Robotic Process Automation and Business Rules: A Perfect Match

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Abstract: Robotic Process Automation (RPA) is a new technology that uses software robots to perform certain tasks in business processes. These robots mimic how humans use software systems when performing repetitive tasks with "robotic" precision, thereby limiting errors and improving efficiency. RPA provides many benefits including increased productivity, better service quality, and decreased delivery time while automating business processes. However, there are several challenges in adopting RPA, the first and foremost of which is to identify the kinds of tasks that lend themselves to RPA. In this paper, we present a novel easy-to-use method that identifies the most suitable processes for RPA; as such, our method will help organizations to effectively adopt RPA. More precisely, this research proposes to compute an RPA score to assess if a process is suitable for RPA. Moreover, this paper aims to provide guidelines for RPA implementation. The novelty of this work is threefold: i) it uses an extensible classification of business rules to weight the RPA score, ii) It is usable and flexible (e.g., we can extend it to support Intelligent Digital Robots -RPA 2-), and iii) it automatically computes the RPA score using the Goal-Oriented Requirements Language (GRL) model evaluation.

1 INTRODUCTION

RPA is an emerging technology that uses software robots to capture and interpret existing applications for processing transactions, manipulating data and communicating with other software systems (IRPAAI, 2018). These software robots are used to perform work that requires manual labor and to automate repetitive tasks across multiple business applications without altering existing infrastructure and systems. RPA provides many benefits including increased productivity, better service quality, decreased delivery time while automating business processes and freeing employees from tedious and repetitive tasks (IRPAAI, 2018). For Anagnoste (Anagnoste, 2018), one of the reasons why companies are starting to use RPA massively is because of the fact that robots can work 24/7 cutting entry costs to 70 percent.

For Alberth and Mattern (Alberth and Mattern, 2017), the RPA automation logic is still mainly rule-based and robots can relieve workers to do routine process work. According to Aguirre and Rodriguez (Aguirre and Rodriguez, 2017), RPA fits well with rule-based processes that involve routine tasks, structured data and deterministic outcomes.

According to Geyer-Klingeberg *et al.* (Geyer-Klingeberg et al., 2018), successful process automation requires assessing the potential for automation. In this context, organizations are constantly looking to effectively identify processes that can be automated using RPA to achieve maximum results (Leshob et al., 2018). Unfortunately, to date and to the best of our knowledge, there is no easy-to-use and automatic method that guides practitioners to identify business processes that are most suitable for RPA.

This paper proposes a semi-automatic and easy-to-use method that computes an RPA score to assess if a process is suitable for RPA. We also provide guidelines for RPA implementation by assigning business rule classes to process activities. The proposed method uses i) business rules that govern process activities to weigh the RPA score and ii) the Goal-Oriented Requirements Language (GRL) to link process activities to RPA objectives/goals and to automatically compute the RPA score using GRL model evaluation.

The remainder of the paper is organized as follows. Section 2 describes the proposed rule-based framework to compute the RPA score of business processes in order to measure their suitability for

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RPA. Section 3 surveys related work. We conclude in Section 4.

2 PROPOSED APPROACH: A RULE-BASED FRAMEWORK TO ADOPT RPA

We propose a four-step method to assign an "RPA suitability score" to business processes to help organizations identify those among their processes that lend themselves to RPA. We start by providing an overview of the method (Section 2.1). Section 2.2 presents the foundations of the method. The four steps of the method are described in sections 2.3 through 2.6.

2.1 Overview of the Method

A business process is a set of activities that together produce a result of value to a "customer" (Hammer and Champy, 1993). Business process involves *automated activities,* performed by an automated (information or otherwise) system, and *user activities* which are process activities performed by a human actor, possibly with the help of one or several information systems. RPA concerns such *user activities* and our method is concerned with scoring such activities.

Our approach relies on assigning an *RPA score* to user activities to assess whether they can be automated with RPA; the higher the score, the higher priority for RPA adoption. We consider the RPA score as a combination of two factors: 1) RPA *potential*, which measures the *feasibility* of automation, and 2) RPA *relevance*, which assesses whether RPA automation is *worthwhile*. The *RPA potential* is a reflection of whether the activity *lends itself to automation*, i.e., involves well-defined (business) logic. RPA *relevance* is a 'cost-benefit' issue: is the activity in question performed enough times to warrant investment in automation.

Figure 1 illustrates the overall approach. The first step assigns a business rule class (or classes) to each user activity of a process. This will enable us to weigh the *potential* of automating user activities with RPA. The second step assesses the *relevance* of using RPA for each user activity. The third step uses a goal-oriented language to create a goal model that links process activities to RPA goals (i.e., the potential and the relevance). More precisely, our approach proposes to use the Goal-Oriented Requirements Language (GRL) (ITU-T, 2012). The fourth step computes the RPA score of the business process using a native GRL model evaluation algorithm.

2.2 Classifying User Activities

Broadly speaking, RPA is suitable for those user activities that are "automatable". A number of research efforts aimed at identifying the required characteristics of process activities that lend themselves to RPA. Table 1 summarizes those criteria.

Roughly speaking, the criteria for automation fall into two categories: 1) the *mechanics* of the user activity, and 2) the *cognitive* or *decisioning* content of the activity. In particular, the *mechanics* of the user activity have to be well-defined, and this is reflected in criteria C1 (availability of a system or systems to support the activity), C5 (well-specified interactions), and C6 (digital availability of relevant data). The *cognitive/decisioning* aspects are captured by criteria C2 (low cognitive requirement), C3 (stable context), and C4 (well-defined rules).

The *mechanics* of a user activity are relatively easy to assess. However, the *nature* of the cognitive/decisioning content of a user activity is more complex to assess. This is the aspect that we propose to tackle.

The *business rules approach* advocates the representation of the *decision logic* within *repeatable* business processes using the *business rules* formalism. The business rules approach covers the full lifecycle of *decision logic,* from the requirements stage (*rule discovery* or *capture*) to *automation* (execution), *testing* and *maintenance* (Boyer and Mili, 2011). Indeed, when the decision logic that underlies a business process activity can be fully expressed using business rules that refer to digitally available data, then the decision can be automated using *rule languages* and *rule engines*. By contrast, if a business decision involves creativity or complex interpretation skills (see criterion C2 in Table 1), then the decision can hardly be *formalized*, let alone be *automated.*

Accordingly, we propose to look at the RPA potential of user activities through the lens of the business rules approach: if the decision that underlies a user activity lends itself to automation under the business rules approach, then it lends itself to RPA–regardless of the technology used by RPA.

Business rules fall into many categories, depending on different characteristics, including their scope (e.g., data versus behavior), modality (guideline versus mandatory), and others (Hay and Healy, 2000; Wagner, 2005; Van Eijndhoven

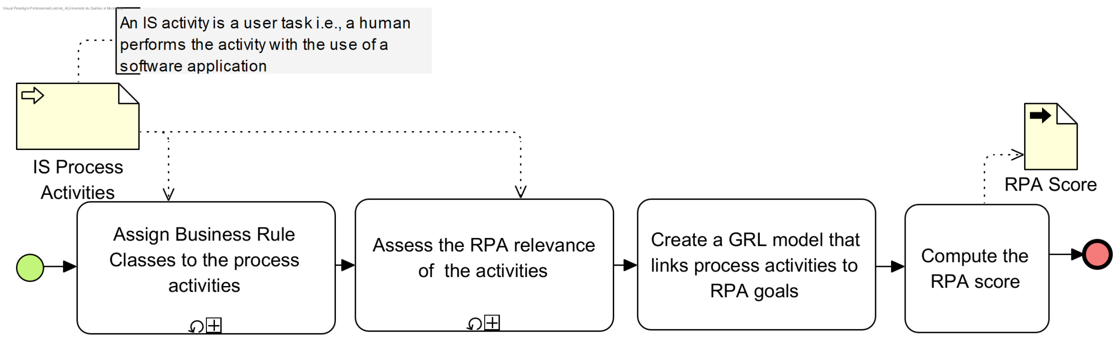

Figure 1: Overall process for assessing business processes suitability for RPA.

Table 1: Criteria to assess RPA suitability of process activities. Adapted from (Asatiani and Penttinen, 2016; Leshob et al., 2018).

Id	Criteria	Description
C1	Access/use of software applications	The activity is performed by a human actor with the use of a system or multiple systems.
C2	Low cognitive requirements	The activity does not require creativity or complex interpretation skills.
C3	Stable context	The activity is executed within stable context (e.g., systems).
C4	Well-defined and stable rules	The activity is based on unambiguous rules.
C5	Well-specified interactions with software applications	The interactions between the activity and the applications are well-specified and predictable.
C6	High availability of digital data	The activity uses available digital and correct data.

et al., 2008; Steinke and Nickolette, 2003). We argue that the different categories have different automation–and thus RPA–potential, and thus, propose to *categorize* the decision logic inherent a user activity, as a first step towards assessing the suitability of a user activity for RPA. But first, we must: 1) adopt a categorization of business rules, and 2) assign an automation score for each category. We discuss both steps in turn below.

Many business rule classifications have been proposed in the literature, including (Hay and Healy, 2000; Wagner, 2005; Van Eijndhoven et al., 2008; Steinke and Nickolette, 2003; Boyer and Mili, 2011). According to Graml, Bracht, and Spies (Graml et al., 2008), a business rule is defined in two different ways depending on which perspective to be addressed: i) from the business perspective, a rule should be seen as a directive, intended to govern, guide or influence the business behavior, ii) from the IT perspective, a rule is defined as an atomic piece of reusable business logic that is specified declaratively. Hay and Healy (Hay and Healy, 2000), classified business rules in three categories: structural assertion, action assertion, and derivation. A structural assertion is a concept or a statement of a fact that expresses some aspect of the structure of an enterprise. An action assertion is a statement of a constraint or condition that limits or controls the actions of the enterprise. A derivation is a statement of knowledge that is derived from other knowledge in the business.

In (Steinke and Nickolette, 2003), authors proposed four classes of business rules: Definition, Guideline, Inference, and Mandate. Definition includes all terms that are specific to the business. Guidelines are the rules that should be followed in most contexts but occasionally needs to be overlooked in a particular situation. Mandates are action rules that cannot be ignored in any circumstances to avoid repercussions on the business. An inference is a rule that creates a new value/fact that is derived using one or more business rules.

In (Wagner, 2005), Wagner classifies business rules in five categories: integrity rules, derivation rules, reaction rules, production rules, and transformation rules. Integrity rules express constraints to data and its interrelationships. Derivation rules create derived facts by using one or multiple already known facts. Reaction rules or more commonly called event-condition-action rules (ECA Rules) verify a condition once a particular event is triggered. After the condition is verified, an action is initiated. Production rules, or also called condition-action rules, verify a condition before initiating an action. Unlike reaction rules, production

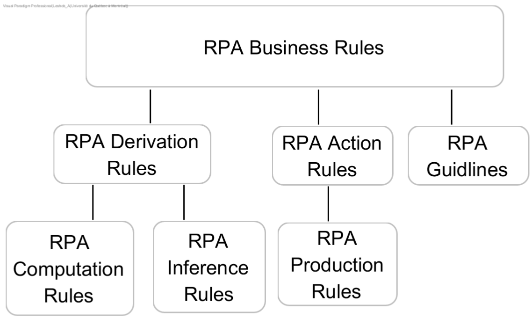

Figure 2: Business rules classification.

rules do not need any particular event to take place to start testing a condition. Transformation rules set limitations to the alteration of an object in a system.

In (Van Eijndhoven et al., 2008), authors split business rules into two main categories: Rules that influence the operational process and constraints. Rules that influence the operational process include derivation rules and action rules. Derivation rules use deduction and/or computation to enact information of a particular process. There are two different types of action rules: condition-action rules and event-condition-action (ECA) rules. The second category is constraints. Those rules restrain an organization or a system by setting limits to its structure, behavior and information.

To illustrate the feasibility of our method, we elaborated a first sketch of an RPA classification model as shown in Figure 2. Recall that all process activities that govern RPA rules are user tasks. Therefore, all RPA rules of the proposed classification model are triggered and/or performed totally or partially by human actors.

1. RPA production rules are condition-action rules that operate within a context (i.e., systems) to produce new facts. RPA production rules use digital data through well-specified interactions with software applications.
2. RPA Derivation rules (RPA computation or inference) create new derived facts from input facts using rules. The difference with production rules is that they have no conditions that trigger the actions.
3. RPA Guideline rules are rules that operate within a stable context, use digital data through well-specified interactions with software applications. However, RPA Guidelines are not stable rules and are not well-defined (see (Steinke and Nickolette, 2003)).

To better explain our approach and for the sake of simplicity, we will support activities that require low

Table 2: RPA business rules.

Business rule class	Criteria				Weight
	C3	C4	C5	C6	
RPA Production	25	25	25	25	100
RPA Derivation	25	25	25	25	100
RPA Guideline	25	0	25	25	75

cognitive requirements. We argue that this does not represent a limitation of our approach since RPA 2.0 robots support intelligent/high cognitive process activities. Therefore, our approach deals with user activities (i.e., the criterion C1) with low cognitive requirements (i.e., the criterion C2) (see Figure 1).

Table 2 shows an example of RPA business rules and their associated RPA potential weights. As illustrated, we assigned a maximum importance value of 25 to each criterion. However, users of our method (e.g., business analysts) can change these default values.

2.3 Step 1: Assign Business Rule Classes to the Decision Logic Underlying Process Activities

This step consists of categorizing the decision logic that underlies a user activity by identifying the types of business rules (business rule classes) that are inherent in that decision. This will enable us to assess the RPA potential of user activities using the values from Table 2. A single decision (activity) may involve different types/classes of business rules. In this case, the RPA potential score may be computed using a weighted average of the values from Table 2.

A key aspect of our approach is our claim that it is easy to implement by users (e.g., business analysts, process engineers) without having to become RPA specialists. Thus, to assign business rules classes to process activities, we adopted a question-based approach using rule definitions to guide the users to select the rules that match the process activities.

Consider the credit card approval process of Figure 3. This process is based on a *service task* activity (i.e., automatic task) and a *user task* activity (i.e., performed by a human actor with the use of software applications). The process starts by receiving a credit card application. The first activity (the service task), then retrieves the applicant credit history. After that, an employee assesses the applicant credit card eligibility. To perform this task, the employee applies *production rules* that are based on whether the credit file history is local (i.e., retrieved from the financial institution country) or retrieved from a foreign country. Therefore, the RPA weight of the activity 'Assess Applicant Credit Card Eligibility' is set to 100 (see Table 2).

2.4 Step 2: Assess the RPA Relevance of the Activities

To assign a relevance score to an activity/sub-process activity, we use a variation of the approach proposed in (Leshob et al., 2018). According to Asatiani and Penttinen (Asatiani and Penttinen, 2016), non-routine tasks with no or little recurring patterns are not relevant for automation with RPA. According to Willcocks *et al.* (Willcocks, 2015; Willcocks et al., 2017) and Asatiani and Penttinen (Asatiani and Penttinen, 2016), the RPA approach is suitable when i) business processes have a high-volume of transactions with manual affordance and ii) the process activities are prone to human errors. Thus, to assess the RPA suitability of an activity, we propose to measure: i) the average number of transactions performed per day and ii) its proneness to human errors. To assess these two metrics, we experimented the resulting quadrant illustrated in (Leshob et al., 2018) in the context of processes from major companies from the banking and insurance domains. In order to propose a method that is easy-to-use and adaptable, we propose to assess the RPA potential of process activities using the model illustrated in Figure 4.

2.5 Step 3: Create the GRL Model

To compute the RPA score of a business process, we propose to use a goal-oriented modeling language. More precisely, we propose to use the Goal-Oriented Requirements Language (GRL) (ITU-T, 2012). GRL allows to i) connect each process activity to the RPA goals (e.g., RPA relevance, RPA Potential) through quantified links, ii) visualize process activities, RPA goals and the links that connect them using a graphical GRL model, and iii) automatically calculate the RPA score using a GRL evaluation algorithm.

2.5.1 Goal-oriented Requirements Language

GRL (ITU-T, 2012) allows to model the objectives, requirements, and their relationships. Figure 5 presents the subset of the GRL intentional elements used by our approach. A goal (or hard-goal) is quantifiable. It is usually related to functional requirements. Soft-goal refers to qualitative aspects that cannot be measured directly (Amyot et al., 2010). Soft-goals are usually related to non-functional requirements. A task is a solution which achieves goals or satisfies soft-goals (Amyot et al., 2010).

Figure 6 illustrates the basic GRL links and contribution types used by our approach. GRL links (section a), such as the contribution and means-end links are used to connect GRL elements (e.g., goals, soft-goals, and tasks) in a goal model. *Means-End* links describe how goals are achieved (Amyot et al., 2010). It is used by tasks achieving goals. Means-ends should only have goals as destinations (Amyot et al., 2010). *Contribution* links specify desired impacts of one element on another element (Amyot et al., 2010). A contribution link can have a qualitative contribution type (Section b of Figure 6), or a quantitative contribution (integer values between -100 and 100) (Amyot et al., 2010). A contribution link can be labeled using icons, numbers, or texts.

2.5.2 Build the Goal Model

The goal of this step is to create a GRL model that links user activities to the RPA high-level objective (RPA SUITABILITY) that assesses if the process is suitable for RPA automation. The resulting goal model links each user activity (hard-goal or simply goal) to the RPA RELEVANCE and RPA POTENTIAL (soft-goals); two subgoals of the high-level soft-goal RPA SUITABILITY. To connect process activities to RPA objectives, we use GRL tasks (solutions) that achieve the goals (through means-end links) or satisfy soft-goals (through contribution links).

After creating the GRL model, the user must quantify it by assigning initial values to the contribution links and intentional elements (goals, soft-goals and solutions). The quantitative values of the contribution links between the GRL tasks and the RPA POTENTIAL soft-goal are based on the weight of the rule class associated to the process activity (see Table 2). The quantitative values of the contribution links between the GRL tasks and the RPA RELEVANCE soft-goal are based on the quadrant (see Figure 4). For the importance values of the intentional elements (goals, soft-goals and solutions), we propose a default quantitative value of 100, which is the higher importance value. The modeller (e.g., business analyst) can modify these default values. For example, the user can assign different values if he/she wants to prioritize the automation of certain tasks.

Figure 7 shows an example of a GRL model for the activity 'Assess Applicant Credit Card Eligibility' of the Credit Card Approval process of Figure 3.

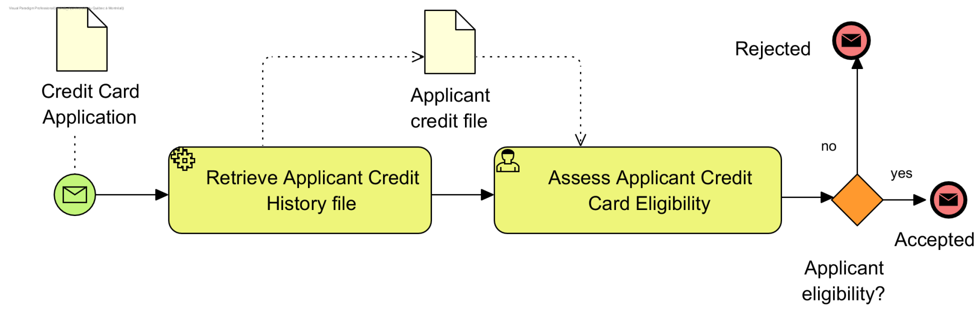

Figure 3: A Generic Credit Card Application Process.

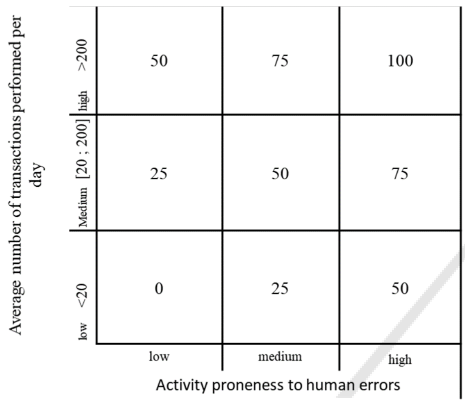

Figure 4: RPA relevance quadrant.

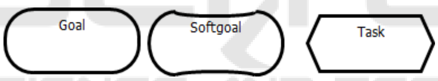

Figure 5: Basic GRL Intentional Elements (adapted from (Amyot et al., 2010)).

2.6 Step 4: Evaluate the GRL Model

GRL provides algorithms to evaluate models, allowing us to compute the RPA score of the business process. To evaluate the RPA score of a process, we propose to use the quantitative GRL evaluation algorithm described in (Amyot et al., 2010). This algorithm uses Integer values for the evaluation. In our case, the RPA score of a process is based on i) the values of the contribution links and ii) the quantitative importance value of the intentional elements.

The algorithm starts by propagating values using a bottom-up approach to obtain *evaluation values* for the intentional elements (see (Amyot et al., 2010)). The evaluation values are propagated through GRL links. For example, the evaluation value of the soft-goal RPA RELEVANCE is computed by i) multiplying the evaluation value of the solution *Credit Card Approver* (i.e., 100) by the value of the contribution link that connects them together (i.e., 75) and ii) then dividing the result by 100 (i.e., (100 x 75) /100).

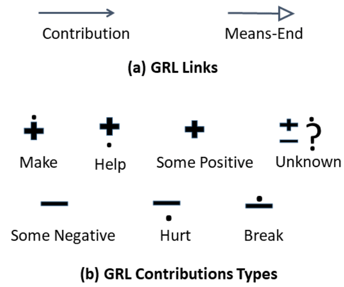

Figure 6: GRL Links and Contributions Types (adapted from (Amyot et al., 2010)).

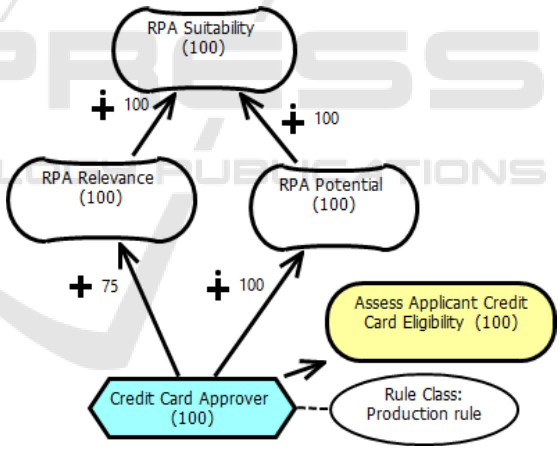

Figure 7: The GRL model for the activity 'Assess Applicant Credit Card Eligibility'.

The evaluation value of the soft-goal (*sgoal.evValue*) reached by N contribution links is the sum of the products of the evaluation value of each source element ($srcElt_i.evValue$) by its contribution value to the element ($elt_i.cnValue$). Then, the result is divided by (N X 100). Therefore, the evaluation value of a soft-goal (*sgoal*) is computed as follows:

$$sgoal.evValue = \frac{\sum_{i=1}^{N} srcElt_i.evValue \times elt_i.cnValue}{Nx100}$$

The algorithm ensures that the evaluation value of each goal will not go above 100. The algorithm also ensures that the evaluation values of each intentional element will not go below -100 where negative values from -100 to 0 are used.

After propagating values, the RPA score is calculated using the quantitative evaluations for actors proposed in (Amyot et al., 2010). Thus, we compute the RPA score of processes using the importance and the evaluation values of its intentional elements (goals, soft-goals, and tasks). Therefore, the RPA score of a business process P is computed as follows:

$$rpaScore(p) = \frac{\sum_{i=1}^{N} ie_i.impValue \times ie_i.evValue_i}{\sum_{i=1}^{N} ie_i.impValue}$$

where $ie.impValue$ and $ie.evValue$ are the importance value and the evaluation value of the intentional element ie respectively.

Finally, we propose to classify the RPA suitability of a process P as follows.

1. If $rpaScore(p) >= 70$, the process is considered as highly suitable for the RPA approach.
2. If $50 < rpaScore(p) < 70$, the process is considered as moderately suitable for the RPA approach.
3. If $rpaScore(p) <= 50$, the process is considered as not suitable for the RPA approach.

3 RELATED WORK

RPA is a new emerging approach to automate business processes. Hence, a limited number of works have been proposed in the RPA literature to tackle the problem of assessing if business processes are suitable for RPA. According to (Willcocks et al., 2017; Willcocks, 2015; Lacity and Willcocks, 2016), RPA fits well when: i) the process is mature and standardized, ii) the volume of transactions is high, and iii) the business rules that govern the process activities are well-defined. For Willcocks *et al.,* (Lacity and Willcocks, 2016), processes with high workload and low complexity are good candidates for RPA automation. Lowers *et al.* (Lowers et al., 2016), suggest that the business function and the industry are important to determine if the RPA approach is appropriate. According to (Lowers et al., 2016), RPA is relevant for standardized and repetitive processes that i) follow well-defined business rules, ii) consume a significant amount of time, and iii) require manual interaction with a computer interface.

In (Leshob et al., 2018), authors proposed a method to analyze business processes and classify them from 'Not suitable' to 'Highly suitable' using an RPA quadrant. The classification is based on: i) the process maturity and standardization, ii) the business rules that govern process activities, iii) the use of interfaces with a software application, iv) the volume of transactions, and v) the degree of the process complexity (Leshob et al., 2018).

In (Asatiani and Penttinen, 2016), authors proposed a set of criteria to assess if a process task is suitable for RPA. These criteria include the: high volume of transactions, need to access multiple systems, low cognitive requirements, easy decomposition into unambiguous rules, proneness to human error, and the limited need for exception handling. In (Madakam et al., 2019), authors identified some processes that are more suitable for RPA based on the business function/industry. These processes include: accounts payable and receivable, invoice processing, purchase to order, payroll, hiring, customer service, cards activation, claims processing, and some specific processes from the banking and insurance domains. The author also pointed out that the rise of artificial intelligence (AI) will enable new functions for RPA as digital robots will become intelligent, allowing them to achieve complex and cognitive tasks such as processing unstructured data.

4 CONCLUSION AND FUTURE WORK

RPA is an emerging approach for automating business processes. It uses software robots that replace humans in order to interact with existing applications through user interfaces for processing transactions, manipulating data and communicating with other systems (IRPAAI, 2018). RPA offers many benefits including improved efficiency, increased productivity, data security, reduced cycle time, and improved accuracy (IRPAAI, 2018).

In this paper, we proposed a novel rule-based method that helps organizations to adopt RPA. More precisely, the method proposed to compute an RPA score to assess if a process is suitable for RPA. The score is based on two goals: RPA Potential and RPA Relevance. The benefits of this work is threefold: i) it uses generic and extensible classification of business rules that govern process activities to weight the RPA score, ii) It is easy-to-use and flexible (e.g., we can extend it to support Intelligent Digital Robots -RPA 2- by adapting the business rule classification), and iii) it automatically computes the RPA score using a native GRL model evaluation algorithm.

This work is still at an early stage. To advance our research project to design a complete end-to-end method, we plan to: i) improve the business rules classification by linking it to RPA properties, ii) support high cognitive tasks as we believe that artificial intelligence will enable software robots to automate more work of humans in the near future, iii) develop a tool that supports the method, and iv) evaluate the method.

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