Assessing Process Suitability for Robotic Process Automation: A Process Mining Approach

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Abstract. Robotic Process Automation (RPA) is a technology for conducting time-consuming business activities. The implementation of RPA requires assessing processes' suitability for automation. Traditionally, this assessment is done manually despite the fact that an accurate depiction of the process could be obtained using Process Mining. However, there is a lack of guidance on how to utilize Process Mining as a data-driven approach for conducting RPA process suitability assessment. For this reason, this research is aiming to propose a framework for process suitability assessment (FPSA). This Framework will provide organizations with a guide on performing a standard, data-driven RPA process suitability assessment using Process Mining. The development of the framework necessitated the identification of a standard set of criteria for assessment as well as a scoring model to measure such criteria. The evaluation of the framework showed evidence of the potential benefits that will ease the process assessment in RPA projects.

Keywords: Process Mining, Robotic Process Automation, Process Assessment

1 Introduction

Digitalization is driving companies to enhance their business processes to provide more value to their customers [1]. Organizations started to use technological advancements, which robotic process automation (RPA) is one of them, to transform their internal operations to deal efficiently with the low-value, time-consuming duties [2]. RPA is one type of process automation technology that uses software system robots or agents to automate administrative work allowing human actors to spend their time doing work that is more advanced. RPA is expected to have a huge impact on increasing productivity and efficiency [3], however, despite the clear benefits of RPA, its application is not a straightforward task with a key challenge of identifying the processes of high potential to be automated [4]. The reason is that RPA is not suitable in the same way for all processes, so, there should be prioritization to the processes before RPA implementation to ensure the fastest return of investment as possible [5].

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There is limited work that directly addresses this problem [6]. Accordingly, there is a need for guiding principles that are clearly defined and based on best practices to aid in process discovery and selection in RPA implementations [6-8]. An important factor in assessing process suitability for automation is the ability to document, in detail, the process, its tasks, its possible paths, and exceptions [9]. In order to get such information, currently, the RPA analysts spend a lot of time trying to get it from the process users. This could lead to many problems if users give wrong information, or important information is not well recorded. The level of error-propagation here is very high because this will not only affect the assessment phase but also, it will affect the phases of developing and testing the software robot because most likely some re-work will be needed to have the software robot executing the process without mistakes [10].

These traditional ways for identifying the processes' information consume a lot of time and effort and may not be feasible if there is a large number of the processes considered for automation [11]. Accordingly, selecting a process for automation should be based on data-driven analysis [12]. Process mining can act as a data-driven and fact-based solution to support different phases of RPA projects [13]. Process mining techniques analyze the event data from execution logs in order to identify valuable insights about business processes as bottlenecks, policy violations, or recommend measures and improvements [14]. However, after investigating the current work of using process mining in RPA projects, it was found that the major efforts are related to the problem of task discovery to be able to select the suitable process tasks for RPA. [11], [15], [16], [17] directed their work for this task discovery purpose. Undoubtedly, there is a lack of using process mining in the initial assessment of the overall process suitability for RPA before selecting the specific process tasks that will be automated.

For this reason, the main research question of this work is "How can process mining be used to assess process suitability for RPA?". However, in order to answer this research question, there is a need for a clear definition of how this suitability assessment is conducted. Furthermore, [18] emphasize that defining what suitability means is necessary to be able to assess processes. In order to answer the main research question of the paper, a sub-question was formulated to be "How can process suitability for RPA be assessed?". Answering this sub-question will provide a formal guide for RPA suitability assessment that can be used to integrate process mining and provide a data-driven solution for RPA suitability assessment based on Process Mining. Accordingly, the goal of this research is highlighted to be:

- Goal 1: Designing a Process Mining framework for RPA process suitability assessment.
  - Goal 1.1: Have a standardized set of criteria to assess process suitability for RPA.
  - Goal 1.2: Provide guidance on how to measure such criteria.

The structure of the paper will be as follows; the research approach followed to design the framework will be explained in section 2. Sections 3 will discuss the proposed framework and its details followed by the evaluation of the framework presented in section 4. Section 5 will present some of the related work, followed by a discussion and conclusion in sections 6 and 7 respectively.

2 Research Approach

To answer the research question and reach the research goal, a scientific method is needed and the approach that is most suitable to address this problem is Design Science Research (DSR). The design-science paradigm is a problem-solving paradigm in information systems research that aims to design new artifacts to widen the organizational capabilities [19]. Hence, to address the research problem, a process mining Framework for Process Suitability Assessment (FPSA) will be proposed. This framework will include a standard set of measurable RPA suitability criteria, standard assessment model, inclusion for organizations' objectives from automation, and the use of process mining as a data-driven source for process assessment.

The framework outcomes and accordingly the design objectives are identified to be: 1) To provide a clear guide for RPA process suitability assessment based on Process Mining. 2) To be easy to use and understandable by analysts with minimum or no Process Mining background. 3) To be based on a standardized set of criteria to measure RPA process suitability. 4) To operationalize how to measure such criteria. 5) To be used to analyze any process regardless of the industry. 6) To incorporate the objectives of each company from the automation initiative. 7) To produce accurate results. 8) To take less time. To design the framework, three design steps were followed. The design starts with collecting the RPA suitability assessment criteria mentioned in the literature and used by RPA experts. The deliverable of this step is a list of RPA suitability criteria mentioned. The second step entails integrating and analyzing the results of the previous step to reach a final list of important and measurable criteria. In this step also, a scoring model for measuring such criteria will be delivered. In the last step, the proposed FPSA will be developed based on existing process mining frameworks.

2.1 Collect RPA Process Suitability Criteria

[20] mention that the design and development of the artifact is a search process that should depend on current knowledge and theories available about the domain of the problem. Accordingly, to be able to reach a standardized set of criteria based on which RPA suitability assessment can be conducted, a Systematic Literature Review (SLR), as well as expert interviews from the qualitative research, are conducted. Investigating prior research and integrating the results with the expert opinions is called consensus-building as mentioned in [20]. Consensus-building will ensure building the artifact based on agreed-upon RPA selection criteria from literature and practice.

2.1.1 Systematic Literature Review

The main aim of following the SLR is to use a systematic approach to identify relevant RPA assessment criteria mentioned in the literature to build on it the proposed artifact. [21] stated that to address any research, a methodological review of past literature is important. Accordingly, the SLR followed to collect RPA suitability criteria is as follows: it started by searching using the relevant search terms where digital databases acted as a base for the search using search terms such as "RPA" and "RPA

Implementation". The search resulted in academic papers as well as industry reports. The selection of the papers was not restricted to academic sources only, some industry reports were used, however, these were restricted to be from top RPA providers or large organizations with successful RPA implementations to ensure the quality of the output. The search was limited to the English publications without specifying certain publication dates as RPA is a recent research area, accordingly, all the publications will be of suitable dates. The resulted articles and reports were further investigated by searching in the articles themselves with keywords such as “Criteria", “assessment", “suitable”, and similar keywords to ensure finding the relevant criteria. Not all the papers found are used as the results showed irrelevant articles. The final list included 42 articles and reports used to collect RPA suitability criteria.

2.1.2 Expert Opinion

Since the main aim of conducting research in Information Systems (IS) is to contribute to effective design, implementation, and use of ISs in organizations [22], an organizational perspective related to how RPA is implemented and how processes are assessed needs to be included to be able to develop a framework that includes and meets the organizational requirements. This step is important to include different perspectives and will enable identifying the most important criteria used in real-life scenarios.

2.1.2.1 Method

To obtain such information, there is a need to use a method that allows capturing the differences between people's perspectives on something based on their experience. This can be done through qualitative research [23]. Qualitative research gathers and analyzes “field-based" data of how people perceive something in a given context [24]. The main aim is to know how RPA analysts perform process assessment, based on which criteria and why these criteria in specific. Accordingly, in parallel to the SLR and to include an organizational perspective in collecting the required criteria for RPA process suitability assessment, expert interviews from the qualitative research are conducted. As explained by [24], the use of qualitative research can serve as a step to produce results by depending on an additional data source, which is the expert opinions in our case instead of only depending on the SLR results.

2.1.2.2 Data Collection Instrument

To obtain the experts' opinions, interviews from the qualitative research will be used. This method is conducted to base research outputs on empirical opinions as interviews allow capturing people's perspectives on something or action [24]. Accordingly, interviews are conducted with RPA experts. The interview questions are open-ended.

2.1.2.3 Sampling

The selection of the experts was based on the purposive sampling technique. [24] indicates that in purposive sampling, the selection is with the purpose of ensuring that these participants will provide the required information. Accordingly, the sample size was small and focused with purposeful selection of the interviewees. The target experts are RPA analysts who are involved or have hands-on experience on how RPA projects are done and how process assessment is being conducted. The initial pool of experts identified was 19 experts. The search was not limited to a specific company or industry to ensure obtaining general information and avoid being industry-specific. These 19 experts were contacted by providing them with the aim of this research. Of these 19, only 13 replied, and accordingly 13 interviews were done. Some of the experts had only technical experience and could not provide information related to the assessment and its criteria. Accordingly, the results of only nine interviews are included and used to develop the framework.

2.1.2.4 Procedure

All the interviews were held virtual except for one interview, which was a face-to-face interview. Each interview took around one hour and some interviews took less time. The time was not important; the focus was mainly on obtaining the needed information. The interview questions were used as a guide, however, in some cases; they were not used in the same order, as the flow was dependent on the experts' answers. The results of both the SLR and the expert interviews will be discussed in the next section.

2.2 Analyze RPA Process Suitability Criteria

The main aim of this step is to analyze the collected criteria from both the SLR and expert interviews to have a final list of criteria as well as build a scoring model to provide RPA process analysts with a standard model to measure such criteria and reach a conclusion about the process suitability for RPA. In order to do so, triangulation and integration of the SLR and expert interviews' results are conducted. [25] state that triangulation is an approach that leads to identifying the similarities and/or differences of the results acquired from different methods. If the results from more than one source are almost similar, this can be an indicator of the validity of the results obtained. The data collected from both sources will be analyzed to obtain a final list of the criteria that will be used for process assessment.

2.3 Develop Framework for Process Suitability Assessment

In order to develop the FPSA, an analysis of the current process mining frameworks and methodologies is conducted. The main reason is that these frameworks provide a guide to base the proposed artifact according to the best practices to ensure covering all the phases needed to conduct complete and successful process mining projects. Accordingly, a search for articles with keywords "Process Mining Framework", "Process Mining Approach" and "Process Mining Methodology" is conducted. Then, from the results, the relevant articles are selected and analyzed. The analysis included the search for other mentioned process mining frameworks and methodologies in the article itself or its references. This step resulted in collecting the main building blocks and components to develop the proposed FPSA. The results of such analysis will be presented in the next section.

3 Results: Framework for Process Suitability Assessment (FPSA)

The results of each step followed to develop the artifact will be discussed in this section.

3.1 Collect RPA Process Suitability Criteria

The criteria resulted from the SLR and the interviews will be presented section.

3.1.1 Systematic Literature Review

The findings from the SLR identified 42 articles that revealed 36 different criteria used in RPA process suitability assessment. These criteria are access to multiple information systems, digital/digitized, manual/low automation rate, digital data, structured data, well-defined/unambiguous rules, deterministic outcome, rule-based/deterministic, value, maturity, standardization, stability, low exception handling, low cognitive requirements, prone to human error, repetitive/routine, volume/frequency, process complexity, process execution time, number of full-time equivalent (FTEs) working on the process, known costs, potential benefits and cost savings, seasonal/temporary, working throughout the day, not suitable for traditional automation, not suitable for outsourcing, availability of IT resources, scalable, back-office process, cross-organizational process, implementation time, implementation effort, scope, a large amount of data in the process, swivel chair process, and organizational readiness.

3.1.2 Expert Opinion

As mentioned earlier, the results of nine interviews were included. The results revealed 20 criteria used in real-life assessments. Ordered from high mentioned to low, the criteria are benefits from automation, rule-based, structured input/output, number of FTEs working on the process, repetitive/routine, well-defined/unambiguous rules, complexity, execution Time, volume/frequency, stability, and system stability, digital, low exception handling, low cognitive requirements, known cost, digital input/output, prone to human error, standardized, manual/automation rate, maturity, and value.

3.2 Analyze RPA Process Suitability Criteria

In this section, the results of the SLR and expert interviews are analyzed to reach a final list of RPA process suitability assessment criteria as well as a scoring model for measuring such criteria. All the criteria mentioned by experts are already mentioned in the SLR. Therefore, the repeated criteria are 20. Accordingly, the selection of the criteria that will be used in the framework will be from these 20. Further analysis of these criteria is done according to the definitions mentioned in the literature. Some criteria, despite their importance, are not mandatory, and process automation with RPA can be performed on processes not fulfilling such criteria. For example, criterion such as that the process should access multiple systems to be suitable for RPA, although in this case automation will generate higher benefits, there are some processes that might be executed on one system and still be suitable for automation. Additionally, there were criteria that cannot be measured such as the value of the process. The analysis did not only depend on the number of times the criterion is mentioned in the SLR and the interviews because some criteria are not mentioned frequently, however, they are important to be included in the assessment, and some other criteria mentioned frequently, however, they are not measurable or cannot be included. The analysis to decide whether the criterion is important to be included in the assessment checked: 1) Whether the criterion measurable or its value can be obtained. 3) Whether the criterion can be measured or assessed using process mining or not.

3.2.1 Final List of Criteria

After the analysis of the criteria, a list of 11 criteria was developed to be used in the process assessment. The 11 criteria, depicted in figure 1, were identified to be measurable that can be used for basing the RPA process suitability decision. The criteria and how they are measured are 1) Low Process Complexity: measured by the number of process activities. 2) High Standardization Level: measured by the total number of selected variances. 3) Rule-based: Process Rules are known or can be extracted. 4) Structured Digital Data: Standard, digital text. 5) Repetitive/Routine: measured by the stable number of executions over time and no large time interval (not seasonal). 6) High Volume/Frequency: measured by the total occurrences. 7) Low Automation Rate: measured by the percentage of events performed by system actors. 8) Low Exception Handling: measured by the percentage of cases neglected out of the total executions. 9) High Number of FTEs: measured by the number of Human actors working on the process. 10) High Execution Time: measured by the average handling time. 11) Prone to Human Error: measured by the rework rate.

These criteria will be categorized into three categories; criteria related to the process characteristics, criteria related to the process performance, and criteria that may indicate the potential savings from automation. Dividing the selected criteria into categories is an approach following the work of [7], [26]. In a like manner as mentioned in [27], these criteria do not mean that a process is only suitable for RPA when it fulfills such criteria, and otherwise, it is not suitable. These criteria are indicators of the higher potential for automation with RPA. For this reason, the artifact ensured including the organizational objectives from automation because the objectives may be different from one organization to another, and accordingly the automation potential, for the same process, may be different from one organization to another. [28] mention that some processes might not fulfill such criteria; however, their automation still will be beneficial and will achieve the business objectives. It is important also to mention that the selected criteria are mainly relevant to selecting processes suitable for simple RPA applications. Other RPA types, such as cognitive RPA for example, may require additional or different criteria for qualifying a process to be suitable for such RPA types. In this case, the scoring model will need to be modified accordingly.

Process Characteristics	Process Performance	Potential Savings
❖ Low Process Complexity ❖ High Standardization Level ❖ Rule-based ❖ Structured Digital Data	❖ Repetitive/Routine ❖ High Volume/Frequency ❖ Low Automation Rate ❖ Low Exception Handling	❖ High Number of FTEs ❖ High Execution Time ❖ Prone to Human Error

Figure 1. Final list of criteria

3.2.2 RPA Suitability Scoring Model

A scoring model was developed to provide a way for measuring the 11 selected criteria. This scoring model consists of five columns as depicted in figure 2. One for the criteria, one for the definition of such criteria, one column to add the values of the criteria that will result from the process mining analysis, another column to add weight for each criterion, the values in this column will be dependent on each organization and their objectives from automation. The last column for the score. In this column, either 0 or 1 can be added. The zero means that the organization sees that this criterion is not achieved in the process and one means that this criterion is achieved. For example, if the average time is 30 days, in some organizations, 30 days is a high average time for a process, so 1 will be added, and in other cases, this might be low, so 0 is added. Therefore, we cannot have a standard value for each criterion that fits all cases.
Since there are 11 criteria, one criterion, which is the structured digital input, will have no weight because if the process input/output is not digital and structured, this indicates that automation with RPA is not possible at all. Accordingly, the 100% weight will be divided into the remaining 10 criteria. In order to use the scoring model to calculate the final process score, the weighted average formula will be used where for each criterion, the weight will be multiplied by the score and summing all of this for the 10 criteria elements. The resulting score will be evaluated according to the scale presented in table 1. This scale was developed taking into consideration the assessment conducted by the major RPA vendors as well as the work of [29] for it to be based on academic sources and best practices.

	Assessment criteria	Definition	Process 1		
			Value	Weight	Score
Process Characteristics	Low Process Complexity	Number of Process Activities			
	High Standardization Level	Total Number of variants			
	Rule-based	Rules can be easily extracted	-		
	Structured Digital Data	Standard, digital text	-	-	
Process Behaviour	Repetitive/Routine	Stable number of executions over time & no large time interval	-		
	High Volume/Frequency	Total occurrences			
	Low Automation Rate	Percentage of events performed by system users			
	Low Exception Handling	Percentage of cases neglected out of the total executions			
Potential Savings	High Number of FTEs	Number of Human actors			
	High Execution Time	Average handling time			
	Prone to Human Error	Rework rate			
		Total	-	100%	
		Weighted Score			

Figure 2. RPA Suitability Scoring Model

70% >=	Highly Suitable
70% - 50%	Moderate Suitability
50% - 20%	Low Suitability
20% <	Not Suitable

Table 1**.** The Scoring Model Scale

3.3 Develop Framework for Process Suitability Assessment

In this section, the steps followed to develop the framework will be discussed.

3.3.1 Process Mining Frameworks and Methodologies

There are different frameworks and methodologies proposed to conduct process mining projects. These frameworks will be used as a base for developing the proposed framework and its steps to ensure conforming to best practices. These frameworks include the work of [14], [30-37]. It can be concluded from the analysis of such frameworks that process mining projects involve five steps of data extraction, pre-processing, process discovery, analysis, and evaluation. However, these frameworks are directed to general process mining projects for process performance analysis, improvement, or re-design. Some of the presented frameworks are directed to specific industries. There is no framework specifically targeting RPA process suitability assessment or targeting RPA projects in general. Nevertheless, these frameworks provide a guide to base the FPSA according to best practices to ensure covering all the phases needed to conduct a complete and successful process mining project.

3.3.2 Proposed Frameworks for Process Suitability Assessment (FPSA)

Based on this analysis, the FPSA is developed. Initially, the framework included sequential flow between the steps; however, the demonstration and evaluation results identified that some other flows between the steps are needed to be included as presented in figure 3.

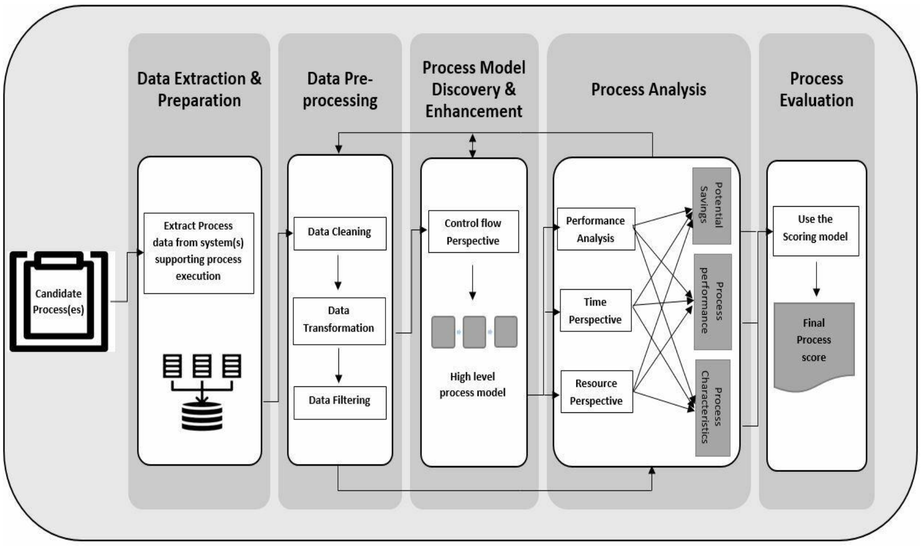

Figure 3. Framework for Process Suitability Assessment (FPSA)

The framework starts with a process or a list of processes that are considered for automation. The data extraction & preparation entails extracting the process data from the information systems supporting process execution and creating the event log that will be used for later steps. This data is to be imported on any process mining tool and in different formats for the subsequent steps. Data Pre-processing is about pre-processing the event log created by cleaning and transforming the log data to remove the missing values in the data and filtering the log data to have a high-quality log that will be used for later steps. Process model discovery and enhancement is about using process discovery algorithms to discover the model of the process. This step is very important as process mining techniques can analyze the event log information to discover the model of the process including the process steps as well as who performs these steps. It can spot the sequence of activities and whether the activity is performed automatically or manually [13]. The selection of which algorithm to be used is dependent on the objectives and required output from the discovery [6].

The fourth step in the framework is the process analysis. In this step, performance analysis, time, and resource analysis are performed to be able to generate the values of each process suitability criterion. The performance analysis will help in obtaining outputs such as number of process executions or different paths [32]. The time perspective will help in obtaining information such as the average time of the process and frequency of activities at a given point in time. The organizational or resource perspective will help in obtaining information related to whether the activity is a human or a system activity and the number of actors working on the process [14]. Finally, in the process evaluation, the scoring model will be filled based on the analysis results to calculate the final score and reach a decision about the process suitability for RPA.

4 Evaluation

4.1 Demonstrating Framework Applicability

In this research, a limitation of the inability to evaluate the framework in a real context using a case study is faced. The main reason is that most organizations adopting RPA are considered large companies that cannot expose their internal process data to be used for research purposes. Accordingly, in order to demonstrate the applicability of the framework, it will be used to assess the suitability of the Purchase to Pay (P2P) process using the event log of the process provided by [38]. As mentioned by [39], P2P process is one of the processes suitable for RPA. The aim of this demonstration is to check whether the framework will correctly classify the process as suitable for automation or not. Simple process statistics analysis was conducted, using Disco[1] from Fluxicon, to evaluate the 11 process criteria. The analysis results were used to fill in the scoring model and calculate the process suitability. For the demonstration, since there are no specific objectives from automation, an equal weight of 10% was added to each of the 10 measurable criteria, as the structured/digital input criterion has no weight in the scoring model as explained. The score of the process was calculated to be 70%, which means that the process is suitable for RPA equivalent to what is mentioned by [39].

4.2 Experts Evaluation

Evaluating the degree to which the artifact helps in solving the research problem will take place by measuring whether the objectives are met or not [20]. [40] mention that a rigid and valid DSR should entail an evaluation of the proposed artifact along with its development approach as well as evaluating its usefulness. Accordingly, an evaluation is conducted with a process mining expert to ensure that the artifact includes the main components needed for any process mining project. Additionally, an evaluation is conducted with an RPA expert to ensure that the artifact is useful in practice. The evaluation criteria selected from [41] are related to the objectives of the solution and are as follows; clarity, ease of use, understandability, completeness, operationality, generality, fit with organization, accuracy, and performance.

Both Experts were involved in projects related to their field, process mining, and RPA respectively. Further evaluation with more experts was not needed as it will not result in any value-adding information, however, it has to be mentioned that further evaluation by applying the framework in a real context using a case study is needed to strengthen the evaluation results. The evaluation results with the experts revealed the following insights; the process mining expert indicated that the proposed artifact includes the main components to enable process assessment based on process mining. The evaluation with the RPA expert indicated that the artifact provides a clear guide that they can use in assessment. Furthermore, the expert also indicated that the artifact provides accurate results in less time and effort compared to a traditional assessment, which indicates solving the research problem. One major comment mentioned by both experts was related to the extraction of process data from the supporting information

[1] https://fluxicon.com/disco/

systems. The experts indicated that some Information systems are legacy systems where the required data for assessment cannot be extracted. This is actually a study Limitation that cannot be addressed in this research.

5 Related Work

Some efforts tried to solve similar problems as presented in this work. From these efforts, the work of [26] who proposed a framework to help organizations select processes that can be automated using RPA. However, the main drawback of their approach is that many of the criteria they discovered are not measurable. Furthermore, the authors did not provide a standard approach for using process mining in their framework. Another work is the work of [29] where the authors proposed a method to assess processes suitability for RPA. Although their work structures the process assessment for RPA, they only depended on six criteria for assessment. Another major drawback of their approach is that they specify certain measurements for the criteria that might not fit all the organizations. Furthermore, the authors did not take into consideration the different objectives that organizations might have from automation. Additionally, their approach still depends on subjective information from the users to evaluate the selected criteria without using a fact-based source of process information.

In a like manner, [6] proposed an approach for RPA process selection. Although their work provides a standard method for RPA process assessment, the authors only depended on some criteria for assessment without basing their selection on a scientific or practical reference. Furthermore, they stated that they did not take into consideration the different objectives that organizations might have from automation. Additionally, in their use of process mining, they did not provide a standard approach for using it.

6 Discussion and Implications

The results of this research reveal that the research goals are met by providing a framework that acts as a standard guiding model using 11 measurable criteria and a data-driven scoring model for assessing these criteria. This framework takes into consideration the organizational objectives from automation by allowing organizations to weigh the importance of each process criterion depending on their objectives, thus, solving the gap mentioned by [6]. The selection of these criteria was dependent on the integration of academic and practical results to ensure including the important criteria. This acts as a step towards providing a standard, measurable criteria for process assessment, thus, solving the gap mentioned by [11].

This framework will complement the work related to task discovery using process mining as the assessment phase is prior to the task discovery in the RPA life cycle. Task discovery, although its importance may become worthless because the initial assessment of the process suitability is not performed well. The framework is built on best practices for conducting process mining projects to eliminate the use of subjective process information. Thus solving the gap mentioned by [12]. The use of the framework can save organizations thousands of dollars and a lot of effort that can be wasted on automating the wrong process, thus, contributing to successful RPA implementations.

However, as mentioned earlier, further evaluation by applying the framework in a real context using a case study is needed to ensure the effectiveness of the artifact.

7 Conclusion, Limitations and Future Work

This study is aiming to propose a process mining framework for process suitability assessment (FPSA). The framework includes a standard set of measurable criteria, a standard assessment model, considers organizations' objectives from automation, and uses process mining as a data-driven source for assessment. The applicability and usefulness of the artifact were demonstrated and evaluated showing evidence of the potential benefits that will ease the process assessment. This study had some limitations, the main limitation is assuming that all the information needed for assessment is recorded in the information systems supporting the processes' execution; however, this might not be the case. Accordingly, future research should be directed to standardizing the logging mechanisms of the information systems.

The second limitation was related to the dependency of the scoring on the view of the organization as they assign 0 or 1 based on their perspective of whether this is low or high. Although this ensures including the organizational objectives, it still may entail subjectivity. Future research should be directed to eliminate or reduce the error percentage of this approach. Another important limitation of this study is the lack of a clear definition of what does it mean for a process to be rule-based to be suitable for RPA. A clear definition of which type(s) of business rules that can be executed by the software robots to qualify a process to be suitable for RPA is needed. Additionally, further work in process mining research is needed to be able to extract such rules from process execution logs.

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