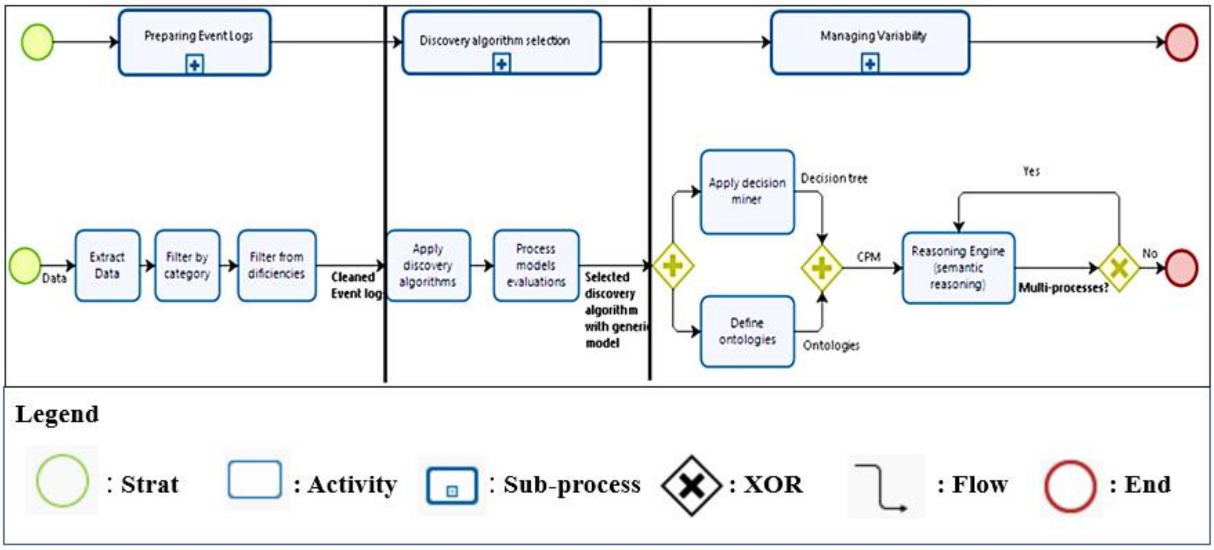

Figure 2. Our Approach for mining self–defined BP

Thus, the cpm enables extracting a process variant, which is a process model different from the original one, but that fits better in the application environment. This approach enables to represent the commonalities of the process variants. By sharing the particularities among multiple variants, this approach also promotes the model reuse (Ayora *et al.,* 2007). Several aspects related to the BP variability have been discussed, such as: management, (re)design, modelling, and configuration. Furthermore, most of the proposed approaches present a low level of automation. Indeed, the configuration of the process variant requires the verification of a syntactical and semantically levels of resulted models, where existing approaches do not differ between planned execution and real process execution, i.e., what happens during the process execution may be not planned to happen. Therefore, the use of process mining techniques is mandatory because they enable the extraction of information from event logs. Thus, by analysing the generated process model, process variants can be discovered, and problems can be corrected. For this purpose, a process mining technique, called decision miner, is selected to analyse decision points that enable detailing variation points, alternatives, and rules. The benefits provided by the semantic enrichment of the bp include the improvement of its representation and understanding; the automation of tasks related to the modelling, configuration, evolution, and the adaptability of the bp according to different requirements. Therefore, it is possible to analyse the cpm in a semantic manner.

- Ontologies and semantic reasoning: The ontology enables to capture, represent, re (use), share and exchange common understanding in a domain (Bogarin Vega *et al.,* 2018). The ontology is composed by commonly agreed terms, thus describing the domain of interest. However, knowledge shared and reused among applications and agents are only possible through the semantic annotation. Semantic annotation enables to reasoning over the ontology, thus ensuring the quality of the ontology by deducting new knowledge (Liao *et al.,* 2015). The semantic enrichment of the BP was proposed to increase the level of BPM lifecycle (Hepp & Roman, 2007) and to compliance checking (Szabo & Verga, 2014). Regarding to the CPM, semantic technologies have been applied for semantic enrichment (El Faquih & Sbai, 2014) and for semantic validation (Fei & N. Meskens, 2010).
- Self-defined BP challenge: the difficulty of representing self-defined bp emerges from its variability (Athukorala *et al.,* 2016) according to different contexts and requirement. Even though managing process variability is a non–trivial task because it requires specific standards, methods, and technologies, it still involves many parameters that are not always formally defined. For example, designing the reference process model, which represent the commonalities from the process family, is a challenge, as well as the necessary adjustments to configure a specific process variant.

To overcome these challenges, it would be useful to represent users' behaviour (information-seeking processes), i.e., to define the generic process model, in order to study the self–defined BP variability and recommend the suitable path to each user.

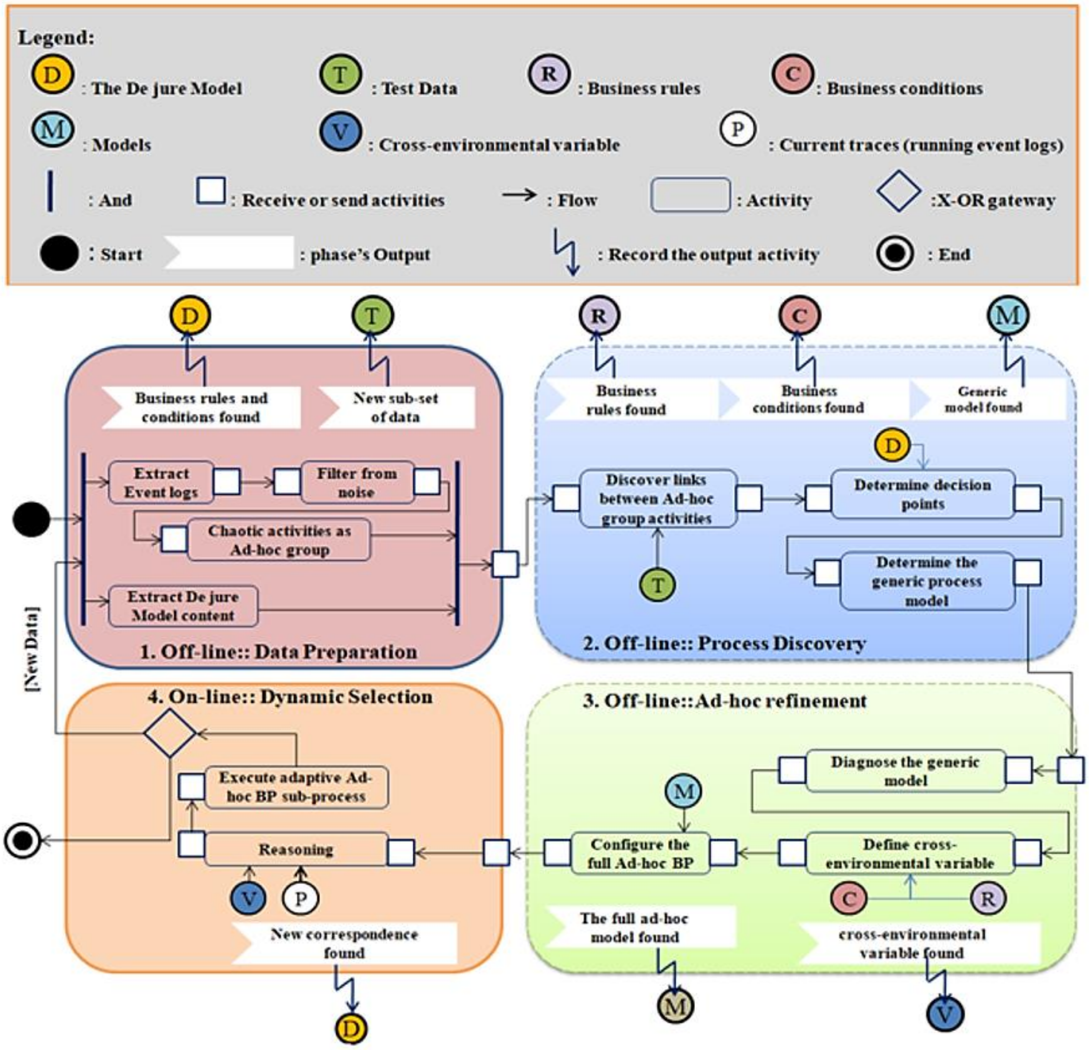

Figure 3. Different views of our proposed dynamic approach

Also, it is useful to manage the process variants through ontologies based on semantic reasoning and Configurable Process Model (Gottschalk *et al.,* 2007), i.e., to select the appropriate process variant according to the combination between different selfdefined BP ontologies. To achieve these objectives, it is required to use process mining algorithms to mine user self–defined BPs. The first step is to select the most preferment algorithm, based on process model quality criteria, to discover the generic process model.

The second step aims at managing existing process variants to recommend the suitable path according to user's objective, requirements, and engine knowledge. This is done by using decision miner algorithm to obtain the CPM (process model with variants details) and by employing related semantic reasoning of the self–defined BP ontologies. Indeed, this contribution can evaluate the performance of process mining algorithms in representing self-defined processes and their ability to generate user's behaviours and identify variation points, alternatives, and rules. Besides, it illustrates the applicability of semantic reasoning as a decision task that can be combined with process mining, to recommend one path instead another.

C. Ad-hoc BP Dynamicity

The concept of dynamicity defines the process that can change some BP activities during runtime under various conditions, which are emerged from real-time variables. It can be adapted according to internal or external environment changes. In this context, we focus on Ad-hoc processes that are characterised by a non-defined workflows design. Indeed, the control-flow between activities cannot be modelled in advance but can simply occur during runtime. Here, users must be able to decide what to do and when. They must also be able to assign work, as sub-process, to other people and create interactions among various users. This puts forward the difficulty of treating dynamically Ad-hoc processes.

In this way, our work (see Figure 3) aims at introducing dynamicity concept into Ad-hoc BP, using process mining techniques. We try to demonstrate how it is possible to extract in-formation from event logs (Off-line), using the process discovery technique, in order to model and configure Ad-hoc BP.

Then, we demonstrate how to select suitable Ad-hoc sub-processes adaptively to specific conditions at run-time (On-line), using the conformance checking technique. The enhancement technique can be applied for re-modelling and re-configuring the Ad-hoc BP. For this purpose, we present our approach of selecting dynamically an adaptive sub-process using process mining techniques. This contribution consists of treating dynamically Ad-hoc BP, using process mining techniques.

On this subject, we try to model Ad-hoc BP sub-processes based on historic events knowledge and to select an adaptive sub-process using running events. In this respect, we present our approach in two views: Off-line and On-line (see Figure 3). In the Off-line view, we analyse event logs in order to discover the generic process model. We can also determine the full Ad-hoc process model by attributing business conditions and rules to the generic process model. In the On-line view, we try to adapt our Ad-hoc BP, i.e., dynamic selection of an adaptive Ad-hoc sub-process according to specifics conditions. These conditions can be defined as a cross-environmental variable that includes business conditions and rules. In this context, business conditions are considered as decision points for each X-OR gateway. Business rules are expressed as a set of rules prescribed as a guide for actions or business behaviours. Cross-environmental variable passes external conditions to internal Ad-hoc BP environment; it may combine business rules, business conditions and optimal performances as a resource, time, etc. To approve these three points, we apply the conformance checking technique.

IV. CONCLUSION

In In this paper, we presented three approaches dealing with unstructured BP challenges using process mining techniques.

The first approach takes into consideration the refined process mining framework. This later contains a set of activities that use extracted information from event logs, discovered models and normative ones. Among these activities, we find those dealing with running events in a SBP context, which are the Detect, the Predict and the Recommend activities. These three activities are nominated as operational support system that performs well on SBP while, it stills a challenging task for an UBP, because of its complex structure. In this regard, a special interest is given to the use of existing process mining techniques to analyse unstructured processes, simplify complex models and providing recommendation. To this end, we have proposed the orchestration of process mining activities into UBP operational support approach through the following phases:

1. Preparing Normative model
2. Detect violations
3. Preparing predictive model and Predictions and;
4. Preparing the recommender model and Recommendations.

The second approach is developed to treat related challenges to self-defined BPs, in terms of process model's representation and variability management. Indeed, we study the applicability of process mining algorithms, to model the generic self-defined process model of user's behaviours in interaction with the e-administration domain (services provided by ministers, municipalities or local communities, and prefectures or states.). In these systems, users can have diverse ways to perform their research according to their objectives. In this context, users apply self–defined processes that may vary in terms of significance, structure, and results. At this stage, the resulted self-defined process model requires variation point elaboration, to define possible choices related to the execution process. To do so, the use of decision miner algorithm is required. This algorithm aims at detailing all sub-processes of the generic self-defined process model for defining self–defined BP ontologies, which are: user objective, user requirement and engine knowledge level. Hence, the configurable process model can be obtained. Last, the combination between the semantic reasoning through ontologies and the CPM can be released, to manage self–defined BP variability.

The third approach aims at treating dynamically Ad–hoc BPs using process mining techniques. Ad-hoc processes are not predefined, and the dynamic selection is not matched. Thus, the lack of adapting processes according to real-time variables is observed. To this end, we present requirements that must be respected in Ad-hoc BP definition. The Ad-hoc BP must be generic and dynamic, i.e., adaptive to real-time variable conditions (changes). Besides, we illustrate how process mining techniques are used to define Ad-hoc BP content and how the CEP tool can be rentable in terms of verifying the cross–environmental variable values and executing dynamically the suitable Ad-hoc BP sub–process. In this context, our approach encompasses two views: The Off-line view aims at constructing generic model, using the process discovery technique in combination with the frequency concept. The On-line view uses the conformance checking technique, to adapt the suitable sub-process of the modelled Ad–hoc BP taking into consideration the dynamicity concept. After execution, all information will be recorded for future improvement of the Ad-hoc BP.

As further research, we plan to approve the applicability of our approaches on concrete cases studies.

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