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Candidate Tasks Selection Framework for Robotic Process Automation Implementation

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이 논문을 공학박사학위 논문으로 제출함

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ABSTRACT

Technology is changing at a faster pace. For sustainable management, many companies are attempting a digital transformation. Digital transformation requires optimizing existing business models and enhancing business process automation. RPA (Robotic Process Automation) is one of the most recently developed technologies for business process automation. RPA is a technology that automates large-scale, manual, repetitive, rule-based tasks performed by humans. The adoption of RPA provides many benefits to businesses by accelerating business growth by reducing many manual and repetitive tasks. However, RPA technology faces several challenges. Among them, the main challenge is that RPA solutions do not identify which of the many business tasks need to be automated. Identification of the tasks to be automated is an important part of business process automation.

The goal of this study is to develop a framework that identifies and selects the tasks that can be and need to be automated by RPA. The proposed framework is based on the process mining technology and user interface log data. The framework for selecting candidate business tasks for robotic process automation consists of two major parts.

The first part consists of a methodology for selecting candidate business tasks for automation with RPA. The approach proposed in this study consists of four steps: user interface log generation, data conversion and filtering to be able to be used by process mining technology, task discovery with process mining, and candidate tasks selection based on specific criteria.

The second part consists of developing a tool to record and generate user interface interactions log. To discover tasks using process mining technology, the use of an event log as input is required. In this study, the user interface log is used as input by process mining techniques to discover the tasks performed on a user interface. The interface log shows a series of tasks in chronological order when the user interacts with different applications and programs (Windows, web browser, application program). The proposed tool allows recording the interactions with the user interface as well as filtering and simplifying the generate log.

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Chapter 1 INTRODUCTION

1.1. Robotic Process Automation (RPA)

Technology is changing at a faster pace. Disruptive firms are one source of technological change, which have the potential to create and develop radical innovations that disrupt existing products and support industrial, economic, and social change [1–6]. Moreover, since the outbreak of the COVID-19 pandemic, digital transformation processes have significantly hastened and become the unchallenged leader of all initiatives launched by those companies and organizations that have been implementing initiatives related to digitization for a long time as well as those that have only transformed their activities in the areas of internal operations and work because of the pandemic [7]. In almost all industries, organizations have started conducting initiatives to explore new digital technologies and get their benefits. This includes transformations of crucial business operations, processes, products, organizational structures, and management aspects [8]. Digital transformation requires organizations to adapt their existing business models and enhance the automation of their business processes [9]. Robotic Process Automation (RPA) is one of the most recent developments to boost the automation level of business processes. RPA is a famous subject in the corporate world [10]. RPA uses many artificial intelligence and machine learning techniques: image recognition, Optical Character Recognition (OCR), etc. It is considered a new wave of digital technologies [11], which is increasingly drawing the attention of industries and administrations. RPA is a new technology that enables the automation of high-volume, manual, repeatable, routine, rule-based, and unmotivating human tasks [12]. This technology utilizes software robots to replace human actions for performing administrative activities [13]. Using bots to execute repetitive tasks saves organizations time and money and reduces errors. Moreover, software bots allow employees to focus more on higher level work instead of on tedious tasks. Consequently, the return on investment is colossal. An example of clerical tasks is the as-is process performed by a human depicted in Figure 1.1. The to-be process performed by a robot is illustrated in Figure 1.2. The to-be workflow is similar to the as-is workflow. However, some tedious tasks that were performed by a human user are now performed by a bot user. RPA has decreased the threshold for process automation. Repetitive activities performed by people can now be handed over to software bots. Software robots replace users by interacting directly with the user interface that was originally operated only by people and do not modify or replace any pre-existing information system in the organization. RPA is considered cheaper than traditional automation solutions. Therefore, it can be exploited to automate routine tasks that are broadly considered not cost-effective [14].

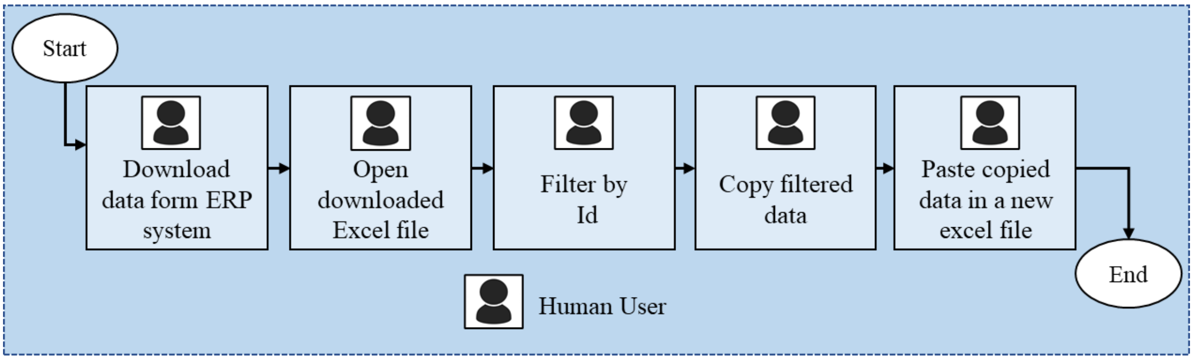

Figure 1.1. Example of routine tasks performed by a human.

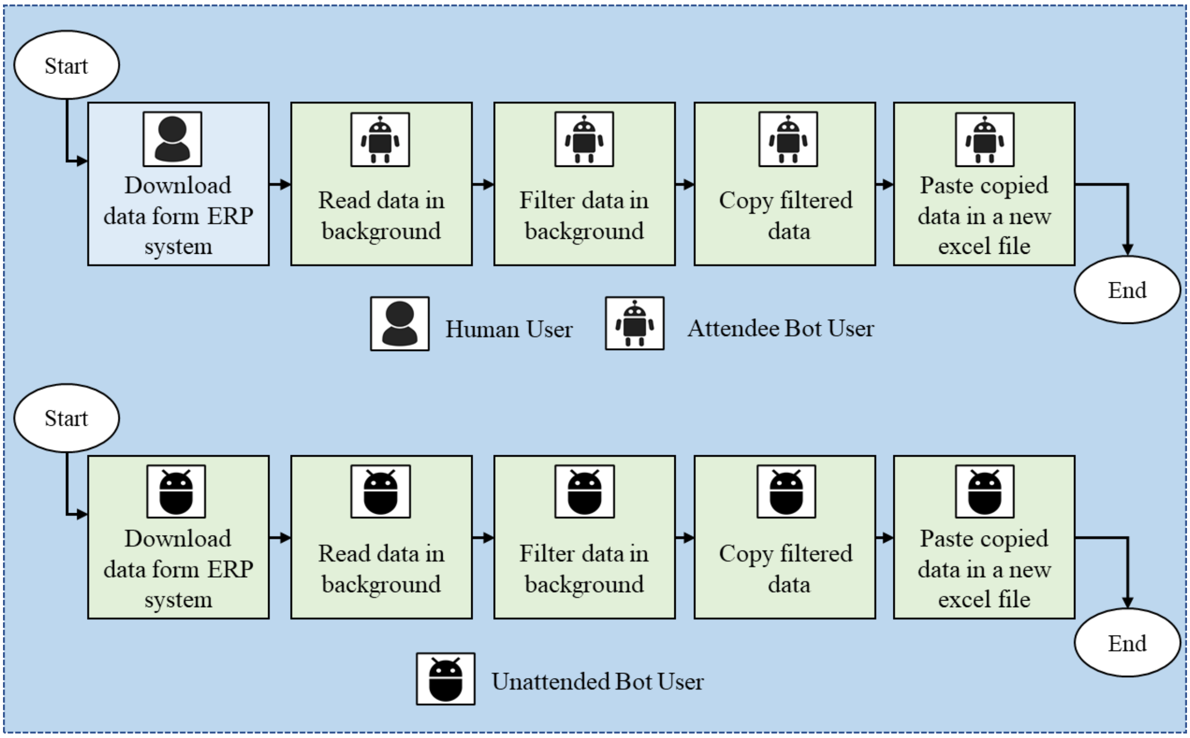

Figure 1.2. Example of routine tasks performed by a bot user.

Robotics Process Automation (RPA) system enables organizations to automate high-volume, repeatable, and unmotivated mass of tasks just like the human user was performing across systems and applications, through the usage of graphical user interfaces. The main objective of robotic process automation is to substitute with a virtual workforce the repetitive and routine tasks handled by humans allowing them to focus more on valuable tasks and problem solving. RPA is defined as a category of tools that enable users to specify deterministic routines involving structured data, rules (if then-else), user interface interactions, and operations accessible via APIs [15]. RPA reduces labor intensive processes through simulating human effort to perform tasks, speeding up the execution of high-volume transactional process [16].

1.2. RPA Elements

Robotic process automation is composed of three components: bots, a studio, and an orchestrator. (1) RPA bots are the virtual workforce that will be executing repetitive and mundane human tasks. They are dedicated to handling an unmotivated mass of tasks so that employees can engage in valuable jobs and problem solving. There are two categories of RPA bots, attended bots and unattended bots. Attended bots are bots configured to work side by side with a human user. The goal is to speed up the repetitive tasks where the tasks need to be triggered by the human user. This type of bot can be used in routine, manual, and rule-based tasks which require human intervention for decision points. Unattended bots are bots configured to work fully independently in the background. This type of bot is dedicated to working without the intervention of a human user and can be scheduled to be started and executed automatically and triggered by a satisfying condition or a business event. Unattended bots can be used in routine, manual, and rule-based tasks which do not require any human intervention. (2) An RPA studio is responsible for configuring the workflow to be executed by the bots which will be mimicking the human behavior. It enables users to create, design, and automate the workflow to be executed by bots. Business users are enabled to configure the bots by record and screenplay capability and intuitive scenario design interface. (3) The RPA Orchestrator is responsible for scheduling, managing, monitoring, and auditing the bots. The bots can be used with third-party applications using Application Programming Interfaces (APIs). The elements of robotic process automation are illustrated in Figure 1.3. A general architecture of robotic process automation which shows a high-level view of layers is depicted in Figure 1.4. The architecture is composed of 3 tiers: client layer, server layer, and persistency layer. The client layer consists of robot, developer studio and admin web browser. The server layer consists of the orchestrator, and orchestrator web services. Finally, the persistency layer consists of a main database which store robot configurations and assigned processes, and an indexer database which store robot logs and index logs.

Integrating robotic process automation with Machine Learning and Artificial Intelligence can aid in the advancement of the capabilities of software bots beyond rule-based processes and in improving business insights and ameliorating data integrity [19]. Furthermore, integrating computer vision applications such as image processing, image detail extraction, text recognition in an image, occurrence detection in an image, etc., can largely help software bots in automating detailed tasks on a graphical user interface [20].

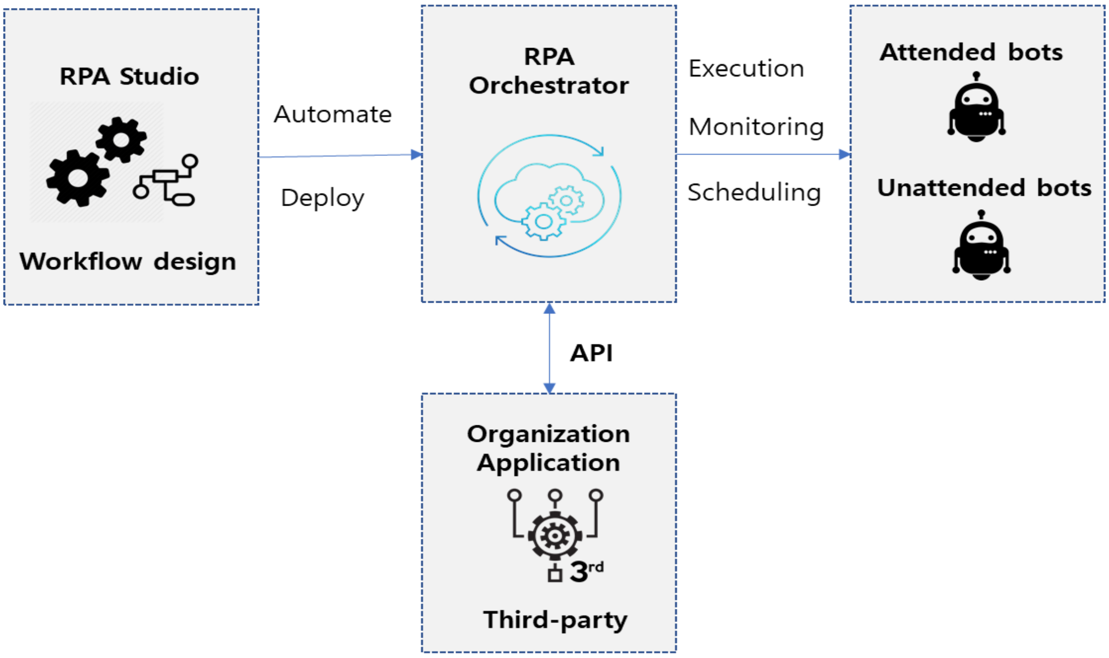

Figure 1.3. Robotic process automation components.

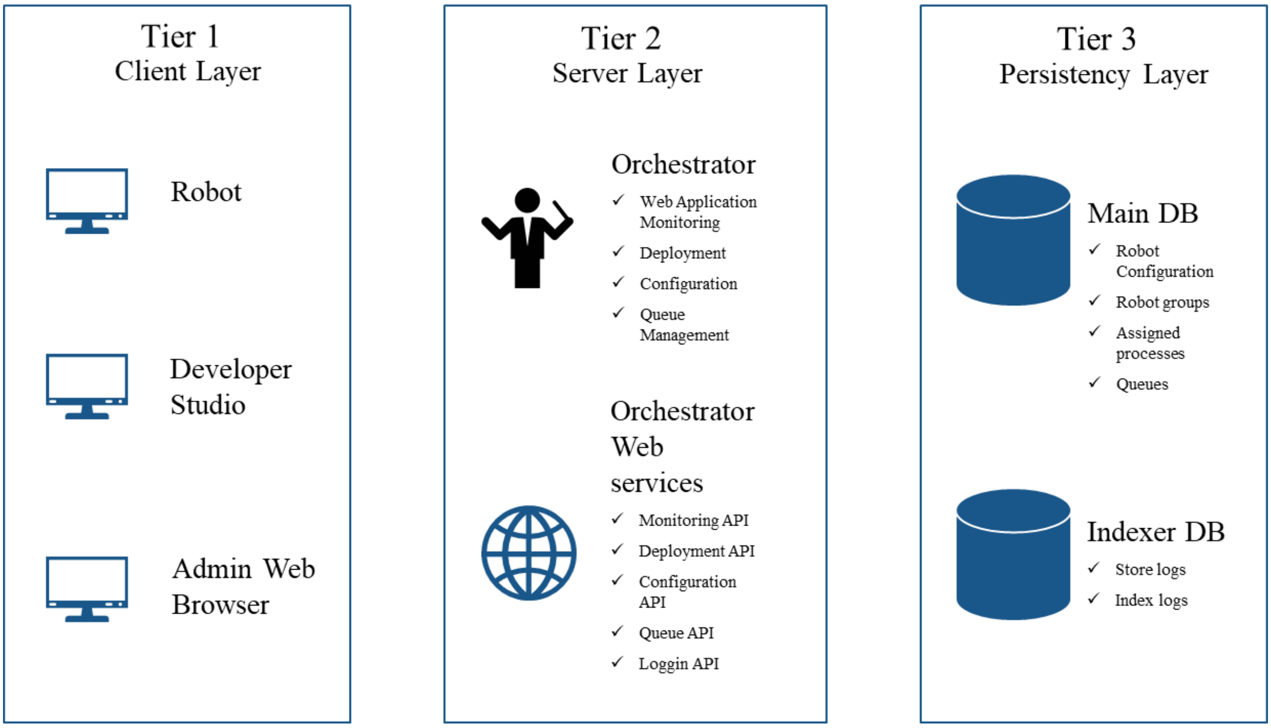

Figure 1.4. Robotic process automation architecture (UiPath based)

1.3. RPA Advantages and Application Area

Robotic automation interacts with the existing IT architecture without the need of complex system integration. RPA aims to transfer the process execution from humans to bots. An average person can work 8 hours a day, while the robot can work 24 hours without fatigue. The average human productivity is 60%, and the error is small, while the robot's productivity is 100%, without any error. Moreover, compared with humans, robots can handle multiple tasks. By assigning repetitive, routine, and high-volume task to robots, human worker become able to perform extra tasks that before was not able to find the time to perform it. Thus, an increasing in the productivity. Some of the benefits of RPA are highlighted in Table 1.1. To benefit from its advantages, RPA technology can be applied to areas [23, 25, 26] where there are processes containing tedious and high-volume tasks to be accomplished by the employee. Some of the application area of RPA is depicted in Table 1.2 and Figure 1.5.

Table 1.1. Benefits of RPA [23]

Benefit	**Explanation**
Improved productivity	More than 60% to 90% of repetitive effort can be removed wit RPA increasing the output for each of your employees
Rapid result and in year benefits	Rapid implementation and results are a key promise of RPA as you can conceive, design, develop, and deploy in weeks, not months or years.
Low startup costs	Each of the bot licenses is less costly compared to other software tools and the bot can perform the work of about two to three Full Time Equivalent (FTE), ensuring the startup costs are low.
Reduced processing costs	The cost of processing is reduced drastically as the bot costs around one third to one fifth the cost of an employee, depending on location.
Improved quality and accuracy	Your bots perform assigned work with 100% accuracy, thereby reducing any rework that may have been required.
Improved compliance	RPA activities are logged and can be reviewed at any time. This gives a greater degree of oversight and control over operations.

Table 1.2. Application Area of RPA

Industry	Usage
Healthcare	• Billing • Patient registration
Human Resources	• New employee joining formalities • Payroll process • Hiring shortlisted candidates
Insurance	• Clearance & Claims Processing • Premium Information
Manufacturing & Retail	• Calculation of Sales • Bills of material
Banking and Financial Services	• Discovery • Frauds claims • Cards activation

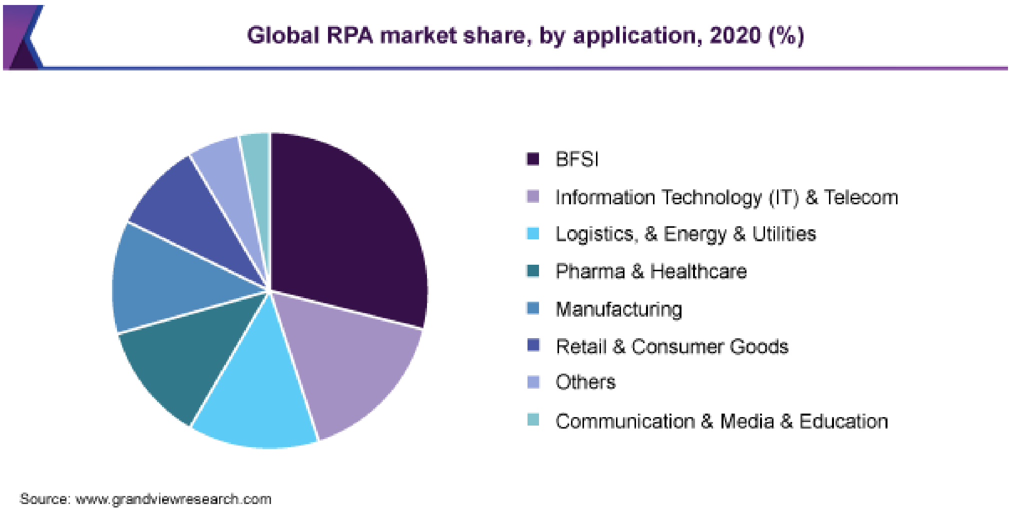

Figure 1.5. RPA Market Share, by Application [27]

1.4. RPA Market Size Transition and Forecast

The technology role is emerging over and over at a faster pace. Many businesses around the world are trying to use Robotic Process Automation (RPA) in many areas to grant a compelling competitive advantage in business process automation. It was predicted in a study by Gartner that companies investing in Robotic Process Automation software will reach $1 billion by 2020, at a growth rate of 41% from 2015 through 2020 [17], nearly $2 billion in 2021 [28] as shown in Table 1.3. This number is huge and shows the massive interest of companies and organizations in adopting RPA to automate a part of their process tasks.

Table 1.3. Worldwide RPA Software Revenue (Millions of U.S. Dollars) [28]

	2019	2020	2021
Revenue ($M)	1,411.1	1,579.5	1,888.1
Growth (%)	62.93	11.94	19.53

The global market size of RPA has been estimated at USD 1.57 billion in 2020, and at USD 1.89 billion in 2021 in another study [27]. It has been predicted to grow at a rate of 32.8% from 2021 to 2028 [18] as shown in Figure 1.6. Due to fact that the pandemic induced work from home, a shift in company business operations is anticipated to favor market growth over the forecast period. The market is expected to grow with the integration of cognitive technologies and changing business processes across enterprises. Furthermore, the growing need for automating redundant tasks is anticipated to drive the market over the forecast period because automation enables quick implementation, execution, and arrangement of the large volume of data in less time than mechanical procedure and it reduces overhead expense for enterprises [27].

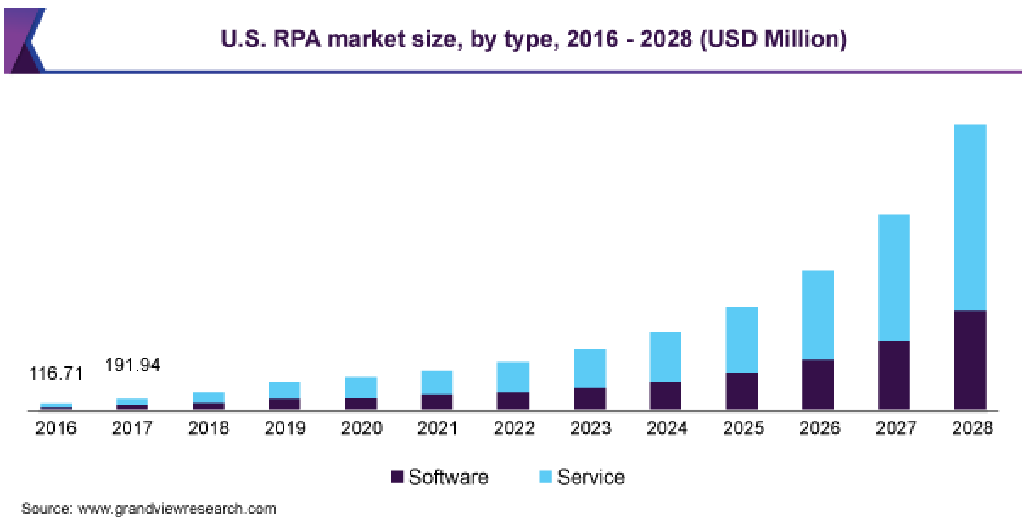

Figure 1.6. RPA Market Size Transition and Forecast [27]

1.5. RPA Implementation Challenges

Robotic Process Automation (RPA) recently gained a lot of attention in industries and academia [23] as it speeds up business growth by reducing a lot of manual and repetitive based work [24]. However, at present, the implementation of RPA still faces many challenges. According to the report of Global RPA Survey 2019 [21] depicted in Figure 1.7, challenges at the organizational structure level include the inability to assess process priorities (40%), lack of risk management tools (28%), insufficient internal staff skills (24%), and the lack of sense of urgency (23%). At the technical risk level, it is information and data security (40%), difficulty in achieving scale (37%), and selection of a suitable development platform (30%). The financial and regulatory aspects include higher implementation costs (37%), inappropriate application scenarios (32%), and external legal regulatory requirements (30%). A further discussion on these challenges is presented in Table 1.4.

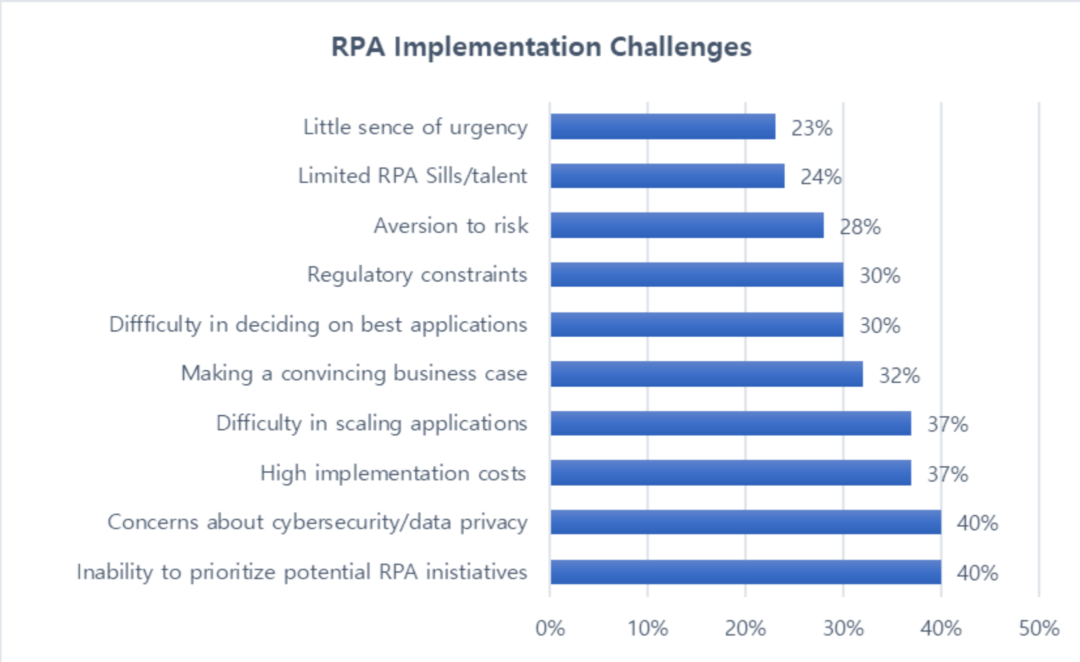

Figure 1.7. RPA Implementation Challenges [21]

Table 1.4. RPA Implementation Challenges by Perspective

Perspective	**Challenges**	**Comments**
Organizational Perspective	Prioritizing potential RPA initiatives	Identifying where RPA is highly likely to provide significant value is challenging. The huge effort will be in this stage when implementing RPA. A poor choice of processes to be automated may result in implementation failure. Approaches for identifying the suitable processes to be automated is strongly required.
	Aversion to risk	Most of organizations prefer not to take the risk in adopting a technology emerging. This can be overcome by applying RPA to many areas as case studies.

	Limited RPA Sills/talent	RPA is still an emerging technology. Therefore, there is a lack in skilled people in RPA.
	Little sense of urgency	It might take a long time to decide implementing RPA for organizations having a little sense of urgency. Many use cases are important to serve for the growth of RPA implementation.
Technical Perspective	Cybersecurity/data privacy	Cybersecurity and data privacy were always considered crucial. RPA is based on mining User Interface data that may include private information. Thus, there is a need for a secure RPA development.
	Scaling applications	When automating a core business process wit h RPA and finding that the business is growi ng rapidly, if that automated process cannot s cale as required, the RPA technology can bec ome an obstacle for growth. Therefore, t echniques to make the scalability easy is needed .
	Deciding on best applications	Ensuring that you are using the right application can be very challenging. There is a need for be nchmarks on how to decide the best application.
Financial and Regulatory	Implementation costs	Process Analysis phase takes a long time in the implementation process. By speeding up this phase, one can reduce implementation costs. So, approaches for accelerating the process analysis phase is needed.
	Convincing business case	A considerable number of use cases is needed to convince businesses.
	Regulatory constraints	New technologies are required to meet regulatory constraints.

Prioritizing potential RPA initiatives or in other words, choosing the candidate tasks to be automated is currently the starting point of robotic process automation (RPA) implementation. Therefore, any poor choice of processes for initial pilot will result in the failure of RPA implementation. In other words, establishing what is in and out of the scope for RPA, which processes should be automated and which routines should be automated in the first place since RPA can automate a wide range of routines, can be seen as the main challenge for RPA implementation. Therefore, there is a need to provide a framework that allows RPA implementer to choose and select the candidate tasks to be automated with RPA tools.

It is not difficult to see that although RPA can quickly achieve process automation functions with a low and lightweight code, due to its deep business integration and its direct impact on achieving business goals and processing business data, etc., RPA should take over companies' great interest in business changes, management design, control, security, operational stability, and mechanisms for dealing with exceptions.

1.6. Contribution and Structure of the Thesis

The first contribution of this thesis is to provide the state of the art of the most important challenges faced during the implementation of RPA. The review we conducted on the challenges shows that identifying the processes to be automated with RPA is outlined to be one of the main challenges of RPA implementation. Since determining what is in and out of the scope for RPA is the starting point of RPA implementation, a poor choice of candidate tasks for automation can widely results in RPA implementation failure. Therefore, the second contribution of this thesis is the development of a framework that allows selecting the candidate tasks that can be and need to be automated by RPA.

The framework proposed to identify the candidate tasks that can be and need to be automated by RPA is based on process mining techniques. This thesis demonstrates that process mining can be used to identify the tasks performed by people while interacting with different user interfaces of various systems and applications to be automated by RPA. A user interface event log which corresponds to the events accruing while interacting with user interfaces of different applications or systems, is required as input to use process mining techniques to identify the tasks that can be automated with RPA. However, existing recording tools do not provide data from which process mining can discover the tasks performed on user interfaces, and existing approaches such as video recording is time-consuming. Thus, the adoption of process mining techniques for RPA is blocked by the absence of tools capable of recording the interactions with the user interface and generating UI logs providing enough information as input for process mining techniques to discover digital tasks that can be automated with RPA. Therefore, the third contribution of this thesis consists of developing a tool, namely User interface Interactions Recorder (UIIR), which fills the gap between robotic process automation and process mining.

The first part of this thesis provides an introduction and an overview on RPA and its elements, RPA advantages and application area, market size transition and forecast, and RPA implementation challenges. Preliminaries are provided in Chapter 2. The first major part of this thesis is presented in Chapter 3 which introduces candidate business digital tasks selection methodology for RPA. The second major part of the present study which is about developing user interface interactions recorder for candidate task selection methodology is presented in Chapter 4. Finally, the thesis is concluded in Chapter 5.

Chapter 2 PRELIMINARIES

This chapter introduces robotic process automation characteristics, outlines the relationship between RPA and business process management, and provides an overview on process mining and robotic process mining.

2.1. Robotic Process Automation Characteristics

A study [29] introduced the main characteristics of RPA as shown in Figure 2.1 which consists of four major traits in order to characterize RPA in a structured way. [29] followed the extensive understanding of the IEEE Corporate Advisory Group (2017, p. 11), that defines RPA as the use of a "preconfigured software instance that uses business rules and predefined activity choreography to complete the autonomous execution of a combination of processes, activities, transactions, and tasks in one or more unrelated software systems to deliver a result or service with human exception management."

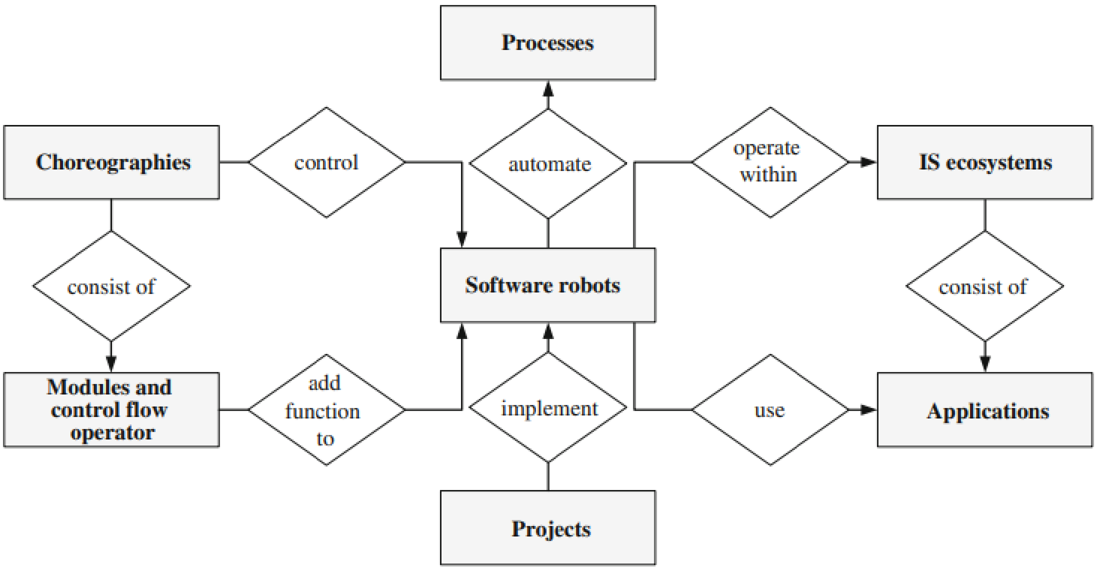

Figure 2.1. The nature of robotic process automation [29]

2.2. Robotic Process Automation and Business Process Management [30]

It is essential to examine similarities, differences, and complementarities between RPA and other technologies. Accordingly, Mendling et al. [31] presented a call for the BPM research community to examine business process management systems (BPMSs) and RPA integration due to the fact that RPA and BPM are both neighboring disciplines which have complementary objectives. On one side, BPM as a multidimensional approach, intents to achieve better business performance via continuous process improvement, optimization, and digital transformation. Business Process Management System (BPMS) as a holistic software platform that covers a broad-spectrum of functionalities such as process design, analytics, and monitoring is usually one of the BPM initiative inescapable perspectives [31]. On the other side, RPA handles discreet, routine, and repetitive tasks and execute processes as a human would.

According to Cewe at al. [35] "BPMS is used to orchestrate end-to-end process, and to manage human, robots and system interactions, RPA is responsible for repetitive sequences of tasks that can be fully delegated to software robots". Due to the fact that these technologies are very often used separately, the authors from business practice [33], [35] strongly proposes merging both to achieve even more business value. In a case of the lack of resources and/or time for completely implementing BPMS, RPA can be a valuable and comparably cheap tool to solve or complement some of the unsatisfied objectives [30].

RPA technology is composed of several building blocks which are similar to business process automation with business processes, activities, and execution constraints as its components. However, the building blocks of RPA have rarely been defined or even identified explicitly. This makes establishing common ground for discussions and research difficult [36]. In order to come over this issue, Maximilian et al. [36] proposes definitions for the building blocks of RPA and highlights their respective characteristics. To continue the analogy with business process automation, RPA also has an equivalent of business processes—RPA bots (cf. Definition 1)—as well as activities—RPA operations (cf. Definition 2). Based on the general definitions of RPA presented in the literature, Maximilian et al. [36] introduced the following definition of an RPA bot based on the general definitions of RPA presented in the literature.

Definition 1 (RPA bot) [36]. "An RPA bot is a machine executable sequence of instructions consisting of RPA operations to automate interactions of human users with computer systems".

Definition 2 (RPA operation) [36]. "An RPA operation is an atomic step in an RPA bot. It represents a single action performed on the system to be automated, usually, but not limited to, via cursor and keyboard interactions on the user interface level".

These RPA operations constitute the smallest building blocks of RPA bots. To a significant extent, these RPA operations are already predefined by several RPA vendors. Examples of RPA operations are internal operations of the RPA software such as a variable assignment, a mouse click on a button, and text extraction from documents [36].

2.3. Process Mining

2.3.1. Process Mining Overview

Process mining has been defined in [37] as a relatively young research discipline that falls between artificial intelligence and data mining on the one hand and process modeling and analysis on the other hand. Moreover, it was outlined in [38] as a recent set of techniques that provide a strong bridge between BI and BPM by combining both process models and event data forming a new form of process driven analytics.

The main idea of business process mining is to extract the execution of business processes recorded in event logs available in today's information system to automatically discover the models of business processes, compare existing business process models with the new automatically constructed ones to identify deviations and bottlenecks, and to enhance the business processes. Process mining techniques exploit event data stored in today's information systems to show how people, machines, and organizations are really behaving. Using event data, process mining provides useful insights that can be utilized to improve processes of different domains.

There are basically four types of process mining [39]. The first type of process mining is process discovery. It is considered the most important type of process mining. Process discovery consists of learning process models from event data by taking only an event log as input and producing a process model which shows what people, machines, organizations are really doing. There are three categories of process discovery perspectives based on the information available in the event data: the control-flow perspective, the organizational perspective, and the case perspective. These categories can be used to analyzed processes from different perspectives. The second type of process mining is conformance checking. This type consists of checking whether the existing model is in conformance with the reality which is recorded in the event log. In other words, it checks whether what we think is happening is conform to what is really happening by identifying commonalities and differences between the existing process model and the recorded event log [23]. The third type of process mining is process reengineering. This type also takes an event log and a process model as input like the conformance checking. Nevertheless, the aim of this type is to change the existing process model not identifying the differences. The process model can be changed to better match reality. The fourth type of process mining is operational support. This type allows people to act at the time the process deviates by providing predictions (e.g., remaining time), warnings, or recommendations [40].

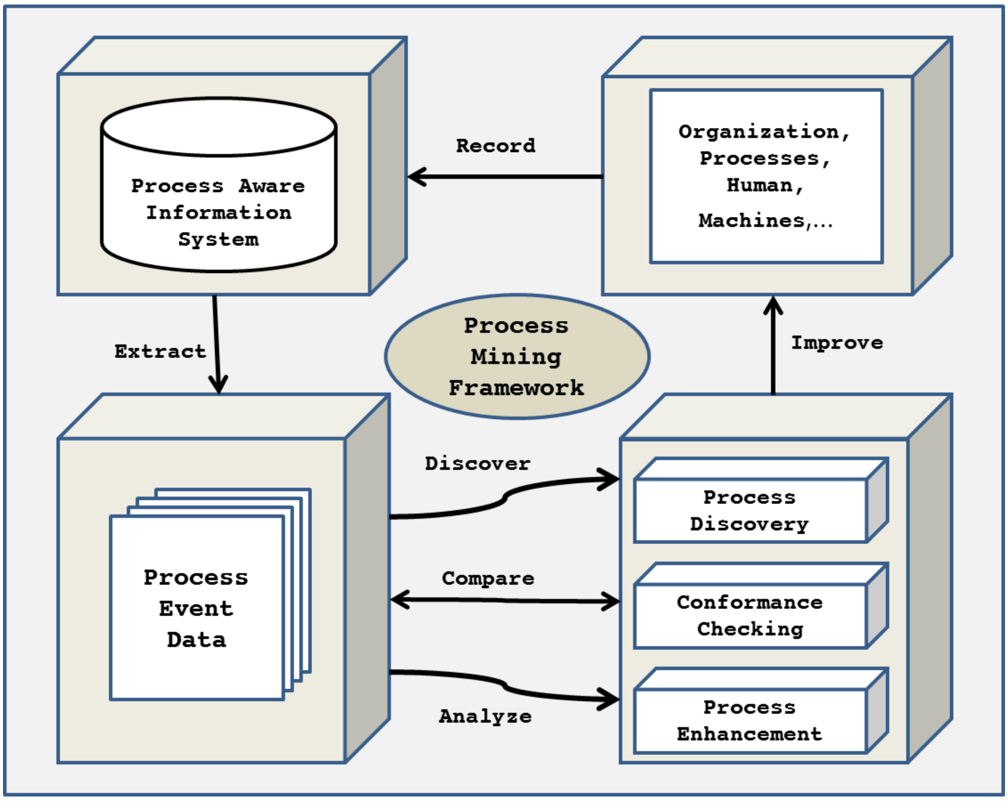

Figure 2.2. Process Mining Framework [41]

2.3.2. Process Mining Event Log

Business processes contain large number of events recorded by today's information systems such as Enterprise Resource Planning systems (ERP), Business Process Management systems (BPM), Workflow Management systems (WFM), etc. [42]. is the stored data consists of a collection of information such as event ID, activity, timestamp and responsible person, etc. This event data is called "Event Logs" [43]. The structure of an event is shown in Figure 2.3. Process mining is a rising discipline in Management Information Systems as well as Computer Science that is based on model driven methods within the data mining techniques that also considers complex business processes [44]. It aims to understand the as-is process from the observed system behavior by deriving process models from these recorded process event logs [45].

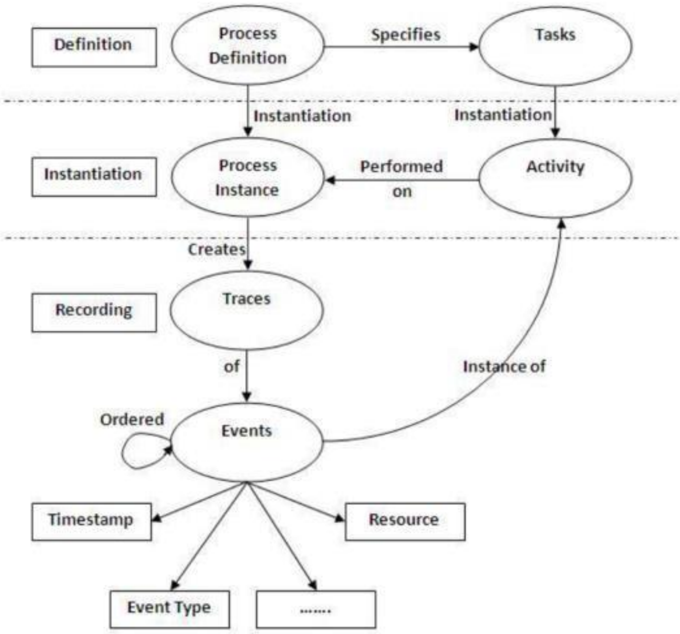

Figure 2.3. The structure of an event log [46]

An event log stores the execution history of a business process. An example of event log is illustrated in Table 2.1. The events in the table are grouped by case and sorted chronologically. The sequence of events that is recorded for a process instance is called a trace. In this example, the trace for case 1 of Table 2.1 is <request purchase, approve purchase, verify approval, finalize purchase, purchase order, receive purchase & verify>.

Table 2.1. Example of event log [41]

Case id	**Event id**	**Activity**	**Timestamp**	**….**
Q521-QZR	N0060	Request Purchase	5/15/2014 16:35	….
	N0070	Approve Purchase	5/15/2014 16:40	….
	N0080	Verify Approval	5/16/2014 16:40	….
	N0090	Finalize Purchase	5/16/2014 17:42	….
	N0100	Purchase Order	5/16/2014 17:30	….
	N0110	Receive Purchase & verify	6/13/2014 10:55	….
Q523-B85	N0060	Request Purchase	5/15/2014 16:36	….
	N0070	Approve Purchase	5/15/2014 16:41	….
	N0080	Verify Approval	5/15/2014 16:41	….
	N0080	Verify Approval	5/15/2014 16:42	….
	N0090	Finalize Purchase	5/15/2014 16:55	….
	N0100	Order Purchase Order	5/15/2014 18:00	….
	N0110	Receive Purchase & verify	6/15/2014 16:44	….

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2.3.3. Process Mining Tools

There are several tools used in process mining. ProM is one of the famous process mining tools. It is an open-source software maintained with Java. Will van der Aalst and his research group developed ProM at Eindhoven University of Technology. Disco tool is another famous process mining tool that was developedon Windows or Mac OsX. My Invenio is also another commercial tool with academic license option. However, it is a web-based system. Therefore, it can be accessed from any device (mobile, tablet, computer) having browser and active internet connection. Table 2.2 presents a comparison of existing process mining tools by Fluxicon. It is a commercial tool but has also an academic license option with full support. It runs on Windows or Mac OsX. Celonis is another commercial tool and also provides an academic license option. It runs.

Table 2.2. Comparison of process mining tools [42]

Features	ProM (6.5.1)	Disco (1.9.5)	Celonis	My Invenio
Import type support	MXML, XES	CSV, XLS, MXML, XES, FXL	CSV, XLS	CSV, XES
Import log size capacity	unlimited	up to 5 million events	Based on the quota of database	30 MegaByte
License	Open source	Evaluation,Academic, Commercial	Evaluation, Academic,Commercial	Evaluation,Academic, Commercial
Output modelnotation	BPMN, WF, Petri nets, ECPs, transition systems, heuristics	Fuzzy model	Fuzzy model andSupport of charts	BPMN, SVG,CSV, XPDL, Activity Map, Social Network
Supported platform	Standalone desktop version	Standalone desktop version	On premise, Softwareas a service version, Web based	Web based only
Filtering data	Yes	Yes	Yes	Yes
Process discovery	Yes	Yes	Yes	Yes
Conformance checking	Yes	No	Yes	Yes

Social network mining	Yes	No	Yes	Yes
Decision rule mining	Yes	No	No	No
Process visualization	Yes	Yes	Yes	Yes
Performancereporting	Yes	Yes	Yes	Yes
Discriminative rule mining	Yes	No	No	No
Trace clustering	Yes	No	No	No
Delta analysis	Yes	Yes	Yes	Yes

Based on the comparison, it looks like the ProM has the largest variety of features and it seems to be the best tools for process mining. However, it has various and too many user interfaces, which is not easy for beginners. The other tools have an understandable user interface and can easily be used. Disco and My Invenio look similar to each to other. Celonis has its unique design and supports for a custom designer like My Invenio. Disco offers a guided data import. However, My Invenio seems to have a problem with data size [42]. It can import up to 30 MB of file size for data. In this study, we decided to use Disco tool to discover processes [42].

2.4. Robotic Process Mining

Robotic Process Mining (RPM) can be seen as an extension of the field of process mining [35]. RPM softwares are tools capable of discovering automatable routines from logs of interactions between workers and Web and desktop applications. Since RPA tools are able to automate a wide range of routines, the following question is raised: (1) which routines in an organization may be beneficially automated using RPA? Leno et al. (2020) [47] envisioned a class of tools, namely RPM tools, that can answer this question. Accordingly, RPM has been defined as set of techniques and tools that can analyze data collected during the execution of user-driven tasks to help in the identification and assessment of candidate tasks for automation that can be executed by RPA bots. Within this context, a user-driven task is a task that engages interactions between a user (e.g., a worker in a business process) and one or more software applications. The envisioned RPM tools take as input logs called user interface log or UI logs containing the interactions of users with the applications. These logs contain event records, such as selecting a field or cell, copying and pasting content, editing fields or cells, etc. Based on a UI log, the aim of RPA tools is to determine automatable routines and their boundaries, gather variants of each determined routine, standardize, and streamline the determined variants, and discover an executable specification that corresponds to a streamlined and standardized variant of the routine. Therefore, the major source of data for RPM tools is a UI log. The routines or tasks produced as output are required to be defined in a platform-independent language which can be compiled into a script and executed by an RPA tool [47].

The first step in an RPM pipeline is to record the interactions between one or more workers and one or more software applications [48]. The recorded data is represented as a UI log – a sequence of user interactions (herein called UIs) such as selecting a cell in a spreadsheet or editing a text field in a form.

Definition 1 (User Interaction (UI)) [48]: A user interaction (UI) is a tuple u = (t, τ,P,Z,φ), where: t is a UI timestamp; τ is a UI type (e.g. click button, copy cell); Pτ is a set of UI parameters (e.g. button name, worksheet name, url, etc.); Z is a set of UI parameters values; and φ : Pτ → Z is a function that maps UI parameters onto values.

Definition 2 (UI Log) [48]: A UI Log Σ is a sequence of user interactions Σ = hu1,u2,...,uni, ordered by timestamp, i.e. ui|t < uj|t for any i, j | 1 ≤ i < j ≤ n. In the reminder of this thesis, we refer to UI log also as log.

2.5. Robotic Process Automation Tools

As the effectiveness of RPA is proven and companies' interest increases, many RPA specialized software tools are being developed around the world. RPA tools such as Blue Prism, UiPath, Automation Anywhere are showing a rapid growth.

- **Blue Prism**

Blue Prism is a leading company that provides RPA solutions and RPA tools and was the first to coin the term Robotic Process Automation. It provides a software platform that helps organizations develop their digital workforce. Blue Prism tool offers a mix of manned and unattended automation that is quite unique in the industry, automating back-office processes while supporting employee repetitive tasks. Blue Prism tool is based on Java & .NET framework and provides an easy approach for bot design based on a drag and drop. Blue Prism is composed of four main components: process diagram, process studio, object studio, and application modeler. Process diagrams are business workflows that are created by utilizing core programming concepts. These graphical representations of workflows are used to create, analyze, modify, and scale business capabilities. Process studio is a platform for creating process diagrams with various drag and drop activities. Object studio is used to create visual basic objects which are used to communicate with other applications. Application Modeler allows creating application models with Object Studio. Blue Prism introduces connected RPA which works in association with artificial intelligence and cognitive capabilities. Blue Prism also provides control room for analyzing bot activities and audit trails. It provides also an integrated cross-platform to support many other AI and cloud technologies. To manage the execution of multiple bots simultaneously, it uses work queues for workload management. Blue Prism also supports intelligent surface automation, multi-language interface support, customized dashboard, robot screen capture, etc to name some. Blue Prism's product 'roadmap' is expected to include the concept of intelligent automation skills and add product enhancements to increase the use of AI within RPA solutions. The future of Blue Prism tool is presented in Figure 2.4 [52].

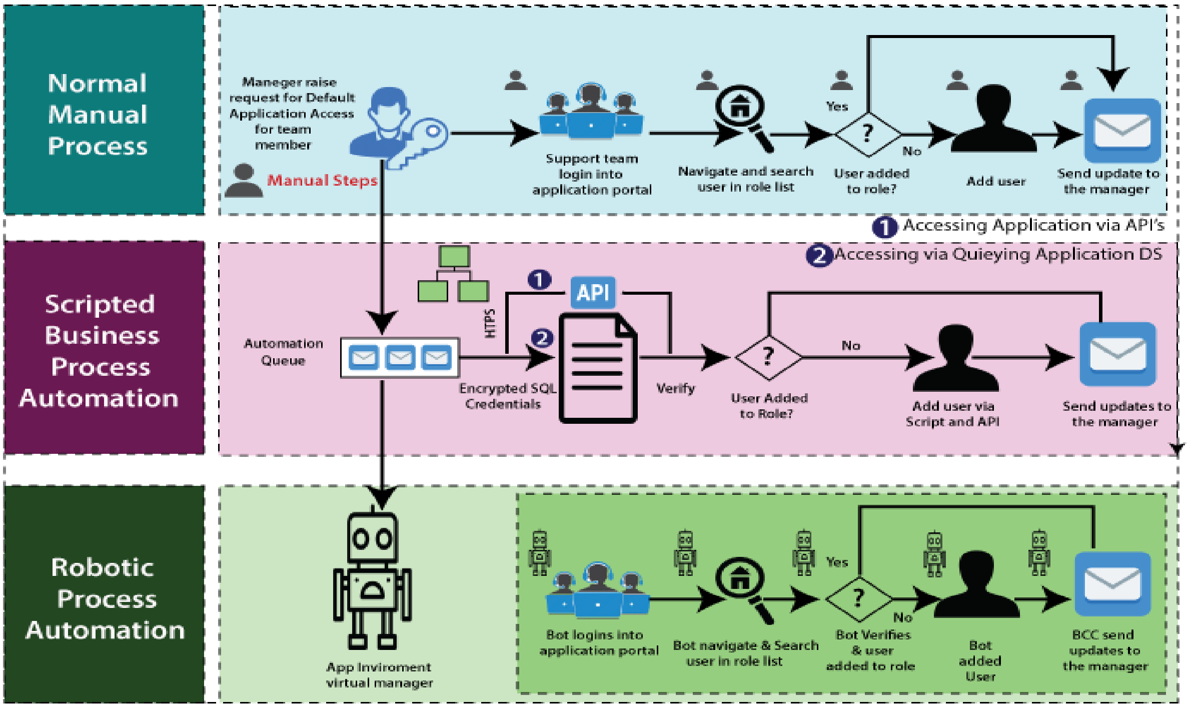

Figure 2.4. Future of BluePrism tool [53].

- **UiPath**

UiPath is a global software company that provides a solution to develop software bots for automating business processes. UiPath tool provides an open enterprise and IT RPA platform to automate business processes across front-office and back-office operations. UiPath's robots offer both human-led and robot-driven automation, so customers can benefit from both unmanned and manned automation. According to Forrester Q2 2018 data released by UiPath, the company announced that it is the most popular RPA platform and considered number one in the industry [52]. UiPath is a web-based architecture developed on the .NET framework. UiPath is composed of three main components: UiPath studio, UiPath Orchestrator, and UiPath Robots. The studio provides various activities and workspace to design and execute a user-defined bot. It can be used easily because it provides a drag and drop approach while working with activities. The role of the orchestrator is to allow the user to upload a bot in the cloud, deploy it and manage its resources. Its role consists also of managing the bot queues, provisioning, configuration, logs, etc. The bots can be used to perform tasks like human employees based on two types of bots attended and unattended. The attended bots need human intervention for completing their tasks whereas unattended bots work independently on their own. UiPath provides five types of recorders: (1) basic recording used for a single activity, desktop recording used for capturing multiple actions which can be between various apps, (2) web recording is used to record web and browser tasks, and images, and (3) Citrix recording is used for virtual environments. Orchestrator is considered one of the most important elements of UiPath as it is used to manage multiple bots in the environment. For establishing communication between the bots, assets have been introduced. Assets can also store user credentials. Queues are used in UiPath to manage workload. It also manages audit trails and logs to keep a check upon the bot activities [55]. Figure 2.5 illustrates the technical architecture of UiPath.

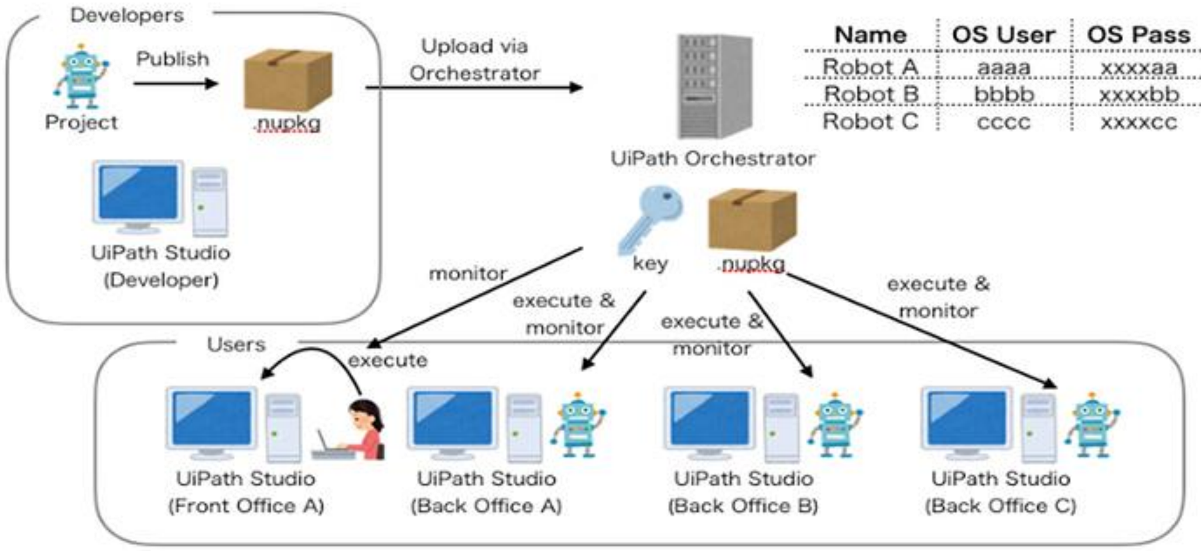

Figure 2.5. The technical architecture of UiPath [54]

- **Automation Anywhere**

Automation anywhere is one of the leading service providers among RPA tools. The architecture of AA is client – server-based. The three basic elements of AA are Bot creator, Control room, and Bot runner. Bot creator provides an easy design and automation process for bots. The control room manages the execution and scheduling of bots in addition to maintaining credentials, managing security issues, and client permissions, and assessing. Bot runner is used to running the bot and recording its analytics which is sent back to the control room. AA provides three types of bot creation called Task Bot, Meta Bot, and IQ bot. Task bots are commonly used to automate rule-based and repetitive tasks whereas Meta bots are used to create building blocks of bots that can be reused in some other task bot. Besides, IQ bots are provided with cognitive and intelligent characteristics utilized for processing unstructured data. AA offers three categories of recorders to record user tasks and convert it into a script that can be executed by a bot. A screen recorder, smart recorder, and web recorder are used to automate the task by mimicking user actions. Some additional features of automation anywhere are BOT INSIGHTS which is an analytics engine of AA that allows to visualize user data and take business insights from it [55]. Figure 2.6 shows Automation Anywhere's Architecture.

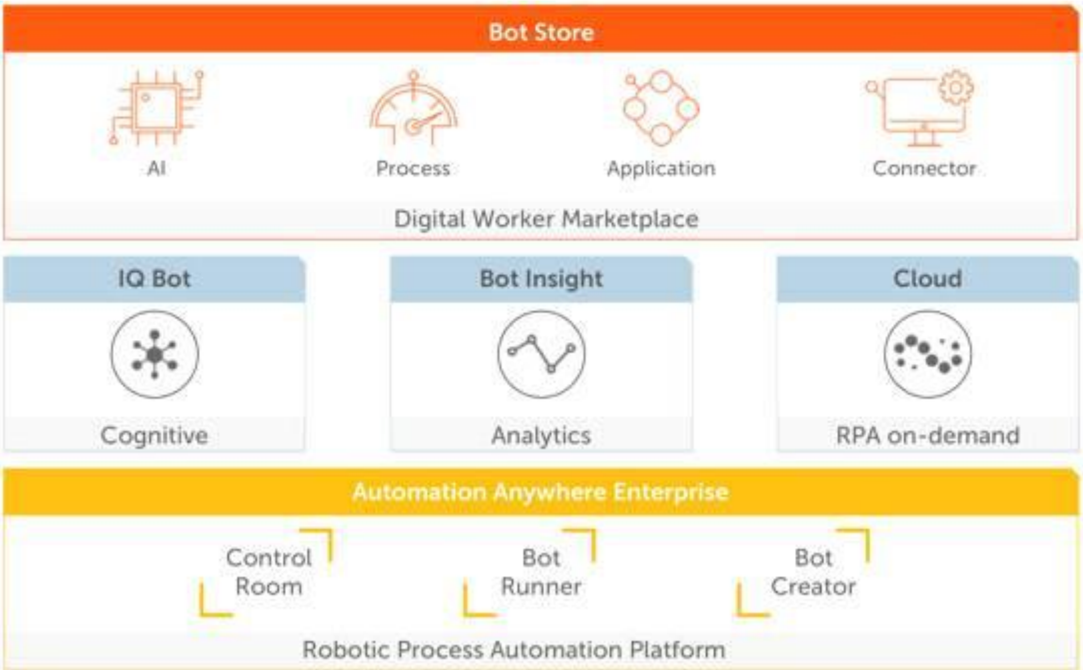

Figure 2.6. Automation Anywhere [52][53]

The key to making a quick transition from a process which is done by a human to an efficient automated process is to choose the right automation software [44]. When organizations decides to implement RPA, they have to find out the best suitable RPA software for their business. There have been over 45 tools that were marketed as RPA around mid-2017 [45]. According to Hindle et al. (2018), Blue Prism is considered the market leader in RPA. Other vendors are, for example, UiPath, Automation Anywhere, Workfusion, and Advanced System concept [46]

Distinguishing “real” RPA applications is important. RPA software does exactly what it is trained to do so there are no terms of “intelligence” in RPA software [47]. Machine Learning is considered a subdivision of Artificial Intelligence that provides learning capabilities. It allows computer systems to learn from data or experience, rather than by following preprogrammed rules [48]. Using AI, it is possible to generate structured outputs from unstructured inputs. Even though RPA does not have self-learning capabilities, it can be used for the further process of the structured output from AI [47]. This is just one of the many examples of how can RPA be utilized as an extension to other existing tools. RPA software is sometimes confused with screen scraping tools. Screen scraping automation tools are easier to learn and cheaper than other process automation tools, but it can sometimes 13 be hard to distinguish between screen automation and process automation tools [49]. Screen scrapers relies only on X and Y coordinates of a screen and understand a window located in a specific location. Recognizing a window defined by a location will no longer work if the window is moved to another screen [50]. For example, Blue Prism is an RPA tool, not a screen scraping tool. It can interact with data through Java, Html, Access Bridge and Surface Automation [50]. Figure 2.7 gives an example of a process that was automated using robotic software from Blue Prism. The process consists of five main tasks as follows: 1. Log in to System 2. Open Excel sheet 3. Get data from Excel sheet 4. Put data information from Excel to Order system 5. Take note of Order reference. A comparative study of the three RPA leaders in is summarized in Table 2.3.

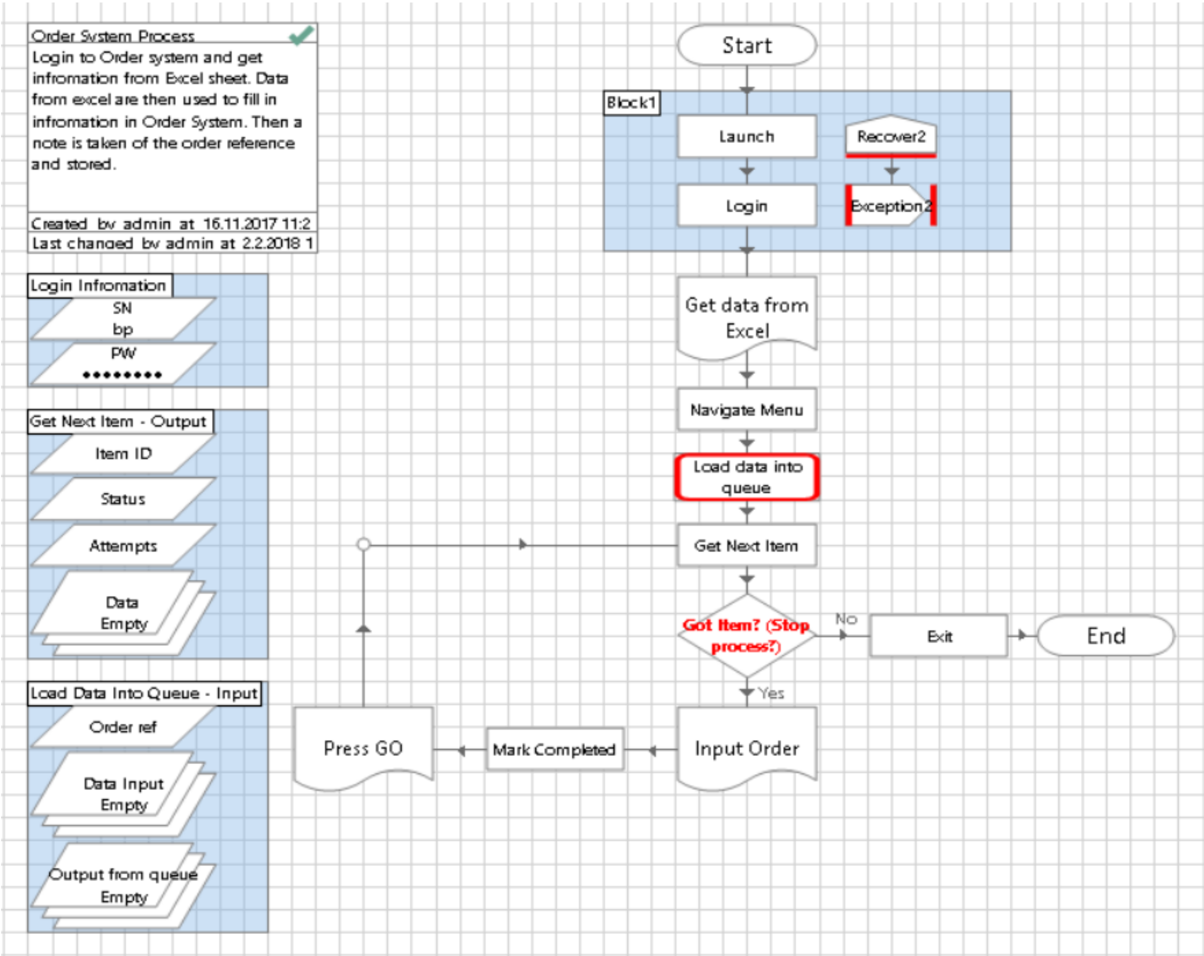

Figure 2.7. Example of a process automation using BluePrism tool [51]

Table 2.3. Comparison between the three RPA leader tools

Comparison Criteria	Automation Anywhere	UiPath	BluePrism
Architecture	Client server architecture	Web based orchestrator	Client server architecture
Popularity	Less popular than UiPath and BP but more than other RPA tools. AA is gaining popularity day by day.	Most Popular RPA tool. Topping the charts from a long time.	Very popular but less than UiPath.
Product Availability	One month trial is available in enterprise edition whereas community edition is available to use with only BotCreator rights. Audit log	Community edition is available for all to use but the bots created cannot be distributed. Enterprise edition is	Provides one month free trial of the product. It has limitation of 15 processes and 1

	and management are not available. No API features are available. Control room repository access is not available	available on 60 days free trial with 1 orchestrator, 10 Licenses for UiPath Studio, StudioX, Studio Pro, 10 Attended, 10 Unattended, 10 Test , 2 AI Robots, 10 Action Center, 1 Insights.	digital worker. In learning edition free licence is given for 180 days with limitation of 1 digital worker and 5 processes.
Usability	UI is complex. More suited for people with proper coding knowledge and developers.	UI is very simple and easy to use. Can be used by naive users too.	UI is simple and provides easy generation of bots.
Type of processes that can be automated	Can be used for back-office and front office automation.	Can be used for back-office and front office automation.	Can be used for back-office automation.
Recorders	Three types of recorderSmart, screen and web. These recorders can be used for desktop as well as web applications.	Five types of recorder – Basic, web, desktop, image and citrix. With a robust set of recorders UiPath makes it easier to capture human actions to mimic it further.	No recorders are available. One has to create a process using drag and drop features.
Cognitive capability	Medium cognitive capabilities	Medium cognitive capabilities	Low cognitive capabilities
Coding requirement	Supports both recordings and drag drop approaches. So coding is not mandatory	Supports both recordings and drag drop approaches. So coding is not mandatory	No recorders but use of process diagrams and in built functionality makes it easy to use. Supports coding but it is not mandatory
Pricing	Cloud starter 9000$ (Customisable) Approx 20000$ annually	Customisable as per requirement Approx 18000$ annually	Around 15000$ annually

Reliability & security	High security is provided. AA provides credential vault to save confidential user information which is encrypted strongly	Credential manager is used to save user data which is sensitive and confidential. Proper encryption has been incorporated.	Security is provided by saving sensitive information in BluePrism credential manager. User can choose algorithm to generate key and where to save it
Encryption Algorithm	RSA with 2048 bit master key is used for encryption AES-256 bit key is used for data encryption	Supports encryption algorithms like AES, DES, RC2, Rijndael, and TripleDES.	Cipher Obfuscation is used for credential information. Source code obfuscation for all codes which reduces risk of attacks or reverse engineering or patching.
Certification	Available online	Available online	Available online
Clients	Google,Siemens,Cisco,Dell ,	PWC, Lufthansa, HP, DHL	O2, Walgreen, Heineken.

Chapter 3 CANDIDATE BUSINESS DIGITAL TASKS SELECTION

Various benefits of implementing RPA within organizations have been reported (e.g., [13,51–66]) as it speeds up business growth by reducing a lot of manual and repetitive work. Nonetheless, as the technology is still new, the implementation of RPA faces some challenges [67]. As is known, RPA solutions automate repetitive manual tedious tasks. These repetitive, manual, and mundane tasks constitute the input for RPA tools. RPA solutions do not identify the tasks that can be or need to be automated. Thus, the question is: Which user work routines can favorably be automated with RPA? This is the main challenge [12]. We need to identify beforehand the tasks that need to be automated to be able to use RPA tools. This work proposes a methodology to identify candidate digital tasks for automation with RPA tools. Digital tasks are tasks performed using a computer by interacting with the different user interfaces of different systems and applications. The proposed approach is based on user interface interaction logs and process mining techniques. Process mining [37] techniques extract knowledge from the event logs that record the execution of business processes, and which are stored in today's information systems such as Enterprise Resource Planning (ERP) systems, Workflow Management (WFM) systems, Supply Chain Management (SCM) systems, etc. One of the main techniques of process mining is process discovery. This technique takes an event log as input and automatically creates a process model which shows how the business process is behaving [68]. Process mining can play a primary role in deciding the tasks that can be automated. Since RPA operates on the user interface level; we can use process mining techniques to discover tasks from the user interface interaction logs. A process is a set of tasks, and a task consists of a sequence of steps. The goal of process mining is to discover business processes that are composed of a set of tasks or operations. However, here, the aim of using process mining techniques is for task discovery not for process discovery. Specifically speaking, the discovery of office tasks performed in a user interface. To perform a specific task (e.g., order handling), a user needs to perform several steps in a user interface. There are basically only two types of actions that can be performed in a user interface: mouse clicks and keyboard. Thus, steps are performed by switching screens with mouse clicks or/and entering different content with the keyboard. To do this, the actions performed in a user interface with the mouse and the keyboard need to be recorded to obtain the data. From the recorded data related to interactions with the user interface, a log can be generated. This log needs to be pre-processed so that it can be ready to be used by process mining techniques.

The contribution of this chapter is to identify the tasks that are a candidate for automation with robotic process automation. This chapter shows how the tasks executed by an employee are discovered using process mining discovery techniques and user interface interaction logs. Then, once all tasks are discovered, the work will show how the manual and repetitive tasks will be selected.

3.1. Related Work

Van der Aalst [69] defines RPA as an umbrella term for tools that operate on the user interface of other computer systems in the same way as humans. IEEE Corporate Advisory Group defines RPA as the use of a "preconfigured software instance that uses business rules and predefined activity choreography to complete the autonomous execution of a combination of processes, activities, transactions, and tasks in one or more unrelated software systems to deliver a result or service with human exception management" [70].

Robotic Process Automation is recently receiving increasing attention from industries and administrations due to the huge desire to implement digital transformation. There are three leading RPA vendors: (1) Blue Prism, (2) the most famous UiPath, and (3) Automation Anywhere. These tools have been demonstrated to be simple and very powerful in cost-saving and other performances. The main idea is that today's information systems are not changed; only the tasks that have been performed by people by interacting with these systems are automated [14].

RPA is related to Workflow Management (WFM) [71], which has been available for several decades. However, workflow management was not that attainable since traditional automation is too expensive. Now Workflow Management might be achievable with robotic process automation.
Various benefits of implementing RPA have been reported (e.g., [72,66]) as it speeds up business growth by reducing a lot of manual and repetitive task based works. However, the implementation of RPA is encountering some challenges. The main challenge is to properly determine first the candidate tasks that can be/ need to be automated with RPA [11]. This challenge is not well researched. The identification of candidate tasks for automation via RPA tools is, so far, a largely unexplored problem [73]. A recent study proposed a methodology to analyze UI logs for the purpose to discover routines for RPA [74]. However, the presented approach focuses only on copying data from a spreadsheet or a form to another. The discovery of candidate tasks for RPA is related also to the field of a webform and automatic completion of tables. This latter consists for instance of detecting patterns from the values present in the cells of a sheet of an Excel file and then automating the completion of the table based on the detected patterns [75]. However, the focus of those approaches is tailored only toward partial automation. Another study proposed a supervised machine learning and natural language processing based approach to automatically determine whether a task in a textual process description is a manual task, a user task where a human user interacts with an information system, or an automated task [9]. Nevertheless, the study does not identify candidate tasks to be automated. Process mining has been shown that it can be used to determine work done by people in [39]. Some other recent studies [76,77,78]

show that RPA can benefit from process mining. Process mining enables process enhancement using event data. The starting of process mining is an event log generated from today's information systems where each event refers to a task executed either by a person or a machine at a specific time and for a specific case. Therefore, we proposed a methodology to determine candidate tasks for automation using process mining techniques and user interface logs generated by recording the interactions with web and desktop applications.

3.2. Proposed Methodology

Robotic process automation tools can automate a lot of user routines in a business process. Thus, which user routines in an organization can be favorably automated with RPA? To answer this question, a class of tools called RPM (Robotic Process Mining Tools) tools has been envisioned in the work [73]. RPM has been defined as a class of methods and tools that will be used to analyze data obtained during the execution of user driven tasks. The goal of RPM is to support the determination of candidate user processes that can be automated by RPA robots. In the same context, this section explains the approach we propose for selecting candidate routines/tasks to be automated with robotic process automation tools. In the next section, the application of the approach with a use case is explained. Since RPA is dedicated to automating manual and repetitive tasks operated on the user interface level, one can record the execution of all tasks and all the interactions between user interfaces. From the record, a UI log can be generated. The UI log shall contain user driven tasks that involve interactions between a user and software applications. This latter can be used then as input by process mining techniques to discover routines. From the discovered model, candidate tasks for automation using RPA can be selected. Therefore, the proposed approach is composed of four steps: user interface (UI) log generation, UI log transformation into a log supported by process mining techniques, routines discovery with process mining, and candidate tasks selection based on specific criteria. An overview of the approach is depicted in Figure 3.1. Each step is explained in the upcoming subsections.

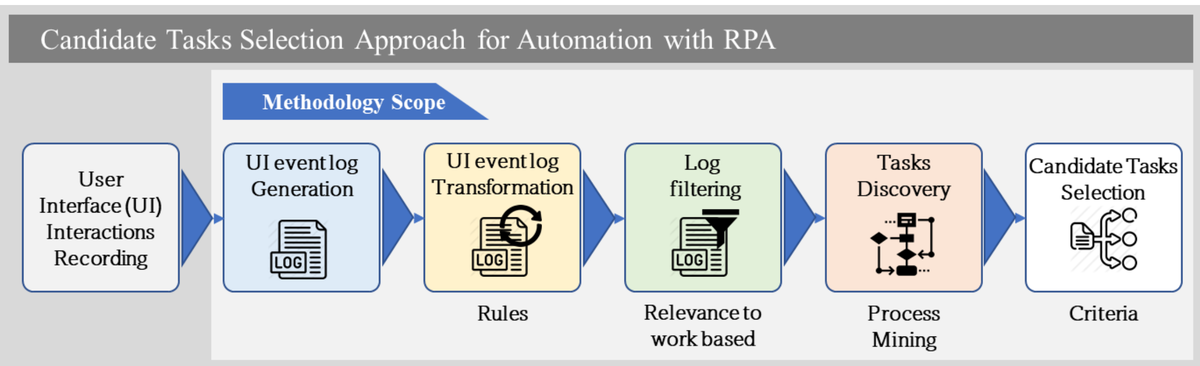

Figure 3.1. Proposed Approach

3.1.1. User Interface Log

Generally, the input of process mining techniques is an event log that contains tasks belonging to a specific business process. Similarly, the input for RPM is a user interface log that also contains tasks. However, this time, the tasks are user driven actions that involve interactions between a human user and software applications. A user interface log represents a sequence of actions performed in chronological order by a user when interacting with different applications (e.g., web, desktop, system, application) when performing an administrative task. We define an example of a user interface log in Table 3.1. Each row refers to a particular action and every action is characterized by timestamps, and other information showing where the action was performed and what objects were involved in performing the action. This work defines the user interface log such that it contains the following elements: timestamp, action type, source type, source name, content, field name, and the field value. The timestamp refers to the time when the action on the user interface was performed. Action type refers to the actions that have been performed on a user interface. Source type, source name, content, field name, and field value are information related to the objects involved in performing the action. For instance, let us consider the first example.

Example 1: Opening an Excel with the name "Order Qty".

Open is the action type. Excel is the source type of the object for which the action was performed and Order Qty is the name of the source, the name of the object for which the action was performed. Let us consider the second example of a task on a user interface.

Example 2: Clicking on the filter button of sheet 1 of an Excel file.

Click Button would be the action type. Sheet 1 would be the source name. The source type is an Excel sheet. Clicking a button with the mouse is an action, but there are many different buttons that can be clicked. To differentiate between them, the type of the clicked button can be recorded in the content column. Let us look at the third example.

Example 3: Selecting the cell of sheet 1 which contains the value "Customer A" from the Customer ID column.

Select Cell refers to the action type. The action type "Select cell" is performed on the source name Sheet 1. The item or the cell that has been selected is "Customer A" which is considered as a field value. This value belongs to the Customer ID which is considered a field Name.

User Interface logs can be obtained using recording tools. Note that the UI event log recording is not in the scope of the methodology presented in this thesis.

Table 3.1 Example of a User Interface log

Case id	Timestamp	Action Type	Source Type	Source Name	Content	Field Name	Field Value
1	2020-08-20 9:29:10	Open	System Folder	Orders			
1	2020-08-20 9:29:16	Open	Excel	Order Qty			
1	2020-08-20 9:29:18	Go to Cell	Sheet	Sheet 1		Customer ID	
1	2020-08-20 9:29:23	Click Button	Sheet	Sheet 1	Filter button		
1	2020-08-20 9:29:27	Select Cell	Sheet	Sheet 1		Customer ID	Customer A
2	2020-08-20 9:33:27	Enter	Web	https://www.erp.kor		Order ID	"OR208201"

3.1.2. User Interface Log Transformation

In this study, we are concerned only with the control-flow perspective of process discovery techniques of process mining to discover a process model showing the interaction of a user with software applications. The control-flow perspective is a category of analysis that consists of discovering the sequences of tasks in a business process. By analyzing how activities are following each other in the event data, we can obtain a model showing the real behavior of the process [79]. The control-flow perspective of process discovery techniques uses the activity name and the corresponding event timestamps to discover a process model. Several action types such as open, go to cell, click button, enter are illustrated in the presented user interface log example (Table 3.1). If we consider the action type as a task and discover a process model using process mining techniques based only on the action type and the corresponding timestamps, we will not get a proper process model which shows the reality. In Table 3.1, for example, there are two actions of type "open". The first "open" is different from the second "open" action. The first one refers to the opening of a system folder with the name "Orders" and the second "open" refers to the opening of an Excel file with the name "Order Qty". The goal from using process discovery techniques of process mining for robotic process automation is to get insights not about how many times the user performed the action "open" or how many times he performed the "copy" action with the mouse but to get insight on how many times he performed the action "open" on the same folder or file, or how many times he did the "copy" and "paste" of the same column of the same worksheet or the same section of a web or a system. Therefore, a transformation of the user event log is needed to obtain the actions name based on which the discovery techniques will be performed.

This work defines transformation rules for transforming the name of the original action which is the action type name illustrated in Table 3.1 into an action name having sufficient information for discovering the tasks model describing the sequence of actions performed on a user interface. For this, let:

- TA be the Transformed Action,
- OA be the Original Action (Action Type),

- ST be the Source Type,
- SN be the Source Name,
- C be the Content,
- FN be the Field Name, and
- FV be the Field Value.

The transformation rules are based on the information available in the user event log that we defined in Table 3.1. The rules differ based on the action type. We defined a set of action types and a set of transformation rules in Table 3.2. For instance, the action type "open" needs the source type and the source name to know what exactly has been opened. Thus, the action type which is the original action OA is transformed as follows: TA = OA + ST + "SN". The source type and the source name have been attached to the original action, and it became "open folder system "Orders"" instead of just "open". This way, we will be able to identify how many times the task "open folder system "Orders"" has been performed when discovering the tasks model. For instance, the action type "Click Button" needs the information in the Content section of the UI Event log to know which button has been clicked. Thus, after using the transformation rule TA = OA + C, the original action "Click Button" will be "Click Button Filter".

Table 3.2. Interface Log Transformation Rules.

Action Category	Original Action	Transforming Rule
Open	Open	TA = OA + ST + "SN"
Close	Close	TA = OA + ST + "SN"
Go To	Go to Sheet	TA = OA + ST + "SN"
	Go to Cell	TA = OA + "FN"
	Go To URL	TA = OA + "SN"
	Go to Messenger	TA = OA + "SN"
	Go to Column	TA = OA + "FN"
	Go to chat	TA = OA + "SN"
Click	Click Button	TA = OA + C
	Click field	TA = OA + "FN"
	Click Item	TA = OA + "C"
Select	Select	TA = OA + FN + "FV"
Copy	Copy	TA = OA + "FN"

Paste	Paste	TA = OA + "FN" Value
Enter	Enter FV	TA = OA + FN+ "FV"
	Enter Message	TA = OA
	Enter Message	TA = OA
Log to	Log to	TA = OA + "SN"

TA, Transformed Action; OA, Original Action; ST, Source Type; SN, Source Name; C, Content; FN, Field Name; FV, Field Value.

After applying the transformation rules, the user interface log depicted in Table 3.1 will be transformed into the UI log shown in Table 3.3. The transformed log is composed of case, action, and timestamp. Now, the action and all elements involved in performing the action are gathered in one column named Action or Step.

Table 3.3. Example of Transformed User Interface log.

Case Id	Action	Timestamp
1	Open System Folder "Orders"	2020-08-20 9:29:10
1	Open Excel "Order Qty"	2020-08-20 9:29:16
1	Go to Cell Sheet 1	2020-08-20 9:29:18
1	Click Button "Filter Button"	2020-08-20 9:29:23
2	Enter Web https://www.erp.kor	2020-08-20 9:33:27

After transformation, the UI log refers to a case, an action, and a timestamp. It can be seen as a collection of cases where a case can be seen as a sequence of events.

Definition 1 (Traces). S is the universe of steps or actions. A trace $t \in S^*$ is a sequence of steps. $T = S^*$ is the universe of traces. Trace t = < Open system folder, Open Excel Order Qty, Go to cell sheet 1, Click filter button > $\in T$ refers to 4 events that belong to the same case (case 1 in Table 3.1). A UI log is a collection of cases. Each case is represented by a trace.

Definition 2 (UI Log). $L = B(T)$ refers to the universe of UI logs. A UI log $U_l \in$ L represents a finite multiset of observed traces. A UI log represents a multiset of traces. For instance, a UI log U_l = [<Open system folder, Open Excel Order Qty, Go to cell sheet 1, Click filter button >, <Open URL kerp.com, login, click dashboard, …, close URL kerp.com>, <open excel orders, copy column customer, past column customer, …, close excel orders>] represents 3 cases (i.e., $|U_l| = 3$).

3.1.3. Relevance to Work-Based Filtering

Office employees are performing their work on a computer. However, while using a computer, one can do other actions on the user interface that are not related to work too. For instance, sending messages on SNS applications. Thus, irrelevant actions to work need to be filtered. This can be done by defining first the list of software applications, systems, and URLs related to work and then performing filtering which removes the cases containing information on actions performed on user interfaces that are not included in the list.

3.1.4. Tasks Discovery from the Transformed UI Log

Process discovery techniques allow, specifically, the control-flow perspective, i.e., the identification of how tasks belonging to a business process are following each other based on the recorded events, and thus provide as result the process model, which shows the full behavior and allows us to have a full understanding of the process behavior. Even though process mining is considered as recent research, there are plenty of process discovery algorithms that have been developed today which discover the sequential behavior of a process and have been successfully applied to different domains [38,80,81]. For example, the α—algorithm [82], the fuzzy miner [83], the heuristic miner [84], the genetic miner [85], the heuristic rule-based algorithm [86], and others [80,87], etc. All these techniques use different methodologies to arrive at the same result which is a model that illustrates the transitions between activities, and they take an event log as input to discover the process model. An example of a discovered process model is depicted in Figure 3.2.

In this study, we would like to use process discovery algorithms but this time by taking a user interface log as input to discover the tasks model which shows the sequence and the transitions between the actions that a user has performed on interfaces of systems and software applications. The approach of this study consists of applying process discovery techniques on the transformed user interface log. An example of a transformed UI log is depicted in Table 3.3.

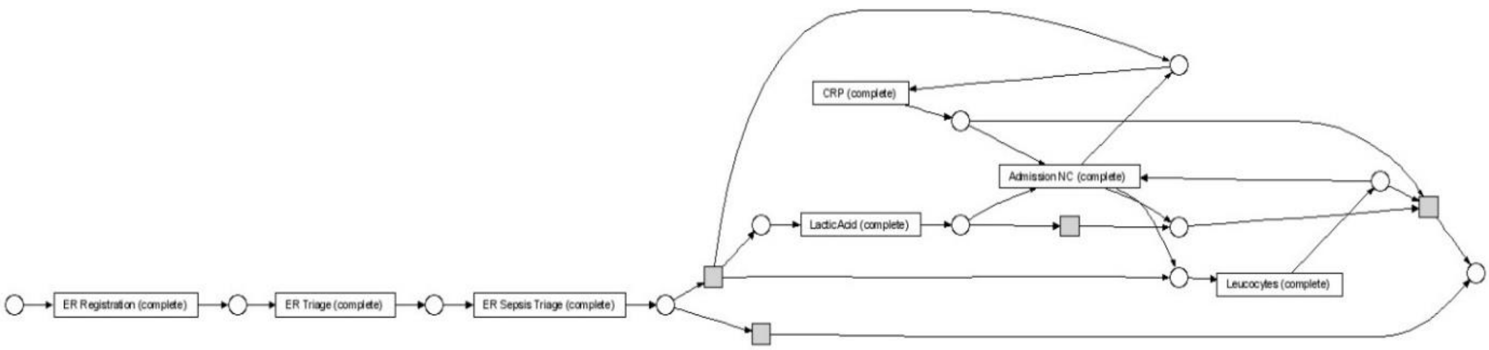

Figure 3.2. Example of a process model discovered by heuristic rule-based algorithm [19]

3.1.5. Candidate Tasks Selection Criteria

After applying a process discovery technique on the transformed UI log, one model will be constructed. This model may contain tremendous cases. For example, (1) performing many operations in sequence on an excel file such as downloading an excel file, sorting data, filtering data, copy and paste data, etc., (2) Opening and closing a folder, (3) sending messages in SNS applications, etc. One model will contain all the actions that were performed in the user interface. A selection of the relevant and candidate cases needs to be performed to reduce the number of discovered cases. Based on the candidate routines, a business manager can decide those are relevant for automation. For this purpose, we defined three criteria: Frequency, Periodicity, and Duration.

Frequency. The aim of RPA is to automate repetitive routines. Routines refer to the same tasks that are performed many times. In other words, performing specific tasks frequently. Using extension techniques of process mining, we can enrich the discovered model with frequency. By applying the case frequency technique, we can display a model showing the frequency of each task and the frequency of each transition from one task to another. Based on this, frequent cases can be selected.

Periodicity. The goal of using periodicity selection criteria is to identify and select periodic cases. Periodic cases are performed frequently but periodically. They are performed every time at the same time (i.e., every Friday).

Unattended bots can be applied on periodic cases if they do not need an intervention of a human. The bots can be scheduled to perform them.

Duration. Identifying cases and tasks that are taking a long time can play a crucial role in the decision of the routines that need to be automated. Routines that take hours by an employee can be performed by RPA bots in milliseconds.

To calculate the duration of a discovered task, the duration of all cases referring to the corresponding task need to be calculated first. Then, the mean duration of the cases related to each specific task is calculated. We defined the formula for calculating the duration of a case in Equation (1) and the formula for calculating the mean duration of a task in Equation (2).

$$T_{Case} = \sum_{i=0}^{n} t_{s_i} + t_{s_i s_{i+1}} \qquad (1)$$

T_{Case}: case duration, the time spent to perform a case,
t_{s_i}: step duration, the time spent to perform a step,
$t_{s_i s_{i+1}}$: the waiting time between the previous and the next step.

$$Mean\_Duration(task_a) = \frac{1}{n}\sum_{i=0}^{n} Tc_i^{task_a} \qquad (2)$$

$task_a$: a given task,
$Tc_i^{task_a}$: the time spent to perform a case related to a specific task $task_a$
n: the total number of cases referring to $task_a$

3.2. Results and Discussion

In this section, we present a use case to illustrate the methodology presented in this study. This section shows how candidate tasks can be selected for automation with RPA.

- **User Interface Log Generation and Pre-processing**

The starting point of robotic process mining is the preparation of the data. This step consists of the identification of actions related to the interaction of the user with the user interfaces and their attributes such as timestamps and case id, etc. To obtain a log, we have recorded the user interface interaction for 8 days, every day for two hours morning. Then we generated a user interface log containing the following columns: timestamps, action type, source type, source name, context, field name, and the field value. After that, we transformed the UI log into a log supported by process discovery techniques using the transformation rules presented in Table 3.2. The transformed UI log contains actions and their timestamps. Finally, we removed from the transformed log any action containing applications or URLs related to sending messages and chatting considered not relevant to work. After finishing the preprocessing of the user interface log, we imported it into the Disco tool [88] and visualized it. The imported user interface log consists of 50 different activities, 11 cases with 113 events.

- **User Interface interactions discovery**

Process discovery techniques take an event log as input and automatically construct a process model. The main idea behind the process discovery is to find the as-is process model. This phase aims to discover using process discovery techniques the cases or the interaction that have been performed in a user interface. In this study, we used the famous fuzzy miner as an algorithm for the discovery. We applied the fuzzy miner [78] using the Disco tool [88] on the transformed and filtered UI log. The discovered model of user interactions with the user interface is illustrated in Figure 3.3. The cases shown in the discovered model are highlighted separately in Figures 3.4 and 3.5 to see clearly process cases. The discovered model shows five tasks consisting of a sequence of steps (action) derived.

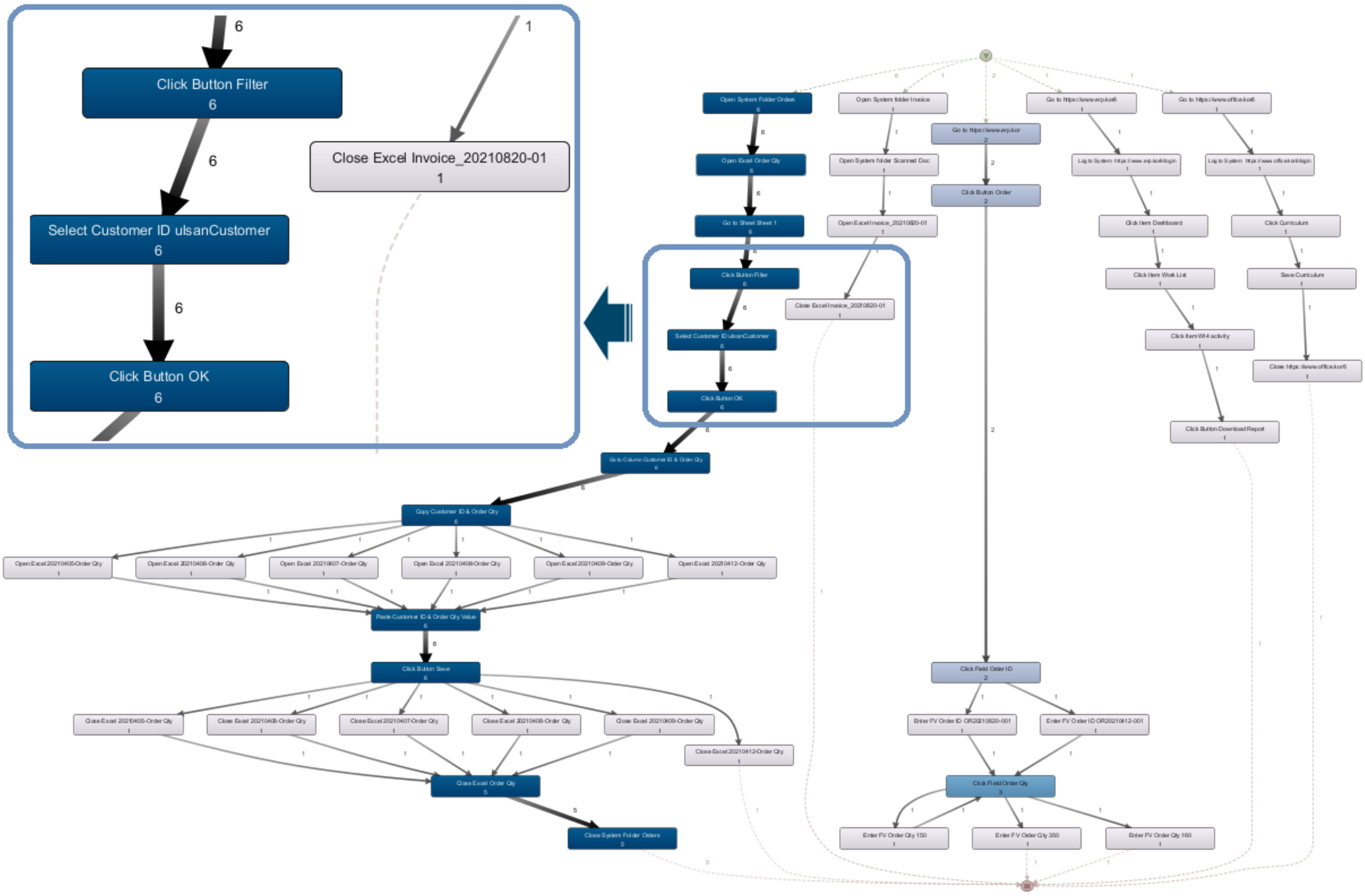

Figure 3.3. User interface interactions discovered with fuzzy miner using Disco tool.

- **Candidate Tasks Selection for RPA**

In this section, we assessed the derived model based on three criteria: frequency, periodicity, and duration for selecting candidate tasks for automation via RPA tools.

- **Frequency Based Selection**

The numbers, the thickness of transitions, and the coloring in the discovered model shown in Figure 3.3 depict how frequently each step (action) and path are executed. The frequency of actions is shown inside the box representing a step of a task. The frequency of transition from one action to another is specified on the edge connecting two actions. The darker the color is the more frequent the action and the transition are. Accordingly, we can see that Figure 3.4 shows a frequent case while Figure 3.5 shows infrequent cases.

Figure 3.4 shows one discovered task consisting of a sequence of steps represented with a darker color. This indicates that those steps are frequently performed. Figure 3.4 also shows some steps that are not frequent. If we look at the steps that are not frequent, we see that they are all executed right after a frequently executed step. By taking a careful look at the frequently executed steps in Figure 3.4—which are Go to URL, Click Button Order, Click Field Order, Click Order Qty, Click Field Total, and at the infrequent tasks which are "Open Excel 20210405-Order Qty" "Open Excel 20210406-Order Qty", "Open Excel 20210407-Order Qty", etc.—we can see that the infrequent steps are the same steps but the entered value is different. They are performed directly after the same frequent step every time. Therefore, this case which consists of a sequence of frequently executed steps and of infrequent steps executed directly after the frequent ones can be classified as a frequently executed case and can be considered as a routine and can be considered a candidate for automation. In contrast, Figure 3.5 shows a discovered task consisting of a sequence of steps with frequencies equal to 1, which means that the performed task is not usually performed. Thus, this type of task cannot be considered as a candidate for automation with RPA.

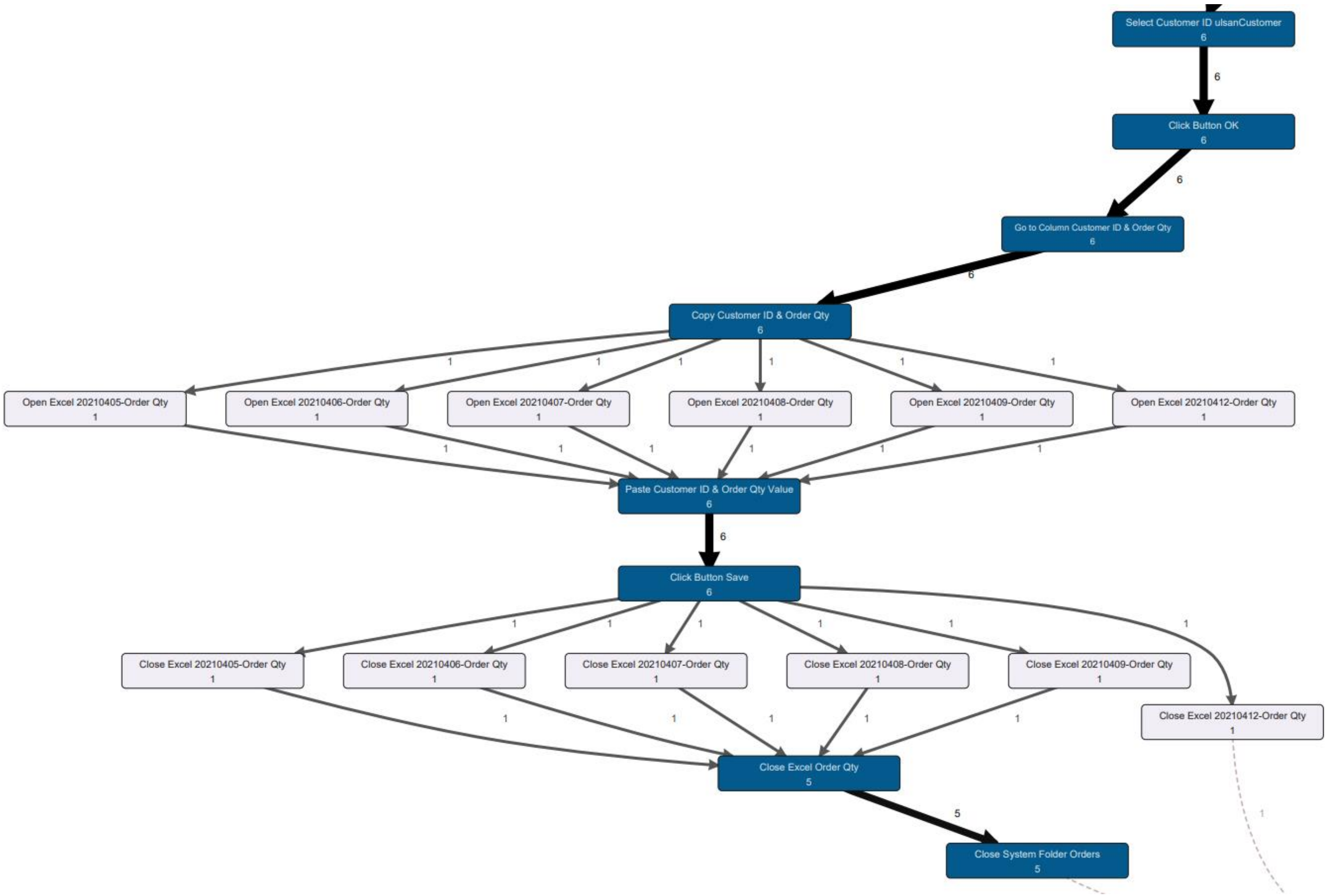

Figure 3.4. Sequence of Frequent steps.

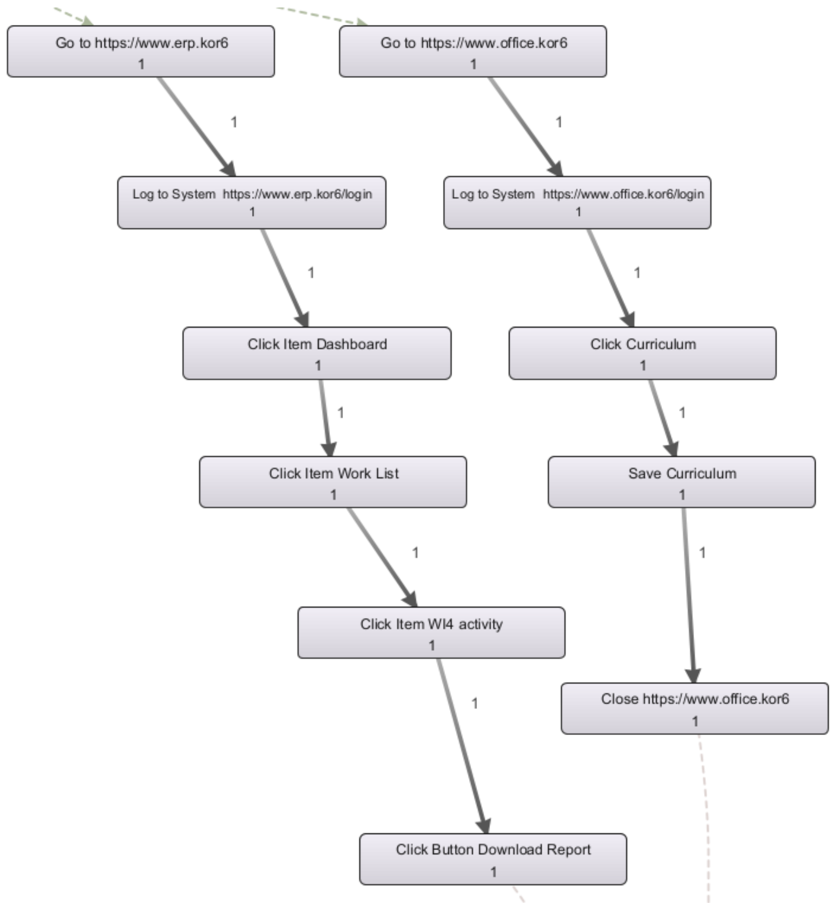

Figure 3.5. Sequence of Infrequent steps.

Note. Figures 3.3, 3.4, and 3.5 are presented in detail in the Supplementary File.

Table 3.4 depicts the number of events and the frequency of each sequence of steps discovered in the model shown in Figure 3.3. We call each sequence of steps a task. The most frequently executed task is Task #1 with a frequency equal to 6. This was followed by Task #2 with a frequency equal to 2. The infrequent tasks were Task #3, Task #4, and Task #5. Their frequency is equal to 1. The most frequent task is Task #1 contains 15 events (i.e., 15 steps) that are executed 6 times. Since the user interface is recorded for one week from 2021.04.05 to 2021.04.12 excluding the weekend, and the frequency is equal to 6, we can conclude that Task #1 is executed every day. Accordingly, Task #1 can be considered as a candidate for automation with RPA. Task #2 is executed through six steps and was not executed every day. At the same time, it cannot be considered infrequent because it was performed twice within eight days. This task needs further investigation which will be outlined in the next section. Based on frequency, it is clear Task #3, Task #4, and Task#5 cannot be a candidate for automation with RPA. These tasks are performed only once. They are irregular tasks and irregular tasks are not the target of automation with RPA.

Table 3.4. Discovered Tasks Frequency.

Tasks	Related Cases	Number of Events	Frequency
Task #1	Case #2, Case #5, Case #6, Case #9, Case #11	14	6
Task #2	Case #3, Case #7, Case #8	6	2
Task #3	Case#1	4	1
Task #4	Case #10	5	1
Task #5	Case #4	6	1

- **Periodicity Based Selection**

A periodic task is a task that repeats itself after a fixed time interval. Identifying periodic tasks and their periodicity is very important for identifying how and when to execute the robot in charge of executing the corresponding tasks. If a task detected to be a candidate for automation with RPA through "frequency", is identified to be periodic, the robot can be configured such that its execution is triggered by scheduling the time of execution based on the detected periodicity. Table 3.5 shows the periodicity of the tasks discovered in the model shown in Figure 3.3. Task #1 has been detected to be frequent in the previous section with a frequency equal to 6. This frequency was equal to the number of days from which the data was obtained. Since it has been executed every day, we can consider the periodicity parameter of task #1 to be "every day". The frequency of performing Task #2 was identified to be equal to two. By investigating the data result, we found that this task is executed every Monday based on the period of the retrieved data. The rest of the tasks are not periodic since they were executed only once during the period of the extracted data. In conclusion, Task #1 and Task #2 can be considered a candidate for automation with RPA. The execution of Task #2 can be scheduled to be executed every Monday by an unattended robot in case it does not require human intervention.

Table 3.5. Discovered Tasks Periodicity.

Table	Related Cases	Periodic	Periodicity
Task #1	Case #2, Case #5, Case #6, Case #9, Case #11	Yes	Every day
Task #2	Case #7, Case #8, Case #3	Yes	Every Monday
Task #3	Case#1	No	-
Task #4	Case #10	No	-
Task #5	Case #4	No	-

- **Duration Based Selection**

The Mean duration of tasks can play a primordial role in choosing between candidate tasks for automation. Automating a frequent task that is taking time to be fulfilled can be more valuable than automating a task that can be performed in just seconds or minutes. The aim is to provide much information that can help in deciding between candidate tasks for automation. For our use case, the duration of all cases has been calculated. After that, the mean duration has been calculated for each task. Figure 3.6 depicts the duration of tasks. As can be seen, Task #1 takes the longest time. This task has been already detected to be the most frequent in the previous section. Thus, automating this task can save a lot of time.

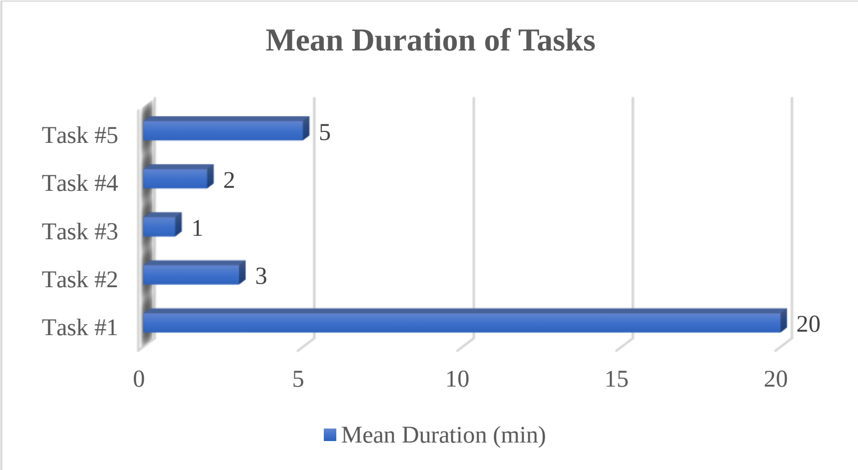

Figure 3.6. Mean duration of tasks.

3.3. Limitations

Robotic process automation (RPA) is a new wave of new digital technologies that are increasingly capturing the attention of administrations and industries. RPA aims to automate manual, repetitive, rule-based, and unmotivating activities performed on a computer. RPA uses software robots to replace specific human administrative tasks. The goal is to allow human workers to delegate their tedious routine tasks to a software bot to allow them to focus more on difficult tasks. RPA tools have been demonstrated as simple and very powerful in cost-saving and other performances. However, to be able to implement RPA, we need first to effectively identify the tasks that are suitable for automation before applying RPA. Therefore, this work introduced an approach for selecting candidate tasks to be automated with RPA. The proposed methodology is based; using process mining techniques; on discovering tasks consisting of a sequence of steps performed in a user interface from a UI log generated from recording the performed actions while interacting with the user interface. This work has shown (1) what information a log should contain to be able to derive tasks, (2) how the log should be transformed to be ready to be used by process mining techniques, (3) how we can discover digital administrative tasks, and how candidate tasks can be selected for automation from the discovered tasks. As a real use case implementation is required for validation, we will consider real event data to validate the proposed framework in future work. As research of using process mining with RPA is so recent, there are some challenges that need to be addressed to be able to use process mining techniques properly to identify candidate tasks for automation with RPA. This study outlines some encountered challenges that need to be tackled in future works.

3.3.1. Challenge 1: Generating Event Log from Recorded Interactions with the User Interface

An event log is a necessary input for process mining techniques. User interface logs cannot be generated by today's existing systems. The only way is to record the interactions with the user interface and then generate a user interface log. The interaction with a user interface is based on clicks with the mouse and content entered with the keyboard. For instance, for us, an action or a step would be opening a google URL. This action is recorded with mouse clicks and URL content entered with the keyboard. When entering for instance "google.com" in the URL section of the browser with the keyboard, it is recorded one letter by letter, and each entered letter is recorded in a separate raw as follows "g", "o", "o", "g", "l", "e", ".", "c", "o", "m". Accordingly, we will have 10 data rows created just for entering "google.com" in the URL section of the browser. An action that we perform in a user interface that seems for a person as one action, is in fact performed by several actions by the system. There is a need to translate or transform the several actions (for the system) that were recorded into one action for us. This is just one example from many cases. Hence, one of the main challenges is to identify how to transform the recording of user interface interaction based on mouse and clicks into a user interface log that can be used by process mining techniques.

3.3.2. Challenge 2: Case Identification

In general, an event log refers to a case, an activity, and a timestamp. It can be seen as a collection of cases where a case can be seen as a sequence of events. To be able to analyze processes with process mining, there is a need to first identify what the appropriate case ID is for your process. Table 3.6 shows an example of an event log generated from an ERP system to be analyzed with process mining. Each row corresponds to an event. In this example, the Order number will be the appropriate case ID to discover the corresponding process model. A case ID usually is unique with which different activities are associated. The performed tasks that are having the same Order number will be in one case. However, the situation of a user interface log is different. A user interface log is generated from recording interactions of a user with user interfaces which are based on clicks with the mouse and entering with the keyboard. The user interface log is different from the general event log generated from today's information systems (e.g., ERP, BPM, etc.). We defined in Table 3.1 the data that should be in the log to be able to discover tasks from it using process mining. When generating a user interface log, we might not have a unique ID with which many actions or steps performed in a user interface are associated. Therefore, the main challenge or the main question is how to define or identify an appropriate case ID of a user interface log. This challenge needs to be addressed in future works to be able to use process mining for selecting candidate tasks for automation with RPA.

3.3.3. Challenge 3: Case Duration

A manual office task that is taking a long time can be performed in just a few seconds if automated with RPA. This will allow saving a lot of time. Hence, calculating the total time spent in performing a specific case can play a huge role in identifying the office tasks that need to be automated. In a user interface, any case can be started with opening an object (e.g., URL, system, etc.) and completed with closing the same object. The duration can be calculated by calculating the time between opening the object until closing it. However, one can open an object to start performing a task and finish performing the task without close the object immediately. In this case, the time calculated from opening the object until closing it will not reflect the real duration spent in performing the task. The challenge here is how to calculate the duration of tasks by taking into consideration real-life situations.

Table 3.6. Example of an event log generated from ERP system to be analyzed with process mining.

Order Number	Task	Timestamp	User	Product	Quantity
8801	Register order	21-05-01 9.15	Soukaina	Fan78	15
8802	Register Order	21-05-02 9.18	Soukaina	Heater100	20
8801	Check Stock	21-05-01 9.25	Younes	Fan78	15
8803	Register Order	21-05-05 9.22	Soukaina	Frotter05	10
8802	Check Stock	21-05-02 9.30	Younes	Heater100	15
8801	Pack Order	21-05-01 10.30	Mohammed	Fan78	15
8802	Pack Order	21-05-02 11.10	Mohammed	Heater100	20
8801	Ship Order	21-05-01 15.20	Safae	Fan78	15

Chapter 4 USER INTERFACE INTERACTIONS RECORDER

Many changes in the global market today along with the rapid development of technologies, has led to the appearance of a new trend called digital transformation today [89]. Digital transformation is defined as the process of changing existing business models as well as creating new ones by implementing today's digital technologies in the process to meet changing business and market requirements [90]. Many industries and organizations have started taking initiatives to explore new digital technologies to crucially transform their business operations, processes, and management strategies, etc. [91]. Robotic process automation (RPA) is one of these new digital transformation technologies that are rapidly and increasingly drawing the attention of businesses. Robotic process automation tools allow mimicking human digital tasks by providing a virtual workforce in the form of a software bot that automatizes manual, high-volume, repetitive, and routine tasks [92].

Plenty of the traditional Workflow Management (WFM) systems initiatives for automation has been around for many decades but failed because the automation turned out to be too much expensive and due to the complexity of real processes [93, 94]. However, RPA turned out to be cheaper than the traditional automation solutions. RPA has lessened the threshold for process automation. Thus, the recent consideration for Robotic Process Automation has opened a new wave of automation initiatives. RPA is defined by Van der Aalst as "an umbrella term for tools that operate on the user interface of other computer systems in the same way as humans" [95]. In RPA, repetitive tasks performed by people are entrusted to software robots. The most important thing is that RPA bots do not modify or replace any pre-existing information system in the organization. They replace users by interacting with the user interfaces of the same pre-existing information system that human users were using before [93]. By automating repetitive tasks with RPA, people can focus more on difficult tasks and problem solving. Many benefits related to RPA implementation within industries and organizations have been communicated [96, 97, 98, 99]. However, the implementation of RPA is still facing many challenges as the research is still new. One of the most important challenges is the determination of business tasks that can be automated with RPA [100]. To automate user tasks with RPA, we need to know beforehand the tasks that need to be automated. Process mining has been outlined that it can be used to identify the tasks performed by people to be automated [93]. Process mining provides a lot of techniques for process improvement that is using event data stored in today's information systems. An event log, where each event represents a task executed either by people, a machine, or a system at a particular time; is the starting point of process mining [101]. Process mining techniques exploit these event data to illustrate how people, machines, and organizations are behaving. There are four main categories of process mining. 1) Process discovery techniques automatically discover, from real process event data, the process model which represent the real behavior of the process. 2) Conformance verification techniques consists of determining and diagnosing the deviations between a process model and reality. 3) Performance analysis techniques consists of identifying bottlenecks, reworks, wastes, etc. in the process. 4) Process reengineering techniques allows changing the existing process model. For more information on process mining refer to [101, 102, 103, 104, 105, 106, 107, 108]. The previous works have proposed [92, 109] methodologies to identify candidate digital tasks for automation with RPA tools that is based on process mining techniques. R'bigui et al. [92] defined a digital task as a task that is performed by a user using a computer by interacting with different graphical user interfaces of various systems and applications. A user interface event log which corresponds to the events accruing while interacting with user interfaces of different applications or systems, is required as input to be able to identify the tasks that can be automated with RPA using process mining techniques. The proposed approaches for detecting routine tasks for automation with RPA using process mining suppose that the UI log already exist or can be recorded. However, existing recording tools do not provide data from which process mining can discover the tasks performed on user interfaces, and existing approaches such as video recording is time-consuming. Thus, the adoption of process mining techniques for RPA is blocked by the absence of tools capable of recording the interactions with the user interface and generating UI logs providing enough information as input for process mining techniques to discover digital tasks that can be automated with RPA. The contribution of this work consists of presenting a tool, namely User interface Interactions Recorder (UIIR), which fills the gap between robotic process automation and process mining.

4.1. User Interface Interactions Recording Methodology

In this section, we discuss the position of UI recorder within the framework of RPA, its architecture, the rules used for recording, and the rule used for simplifying and reducing the generated UI log.

4.1.1. User Interface Interactions Recorder's position within RPA Framework

Robotic process automation tools are capable of automating tasks belonging to a business process. However, employees are performing plenty of and various tasks within an organization. Not all of them need to or can be automated with RPA tools. Thus, the main question is which of the tasks performed by a user worker need to be automated to enable business growth and can be automated with RPA. A term called Robotic Process Mining (RPM) has been introduced in [110] to refer to a category of techniques that enables discovering and analyzing candidate tasks that can be automated with RPA robots from data collected during the execution of user based tasks. RPM techniques is a subclass of process mining techniques. Process mining allow discovering processes from an event log containing a chronological order of executed tasks recorded with today's information systems such as Enterprise Resource Planning (ERP), Business Process Management (BPM) systems, etc. while robotic process mining should allow discovering tasks from a graphical user interface log containing a chronological order of executed actions performed on user interfaces of different systems and applications. RPM techniques need to be applied before implementing RPA to identify the tasks suitable for automation with RPA. We proposed in the previous study [92] an approach for RPM consisting of four major steps.

- UI interaction recording. This step consists of recording the interactions (i.e., actions), which is based on mouse clicks and the keyboard, of a human user with different applications such as web, desktop, system, application, etc. while performing his administrative tasks. This step is the major scope of this study. Figure 4.1 shows the position of UI interactions recording within the pipeline of RPA framework.

- UI log transformation and filtering. This step consists of transforming the generated UI log into a log supported by process mining tools. UI log transformation rules is defined in [92]. The rules differ based on the type of the action performed. For more details on the transformation rules refer to [92]. This step also addresses the filtering of the generated UI log. While performing their tasks using a computer, employees can do other actions also which are not related to work on a computer such as opening personal email or sending SNS messages. This type of actions needs to be filtered to keep only actions relevant to work.

- Task discovery. Each task performed using a computer is composed of a set of performed actions. Thus, during this stage, the conducted tasks need to be identified or discovered based on the sequence or the chronological order of the performed actions. The process discovery category techniques of process mining [111, 112, 113, 114, 115] allow us to do this job based on UI log data.

- Candidate tasks selection. After discovering all tasks performed while interacting with different applications and systems, the tasks that need to and can be automated need to be determined. This identification of candidate tasks can be done using different methods for instance criteria based selection such periodicity, frequency, etc.

After candidate tasks are appropriately identified in the last step of RPM, RPA can be implemented by creating software robots in charge of executing the selected tasks. As can be seen, UI interactions recording can be considered the most important step is it is the starting point of all the pipeline of RPA Framework. Without a UI log, process mining techniques cannot be used to enable RPA.

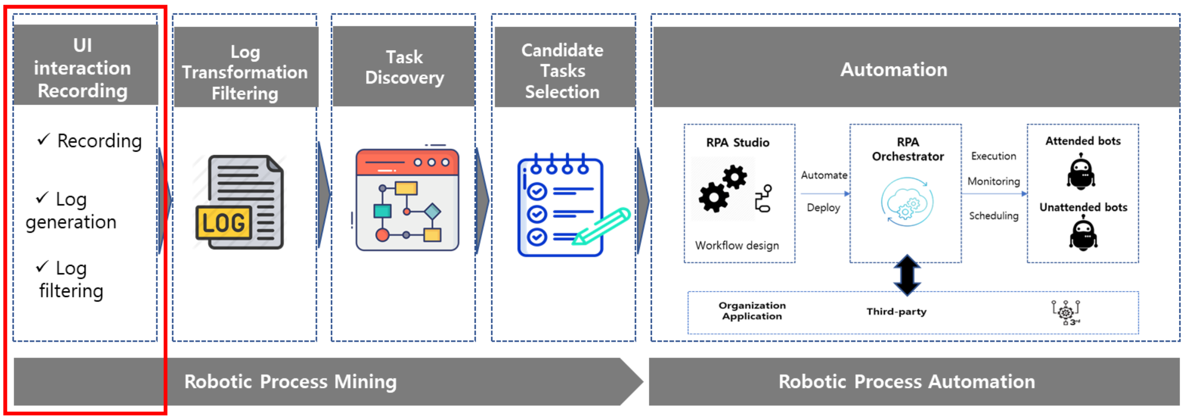

Figure 4.1. User Interface Interaction Recorder within RPA – Research Scope highlighted

4.1.2. User Interface Interactions Recorder Architecture

User Interface interaction recorder (UIIR) records the actions performed on (i) chrome web browser, (ii) windows applications such as interaction with windows folders, notepad, (iii) and Microsoft applications such as Excel, PowerPoint, and Word. We developed a plugin for recording actions conducted on the web browser as well as a windows program which records keyboard usage and mouse clicks performed on windows and Microsoft applications. Both plugin and windows program are surveying the events of the performed actions and then sending the information to the logging component for generating and updating the UI interactions log in real-time.

Before starting the recording, the target user needs to sign in into the recoding tool UIIR with his id and password to differentiate between users using for example the same computer. The recording of the actions performed on web browser and those performed on windows and Microsoft applications starts automatically after sign in. The logs are stored directly to a server database as shown in Figure 4.2. After stopping the recording, one integrated UI log, which integrates both the log generated from the web and the log generated from windows program, is generated. The log can be any time downloaded by user id and by date. Then the generated raw UI log is reduced and simplified with a filtering program that we developed as well. Figure 4.3 shows the architecture of the recorder UIIR.

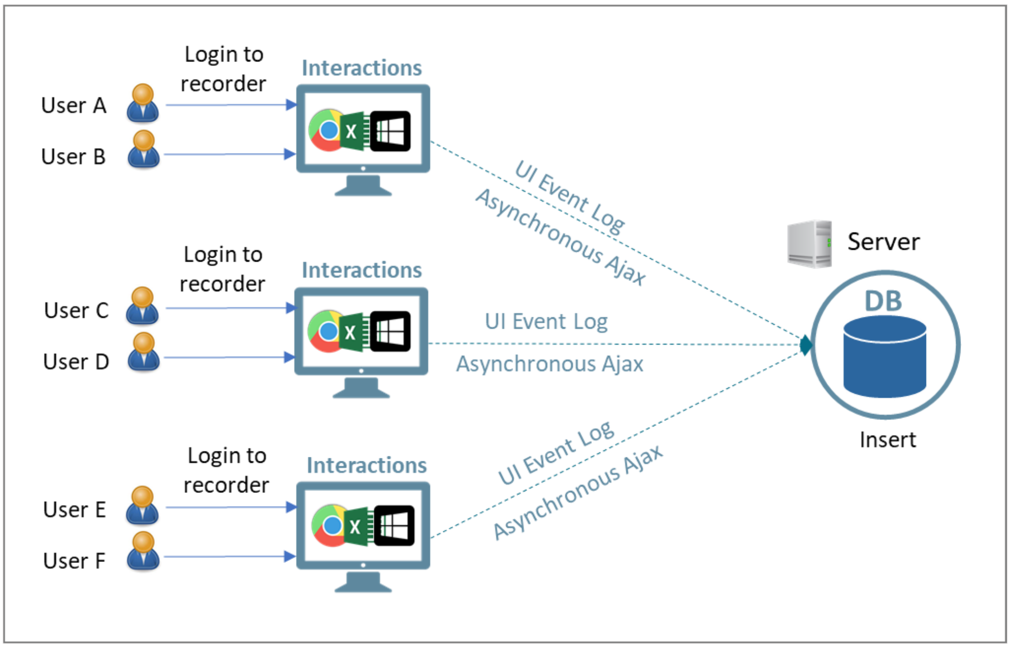

Figure 4.2. User Interface Interactions Recording Process

UIIR tool allows recording all the data involved in the context of each captured action. For instance, for an action performed in web browser, UIIR records the information about the URL link, the button clicked, active UI, the data entered, etc., and for an action performed in an Excel file, it captures information about the path of the spreadsheet, the active sheet, the cell and its value, the button clicked, etc. The tool generates a log in the format of Excel file which can be converted easily into and CSV file that is one of the formats required by process mining tools for further analysis.

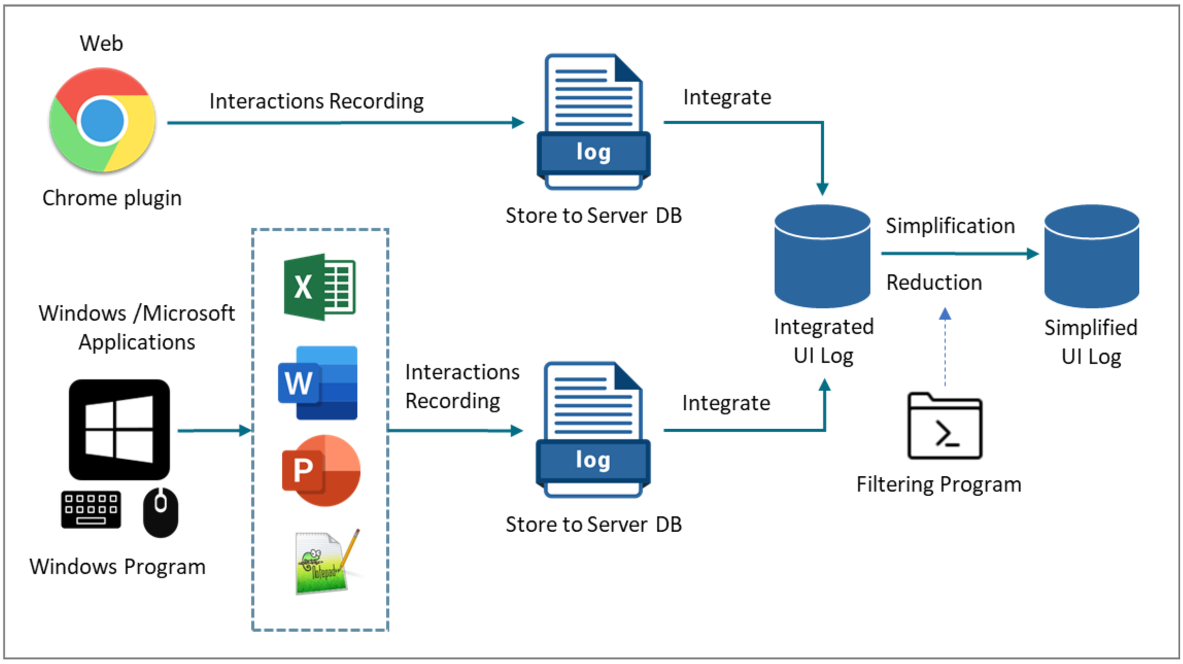

Figure 4.3. User Interface Interactions Recording Architecture

4.1.3. **User Interface Interactions Recording Rules**

To generate UI logs that can be processed with process mining techniques to identify the digital tasks that can be/need to be automated with RPA, the recorder tool should ensure that the recorded information is suitable for this analysis. First, two main questions need to be answered when developing the user interface interactions recorder and logger: (1) What should be recorded? and (2) what should not be recorded? The tool should record only meaningful and value adding actions and data. This work presents a set of rules applied to record actions performed on different UIs.

R1. Recording Significant Actions.

To perform specific digital tasks, users perform many actions on different applications and UIs. However, while interacting with these systems and UIs, not all performed actions are significant.

There are two types of actions: actions performed with the mouse and actions performed with the keyboard. Each of these actions is performed on a specific user interface. The actions that can be performed with a mouse are moving the mouse, right click, left click, and scrolling. For instance, actions of scrolling and moving the mouse are not meaningful as they do not impact the outcome of a task. Right and left clicks can be irrelevant based on what has been clicked and based on which UI the clicking action is performed. For instance, clicking on the background of a desktop or of a website, etc. is not meaningful. Hence, this type of actions should not be captured. However, for instance, button clicks are relevant actions that need to be recorded. We define below an example of a set of actions that are essential and need to be captured in the log.

- Mouse clicks actions. We defined six types of mouse clicks that can be a part of a performing task and should be captured: button clicks, checkbox clicks, text filed clicks, URL link clicks, selection related clicks, and general clicks (e.g., menu) actions. The recorder should differentiate between all these type of mouse clicks.

- Copy and paste actions. These two actions can be performed using only mouse clicks (i.e., left click + copy/paste button click) as well as they can be performed using the keyboard (i.e., copy=ctrl + c, paste = ctrl + v). Performing the copy action is preceded by a selection action with the mouse which allows selecting the content to be copied., and the paste action is preceded with a mouse click such as text field click which allows specifying the place where the copied content should be pasted. The actions performed by typing ctrl + c/ctrl + v in the keyboard are converted into copy and paste actions respectively, and the actions performed by left click action + copy/paste button click action are converted into one action copy and paste respectively.

R2. Recording Relevant Data.

Open, click button, copy etc. are the name of the recorded actions which is performed by a user. Considering only the name of the actions conducted is not enough to identify the performed task.

Information related to what has been opened, what URL has been opened, which folder has been opened, what is the path of the opened folder, which excel sheet has been opened, which cell has been modified, which button has been clicked, what content has been copied and pasted, what content is entered with the keyboard, etc. is necessary to be able to extract the performed task and need to be captured. Moreover, timestamps are the time at which the actions are performed. Hence, timestamp information is also essential in order to identify the order of actions. In conclusion, besides the performed actions, the recorder should also capture the data that supports them.

R3. Different Applications‘ UIs Recording

A task consists of a set of actions. One task can be performed using different user interfaces such as web-based applications and systems, Microsoft applications such as Excel, word, ppt, etc., windows applications such as folders, etc. The interactions between different UIs to perform a task need to be recorded. For instance, filtering and copying data from an Excel sheet and pasting it in a web-based system such as ERP. As can be seen, this task is performed through filter, copy, and paste actions and through two user interfaces Excel, and web-based system.

R4. Privacy Aware Recording

The goal of recording the interactions of users with different user interfaces of various systems and applications is to generate a log that will be analyzed to discover the tasks that has been performed and identify the ones that can be and need to be automated with RPA. The generated log will be analyzed using different techniques such as process mining by managers who will decide the tasks to be automated. Since, all interactions will be recorded, private and personal data also can be recorded. Therefore, there is a need to protect users ‘privacy. In this recorder, we took into consideration some of the privacy issues. For instance, all entered passwords are not recorded as they are, but the entered passwords are recorded with the word “password”.

4.1.4. UI log filtering – Simplification

Since, UIIR recorder records the performed actions in detail, the generated log needs to be simplified. Therefore, we developed another tool for filtering and simplifying the generated UI log. We define below some examples of simplification and filtering that can be performed by the filtering tool.

- ***Keyboard entering simplification***

Recording some content and values entering with the keyboard can also be meaningful. however, each letter or number entered with the keyboard is recorded as one actions. For instance, the actions of opening the following URL: www.google.com by typing it with the keyboard will be indeed recorded not in one action but into 14 actions, which means 14 rows will be generated in the log (e.g., {w} in one row, {.} in one row, etc.). After filtering the raw log with the developed filtering tool, the 14 actions are simplified into one action recorded in one row where the content of the action is recorded as www.google.com.

- ***Mouse clicks simplification and filtering***

Every mouse click is composed of a set of {pressed, released} which means two actions/two rows are recorded. When we press the mouse, it is recorded in one row and when we release the mouse, it is recorded in one row. All released clicks are deleted to keep only meaningful rows.

Moreover, the set of {pressed, released} can be the result of a single click as can also be the result of a selection. The only difference is the position of the press and the release. Thus, the log can be simplified with the tool such that if the position of the pressing is equivalent to the position of the release, then the action is converted to a click action and if the position of the press is different than the position of the release, then the action is converted to a selection action.

- ***Simplification related to copy and paste actions***

When copying and pasting a content with CTRL+C, and CTRL+V, the actions are recorded in two rows respectively. The tool converts the CTRL+C into “copy” recorded in one row and converts the CTRL+V into “paste” recorded in one row.

- ***Redundant actions filtering***

Log reducer tool filters also redundant rows (i.e., deletes rows having identical information in all columns), double copying, copying actions without the corresponding pasting actions.

4.2. Results and Discussion

This section presents a case study to demonstrate the User Interface Interactions Recorder (UIIR) and to demonstrate that the generated log is useful for process mining investigations.

The case study consists of (1) logging to a web-based online shopping system, (2) downloading all orders, (3) opening the excel sheet of the orders, (4) filtering the orders based on delivery completed status, (5) copying filtered orders, and (6) pasting them in a new excel sheet called completed orders. UIIR tool records the performed actions. The generated log can be downloaded by selecting the date or the period as shown in Figure 4.4. After downloading the produced log, it is filtered with the simplification tool as shown in Figure 4.5. A fragment of the generated log after filtering is shown in Figure 4.6. To test the produced UI log, it needs to be used as input by process discovery techniques. For this purpose, we used the Disco tool [33], a process mining tool that is based on the fuzzy algorithm [34] that allows discovering process models from an event log. In our case, the aim is to discover the performed task that consists of a set of actions performed using the keyboard and the mouse on different user interfaces of different applications.

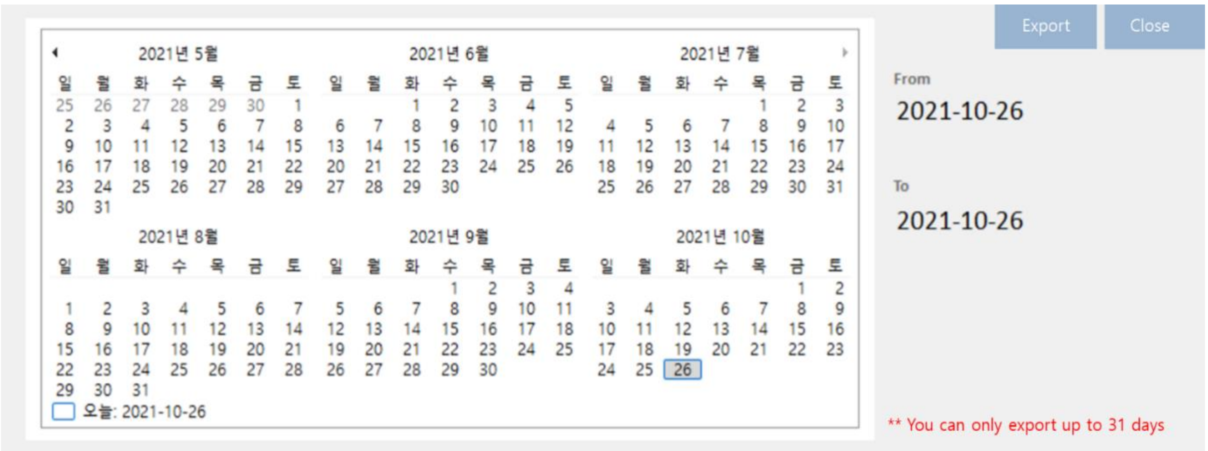

Figure 4.4. Log exporting screen based on period selection

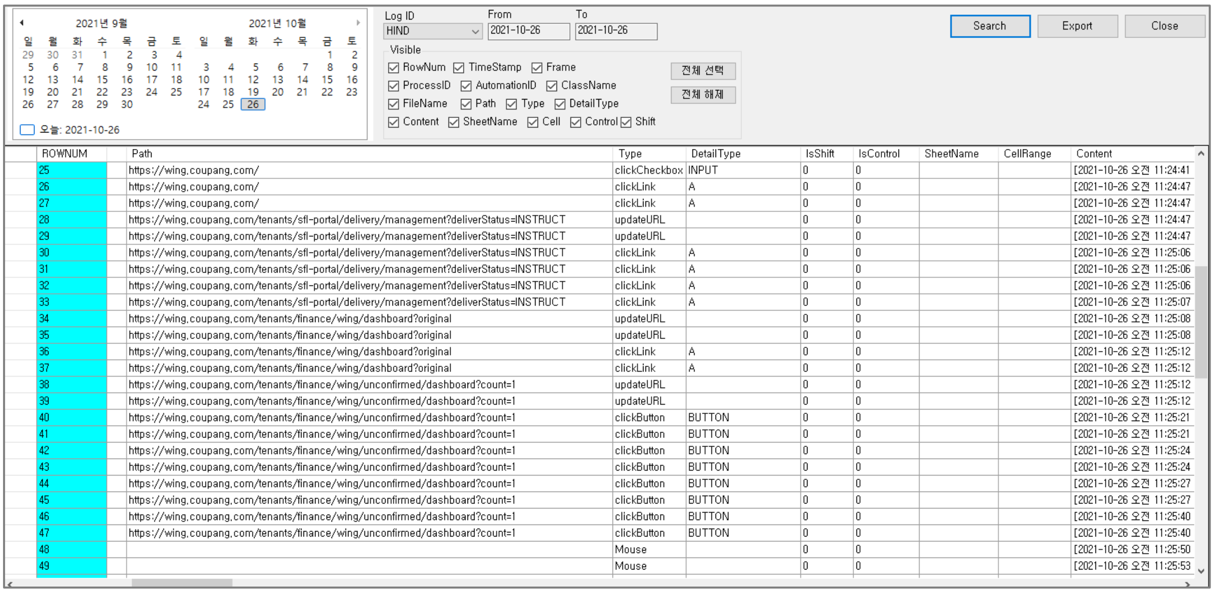

Figure 4.5. A screen of the UI log filtering with the simplification tool

Figure 4.7 illustrates the model of the performed task that has been discovered automatically with a process discovery technique from the recorded UI log depicted in Figure 4.6. The model shows the sequence of the actions performed while interaction with a web-based sales system and excel application interfaces.

Based on the result, we can see that the produced model is understandable. It shows that the performed actions are discovered in the correct chronological order. Also, the information provided in every discovered action, provides a full understanding of what action has been performed, on which system or application the action is performed, which button has been clicked, which content has been entered with the keyboard, which folder and link address are involved, etc.

	B	F	H	I	J	M	N	O	P
1	TimeStamp	Frame	Path	Type	DetailType	SheetNar	CellRange	Content	AutomationId
5	2021-10-27 오후 12:16:02 +00:00	new tab	https://wing.coupang.com/login?retu	navigate_to					
6	2021-10-27 오후 12:16:02 +00:00	https://wing.coupang.com/logir	https://wing.coupang.com/login?retu	updateURL					122
7	2021-10-27 오후 12:16:02 +00:00	login ? 쿠팡 Wing	https://wing.coupang.com/login?retu	updateURL					122
8	2021-10-27 오후 12:16:14 +00:00	login ? 쿠팡 Wing	https://wing.coupang.com/login?retu	clickTextField	INPUT			mhbeauty	userID
9	2021-10-27 오후 12:16:14 +00:00	login ? 쿠팡 Wing	https://wing.coupang.com/login?retu	clickTextField	INPUT			pw	userPW
10	2021-10-27 오후 12:16:26 +00:00	login ? 쿠팡 Wing	https://wing.coupang.com/login?retu	clickButton	BUTTON			[clickButton] login	btnLogin
11	2021-10-27 오후 12:16:27 +00:00	https://wing.coupang.com	https://wing.coupang.com/	updateURL				[updateURL]	122
12	2021-10-27 오후 12:16:31 +00:00	Coupang Wing - RBIGUI HIND,	https://wing.coupang.com/	clickButton	BUTTON			[clickButton] Close	
13	2021-10-27 오후 12:16:31 +00:00	Coupang Wing - RBIGUI HIND,	https://wing.coupang.com/	clickButton	BUTTON			[clickButton] Close	
14	2021-10-27 오후 12:16:34 +00:00	Coupang Wing - RBIGUI HIND,	https://wing.coupang.com/	clickLink	A			[clickMenu] Setllement	
15	2021-10-27 오후 12:16:36 +00:00	Coupang Wing - RBIGUI HIND,	https://wing.coupang.com/tenants/fir	updateURL					122
16	2021-10-27 오후 12:16:45 +00:00	Coupang Wing - RBIGUI HIND,	https://wing.coupang.com/tenants/fir	clickLink	A			[clickLink] Unconfirmed Sales	
17	2021-10-27 오후 12:16:45 +00:00	https://wing.coupang.com/tena	https://wing.coupang.com/tenants/fir	updateURL					122
18	2021-10-27 오후 12:16:52 +00:00	Coupang Wing - RBIGUI HIND,	https://wing.coupang.com/tenants/fir	clickButton	BUTTON			[clickButton] Request Excel Download	
19	2021-10-27 오후 12:16:56 +00:00	Coupang Wing - RBIGUI HIND,	https://wing.coupang.com/tenants/fir	clickButton	BUTTON			[clickButton] Confirm	0
20	2021-10-27 오후 12:16:56 +00:00	Coupang Wing - RBIGUI HIND,	https://wing.coupang.com/tenants/fir	clickButton	BUTTON			[clickButton] Confirm	0
21	2021-10-27 오후 12:17:00 +00:00	Coupang Wing - RBIGUI HIND,	https://wing.coupang.com/tenants/fir	clickButton	BUTTON			[clickButton] Download	0
22	2021-10-27 오후 12:17:00 +00:00	Coupang Wing - RBIGUI HIND,	https://wing.coupang.com/tenants/fir	clickButton	BUTTON			[clickButton] Download	0
23	2021-10-27 오후 12:18:04 +00:00	UNCONFIRMED_SNAPSHOT_RE	D:₩Work₩My work₩RPA₩3. Third Ar	EXCEL	Excel Opened				
24	2021-10-27 오후 1:26:59 +00:00	UNCONFIRMED_SNAPSHOT_REPORT_DETAIL_LIST-20211027.xlsx - Ex		[Mouse] Select				[X:-909>-172,Y:349>: 346]	
25	2021-10-27 오후 1:27:17 +00:00	UNCONFIRMED_SNAPSHOT_RE	D:₩Work₩My work₩RPA₩3. Third Ar	EXCEL	ll Selection Chang	Excel Data	$A$1:$L$14	[EXCEL] [{Order No},{Product No},{Product Name},{Customer Name	
26	2021-10-27 오후 1:27:25 +00:00	UNCONFIRMED_SNAPSHOT_REPORT_DETAIL_LIST-20211027.xlsx - Ex		Copy	영어			[EXCEL] [{Order No},{Product No},{Product Name},{Customer Name	
27	2021-10-27 오후 1:28:13 +00:00	Completed orders.xlsx	D:₩Work₩My work₩RPA₩3. Third Ar	EXCEL	Excel Opened				
28	2021-10-27 오후 1:28:17 +00:00	Completed orders.xlsx	D:₩Work₩My work₩RPA₩3. Third Ar	EXCEL	ll Selection Chang	Sheet1	$A$11:$L$19		
29	2021-10-27 오후 1:28:20 +00:00	Completed orders.xlsx - Excel		Paste	영어			[EXCEL] [{Order No},{Product No},{Product Name},{Customer Name	
30	2021-10-27 오후 1:28:36 +00:00	Completed orders.xlsx - Excel		Click	BUTTON			Save	A21
31	2021-10-27 오후 1:28:38 +00:00	Completed orders.xlsx	D:₩Work₩My work₩RPA₩3. Third Ar	EXCEL	Excel Saved				
32	2021-10-27 오후 1:28:36 +00:00	Completed orders.xlsx - Excel		Click	BUTTON			Close	A21
33	2021-10-27 오후 1:28:43 +00:00	Completed orders.xlsx	D:₩Work₩My work₩RPA₩3. Third Ar	EXCEL	Excel Closed				

Figure 4.6. A fragment of the recorded UI log

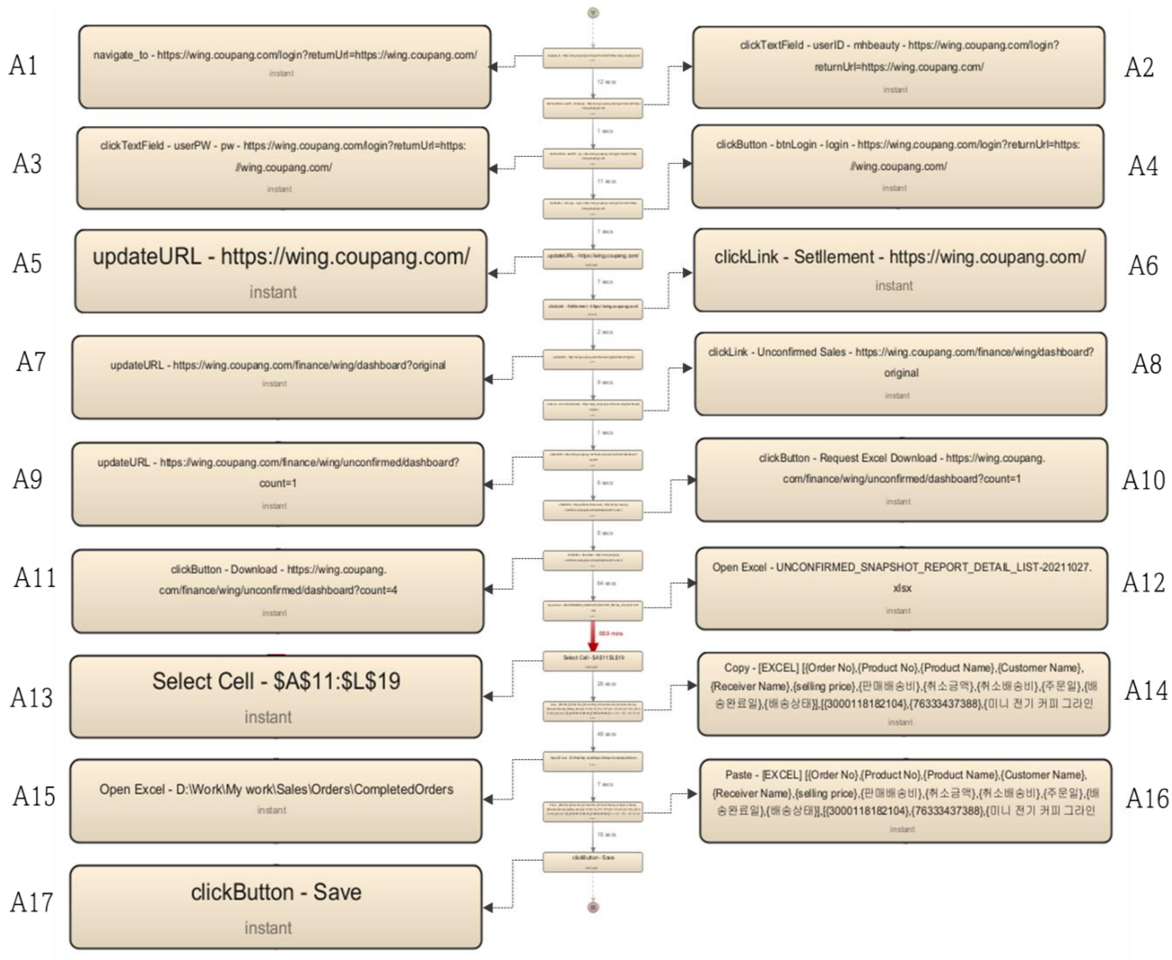

Figure 4.7. The set of actions (17 actions) of the performed task discovered with process mining from the recorded and filtered UI log

This chapter shows that the UI log generated by the user interface interactions recorder (UIIR) and simplified with the filter tool can successfully be used by process mining techniques to discover the actions performed while interacting with different UIs of different systems and applications.

Chapter 5 CONCLUSION

Today's business environments face rapid digital transformation, engendering the continuous emerging of new technologies. Robotic Process Automation (RPA) is one of the new technologies rapidly and increasingly grabbing the attention of businesses. RPA tools allow mimicking human tasks by providing a virtual workforce, or digital workers in the form of software bots, for automating manual, high-volume, repetitive, and routine tasks. The goal is to allow human workers to delegate their tedious routine tasks to a software bot, thus allowing them to focus on more difficult tasks. RPA tools are simple and very powerful, according to cost-saving and other performance metrics. However, the main challenge of RPA implementation is to effectively identify the candidate task that need and can be automated with RPA to be able to implement RPA. Therefore, this work introduced an approach for selecting candidate tasks to be automated with RPA. The proposed methodology is based; using process mining techniques; on discovering tasks consisting of a sequence of steps performed in a user interface from a UI log generated from recording the performed actions while interacting with the user interface. This work has shown (1) what information a log should contain to be able to derive tasks, (2) how the log should be transformed to be ready to be used by process mining techniques, (3) how we can discover digital administrative tasks, and how candidate tasks can be selected for automation from the discovered tasks.

The proposed approaches for detecting routine tasks for automation with RPA using process mining suppose that the UI log already exist or can be recorded. However, existing recording tools do not provide data from which process mining can discover the tasks performed on user interfaces, and existing approaches such as video recording is time-consuming. Thus, the adoption of process mining techniques for RPA is blocked by the absence of tools capable of recording the interactions with the user interface and generating UI logs providing enough information as input for process mining techniques to discover digital tasks that can be automated with RPA. Therefore, this work developed a tool, namely User interface Interactions Recorder (UIIR), which fills the gap between robotic process automation and process mining. The proposed and developed tool can record the tasks performed by a user while interacting with different applications and systems. The tool is capable also simplifying the generated UI log by filtering irrelevant and redundant events and data. The work shows that the UI log generated by the user interface interactions recorder (UIIR) and simplified with the filter tool can successfully be used by process mining techniques to discover the actions performed while interacting with different UIs of different systems and applications.

In future work, we will improve the proposed tool for recording and generating UI log to dominate more complex cases. Moreover, we will apply more real event data to validate the proposed framework for selecting candidate tasks to be automated with RPA.

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국문 요약

오늘날 기술은 더 빠른 속도로 변화하고 있다. 지속 가능한 경영을 위해 많은 기업들이 디지털 트랜스포메이션을 시도하고 있다. 디지털 트랜스포메이션을 위해서는 기존 비즈니스 모델을 최적화하고 비즈니스 프로세스 자동화를 강화해야 한다. RPA (Robotic Process Automation)는 최근에 개발된 비즈니스 프로세스 자동화 기술 중 하나이다. RPA는 사람이 수행하는 대규모, 수동, 반복, 규칙기반 작업을 자동화하는 기술이다. RPA를 도입하면 많은 수작업과 반복 작업을 줄여, 비즈니스 성장을 가속화함으로써 비즈니스에 많은 이점을 제공한다. 그러나 RPA 기술은 몇 가지 문제에 직면해 있다. 그중 주요한 과제는 많은 비즈니스 작업 중 자동화해야 하는 대상을 RPA 솔루션이 식별하지 못한다는 것이다. 자동화 대상 작업을 식별하는 것은 비즈니스 프로세스 자동화의 중요한 부분이다.

이 연구의 목표는 RPA에 의해 자동화될 수 있고, 자동화되어야 하는 작업을 식별하고 선택하는 프레임워크를 개발하는 것이다. 제안된 프레임워크는 프로세스 마이닝 기술과 사용자 인터페이스 로그 데이터를 기반으로 한다. 로봇 프로세스 자동화를 위한 후보 비즈니스 작업을 선택하기 위한 프레임워크는 두 가지 주요 부분으로 구성된다.

첫 번째 부분은 RPA를 사용한 자동화 대상 후보 비즈니스 작업을 선택하는 방법론으로 구성된다. 본 연구에서 제안하는 접근 방식은 사용자 인터페이스 로그 생성, 프로세스 마이닝 기술에서 사용할 수 있는 데이터 변환 및 필터링, 프로세스 마이닝을 통한 작업 발견, 특정 기준에 따른 후보 작업 선택의 4단계로 구성된다.

두 번째 부분은 사용자 인터페이스 상호 작용 로그를 기록하고 생성하는 도구 개발로 구성된다. 프로세스 마이닝 기술을 사용하여 작업을 검색하려면 이벤트 로그를 입력 데이터로 사용해야 한다. 사용자 인터페이스 로그 데이터는 프로세스 마이닝 기술을 적용하여 작업을 발견하기 위한 입력 데이터(이벤트 로그)로 사용한다. 인터페이스 로그는 사용자가 다른 애플리케이션 및 프로그램(Windows, 웹 브라우저, 응용 프로그램)과 상호 작용하는 일련의 작업을 시간순으로 표시한다. 제안된 도구는 사용자 인터페이스 상호 작용을 기록하고 생성된 로그 데이터를 필터링 및 단순화하는 기능을 포함한다.