Process Mining Enabled Cognitive RPA to Automate Data Entry Tasks in ERP Systems

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Abstract: Manual data entry tasks are a common source of inefficiency in organizations. They are time-consuming and prone to errors. RPA is an emerging automation approach that is non-intrusive and mimics the user interaction with interfaces. It could be used along with an AI tool such as NLP to automate data entry tasks that come from unstructured sources such as emails. This paper proposes a cognitive RPA framework that utilizes process mining to find, select and configure cognitive RPA to automate data entry tasks to ERP systems. Process mining is used to extract process models generated from event logs to allow for the accurate analysis of tasks. The framework also utilizes the concept of UI logs for the configuration steps. A proof of concept NLP model was developed, and the framework was evaluated by an expert to validate its potential and highlight areas for improvement. While limitations exist, such as the small NLP training dataset, the paper demonstrates the potential of this approach for improving efficiency, reducing errors, and enhancing decision-making in organizations. Future work includes expanding the training data and exploring user interface design for error correction.

1 INTRODUCTION

In today's fast-paced world, there is very small to no room for errors for organizations to remain competitive. Business makers do realize that, which is why they keep incorporating IT solutions into their business. In fact, the whole goal behind industry 4.0 is to incorporate even more IT solutions that are based on artificial intelligence and machine learning to allow for faster execution of tasks with as few errors as possible. They also realize the importance of ERP in this competitive environment and are actively seeking new ways of making it more effective.

In this section, first the motivation for researching this topic will be discussed, following that the problem discussed in this paper will be defined. Finally, the solution approach will be briefly discussed.

1.1 Motivation

ERP systems have an important role in today's organizations. An ERP system enables the monitoring, controlling and integration of the various activities of the organizations (Barna, 2022). One of the goals of ERP systems is to provide the right people with the right information at the right time. As such, ERP systems eliminate silos and allow for the integration of data in a central repository (Zaitar, 2022).

This however, requires that the data available and entered to the ERP system is accurate and error free. Employees need to interact with many documents daily, and ERP system can assist them in processing even more data (Barna, 2022).

Human errors can occur during the manual entry of documents to the ERP system. The goal for utilizing RPA, as will be discussed in section 2.1, is to eliminate errors and reduce costs (Madakam et al., 2019). The utilization of process mining for RPA implementation comes from the understanding that traditional techniques such as interviews or recordings, can be time-consuming which prevents the solution from being scalable in large organizations having many routine tasks (Leno et al., 2021). Thus, it is important that we identify a framework that efficiently utilizes the implementation of RPA using process mining.

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1.2 Solution Approach

This paper conducts a literature review in order to identify the state of the art in the area of implementing cognitive RPA with the help of process mining in section 3. This is to identify what is the research gap based on what has been already revealed and achieved in previous research.

The paper then utilizes design science research methodology, as described in section 4, in order to address the research gap. The goal of this work is to propose a framework that could be used for future implementations of cognitive RPA.

2 PRELIMINARIES

In this section, the basic concepts and terminologies used in this paper will be defined and explained. These concepts are essential to understand the rest of the paper. The concepts to be discussed are Robotic Process Automation (RPA), Process Mining, and Extended Event Logs in that order.

2.1 Robotic Process Automation

Robotic process Automation is an emerging approach that uses software robots to replicate human interactions. It is usually used to automate mundane tasks such as copying and pasting data (Ribeiro et al., 2021; El-Gharib and Amyot, 2023). RPA is used and preferred over traditional automation solutions since it directly interacts with the graphical user interface (GUI) making it a non-intrusive technology that is easier to adopt (Madakam et al., 2019). It is generally used to automate repetitive, rule-based, routine, high volume tasks (Ribeiro et al., 2021; Madakam et al., 2019).

RPA could also be paired with AI tools such as NLP to give it cognitive abilities. Such cognitive integration with RPA makes it better aligned with the goals of industry 4.0 (Ribeiro et al., 2021).

Recent papers, discuss how process mining could be used as an enabler for robotic process automation. This is because it allows the discovery of business processes through event logs (Van Der Aalst et al., 2012). The following section 2.2, will discuss and define the concept of process mining in more details.

2.2 Process Mining

Process Mining is a discipline that aims to extract process models from event logs generated by process aware information systems (PAIS) instead of relying on outdated process models, or models that are not actually followed and conformed to by the employees (Dakic et al., 2018). This allows for more transparency when conducting business process analysis, since you see the As-is process actually carried out (Dreher et al., 2020; Van Der Aalst et al., 2012).

There are 3 types of process mining: A) Process Discovery which aims at discovering process models from event logs, B) Conformance Checking which takes as input process model and event log to output diagnostics and C) Process Enhancement which takes input event log and model to output a new enhanced model (Van Der Aalst et al., 2012).

Process Mining is defined to be the semi-automatic approach to discovering process knowledge from event logs. It is also seen as an enabler in other areas such as simulation, prediction and robotic process automation (Van Cruchten and Weigand, 2022).

The following section, 2.3, will discuss the concept of extended event logs and how it could be used to enhance the process mining analysis.

2.3 Extended Event Log

As mentioned in the previous section 2.2, event log is the entry point to any process mining project. There are different formats to event logs including MXML and the widely used XES. Recently, it has been proposed by (Kassem, 2024) the concept of extended event logs. These are hierarchical logs aim to be generic and comprehensive.

The proposal of extended event logs, is based on SAP ERP system but is intended to work generically with any ERP system given that they record the same data.

The extended event log is intended to be a generic & comprehensive log that could be used for any process mining project regardless of the objectives. This isn't easily achieved with traditional logs since they have to be manually collected for a specific purpose, thus, the objectives of the process mining project has to be well-defined in advanced (Van Der Aalst et al., 2012).

Including the task steps would allow for richer analysis and could provide the analyst and potentially the business user with deeper insights into the process. This is enabled by the trace files of the ERP systems that record the user interaction data (Kassem, 2024; Kassem and Turowski, 2018).

Figure 1, shows the proposed structure of the extended event log. Like standard event logs it can show the different cases & activities involved in the cases. It extends the traditional event logs by adding the activity steps, business objects and attributes.

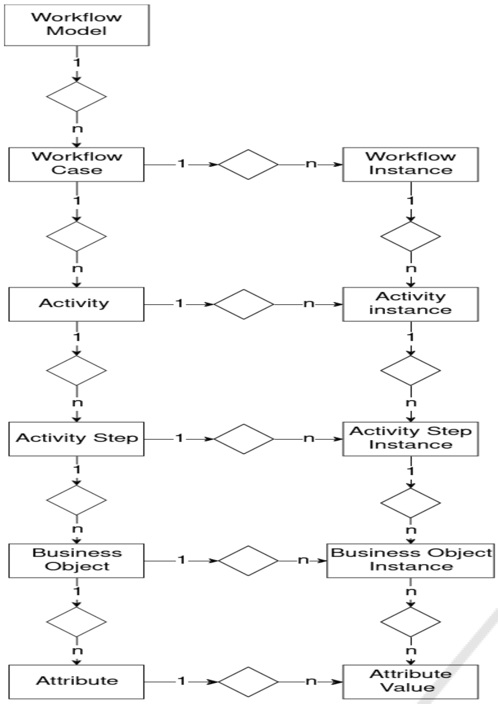

Figure 1: Meta Description of Extended Event Log, Adopted from: (Kassem, 2024).

The *activity steps* are defined as: the sequence of tasks carried out by the user when interacting with the GUI to execute an activity.

Business Object: represents the appearance of an active actor, such as client, customer, product, etc.

Attributes: Offer additional features such as name, age, description, etc.

3 LITERATURE REVIEW

In this section, the paper will present the state of the art in the area of utilizing process mining to configure RPA. We will first summarize academic papers discussing what has been achieved in this field which will be followed by a discussion of these papers in order to identify the research gap. There are more papers which have been identified during the literature review, we have only included a representative sample.

3.1 State of the Art

In this section, the paper will present a summary of a sample papers that have discussed related work. The section is split into two subsections, the first discussing the intersection of process mining & RPA and how process mining has been used as an enabler for RPA implementation in previous work. The second section discusses the area of intersection of NLP & RPA and how NLP has been used to enable cognitive RPA.

3.1.1 Process Mining for RPA Implementation

When wanting to implement RPA solution for any organization, 4 steps need to be carried out. Performing RPA workshop to analyze the business process and identify areas applicable for RPA configuration. Secondly, Breaking down the process into steps with the help of an employee. This is important to create the rules needed for the RPA. Third, create a business proposal. In this step, the as-is process of the business is mapped out and documented along with the to-be process. This is to identify what will change and how to ensure smooth transition. Finally, the RPA is implemented and configured to carry out the process as per the identified rules (Asatiani and Penttinen, 2016).

In their paper (Leno et al., 2021), have exposed a new vision for RPM, where process mining utilize UI logs in order to implement RPA routines. UI log is a more detailed event log that captures user interaction with the UI such as pressing a button. Like standard event logs, each entry has a timestamp, the event type, source and arguments or the parameters needed for the action. Parameters are used when filling a text box for example.

In (van der Aalst, 2021), the authors describe different uses for the integration of RPA and process mining. They highlight that process mining could be used before introducing the RPA in order to detect routine work that could potentially be automated by RPA. They also propose a scenario where process discovery is utilized to ensure the accurate programming of RPA. This depends on having a log that captures the user interaction with the UI.

A paper by (Choi et al., 2022), proposes a tool ”User Interface Interactions Recorder” with the aim of recording significant and relevant actions performed by users in order to output a log suitable for process mining analysis. The authors recognize that a proper implementation of RPA requires the availability of UI logs that capture the user interaction. Such logs could be used to identify the candidate tasks for RPA as well as aid in the implementation and programming of the RPA.

3.1.2 NLP for Cognitive RPA Implementation

In their paper (Wroblewska et al., 2018), the authors discuss how a document could be processed by NLP. In their application, the document is first scanned using OCR, so it could be analyzed and processed by the

NLP. The document is then classified by the NLP, this is important since this classification dictates which information will be found and extracted from the document. The extracted information could then be sent and used by the RPA.

In another paper the process is described as, the RPA pulls new information from emails. This data is then processed with NLP to extract relevant information. This information, in the context of this paper, is discounts and sales information. Thus, the final step is applying the relevant discounts as per the information retrieved. In his paper, he also discusses other scenarios where cognitive RPA has been used. Such as, processing emails to issue refunds automatically and other uses for automating customer service using the technology (Schatsky et al.,).

Extracting information from documents is not an easy task and can prove to be very time-consuming. Thus, automating this process with NLP is really beneficial. The process of NLP concerned with finding and extracting useful data from unstructured text is called "Information Extraction" and is achieved with the help of named entity recognition (Yanti et al., 2021). NER is used in two tasks, (1) identifying entities and (2) categorizing those entities (Yanti et al., 2021; C.P. and Sunitha, 2020).

One tool to use for NER is spaCy. spaCy is a python NLP library that could be trained to identify specific entities that it does not know, or in languages with which it has not been pre-trained for (Chantrapornchai and Tunsakul, 2021; C.P. and Sunitha, 2020) It does not offer the highest accuracy, but it has superior performance to other available tools.

The main steps involved to build a spaCy NER model are, collecting the texts, vocabulary building or data labeling; which is the process of defining which entities should be extracted and what are their category (labels with spaCy terminology), finally, the model building and testing (Yanti et al., 2021; Satheesh et al., 2020; Chantrapornchai and Tunsakul, 2021).

3.2 Discussion

In light of what has been reviewed in the previous section 3.1, it is shown that there is a lot of development in the area of RPA as well as cognitive RPA. The literature shows many examples of the utilization of NLP in order to enable RPA in the context of automating tasks that deals with unstructured data but are otherwise routine. This enhances the accuracy, eliminates human errors, and speeds up the process.

On the other hand, the literature also shows that there is a growing interest in the integration of process mining with RPA. This is achieved using the notion of UI logs. Not only does this allow us to identify the candidate RPA tasks, but they also aid in the accurate programming of the RPA.

However, the literature does not show any work that combines the two concepts. The literature does not show any work that uses process mining to find the candidate tasks for *cognitive* RPA and how to program them accurately. This is the research gap that this paper aims to fill. The paper proposes a framework that uses process mining, with the help of extended event logs, to identify the candidate tasks for cognitive RPA and how to program the bots accurately.

4 METHODOLOGY

This paper utilizes Design Science methodology as proposed by (Peffers et al., 2007), in order to propose a framework that addresses the research gap identified in the literature review. The methodology is chosen due to its iterative nature and its focus on creating an artifact that solves the problem.

The methodology constitutes 6 phases as follows:

1. Problem Identification: The problem is identified based on the conducted literature review.
2. Objectives: The objectives of the solution are identified and logically inferred from the previous step.
3. Design and Development: The artifact addressing the problem and objectives identified is developed.
4. Demonstration: The artifact is used to demonstrate how it solves the problem.
5. Evaluation: The artifact is evaluated based on how well it sponsors the solution to the problem.
6. Communication: The designed artifact and the problem it solves is communicated to the relevant stakeholders.

5 RESULTS

In this section, the paper will present the results of carrying out each phase of the methodology.

5.1 Problem Identification

The problem of this paper has been identified using the Literature Review conducted in section 3. The problem is the lack of proper framework to integrate process mining data with cognitive RPA configuration. This integration can prove to be beneficial for organizations that are looking to implement RPA solutions for their routine and repetitive task but deals with data in unstructured formats such as emails, documents, and other forms of textual data.

5.2 Objectives

The objectives of this paper are to propose a framework that integrates process mining data to identify candidate tasks for cognitive RPA and to aid in the configuration of the cognitive RPA.

5.3 Design and Development

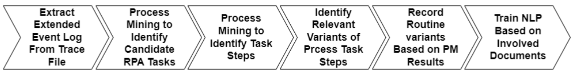

Figure 2: Framework For Cognitive RPA Implementation Using Process Mining.

Based on the conducted literature review in section 3, we have identified the tasks that should be carried out in order to implement cognitive RPA based on process mining data. These tasks are shown in figure 2. The tasks are similar to what was initially proposed in (Asatiani and Penttinen, 2016) except we no longer rely on employee interviews to identify task steps. Instead, we rely on data from extended event logs to identify the steps.

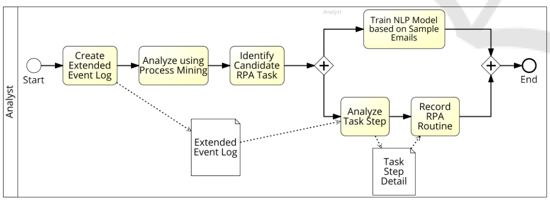

Figure 3: Proposed Tasks To Be Carried Out By Analyst.

The framework contain tasks that could be split into two groups, the tasks that should be carried out by the analyst, those are shown in figure 3, and the tasks that should be carried out by the cognitive RPA, those are shown in figure 4.

The choice of using extended event logs was made since these logs are comprehensive as discussed in section 2.3. This is important since the task steps are needed to configure the RPA (Kassem, 2024).

Extended event logs can also discover different variants of the task steps. An example on this would be picking a different logistics company to deliver a specific category of products. Thus, instead of enforcing a standard set of tasks that are to be carried as is (Leno et al., 2021), we can allow for the configuration of some variants based on different attributes.

Process mining can help us to analyze the process data and generate process models that could be used to identify candidate tasks and also to visualize the steps required to be carried out by the RPA. Thus, the focus of this paper is on process discovery in order to discover the process tasks and tasks steps this is based on what has been discussed in the literature in section 3.2.

Training the NLP model and configuring the RPA are two steps that could happen in parallel, given that we know which data will be used and provided by the NLP for each routine. The model will be trained based on the documents involved in the process. The RPA will be configured based on the identified relevant tasks. Whether, the email contains a purchase order or a request for quotation, dictates which modules will be opened by the RPA and what type of information needs to be extracted from the email by the NLP model.

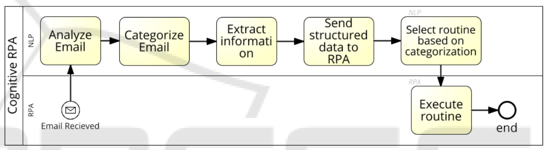

Figure 4: Proposed Steps To Be Carried Out By RPA.

The RPA tool which will be used should have integration with AI models to allow for the integration with NLP or should be able to run python scripts. Most RPA tools whether open source or not do have that option which could then be used to configure SpaCy to do the analysis. The cognitive RPA should then carry out the tasks in figure 4.

5.4 Demonstration

In this phase, the framework is demonstrated. This work is part of a bachelor thesis, as such, we were unable to fully implement the framework, or get the required number of data to train the NLP model in a real environment. However, we have implemented a simple NLP model using SpaCy to demonstrate the concept. An expert interview was also conducted to validate the framework.

5.4.1 Technical Demonstration

To demonstrate the concept, we have implemented a simple NLP model using SpaCy. The model used was NER, it was created to identify the entities in a purchase order email. The data set wasn't large enough consisting of just 40 emails. The model was able to

```
========================== Initializing pipeline ==========================
[+] Initialized pipeline

============================ Training pipeline ============================
[i] Pipeline: ['tok2vec', 'ner']
[i] Initial learn rate: 0.001
E    #       LOSS TOK2VEC  LOSS NER  ENTS_F  ENTS_P  ENTS_R  SCORE
---  ------  ------------  --------  ------  ------  ------  ------
  0       0          0.00     49.30    0.00    0.00    0.00    0.00
  9     200          9.03    430.35   96.55   93.33  100.00    0.97
 21     400          0.00      0.00   96.55   93.33  100.00    0.97
 36     600          0.00      0.00   96.55   93.33  100.00    0.97
 54     800          0.00      0.00   96.55   93.33  100.00    0.97
 76    1000          0.00      0.00   96.55   93.33  100.00    0.97
103    1200          0.00      0.00   96.55   93.33  100.00    0.97
136    1400          0.00      0.00   96.55   93.33  100.00    0.97
176    1600          0.00      0.00   96.55   93.33  100.00    0.97
225    1800          0.00      0.00   96.55   93.33  100.00    0.97
```

Figure 5: SpaCy NER Model Results.

identify the entities in the email with an accuracy of 97%. The results are shown in figure 5.

The model was trained using 40 emails split into 80/ 20 for training and validation. The model was then tested on 5 emails that were not part of the training set.

The emails contained features such as, quantity, price, product name, product ID, and person names.

We find that the model has a 0 loss value, which indicates that the model has had high accuracy, it had a precision of 93.33% which indicates that the model was reasonably classifying positive samples. Finally, it had a very high recall of 100%. This gives the model a total accuracy score of 0.97 which is high enough to allow us to categorize the model as accurate.

The following section will discuss the expert interview that was conducted to validate the framework.

5.4.2 Expert Interview

The goal of the interview was to validate that the proposed framework would in fact add value to the current business process and has the potential to be adopted, this is also to address the limitation that a full scale implementation was not feasible.

The interview was conducted with the Enterprise Sales Operation Head of a telecommunication company that requested their name not to be disclosed. The company operates on B2C and B2B basis, offering a variety of products from landlines, ADSL, and mobile services. To their business customers, they offer many internet services and bundles as well as data centers and cloud solutions.

The business process starts when they receive a PO from a client. The PO should then be analyzed for the needed product/ service, quantity, terms & conditions, etc. The data should then be entered to their E-CRM, where it's forwarded to the operations head so that meetings with the client and developers should be carried out.

The process of copying the data to the ECRM is done manually, an employee has to go through the PO document sent by the client to extract the relevant data. The interviewee was then shown the process we propose and was explained how the automation would take place.

The interviewee mentioned that they have attempted automation before, given the errors that would result from manual entry and how the process is time-consuming, using structured templates that would always follow the same format. This however, was not feasible since they were unable to enforce the template upon their clients.

We had positive feedback when asked about the impacting response times. They said that it could potentially increase their response times. When the data is extracted and inputted faster, they can allocate the resources and make key decisions faster increasing response times and the initiation of the following processes.

One of the things that concerned them is the ability to edit data. As a service provider, they do need to change data frequently. An example scenario for that is the project manager having to reschedule a meeting with the client or the dev team. This can affect other deadlines on which the system has to update. Thus, they believe that a key feature for them is the ability for the cognitive RPA to receive an email with new data which it will then be used to overwrite old data on the ECRM.

In conclusion, the framework received positive feedback assuming that it has a high accuracy rate. The management of the company is willing to invest in such a technology and believes that it will add value to the business, fasten response times, help with better decision-making and give them a competitive advantage. The idea that the technology is non-intrusive and would work directly on the presentation layer with their current infrastructure appealed to them. Their main concern is having an easy and intuitive GUI that the back-office employees could work with, and proper training is to be provided where required.

The following section will evaluate the framework based on the NLP results and the conducted interview

5.5 Evaluation

As previously mentioned, a simple NLP model was developed with spaCy as a proof of concept. The model alongside the diagrams of the framework have been used in an interview with an expert to validate it.

Based on the technical results and the literature review conducted, we know that, given an appropriate data set, an accurate NLP model could be developed and trained to extract relevant information from unstructured documents. It is also the case that an RPA could be used alongside the NLP model to enable the cognitive RPA, as has been mentioned in the literature review. It is also the case that process mining, specifically process discovery on both event logs and UI logs could significantly empower the identification and configuration of RPA tasks. The utilization of the extended event logs only enable richer analysis given their hierarchical nature.

Based on the conducted interview, the main area of concern was how to correct errors. Our framework did not include steps for error handling which had to be addressed. Thus, we have added steps to the framework to be carried out by the cognitive RPA as shown in figures 6 & 7.

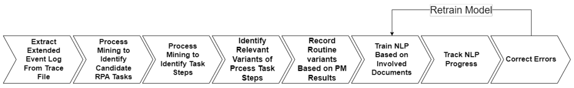

Figure 6: Enhanced Framework For Cognitive RPA Implementation Using Process Mining.

In figure 6, we add two steps where the progress of the NLP is monitored, if errors occur they should be corrected and the model should be retrained based on the errors. This would allow the model to get even better with time. The framework proposes continues iteration over steps 7 through 9.

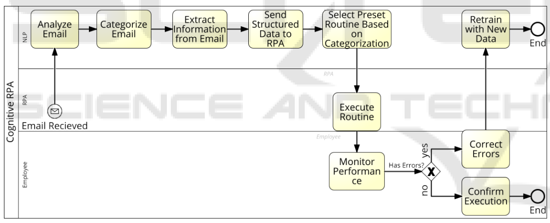

Figure 7: Enhanced Proposed Steps To Be Carried Out By RPA.

In figure 7, we show how this impacts the process and the tasks to be carried out. We introduce a new pool for an employee to actively monitor the decisions made by the cognitive RPA and either push the execution of routines if they lack errors or to carry out error correction if needed. Upon correcting the errors made by the RPA, the NLP model should be fed the data and retrained, and the corrected data should be pushed to the RPA routine so that it's correctly executed.

5.6 Communication

As for the 6^{th} and final phase of the methodology, communication, we have conducted an expert interview which also serve as communicating the work as well as validate it. The paper is sent to publication and served as a bachelor thesis that's should be available through the university's library.

In the next section we will discuss limitations, future work and conclude this work.

6 CONCLUSION

In this paper, we proposed a cognitive RPA framework with process mining for automating data entry tasks from emails. We demonstrated the concept using a simple NLP model for entity extraction from purchase order emails. An expert interview with a representative from a telecommunications company provided valuable insights and validated the framework's potential benefits for real-world application. The interview also aided in the enhancement of the framework.

However, we do acknowledge some limitations in this work. The NLP model was trained on a small and limited data set. The model should be trained on a larger and more diverse dataset with various email formats and documents. The paper also did not discuss or explore the user interface design, especially in the area of error corrections. This was out of scope but should be addressed in future work. In this paper, we also did not carry out any actual process mining tasks, it has been assumed that it has been carried out and well-defined in the literature.

Future work should be directed toward expanding the NLP model training set. Additionally, more empirical research is required where the model is fully implemented in case study to validate in real world scenarios. As of now, there are no tools that could directly analyze the extended event logs, such logs should be flattened out for analysis. Thus, future work should also address this in order to unleash the potential for richer process mining analysis that could be enabled by such logs.

Overall, this work demonstrates the potential of cognitive RPA frameworks with process mining to automate data entry tasks and streamline business processes. By addressing limitations and exploring future work directions, we believe this framework can contribute to improving efficiency, reducing errors, and enhancing decision-making capabilities within organizations.

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