S4BP: An Approach for Assessing Business Process Stability

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Abstract: Achieving business process (BP) stability is a fundamental objective for organizations, pursued for a variety of reasons including consistency in operations and product/service delivery, reduced costs and rework, and clear metrics for process improvement. Nevertheless, the subject has received little attention in research, from vague definitions to mingled concepts involving BP flexibility and changes. This paper addresses the stability of BP in the context of Business Process Management (BPM). Specifically, it proposes a clearer definition of BP stability, as well as a step-by-step Stability for Business Processes approach (S4BP) based on Process Mining techniques to evaluate and predict stability for a certain BP. The proposed approach is demonstrated through a software implementation in the form of a ProM plugin, and validated using a case study with public datasets from the Business Process Improvement (BPI) Challenge.

1 INTRODUCTION

Business Process Management (BPM) serves as a valuable approach for addressing organizational and strategic challenges by promoting both stability and flexibility in business process (BP) models **(**Cognini et al, 2016**)**. Stability control is critical in BP, as it enhances customer satisfaction. By maintaining stable processes, organizations can ensure timely delivery of products or services, which significantly contributes to customer satisfaction and loyalty. Moreover, assessing process stability is crucial for maintaining high operational quality (Willis et al, 2018). Stable processes provide a robust foundation for informed decision-making and support continuous improvements for smoother business operations.

It is beneficial for a process to be both innovative and capable of adapting to changes (Ben Haj Ayech et al, 2021). However, it is also necessary to have stable processes that resist modifications across different versions, as this is essential to ensure the reliability and consistency in the long term (Kelly, 2006).

A stable environment thus promotes rational decision-making through comparative solution evaluation, rather than being driven by pressing deadlines. This strengthens the organization's ability to optimize its processes, improve execution, and adapt its choices in response to changing conditions and emerging opportunities.

BP models exhibit considerable dynamism and often require modifications (Ben Haj Ayech et al, 2021). According to Baumgraß et al. (2014), process data can evolve over time, making its correlation with processes particularly complex. This dynamic nature of process data can have significant implications for process stability. Therefore, there is a need to assess the stability of business processes by analyzing variations over specific periods of time, to ensure their reliability and consistency.

Despite exiting several research works that offer various definitions on the concept of stable processes in different domains, *BP stability* is, to our knowledge, yet to be addressed in the specific domain of BPM. This work presents our contribution to the theme, beginning by the proposal of a definition of stability specific to BP, supported by a systematic

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approach and an implementation of a plugin in the ProM tool for validation, including the use of Process Mining techniques over a public dataset of BP.

The paper is structured as follows: Section 2 provides background on stability, BP and Process Mining techniques, highly involved on our proposed approach. In Section 3, we address related work, and in Section 4 we propose our S4BP approach. Section 5 presents the implementation and validation of the approach on ProM, and finally, Section 6 concludes the paper and presents future work.

2 BACKGROUND

The concept of stability is generally implicit, acknowledged, but rarely formally defined. Few precise definitions of stability are available, and these are mostly associated with software development processes. For instance, the work of (Yau et al, 1980) introduced a definition of code stability, followed later by a definition of design stability (Yau et al, 1985). Another definition is proposed by (Kelly, 2006) for the stability of a design characteristic, suggesting that if the value of the metric associated with that characteristic exhibits slight variations between two or more versions of the software, then that characteristic can be considered stable. According to this study, limited variation indicates that, despite the changes made, the design retains fundamental elements that remain constant.

Despite the importance of BP stability and its impact on various organizational factors, much of the existing literature does not address the measurement of stability in BP or the prediction of their subsequent changes. On the contrary, the concept of BP flexibility was earlier defined for instance, in (Daoudi et al, 2005), (Pesic et al, 2006), (Schonenberg et al, 2008) and (Regev et al, 2006) and is widely used in literature, including well defined ways to measure it (Mejri et al, .2018), (Mejri et al, 2024).

Nevertheless, process stability is a significant concept in Business Process Management (BPM) that can also be defined and measured using various quality metrics, such as precision, complexity, and outcome prediction (Jongchan, 2021). For this purpose, Process Mining includes data science techniques that aim to discover, monitor, and improve actual BP by extracting valuable metrics and insights from event logs (Van der Aalst et al, 2021). The objective of process discovery is to automatically identify the schema of a process from an event log (Van der Aalst et al, 2011). Although the majority of BP undergo dynamic evolution over time, often in response to internal and external factors, current process mining approaches often assume processes are in a stable state. Consequently, an increasing number of algorithms have been developed to compare different variants of the same process (Hompes et al, 2015) (Luengo et al, 2012). The primary aim of process discovery involves the automated extraction of a process schema from event logs (Van der Aalst et al, 2011). As a result, a growing array of algorithms has been developed to analyze different variants of the same process or to identify shifts in processes over time (Lavanya et al, 2015). These algorithms play a vital role in recognizing and comprehending alterations in BP, thus enabling organizations to seize new opportunities and ensure ongoing improvement.

Moreover, Process Mining can be employed iteratively, facilitating the creation of more comprehensive data records, including actor names, notes, dates, and the curriculum elements such as required work, essential concepts to be grasped, and the instructor's primary goals. This iterative approach enables swift identification and resolution of encountered issues for future enhancement. Process mining techniques aim to convert data collected during process execution into actionable information and knowledge (Bergaoui et al, 2024).

3 RELATED WORK

This section provides an overview of existing research related to BP stability. We begin by discussing BP discovery techniques, which can serve as a foundation for any stability assessment. Understanding how processes are extracted and represented is crucial for subsequent analysis. Next, we explore various metrics used to evaluate BP stability, highlighting key indicators that help quantify stability and its influencing factors. Finally, we identify existing research gaps in BP stability studies, emphasizing the need for further investigation and positioning our contribution within this context.

3.1 BP Discovery

One of the most studied Process Mining techniques is the automated discovery of processes (Adriano et al, 2018). These techniques take an event log as input and generates a BP model that captures the control-flow relationships among tasks observed or inferred from the event log. The model produced must meet several criteria: it should be able to generate each trace present in the log, create traces similar to those in the event log, and produce traces that are not in the log but are identical or similar to the traces of the process that generated the log.

Several approaches have been proposed in the literature to identify changes made to BP models. The work of (Günther et al, 2008) integrates Process Mining with adaptive process management, utilizing log files from Process Mining to enhance adaptive management systems. Their research emphasizes a flexibility metric that facilitates modifications and changes in dynamic BP models during execution. By employing Process Mining as an analytical tool, they offer insights into when and why process changes become necessary, thereby improving support for flexible processes. (Berti, 2016) further develops Process Mining techniques to enhance the prediction and detection of dynamic changes in BP using various algorithms, statistical tests, and probabilistic approaches. Another significant contribution is BPMN-CM (Business Process Model and Notation Change Management), introduced by (Kherbouche, 2013), which assists in managing the evolution of BP models by analyzing the impact of changes to ensure model consistency after each modification (Ben Haj Ayech et al, 2021). Moreover, (Maaradji et al, 2017) focus on extracting information regarding change techniques in systems by analyzing collected data to compute relevant timestamp differences. Their method, which detects progressive drifts, represents a family of techniques aimed at identifying changes in BP. Their empirical evaluation demonstrates that this method achieves higher accuracy and shorter detection times in identifying typical change patterns compared to existing methods. Additionally, (Alejandro et al, 2018) utilized interaction data from 101 university students, mining 21 629 events to assess the models produced by different algorithms in terms of fitness, precision, generalization, and simplicity metrics. They compared results from algorithms such as Heuristic Miner, Evolutionary Tree Miner, Alpha Miner, and Inductive Miner, finding that the Inductive Miner algorithm yielded the best performance overall, particularly when various metrics were weighted.

(Carlos, 2022) compared Process Mining tools and algorithms, noting that Alpha Miner, as the initial algorithm for process discovery, generates a Petri net model by first identifying existing traces, analyzing the sequence of activities, and creating a relationship matrix. The study also highlights Heuristic Miner, which constructs the process map by considering the frequency of events rather than solely the sequence, focusing on the most frequent paths while disregarding those that appear less often.

Although these related works mention important BP flexibility and changeability metrics and approaches, we have observed a significant lack of research focusing on the stability of BP, despite their crucial importance for the operational efficiency of organizations. This work aims to establish a conceptual framework that will allow us to contribute to a better understanding of the interactions involving the definition, assessment and prediction BP stability.

3.2 BP Metrics Related to Stability

This section discusses metrics that can be used to compute BP stability. According to (Adriano et al, 2018), the Process Mining-related *fitness* metric measures a BP model's capacity to reproduce the behaviors represented in an event log, where a score of 1 indicates complete reproduction of all traces. *Precision* assesses the model's ability to generate only the behaviors found in the log, with a score of 1 indicating that all traces produced by the model are contained within the log.

The frequency and extent of modifications made to process models over time are captured by the number of changes. These changes can stem from various factors, such as evolving business needs, new regulations, or efforts to improve performance criteria (Philip et al, 2011). The number of variants in BPM serves as a metric for assessing process model *variability*, which is contingent upon the specific needs and circumstances of the organization (Fredrik et al, 2012). Model *redundancy* in BPM is another crucial metric, referring to the presence of duplicate or unnecessary elements within BPM models, which may lead to confusion, inefficiencies, and errors (Fei et al, 2021).

Generally, these metrics are evaluated for a certain period of time within process event logs, ranging between BP perspectives such as control-flow (the sequencing, frequency and timing of activities), resources (e.g., teams allocated to activities) or data (documents' states along process execution). Nevertheless, by themselves these metrics are poor to assess BP stability, since it usually implies calculation logic and evolution over time. Additionally, prediction techniques can be further applied around this calculation logic, as for example using linear regression predict various events, which not only enables effective management of product quality but also allows for the analysis of a wide range of data (Gezani et al, 2015).

3.3 BP Stability Research Gap

From our point of view, organizations can pursue stability in their BP for several reasons. A stable process guarantees consistent and predictable outcomes, which are essential for fulfilling customer expectations and sustaining a strong reputation. Furthermore, stable processes facilitate smooth operations, minimizing the need for frequent adjustments, thereby increasing efficiency and productivity. Additionally, a stable process contributes to cost reduction by decreasing material waste and unexpected downtimes, resulting in cost savings and more environmentally friendly operations. Timely delivery of products or services from a stable process enhances customer satisfaction and loyalty, while also enabling the achievement of desired outcomes and meeting customer specifications. Moreover, stable processes provide a solid foundation for predictability, informed decision-making and optimization of business operations, allowing organizations to swiftly adapt to changing market conditions and scale their operations accordingly.

To the best of our knowledge, this concept of BP stability and the way it can be achieved remains a rather unexplored research theme.

4 THE S4BP APPROACH

In this section, we present the ***S4BP*** approach, which aims to assess and ensure the stability of BP. First, we define the concept of business process stability, identifying its key characteristics and its importance in the context of our study. Then, we detail our methodological approach, explaining the steps followed, the principles adopted, and the tools used to evaluate and predict the BP stability.

4.1 BP Stability Definition

In this paper, we consider a business process to be stable when it evolves in a controlled and predictable manner, based on the analyzed perspectives, applied metrics, and their trends over time. We define *BP stability* as the ability of a business process to maintain structural consistency and operational predictability in the face of changes and evolutions. In addition, we introduce a formal definition, encompassing three main process key components: perspectives, metrics and trend analysis. Perspectives cover the process control-flow, data, and resource dimensions. Metrics include calculated values over the data of these perspectives. Examples include similarity metrics, number of variants, change frequency, and process fitness. Trend analysis consider the evolution of these metrics over different periods of time.

Building upon these foundational concepts, we propose a formulation where PS represents process stability, defined as a function of various factors, including distinct process perspectives, metrics calculation logic, and trend analysis. We can then formulate the process stability as follows:

$$PS = \mathrm{f}(\mathrm{PP}, \mathrm{T}, \mathrm{M}, \mathrm{C}) \quad (1)$$

Where:

- PP refers to the process perspectives, including control-flow (CF), data (D), and resources (R), defined as:

$$\mathrm{PP} = \{\mathrm{CF}, \mathrm{D}, \mathrm{R}\} \quad (2)$$

- M denotes the set of metrics used for assessing stability, defined as:

$$\mathrm{M} = \{\mathrm{metric1}, \mathrm{metric2}, \dots, \mathrm{metric}n\} \quad (3)$$

- T is trend analysis, representing time intervals over which metrics are evaluated, expressed as:

$$\mathrm{T} = \{\mathrm{t1}, \mathrm{t2}, \dots, \mathrm{tn}\} \quad (4)$$

- C represents the stability calculation logic, involving an aggregation function over the specified trend analysis time periods *t*.

Having this formulation, we can now proceed with the proposal of an approach to apply it concretely.

4.2 Approach

Our proposed S4BP approach foresees the application of the previous definition into five key phases: *Requirements specification*, *Process Discovery*, *Stability Discovery*, *Evaluation*, and *Prediction*, as illustrated in Figure 1.

In the *Requirements specification* phase, users define the parameters for subsequent phases. This phase is fundamental, as it ensures that the following steps are aligned with the user's objectives and needs. During this phase, the user has the option to specify process perspectives to be analyzed, select the available process metrics to be calculated, and define time periods for the trend analysis. For instance, a user can select *control-flow* as the process perspective to be analyzed, and choose *model similarity* as a process metric, in order to perform a trend analysis of model similarity over time. To define this trend analysis, the user can establish monthly time periods.

Within this example, for a certain process, process model similarity will be computed between consecutive months, where for each month, a process model will be considered, taking as input all the cases which happened during that month. Furthermore, a process engineer can choose a prediction technique for predicting this model similarity evolution (for instance, Simple Exponential Smoothing or linear regression).

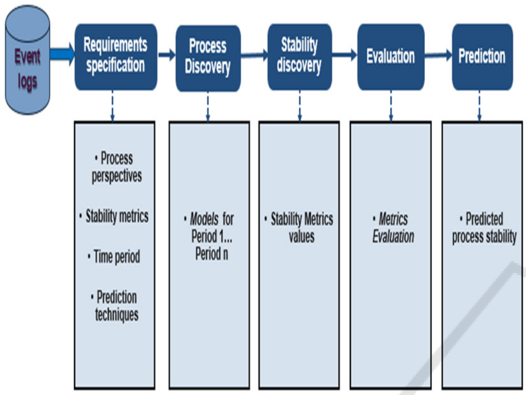

Figure 1. The S4BP approach.

In the second phase, titled *Process discovery*, the approach foresees the discovery of process models (for instance in the form of a Directly Follows Graph for the control-flow perspective, or a Social Network Analysis for the resources perspective), transforming raw process data extracted from event logs into actionable process models. The application of this algorithm will facilitate the visualization of control flow relationships, organizational roles, and interactions among various activities, thereby providing a deeper understanding of the current operation of BP.

We then move on to the next *Stability discovery* phase, where the selected process metrics are computed. For instance, considering the model similarity metric mentioned above, this phase takes care of all associated comparisons and calculations, as well as the computational effort to draw the evolution of stability for this metric. In this case, the goal is to present a trend analysis to thoroughly examine the evolutions and adjustments made to the models within certain time periods.

Based on these results, the user can make informed decisions regarding which models exhibit consistent behavior or require further attention. Additionally, the metrics serve as a foundation for applying an appropriate prediction technique in the final phase, named *Prediction*. In this phase, the user can estimate future process stability, allowing for proactive adjustments and ensuring long-term process efficiency.

5 PROTOTYPE DEVELOPMENT AND EXPERIMENTATION

In this section, we present the **prototype development and experimentation** process, which serves to validate our approach through practical implementation. First, we introduce the **developed mockups,** which provide a visual and conceptual representation of the proposed solution. These mockups illustrate the key functionalities and user interactions, offering an initial framework before full implementation. Next, we detail the **ProM plugin implementation and experimentation**, where we describe the integration of our approach into the **ProM** framework, followed by a series of experiments to assess its effectiveness.

5.1 Developed Mockups

To validate our S4BP approach we have developed mockups for a software application that illustrate the appropriate user interaction. The first interface of our prototype foresees the upload of a process event log dataset as shown in Figure 2.

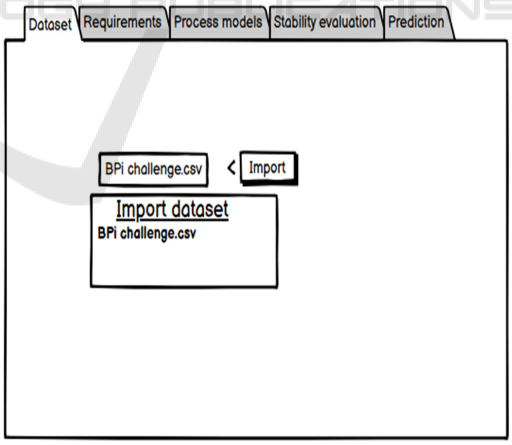

Figure 2. Import dataset interface.

The *Requirements* phase of S4BP approach is prototyped in Figure 3, which involves selecting all the parameters necessary for the subsequent phases. Here, the interface delineates the parameters selected by the user. The process perspective defines the specific viewpoint to be assessed, utilizing a tailored set of metrics. In this example, we present the selection of the process *control-flow* perspective. The selection of the associated process metrics is contingent upon the selected perspective. For instance, the assessment of stability from the control-flow perspective can include (as examples) the 'model similarity' and 'number of traces per variant' metrics.

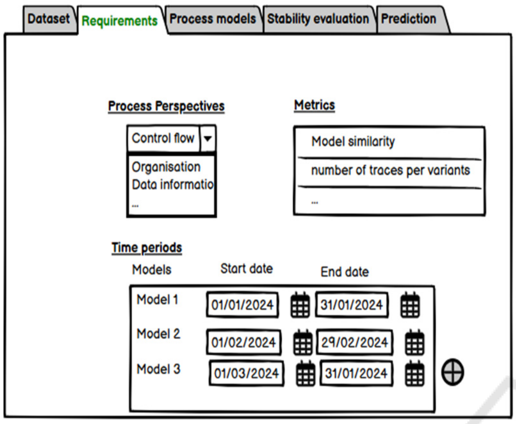

Figure 3. Selecting parameters interface.

Furthermore, regarding stability trend analysis, the user has the chance to specify the period of time from which a process model is discovered, and choose the desired number of process models to assess. These discovered models will be presented in a list format (Figure 4).

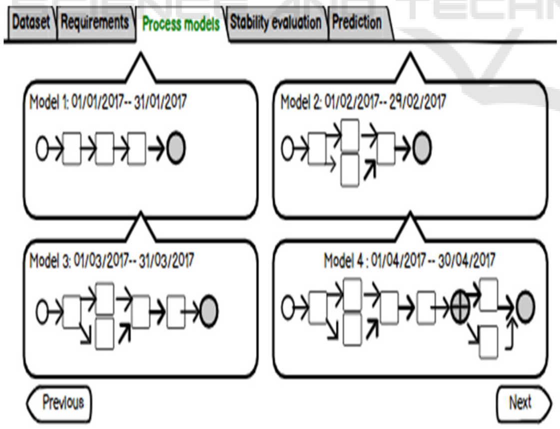

Figure 4. Process models discovery interface.

For the *Stability discovery* phase (Figure 5), we illustrate it with an example of a chart, showing the evolution of the chosen metric over time. This chart provides a visual analysis of how the process models have evolved over the chosen time periods.

Finally, Figure 6 presents what can be a predictive analysis regarding the chosen process metrics and, therefore, its stability forecast. In this example, the predicition result is shown in the form of the predicted evolution of model similarity for the next months.

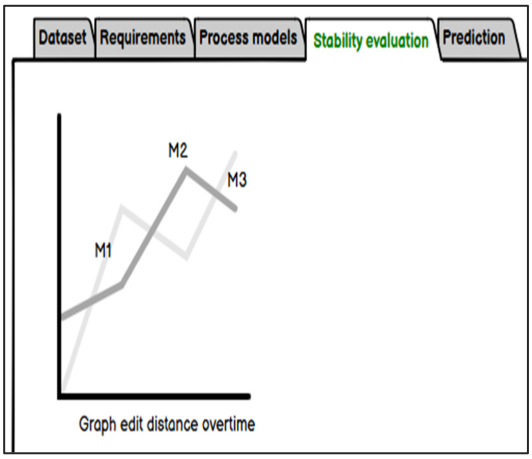

Figure 5. Stability evaluation interface.

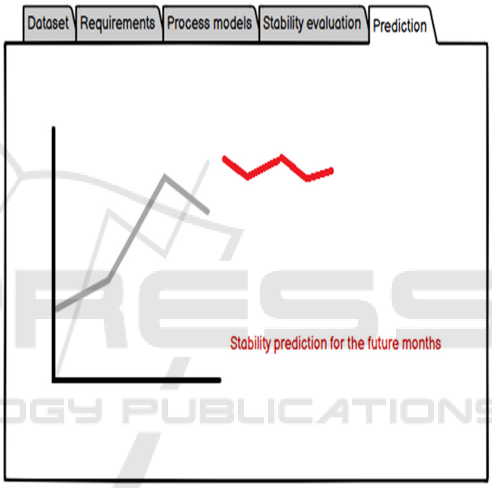

Figure 6. Prediction stability interface.

5.2 ProM Plugin Implementation and Validation with a Running Case

In this section, we will consider the implementation of our S4BP approach using ProM – a powerful and widely used framework for Process Mining and workflow analysis – and we will illustrate and validate this implementation with a running case to demonstrate the practical applicability of our approach. For the latter, we used a public dataset of the BPI Challenge initiative. This dataset has been widely used in Process Mining research to explore performance analysis, compliance checking, and bottleneck identification, offering valuable insights into real-world. It includes event logs detailing

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various processes such as application submission, document verification, offer creation, and final loan approval or rejection and several other types. In our work, we analyzed the "Caravan Camper" process to assess its stability and develop predictions for the following months. The process starts with submitting the loan application online or in-person, specifying the loan purpose as "Caravan/Camper". An initial assessment is made, including an automatic credit check and repayment capacity evaluation, with a manual review if inconsistencies arise. The bank then sends loan offers, which may be adjusted by the client, via email, postal mail, or online. Post-offer follow-up, typically taking 15 days, and document validation (proof of income, purchase, and insurance) can cause delays. The final decision results in acceptance, rejection, or cancellation, with higher conversion rates if processed in under 30 days. Average processing time is 22-30 days, with delays caused by client waiting times, incomplete documents, and offer adjustments.

For the implementation part of our approach, we chose ProM since it is a widely recognized software tool in the field of Process Mining, which foresees a plug-in architecture allowing anyone to develop their process analysis and computational programs.

For this initial implementation effort, we chose some predetermined parameters from our S4BP approach. For instance, for the *Process discovery*, we employed the Inductive Miner algorithm, which generates monthly models in the form of Petri nets, as shown in Figure 7.

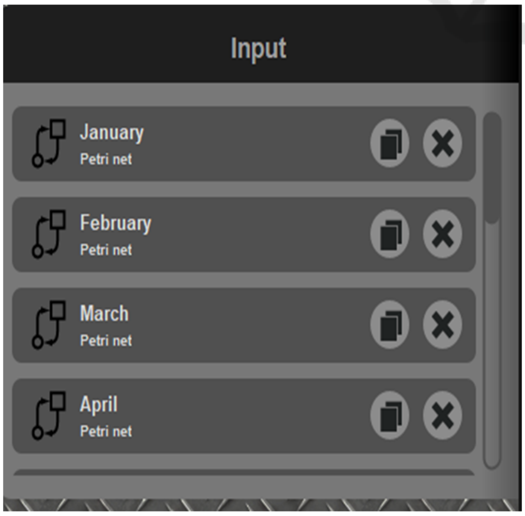

Figure 7. Import of 12 Petri nets models.

To evaluate the stability between the different discovered models, we selected, as the stability metric, the Graph Edit Distance algorithm to compute model similarity. We then adapted the algorithm to display the results in our prototype and to apply evolutionary modifications. Regarding the process perspectives, we focused on the *control-flow*, and for the trend analysis, we segmented the dataset into monthly time periods, with each segment representing traces initiated within a specific month.

We extended the algorithm's capabilities to support the simultaneous comparison of the multiple discovered Petri net models, thereby overcoming the original limitation of comparing pairs of models one by one.

Our S4BP approach allowed us to evaluate the stability and the fluctuations in the process and anticipate future trends. Figure 8 shows the results of this evaluation, comprising, as metrics, the aforementioned model similarity, checked sequentially between the monthly generated models, two at a time. We can observe slight variations in process stability, reflecting deviations over the year. Additionally, the prototype enables users to choose prediction techniques, such as linear regression or ARIMA to forecast future stability for the next three months, as shown in Figure 9. These results suggest that the future models are expected to become increasingly stable, though some variations are still anticipated.

Model A	Model B	Similarity
January	February	0.6842860366550694
February	March	0.7709376534961057
March	April	0.711324738956318
April	May	0.7041613195763394
May	June	0.7001704910979105
June	July	0.7036290702051572
July	August	0.7040624057300651
August	September	0.7024998349630038
September	October	0.7109433317502938
October	November	0.6678956228956229
November	December	0.7202765541856693

Figure 8. Comparison results, considering model similarity over a 12-months period.

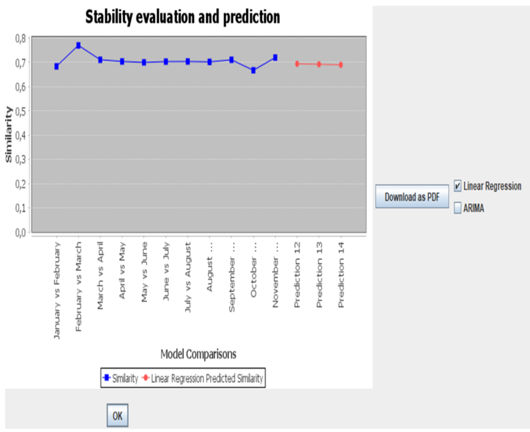

Figure 9. Stability evaluation and prediction result.

6 CONCLUSIONS

In this paper, we addressed the critical issue of stability in BP by proposing a formal definition and a systematic approach named *S4BP* that encompasses five essential phases, each designed to allow for BP stability assessments.

We then validated the S4BP approach through software prototypes for user interaction and an exploratory software implementation, using the ProM software tool. This implementation not only compares successive versions of the models to evaluate their stability but also predicts their future stability, thereby offering organizations valuable foresight into their process dynamics.

For future work, we plan to test our prototype in a real-case study. This step will involve evaluating and validating our S4BP approach in a concrete environment, incorporating predictions and real-time monitoring. The goal is to compare the results obtained by the prototype with those observed in the actual situation, to confirm the reliability of our S4BP approach. Future work will also focus on developing a platform to automatically calculate process stability and generate charts, particularly through dashboards. This platform will be designed to evaluate stability from various perspectives, not only concerning control-flow, but also other relevant perspectives of business processes.

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