Interpreting business process case outcome prediction with XAI

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Abstract

Machine Learning (ML) interpretability techniques were crucial for enhancing Predictive Process Monitoring (PPM) within Business Process Management (BPM), ensuring the strategic integration of ML rather than its mere adoption. VisInter4PPM was proposed previously as a business-oriented approach to visually support interpretability in predictive process monitoring. The VisInter4PPM framework was designed to bridge the gap by providing actionable insights into process predictions. It relied on the results of the SP-LIME interpreter to generate explanations about the influence of each business process activity on the case outcome.

In this paper we present the last version of VisInter4PPM, two results will be presented, the fist one for a synthetic event log, which represented an illustrative health insurance claim management process in a travel agency (a binary class prediction problem); and, a second one for a real event log, which referred to a loan request business process, represented in a real-world event log of a financial institution (a multi-class prediction problem).

The utility of the framework was validated in two design cycles through an expert evaluation. The evaluation confirmed that VisInter4PPM successfully met the needs of business experts by projecting interpretability directly into process models in BPMN notation, which is typically a more familiar working environment for them. This approach not only supported but also enhanced decision-making in complex business environments, making a compelling case for the essential role of ML in modern BPM. This research offered both a methodological framework and empirical evidence essential for advancing ML transparency in BPM, positioning this study as a useful resource for practitioners aiming to navigate and lead in the ML-driven evolution of business processes.

Keywords: Process mining, Predictive process monitoring, PPM, Explainable machine learning, Interpretable machine learning, XAI, LIME

1 Introduction

Actually Predictive Process Monitoring (PPM) use Machine Learning (ML) techniques in Business Process Management (BPM) for organizational context. This techniques have good accuracy in

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predictions of, for example, the next activity or outcome case. But, as occurs in other ML applications this techniques are still black boxes and do not provide a good human interpretation of how they obtain a predicted value [4, 9, 8]. This kind of analysis has been even more relevant for certain application contexts in which the decision cannot be based solely on the result of an artificial intelligence algorithm, but human approval is necessary [21].

Also, awareness and training on potential issues, both technical and non-technical, is an urgent need today, particularly when applying ML models in real-life applications. Given this, post-hoc Explainable Artificial Intelligence (XAI) techniques are being designed to make these models more interpretable [3]. More reasons supporting the need to explain the logic of an ML algorithm are: explain to justify decisions made using an underlying model; explain to control a model, by debugging and identifying possible failures; explain to improve the accuracy and efficiency of your models; and, explain to discover novel knowledge, identify relationships and patterns [26, 2]. Therefore, there is an increasing need to support decisions with white-box models in critical contexts, where experts require a high degree of understanding of the model's decisions to make informed and accurate choices.

The importance of this framework is on the application for real cases, for example, consider a real-world delivery company with a logistics process that is recorded in an information system. Each instance of the process can result in one of three outcomes: package delivered on time, package delivered late, or package not delivered. An instance represents a sequence of steps that may be similar to or different from those previously executed. In this company, business experts use predictive monitoring to analyze and optimize the process through ML model that predict the outcome of each instance. Beyond knowing the predicted outcomes, these experts are also interested in identifying the specific activities that influenced the ML model's predictions, helping them understand the factors that led to each outcome within the context of the business process. Another notable example in the context of process mining is the healthcare field, where a doctor must decide how to treat a patient with the assistance of a ML model that tracks the patient's progress. In fact, an obstacle to the adoption of advanced ML techniques in process mining within this context is the reluctance of doctors to use systems they do not fully understand, particularly black-box systems [24, 14, 13].

Visual interpretability enhances decision-making by providing domain experts with information associated with the process model, enabling better understanding and rapid analysis—an aspect not yet highlighted in the reviewed works. Business process models gain more value for decision-making when associated with predictions and automated decisions. Visualizations of these decisions provide even more insights [15, 6]. Process models in Business Process Model Notation (BPMN) are easier to interpret for most users and business experts [24]. Involving domain experts, who sometimes participate directly or indirectly in monitoring to improve business processes, is challenging due to their expensive and limited time [16, 13, 7]. Recent research in process mining also emphasizes the need to present the results of ML techniques in a graphically interpretable form to facilitate understanding in business processes [23, 24, 14]. These visual results support business experts in their monitoring and optimization tasks. In [18], the study found that decision-making using diagrams is simpler for users without machine learning experience.

This paper shows the last review of a doctoral thesis whose main goal was to develop a business-oriented the framework to visualization supported interpretability of prediction results in process mining, this framework was named VisInter4PPM and was initially published in [12, 11].

2 Method

This is an *empirical research* study as the conclusions to be drawn will be based on the analysis of the results obtained from computational experiments. We classify it as *applied design research* [27] since it seeks to generate knowledge that can be used to contribute to the state of the art and the state of the practice with regard to process mining challenges.

The technical procedures that followed in the experiments involve the following:

- Problem identification and definition of expected outcomes: A literature review was conducted in a exploratory analysis and the studies obtained were discusses in our research group.

- Framework design and development: The process models were designed in BPMN and manipulated in XML file format. Computational routines available in Python libraries for ML models, the LIME algorithm, and other specific routines were adapted and programmed using Python. The scripts of full framework VisInter4PPM developed are published in public repository [10].
- Demonstration: Synthetic event logs of a structured process were used to conduct experiments to validate the framework's characteristics. This event log was provided by the authors Rizzi, et al. [19]. Subsequently, public domain event logs [25], corresponding to an unstructured real-life process were used for validation experiments of the proposed framework's effectiveness.
- Evaluation: The quality of the visual results provided by the framework VisInter4PPM together with experts working in the business process area. A careful evaluation protocol was established both qualitatively (interviews) and quantitatively (surveys) and implement the main contributions in the framework. This protocol was applied equally in two design cycles to: *(i)* evaluate the validity of the the framework VisInter4PPM v1.0 against the planned objectives; *(ii)* assess whether the the framework VisInter4PPM v2.0 addresses the stated problem.
- Communication: Scientific articles were published with the proposed framework and the first design validation [12, 11].

3 Background

Process mining is based on key concepts such as event, case, trace, log, and attribute. An event e refers to the execution of a business process activity at a specific time, by a specific resource, and with a specific cost. A case c represents a process instance and is made up of events, with each event linked to one case. A trace ς is a required attribute of a case and represents a sequence of unique events. An event log L consists of multiple cases, ensuring each event appears only once throughout the log. Each event in the log includes attributes like identifier, timestamp, activity, resource, and cost, while cases may also include optional attributes related to specific business data [24].

Prediction of case outcomes involves using a predictive model to forecast the final result or status of a particular case within a business process. By analyzing historical data and the current attributes of the case, the model can predict outcomes such as whether the process will be successfully completed, if there will be problems, or if it will meet performance targets [1]. This form of prediction is critical in fields like business process management, healthcare, and customer service, enabling stakeholders to make informed decisions and take proactive steps to ensure favorable outcomes [24].

In machine learning (ML), two key concepts related to this are Interpretable Machine Learning (iML) and Explainable Artificial Intelligence (XAI). Interpretability focuses on providing enough understanding of a model's behavior to support downstream tasks, without requiring detailed knowledge of every computation for each data point. In contrast, explainability demands a more in-depth comprehension of the model to adequately support subsequent actions [5, 20].

An iML system can explain its decisions in a way that humans can fully grasp the reasoning behind them [9, 21, 22]. This means that the explanation is understandable to humans, regardless of the features or complexity used by the prediction model [17]. Interpretability techniques are particularly valuable for business experts, as they provide insights into how a predictive model arrives at its results [9, 8]. This study specifically focuses on interpreting categorical predictive models.

4 Proposed framework: VisInter4PPM

The framework developed in this thesis, which was called VisInter4PPM for its meaning visual interpretability for PPM. The following sections explain the concept of the proposal, the internal structure, the algorithm and the working method of developed.

4.1 A business process oriented approach

VisInter4PPM is a business-oriented approach designed to visually support the interpretability of results in PPM. VisInter4PPM provides process experts with the ability to visualize the process activities that influenced the decisions of the SP-LIME interpretability algorithm on a previously trained ML predictive model.

As explained in the previous chapters, the LIME algorithm from the XAI area is capable of obtaining results that allow human interpretation of a prediction considering the type of data used. As illustrated in Figure 1 (a), an ML model that detects the type of content in a text based on a paragraph of a document could be interpreted with LIME. In this interpretation, it is possible to highlight which words influenced the ML model's decision the most and least in determining the type of content of the text, in this case: Atheism. For this case the standard result of the algorithm shows a bar graph with the importance of each word . In Figure 1 (b) another application context is shown, that of image recognition. Here the LIME algorithm manages to highlight the parts of the image that led the ML model to predict that this photo corresponded to a dog playing an electronic guitar.

Similarly, VisInter4PPM improves the understanding and interpretation of complex ML models by visually showing the parts of the process (activities) within a BPMN process model so that humans can quickly identify the reasons, in the context of the business process and event log file, for the decisions made by the ML model. This is exemplified in Figure 1 (c) within the dotted lines.

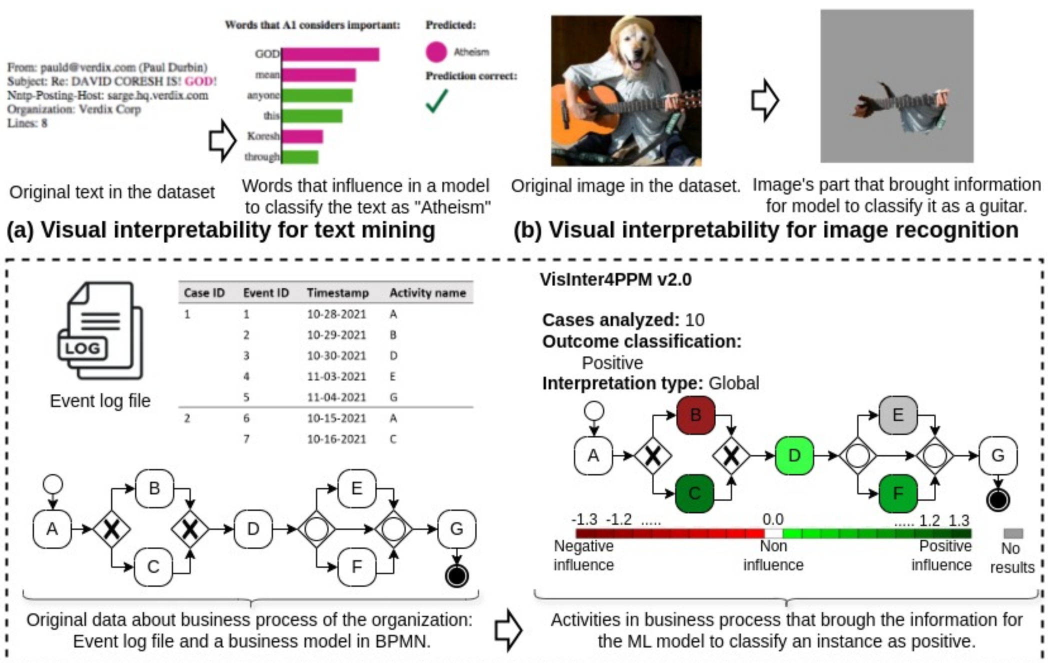

Figure 1: From interpretability for texts and images towards interpretability in predictive process monitoring. Part (a) and (b) ware adapted from the original LIME algorithm paper [17].

VisInter4PPM receives as input the event log file in **.csv* file format, and the process diagram in BPMN and in **.xml* file format, both corresponding to the business process to be interpreted. The VisInter4PPM framework involves the traditional stages of machine learning such as data preparation, model training (for this thesis the Random Forest and k-NN techniques were used). In these stages, the event log is manipulated and used until a predictive ML model is obtained. Then, to perform the interpretability of the trained model, the SP-LIME algorithm is applied, which receives as input both the trained ML model and the event log with the cases to be analyzed. In its standard version, SP-LIME results in a bar graph image where the labels of each bar are the characteristics of the dataset used. This result does not make sense for a business process. Therefore, at this point, the raw matrix of values that gave rise to such image is extracted from the SP-LIME algorithm. This flow is shown in Figure 2.

4.2 VisInter4PPM framework architecture

At this point, the contribution of this work to the area begins. The VisInter4PPM framework takes as input this matrix of values resulting from the SP-LIME algorithm and the BPMN process diagram.

The activities that occur within the process are identified and mapped with their corresponding column in the LIME value matrix to know their influence on each case or instance of the sub-analysis event log. Once the numerical value corresponding to the influence of each activity at the output of the ML model is identified, this value is transformed into a corresponding color in hexadecimal that represents its corresponding meaning within the process, for this the Algorithm *decimal_to_hex_color* was used [10]). Then this new number in hexadecimal is mapped in the BPMN diagram for visualization. Here, an aggregate visualization is also obtained that represents a global interpretation result. This final result is already understandable for various analyses by process experts and can be used for decision making. The VisInter4PPM framework is shown within the dotted lines in the Figure 2

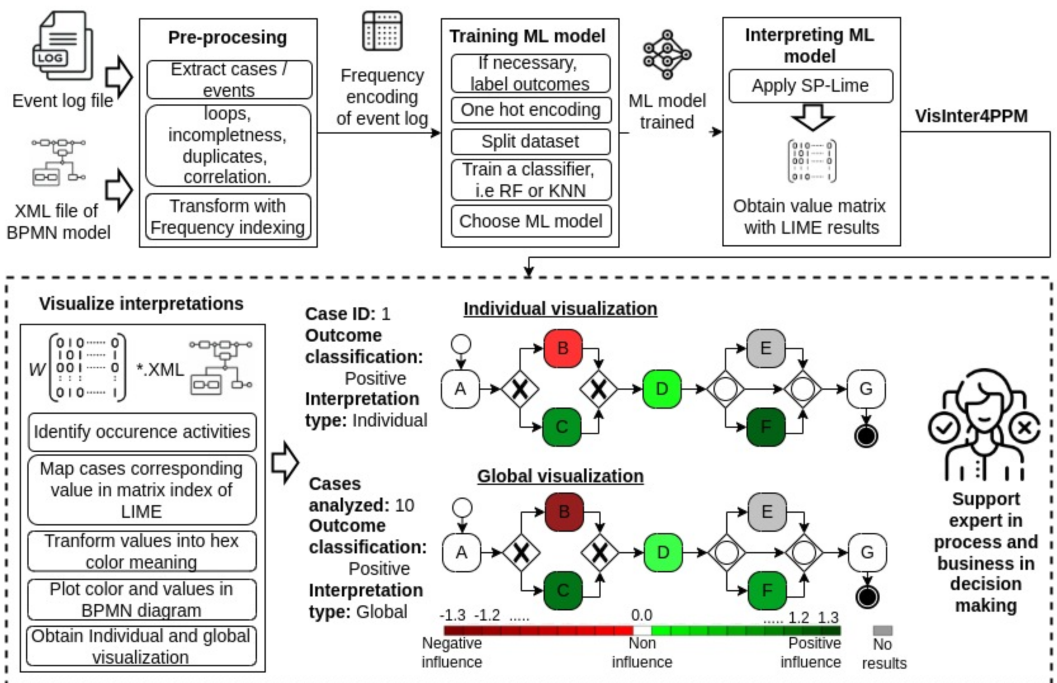

Figure 2: VisInter4PPM – a developed structure overview.

The *decimal_to_hex_color* algorithm [10] was developed specifically for the transformation of each of the values (that refer to an activity executed in a case or instance of the process) of the resulting matrix of SP-LIME. This algorithm receives a value from the matrix and transforms it into a hexadecimal value of red (negative influence) or green (positive influence) whose intensity is proportional to the highest value found for that case. The gray color is assigned to activities not executed and white to those that were executed but without influence for the prediction. The numbers were adjusted until finding a balance that is visually good after the experiments.

4.3 Visualization supported interpretability of prediction results

The approach is divided into two main stages: the first involves the development of a non-interpretable predictive model and the application of SP-LIME to create a locally interpretable predictive model; the second focuses on the visual projection of SP-LIME explanations onto the process model. This allows for both local explanations at the instance level and global explanations that provide insights into the overall behavior of the predictive model. As discussed in previous works [12, 11], the method entails filtering the event log, constructing the predictor, and applying SP-LIME, currently focusing on the control flow perspective, with the resulting explanations adapted for business analysis.

SP-LIME explanations are visually projected onto the process model by coloring activities based on their influence on predictions: green for positive influence and red for negative. Users can opt for a local interpretation by selecting specific instances for detailed analysis, or a global interpretation, where an aggregated view across all instances provides broader insights. This approach, previously detailed in [12, 11], supports both granular and comprehensive analyses, enhancing the understanding of how individual features impact predictions and facilitating strategic decision-making in business processes.

Once technical and user evaluations were carried out, the suggested improvements were included in the VisInter4PPM framework. With this improved version of the VisInter4PPM v.2.0 framework, new plots were generated to apply the second evaluation cycle. Figures 3 shows the result obtained with this new version. In a similar way to the procedure carried out in the synthetic event logs. These figures were used to apply the second evaluation cycle. Figure 4 shows the result obtained with this new version. This Figures show the results for two kind of event logs, one synthetic that represent an illustrative health insurance claim management process in a travel agency (a binary class prediction problem), and a real event log, which referred to a loan request business process, represented in a real-world event log of a financial institution (a multi-class prediction problem)

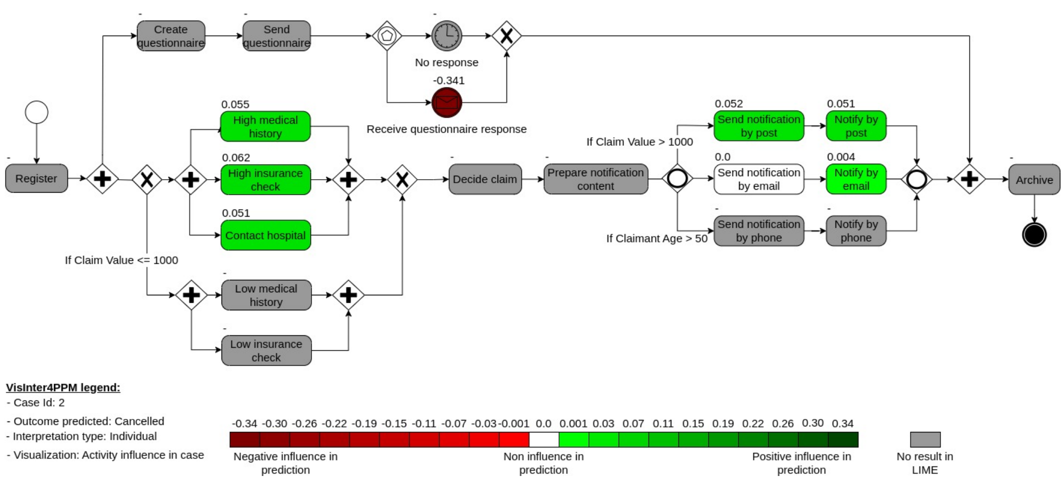

Figure 3: A representative instance for the negative class (the prediction is that the claim will be rejected) in the synthetic event log (travel agency claim process) using VisInter4PPM v2.0.

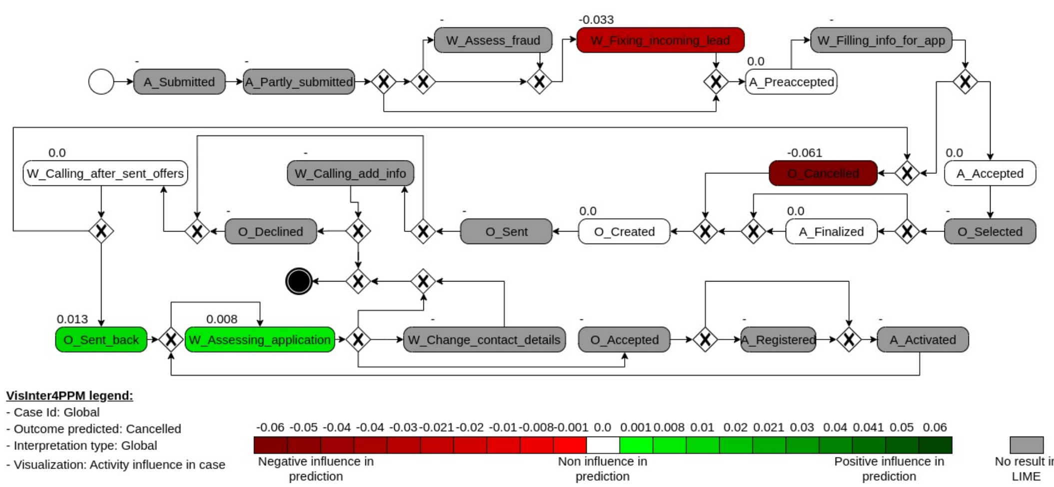

Figure 4: A global representation for the canceled class (the prediction is the the loan application will be canceled) in the real-world event log (process of a financial institution) using VisInter4PPM v2.0.

5 Study design for user evaluations

This study was structured to gather expert feedback on the interpretation of VisInter4PPM results and to identify potential improvements based on user needs and preferences. Following the approach of [18], who evaluated prediction interpretation methods for PPM to assess their understandability, usefulness, and ease of use for business experts, our study similarly examined various explanation plots at the event, trace, and log levels.

We performed two design cycles to validate the framework. In each cycle we performed the same procedure. In summary our validation protocol consisted of four stages. First, we selected 8 researchers and industry professionals with diverse backgrounds ranging from very experienced in BPM to very experienced in ML and XAI, with some having knowledge in both areas. Second: qualitative evaluation, we conducted virtual interviews with each one showing the same scenarios and same questions. Third: quantitative evaluation, we asked the experts to self-evaluate their technical knowledge and make a quantitative evaluation of the same scenarios shown in the interview. Fourth: analysis of the results, all the information captured from the experts was carefully analyzed and discussed with the authors of this work.

The design aims to evaluate the usability and ease of use of VisInter4PPM plots, drawing on expert opinions collected during interviews. The evaluation involved two scenarios: one using a synthetic event log and the other using a real-world event log. In both cases, we selected the most representative cases for expert participants to analyze.

In the first design cycle, it was evident from the experts' responses that there was a noticeable improvement for this version of the VisInter4PPM framework. They were much more confident and secure in their answers. They performed more objective analyses regarding the process flow and the importance of certain activities for the final result, even though this was not asked directly. They also expressed greater enthusiasm about the usability of this technique and its potential for use in real environments.

In the second design cycle, experts answered the questions more easily and quickly pointed out the correct answer (for example, which activity was the most influential in the prediction). They also highlighted the importance of this work in their activities in the industry both to optimize the predictive technique and to understand the behavior of the algorithm with the business process data. Almost all experts preferred an interpretable visualization plotted on the process model over a bar chart or statistical graph. Regarding the visualization of the results, experts with a more BPM-oriented background were even able to identify other potential problems in the process instance.

6 Conclusions

Application of XAI in process mining area, such as the VisInter4PPM approach, are critical in fostering transparency and fairness in organizational decision-making by providing business analysts with accessible insights. This study shows the idea behind VisInter4PPM framework (whose already introduced in our previews work). It employs SP-LIME for explaining predictions for the outcome case for a instance. It was tested for binary and multi-class classification models and based on synthetic event logs, focusing on the control flow perspective of a process.

The findings indicate that frameworks like VisInter4PPM, which demonstrate the impact of activities on prediction results, enhance interpretability in PPM. Specifically, illustrating activity influence on predicted outcomes via process models significantly aids in understanding and interpreting these predictions. This approach enriches the analysis of case behavior, thereby bolstering support for decision-making. Such improvements are poised to streamline understanding and interpretation of the plots, thereby boosting VisInter4PPM's usability and applicability in PPM interpretability.

The study also showed the influence of the experts' training on the interpretation of the results. For instance, business analysts unfamiliar with ML may prioritize details of the process model, such as activity names or event types, over the core insights that the plots aim to convey. In this context, VisInter4PPM's process model-based plots align more closely with the expertise of business analysts and managers, thereby facilitating more accurate interpretations. This research advances transparency in Business Process Management (BPM) and highlights the role of machine learning in supporting complex business decisions.

With the expert evaluation, we not only validated VisInter4PPM's utility in enhancing PPM interpretability but also highlighted avenues for further refinement, particularly in tailoring the framework to diverse practitioner backgrounds. Furthermore, two validation cycles were carried out with experts for each version of the framework. This prevents possible biases in the analysis and improves reliability in the final solution achieved.

Future developments of VisInter4PPM involve incorporating visualization elements that facilitate alternative analysis perspectives (such as resource, timestamps and costs), commonly employed in the field of process mining. Exploring alternative methods for visualizing in a “business oriented” manner the results of a classification model interpreter is another avenue for future research. Also, the research could be oriented to experiment with alternative explainability techniques. Other opportunities for future work in this area is related to other applications for business as process intelligence, model improvement, process optimization, as well as more in-depth analysis of root cause analysis that consider this vision.

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