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EFFECTS OF INTELLIGENT PROCESS AUTOMATION IMPLEMENTATION ON USED TIME AND MANUAL WORK IN FINNISH ACCOUNTING SOFTWARE

Examiners: Professor Mikael Collan
Post-doctoral Researcher Jyrki Savolainen

ABSTRACT

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Keywords: Financial administration, robotic process automation (RPA), intelligent process automation (IPA), case study

Robotic Process Automation and AI are rapidly changing the everyday tasks of accounting and financial management, advancing the long process of the transformation from pen and paper to digital processes, to a whole new and accelerated level. This thesis studies the effects of an Intelligent Process Automation (IPA) implementation on the usage of Finnish accounting software through a case study.

The research was conducted as a single quantitative study, that consists of analyzing secondary, partly compiled data, collected by the case company of the usage records of their software. Literature suggests that the most suitable processes for RPA and AI would be repetitive, rule-based, and time-consuming. Therefore, the data was categorized into accounting processes to see which ones are the most time-consuming and take the most manual labor overall. For analysis of the effects of the case company IPA implementation, variables of time spent per voucher and records made per voucher were constructed. The differences in these variables were analyzed between the time points before implementing the solution (Q1/2020) and after the first three months of implementing it (Q1/2021).

The results show that the most labor-heavy and time-consuming processes are purchase-to-pay and general bookkeeping, followed by order-to-cash. From the automated processes in this case study, the bank statement handling had relatively more benefits from the automation than the pay-to-purchase process. The results did not indicate the case company’s IPA implementation generating on average significant time-savings or reduced manual labor suggested by the previous research, in the pilot phase of the first three months, for the sample group. There were high variations in the effects, with some customers gaining notable benefits, whereas for others the implementation did not yet yield savings.

TIIVISTELMÄ

School of Business and Management
Strategic Finance and Business Analytics

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Älykkään automaation vaikutukset käytettyyn työaikaan ja manuaaliseen työhön suomalaisessa taloushallinnon ohjelmistossa

Pro gradu -tutkielma
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64 sivua, 14 kuviota, 10 taulukkoa, 1 liite
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Hakusanat: taloushallinto, ohjelmistorobotiikka (RPA), älykäs automaatio (IPA), case-tutkimus

Ohjelmistorobotiikka ja älykäs automaatio ovat nopealla tahdilla muuttamassa taloushallinnan ja kirjanpidon arjen työtehtäviä, nostaen jo pitkään käynnissä ollutta alan digitalisaatiota ja sähköistämistä edelleen uudelle tasolle. Tämä opinnäytetyö tutkii tapaustutkimuksena älykkään automaatioratkaisun vaikutuksia suomalaisen taloushallinnon ohjelmiston käyttöön.

Tutkimus toteutettiin kvantitatiivisena tutkimuksena, jonka aineisto koostui case-yrityksen loppuasiakkaiden taloushallinnon ohjelmiston käyttödatasta. Aiemman kirjallisuuden perusteella toistuvat, säännönmukaiset ja aikaavievät prosessit sopivat parhaiten automatisoitaviksi ohjelmistorobotiikalla. Tämän perusteella yrityksen keräämä ja osittain koostama aineisto kategorisoitiin eri taloushallinnon prosesseihin, joiden perusteella pystyttiin tunnistamaan eniten aikaavievät sekä eniten manuaalista työtä vaativat prosessit. Älykkään automaatiototeutuksen vaikutusten arviointiin luotiin muuttujat käytetty aika per tosite, sekä tapauhtumat per tosite. Näiden muuttujien muutosta tutkittiin ajalta ennen älykkään automaation käyttöä (Q1/2020) ja sen ensimmäisten käyttökuukausien (Q1/2021) välillä.

Tulosten perusteella eniten aikaa vievät ja manuaalista työtä aiheuttavat prosessit olivat ostolaskujen käsittely ja kirjanpito. Case-tapauksen kahdesta automatisoiduista prosessista tiliotteiden käsittely hyötyi suhteessa enemmän automaatiosta kuin ostolaskujen käsittely. Tulosten mukaan case-yrityksen IPA-toteutus ei tuonut pilottivaiheen ensimmäisen kolmen kuukauden aikana kirjallisuuden perusteella odotettavissa olevia hyötyjä ajan ja manuaalisen työn säästämisessä. Testiryhmän jäsenten tulosten välillä oli suurta vaihtuvuutta, osan saadessa huomattavia hyötyjä IPA-toteutuksesta, kun taas osalla työn tai ajan säästöjä ei vielä toteutunut.

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List of abbreviations

AaaS	Automation as a Service
AI	Artificial Intelligence
A/P	Accounts Payable
API	Application programming interface
A/R	Accounts Receivable
CRPA	Cognitive Robotic Process Automation
FTE	Full-time equivalent
IA	Intelligent Automation
IPA	Intelligent Process Automation
IT	Information Technology
J/E	Journal Entry
ML	Machine Learning
OCR	Optical Character Recognition
ROI	Return on investment
RPA	Robotic Process Automation
SaaS	Software as a Service
UI	User Interface

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1 INTRODUCTION

1.1 Background of the study

Businesses are always looking for ways to improve their profitability, reduce costs of their operations, and finding new value creation opportunities. Automation has lately been one solution to those purposes, and developments in Robotic Process Automation (RPA), machine learning, and artificial intelligence have accelerated these implementations throughout the business field. (Kokina & Blanchette, 2019, 12-13) RPA is a technology, that can capture data and do predetermined repetitive, structured, rule-based tasks like a human through automation, such as cut-and-paste information from one software to another or create and send out an invoice on receiving a sales order (Osman, 2019, 70; Schmitz, Stummer & Gerke, 2018, 353).

The concept of RPA and its implementations have been surging in the last two years; the RPA market alone has been expected to grow to a roughly 200-billion-dollar industry over the years 2019-2022, with the majority of the Fortune 1000 companies implementing it in some form (Papageorgiou, 2018, 27). One of the biggest RPA technology providers, UiPath, was ranked second in the Financial Times' list of Americas' fastest-growing companies in 2020 (Financial Times, 2020).

Research and consulting company Gartner (2020) predicted that global RPA software revenue would reach $ 1.89 billion in 2021, increasing 19.5% from 2020. Consulting company Deloitte has conducted a global survey on RPA usage in the last five years and found a rapid increase in the area. In 2015 their survey found 13 % of responding companies planning on increasing automation with RPA, whereas their similar survey 2020 found that 78 % of their respondents had already implemented RPA and 16 % intended to do so in the next three years. (Deloitte, 2020)

Even though RPA itself has been around less than ten years, the recent trend has been to enhance its capabilities with AI, to reach Intelligent Process Automation (IPA) (Petkov, 2020, 102). Where RPA is taking on tasks of human workers which are time-consuming, repetitive, and rule-based (Taulli, 2020, 88; Leshob, Bourgouin & Renard, 2018, 53), IPA will add the capability to use unstructured data and decision-making (Burgess, 2018, 64). As the fields of RPA and IPA are relatively new there are not many long-time studies presented, but there is high scientific interest around the topics; the scientific production about RPA has nearly doubled from the year 2018 to 2020 and for AI the hype has been very much on the surface. (Enríquez, Jimenez, Domínguez & Garcia-Garcia, 2020, 39126; Hindel, Cabrera & Stierle, 2020, 1760)

1.2 Motivation

Previous studies have found that the actual time and cost savings of RPA have been difficult to measure (Cooper, Holderness, Sorensen & Wood, 2019, 30; Kokina & Blanchette, 2019, 13; Suri, Elia & Hillegersberg, 2017, 89). This study will examine the time saving and reduction of mundane manual work that automation by RPA and machine learning application can have in accounting through a case study. The case company has deployed a generalized IPA solution for accounting offices, that is integrated into accounting software and aims to automate multiple accounting processes from Purchase-to-Pay and Order-to-Cash processes, and reconciliations to allocating bank statements. The aim is to do the journal entries and allocations with minimal human interference.

Accounting has long been a profession, that consists of several routine-like procedures and standardized forms and tasks that are executed in monthly or yearly cycles, and this makes it an optimal field for automatization by RPA (Kokina & Blanchette, 2019, 12-13). Therefore, there is no denying, that emerging technologies such as RPA and AI will have a significant effect on accounting processes and roles of the workers (Smith, 2020, 20). Even though most of the largest Finnish accounting software providers have already implemented several forms of automation to ease the repetitive processes in accounting, public accounting is facing difficulties to handle all the different automation rules for different clients (Accountor Finago 2021; Cooper et al. 2019, 16, 22; Heeros 2021; Visma Solutions 2021).

For accounting firms, the most profitable angle is to program robots that are adaptable for multiple customers, requiring minimal modifications for customer-specific tasks

(Cooper et al., 2019, 22). The case company's IPA solution will try to answer this need by creating one UI where the accounting office can maintain the RPA rules for their clientele. AI is included in the solution through machine learning, to learn from the customer companies' previous accounting material. This study will compare numerical data of the time spent on, and the site loadings made for the end customer companies inside the accounting software, from time periods before and after implementation of IPA. The initial sample will consist of 71 pilot phase companies that are public accounting customers.

1.3 Objectives of the research

The aim of this study is to determine the possible time save obtained and manual work reduced with implementing an RPA and AI solution on accounting software and public accounting, and to find out which of the automated processes have gained the most advantage. The majority of the conducted studies in the subject of RPA and IPA have been qualitative interview studies, and therefore examining numeric data on the subject will provide a new angle of insights for example on determining the ROI or general benefit potential for RPA and IPA projects. This will be examined through the following main research questions, with the one regarding the empirical part of this study being built on exploration of two sub-questions:

1. *According to the current literature, what are the benefits and time savings gained from IPA implementation on accounting?*

2. *What are the time and manual work savings gained from IPA implementation on accounting based on the data of 52 public accounting customer companies?*

2.1. Which of the accounting processes seem to be the most time-consuming and manual work-heavy according to case company data?

2.2. Which of the automated accounting processes have the highest advantages from the case company's IPA implementation?

A general hypothesis is that successfully implementing RPA with machine learning application will reduce the time and manual work required for accounting (Petkov, 2020, 102; Cooper et al. 2019, 16; Lacity & Willcocks 2016b, 18; Aguirre & Rodriguez, 2017, 5; Burgess, 2018, 57; Osman, 2019, 71; Willcocks, Lacity, & Craig, 2015, 4-5; Moffitt, Rozario & Vasarhelyi, 2018, 8). Reducing manual work required for the accounting processes will usually lower also the time spent on them, but it can also help with employee satisfaction by shifting the mundane routine tasks for robots and freeing time for more analytic tasks (Madakam, Holmukhe & Kumar Jaiswal, 2019, 6; Lacity & Wilcocks 2016a, 47).

Therefore, we can state the hypothesis that the time spent per task is reduced by RPA-ML. Analytically, we write the hypothesis to be following:

H1: $\mu < 0$, where μ is the difference in time spent and manual labor done per voucher
H0: $\mu \geq 0$

To have a measurable quantitative answer to the second research question, data from the case company is constructed to form metrics for the time used and manual work done in the accounting of the end customer companies. The metrics are then compared to the time before the IPA implementation and to a control group.

The first sub-question helps to build the foundation on what to compare the results of the sample companies using the RPA solution. The processes that are tedious, time-consuming, repetitive, frequent, rule-based, high-volume, prone to error, and not available for API are the best ground for RPA solutions (Taulli, 2020, 88; Leshob, Bourgouin & Renard, 2018, 53). The second sub-question aims to fit these specifications with the time-consuming element as well as the tediousness based on the manual work done in the software. The selection of processes most benefitting from the automation is one of the most critical for the successful outcome of the RPA implementation (Matthews & Greenspan, 2020, 91). Therefore, examining it can be useful for companies planning to start using these technologies, and give insights on where it is best to start the RPA or IPA implementations.

1.4 Research method

The research is conducted as a quantitative case study, where statistical analysis is done on numerical data gathered by the case company. According to Gibbert, Ruigrok & Wicki (2008, 2) case studies seek to study a phenomenon in a certain context, rather than as independent of context. In this study, the context is the case company and its customers.

Data for the study was collected on end customers of the case company, that had an IPA solution implemented for their cloud-based accounting software. The initial sample size before data cleaning was 71. The sample group's usage data was examined to determine which accounting processes were taking the most time and required the most manual work. These metrics were derived from the time spent in the accounting software, and the different site loadings ("clicks") made. The results are compared to the same customer company's previous usage data, and as well to a separate control group.

The methodology of this study and the analysis of the data is described in more detail in chapter 3.

1.5 Research delimitations

The empirical data of the research is based on the case company and its customers. The data analysis is based solely on the usage data retrieved from the accounting software, so time spent working on customers bookkeeping outside the software is not measured. The study is also limited Finnish market since the case company and all the sample companies are Finnish, and they follow the country's accounting standards and customs. This is seen for example in the fact, that most of the sample customers use already electronic invoicing and other prior automation related to business administration before the IPA solution examined in this study.

The empirical part is concentrating on the distinct processes of business administration and accounting, which are covered in the IPA solution provided by the case company.

Some processes such as HR and payroll processes are therefore completely excluded since they are not yet part of the provided solution. The study measures only the effects on the usage of the accounting software, and creation and management of the automation rules, flows and predictions are done in a separate UI. Therefore the time spent on setting up and maintaining the IPA solution is not considered in this study.

RPA is often combined with AI for more intelligent automation solutions (Taulli, 2020, 6). The subject of AI is covered in the theoretical part of the study only from the perspective of being an addition to RPA, and further theoretical study of Artificial Intelligence is left out. Also, articles on RPA and AI that were completely from a different field than financial and business management (such as medical care) were mostly left out of the scope.

1.6 Structure of the study

The study is divided into five main chapters. The first main chapter introduces the subject and its background, describes the aims of the study, research method, and its delimitations. After the introduction, the second main chapter goes through the theoretical frameworks of RPA, AI, their applications in accounting, and benefits and challenges they have been reported to have in preceding literature. The third main chapter presents the data and methodology used in the empirical section of the study. The actual empirical section of the study is concluded in the main chapter four, where the results of the analysis are gone through and discussed, and limitations of the study are presented. The final chapter concludes the study with a summary and conclusions and is finished with suggestions for further research.

2 THEORETICAL FRAMEWORK

In this section, a literature review and earlier studies on the topics of RPA, robotics in accounting, and the time and costs savings from automation are presented. The majority of the cited research in this study is peer-reviewed scientific journals from the past three years, that are gathered from LUT Finna-database and ResearchGate.

2.1 Key concepts and definitions

The key concepts applied in this research are shortly presented and explained in this chapter. The center of this study is in RPA, Robotic Process Automation, which is non-invasive software, usually called robots or bots, that automate repeatable and rule-based tasks by mimicking actions performed by human users on computers (Madakam et al., 2019, 4). To open up the concepts of RPA, they are defined also separately. A process can be defined as a conversion from input to output. With RPA it often refers to automated tasks or series of them. (Madakam et al., 2019, 3)

A robot is defined by The Institute of Electrical and Electronics Engineers as “being an autonomous machine capable of sensing its environment, carrying out computations to make decisions, and performing actions in the real world.” (IEEE Corporate Advisory Group, 2017). Automation is the use of machines or computers that can operate without human interference. Automation can perform physical tasks, or nonphysical tasks for example by using software robots. (Matthews & Greenspan, 2020)

Artificial Intelligence, AI, is the ability of a computer or computer-controlled robot to perform tasks traditionally possible only for intelligent beings, such as the ability to do conclusions, discover meaning, generalize or learn from previous experiences (Encyclopedia Britannica, 2021). Combining RPA and AI is often called IPA, Intelligent Process Automation. In some references, the combination is however called Intelligent Automation (IA) or cognitive RPA (CRPA) (Taulli, 2020, 6; Matthews & Greenspan, 2020, 97). IPA is broadening the automation of RPA solutions being capable of decision-making and turning unstructured data into structured suitable for robots to process (Burgess, 2018, 64).

The empirical part of this study concentrates on the field of accounting. Accounting is an essential part of the back-office processes of business institutions. The purpose of accounting has remained the same for centuries; recording, analyzing, monitoring, and evaluating the financial condition of companies, reporting taxes, and supporting other functions of the company with financial data. Through wider use of computers and the internet, accounting has shifted from paper to computerized and cloud-based software. Automation of the profession has advanced to more moderns stages including mobile apps and electronic payslips. (Yadav, 2015, 26) Public accounting refers to a business model that provides accounting services to other companies. The majority of accounting of business institutions is outsourced to accounting offices instead of having them as in-house service. (Cooper et al., 2019, 6)

The time savings are considered in this work through time spent on creating a journal entry (or “voucher”) in accounting. Journal entries are records of the business transactions the company has made. They should include the date, the credited and debited amounts that are in balance and their accounts, a unique reference number, and a description of the transaction. (Finnish accounting act 2:5.2)

2.2 Robotic Process Automation

2.2.1 Introduction to RPA

Robotic Process Automation is a technology, that can capture data and do predetermined repetitive, structured, rule-based tasks like a human. RPA differs from traditional software or macros since robots can communicate and carry on tasks between multiple information systems. (Osman, 2019, 70) The robots, or bots in short, can increase efficiency and accuracy since they do not tire or make human errors (Taulli, 2020, 3). The IEEE (Institute of Electrical and Electronics Engineers) Standards Association’s definition of Robotic Process Automation is such:

> *“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" (IEEE Corporate Advisory Group 2017).

For automating tasks, RPA uses series of actions in the user interphase of the legacy systems in use like cut-and-paste information from one software to another, read and write of a database, extraction of content from a document, and opening a webpage and logging in (Taulli, 2020, 3). The configurations for RPA can be done by human creating a suitable flowchart of the automated process (Lacity et al. 2016, 23), but many advanced RPA editors also offer a record button, that creates the flowchart by following the user's actions (Moffitt et al., 2018, 2). A distinction should however be made that not all automation substituting human labor is considered RPA; for example, higher automation embedded in a software system as part of a normal functionality is plainly seen as a more powerful system rather than RPA (Burgess, 2018, 60).

Different industries and functions have varying emphases in the use of RPA. RPA in general is most used in back-office tasks and accounting across industries. Besides that, the financial industry has used it in for example in loan processing and credit checks. In the supplier industry, RPA was reported to be used for back-office tasks and data retrieval from the web and internal systems. The energy sector has emphasized the use of back-office tasks like HR tasks, travel expenses and payroll. The manufacturing industry has reported use in supply chain processes. (Eikebrokk, Olsen, 2020, 120) Service automation is used in different fields that have customer service needs. It can help to get an answer to a customer more quickly, and by that improve customer and employee satisfaction, and costs savings through the saved time of human labor. Besides that, service automation with robots provides greater workforce flexibility, since scaling the robot workforce is significantly quicker than hiring and training new employees. (Lacity, Wilcocks, 2016a, 44).

RPA can be categorized into three broad types of approach; attended RPA, unattended RPA, and Intelligent process automation. Attended RPA (or Assisted RPA) is used alongside human workers, mainly to take data from and to them. (Taulli, 2020, 6) An example of this could be a call center worker, who gets a call from a client who wants to update their address. After the call, the worker can assign a bot to update the address in the company’s multiple systems, and the human worker can go on and take another call. (Burgess, 2018, 61) Unattended RPA (or Unassisted RPA) bots work independently usually in the back-office tasks without active human intervention. They can for example be scheduled to work once per week or run after a certain alert. (Taulli, 2020, 6)

Intelligent process automation or IPA (sometimes referred to as cognitive RPA or Intelligent Automation IA) is the latest generation of RPA, which uses AI to learn over time. This technique is used for example to interpret and handle documents such as invoices. (Taulli, 2020, 6) Most of the IPA solutions use a branch of AI called machine learning. Machine learning is a system that is given a training set of data and based on that it will learn to predict outcomes on similar cases. (Bell, 2020, 3-4) IPA will be presented more thoroughly in detail in chapter 2.3.

The criteria for applicable tasks for RPA are that the tasks are tedious, time-consuming, repetitive, frequent, rule-based, high-volume, prone to error, and not available for API (Anagnoste, 2013, 307; Leshob, Bourgouin & Renard, 2018, 53; Taulli, 2020, 88). That means the applications for RPA can cover all tasks include capturing data and doing repetitive, structured, rule-based tasks. (Osman, 2019, 70) The classical business processes where RPA is implemented include help desk, sales process support, scheduling systems, form processing and business administration, and examples of specific tasks could be employee on-boarding, invoice processing, payments, conveyancing processing, benefit entitlement checks, and IT service desk requests (Burgess, 2018, 60; Ng, Chen, Lee, Jiao & Yang, 2021, 4). Table 1 presents a way of classification for tasks that are easy and difficult to automate.

Table 1 Automatable task classification (Matthews & Greenspan, 2020, 90-91)

	Manual	Cognitive
Easy to automate	Simple Repetitive Frequent/ Easy to anticipate E.g. Employee onboarding	Complex Mostly repetitive Frequent/ Easy to anticipate E.g. Insurance application
Difficult to automate	Simple Creative Occasional E.g. Premium negotiation	Complex Creative Occasional E.g. Evolving process

The lifecycle of RPA can be divided into six phases; Analysis, Design, Construction, Deployment, Control and Monitoring, and Evaluation and Performance (Enríquez et al., 2020, 39126). For a successful RPA implementation, all of these phases should be planned and executed (Smith, 2020, 147). Setting up a center of excellence and give someone the responsibility of the company's RPA as a whole, and training of other employees supported by proper change management were seen as crucial success factors (Anagnoste, 2013, 307).

2.2.2 Benefits of RPA

The biggest benefits of RPA implementations come from cost savings of reducing human labor and making it more efficient, but it also increases the consistency of the work done (robot does the process 100 % similarly every time), leaves full audit log if needed, and the robots can work without breaks, vacations, or sick days. Some companies also see RPA as a possibility to bring some outsourced simple services or backend processes back in-house, since it can reduce costs and lower risks. (Burgess, 2018, 59-61; Fernandez & Aman, 2018, 128) The broader benefits of RPA, that can also contribute to the reduction of human labor, have been gathered as an illustration to Figure 1. The time-savings and reduced labor are also discussed more further in the capter.

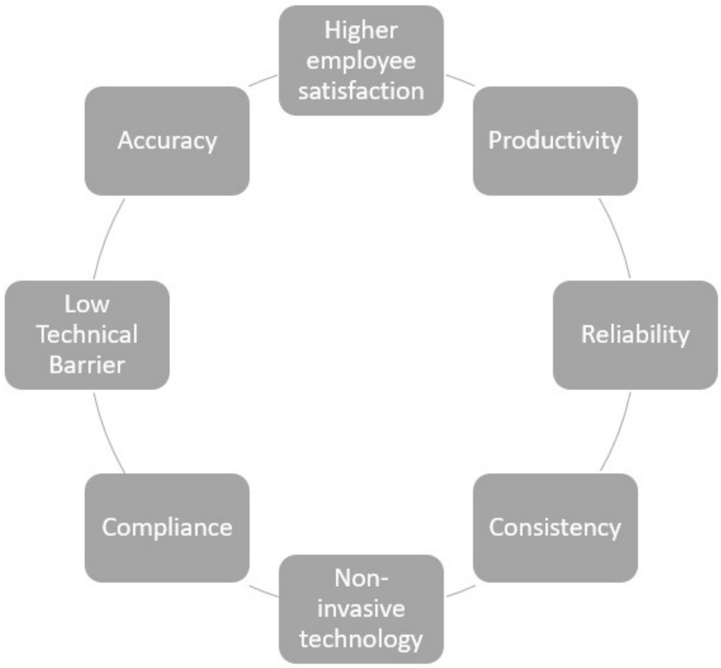

Figure 1 Benefits of RPA (Madakam et al., 2019, 6)

RPA can result in higher employee satisfaction by giving the employees an opportunity to engage in more meaningful tasks by automating the tedious and labor-heavy routine processes. (Madakam et al., 2019, 6; Lacity & Wilcocks 2016a, 47) Productivity will increase as the bots can do many tasks much faster than their human counterparts, one study describing even turning a 16-hour task into a 17-second one (Cooper et al., 2019, 16). This being said, the robots still are restricted to the architectural rules and compliance of the legacy systems, such as if the change between two databases takes one minute, that will be the same for a robot and a human worker (Matthews & Greenspan, 2020, 95).

RPA robots are also reliable in the sense that they work tirelessly without interruptions, not requiring breaks or calling in for sick. The consistency of the processes increases as the bots do the routine tasks similarly every time and do not deviate from the set of rules they are given. This also increases the accuracy within the tasks, when human errors and differences in decision-making are left out. (Madakam et al. 2019, 6) Compliance will increase since the robots leave a full digital audit trail if their actions are logged. The robots can also be programmed to do regular internal control activities, and they can possibly spot irregularities that humans would not. RPA can also be seen as lowering risk management since they decrease fraud risk and reduce human errors or deviations from regulatory rules. (Kaya, Turkyilmaz & Birol, 2019, 245)

RPA is so-called “light-IT”, as it is non-invasive technology, that does not alter the underlying legacy IT systems, but is rather working on top of them as a human worker would be (Willcocks et al., 2015, 5). RPA can be implemented without coding skills which makes it a low technical barrier initiative. The providers of RPA solutions are creating more and more easy-to-implement solutions. Nevertheless, some programming skills can help with the robustness of the robots, and other technical skills requiring technologies such as artificial intelligence and increasing back-end automation are seen to increase also RPA solutions applicability. (Hindel, Cabrera & Stierle, 2020, 1760) That said, the easiness of RPA especially with service providers' more and more advanced front-end applications makes the training costs for RPA initiatives relatively low (Matthews & Greenspan, 2020, 255). The capability of implementing the RPA solutions without explicit help from the IT department will conserve IT resources (Schmitz et al., 2018, 354). In a modern company, there is usually multiple software that the worker needs to visit and retrieve information from. Since RPA can replicate the rule-based actions that humans would take in their work in the presentation layer of the software, there is no need for costly changes on the underlying software. (Burgess, 2018, 57)

In general, the studies are coherent on the fact that successful implementation of RPA and AI will result in reduced manual work (Aguirre & Rodriguez, 2017, 5; Cooper et al. 2019, 16; Lacity & Willcocks 2016b, 18; Petkov, 2020, 102; Suri, Elia & Hillegersberg, 2017, 90) and working time savings (Burgess, 2018, 57; Cooper et al. 2019, 16; Fernandez & Aman, 2018, 128; Lacity & Willcocks 2016b, 18; Moffitt et al., 2018, 8; Osman, 2019, 71; Willcocks et al. 2015, 4-5). It should be noted that not all RPA implementations end in success, as even 30-50 % of RPA projects are reported to fail (Moffitt et al., 2018, 9). Multiple studies have also stated, that measuring the actual time and cost savings of RPA has proven to be difficult (Cooper, Holderness, Sorensen & Wood, 2019, 30; Kokina & Blanchette, 2019, 13; Suri et al, 2017, 89)

The reported results vary very widely for RPA solutions. Determining the value of RPA solutions has not yet been standardized, and the ROI metrics that companies are using vary but usually include some metrics of improvement in efficiency, effectiveness, and accuracy (Harrast, 2020, 214). A case study by Lacity & Willcocks (2016b, 18) presents Telefónica O2 training four people from their personnel and deploying over 160 robots to process 400 000-500 000 transactions monthly, and therefore stating return on investment of 650-800 % by three years by saving hundreds of FTE's. To be profitable, the study concludes that with Telefónica O2 the processes automated with RPA needed to be at least three FTE's worth in labor, even though the process itself would be very suitable for automation on its own (Lacity & Willcocks, 2016b, 23). Another study by Lacity, Willcocks & Craig (2015, 8) suggests that RPA robots can free three FTE's worth of human labor.

In theory, RPA could replace all the transactional work made by humans, and do it up to 50 % of the costs (Burgess, 2018, 57). Osman (2019, 71) examined in her journal article ten case studies of implementing RPA and found that the robots reduced significantly the execution time of the processes, and showed evidence of some cost reductions. Harrast (2020, 214) points out, that companies should start the automatization of processes with RPA from the stable and low complexity tasks, to receive the best possible ROI for investing in the new technology. Petkov (2020, 102) states that the greatest benefit from IPA implementations is reductions of the costs in long run by lowering the reliance on human function in certain tasks. The fixed costs from implementation would cover creation, planning and implementation, but also costs of maintaining should be taken into account (Petkov, 2020, 102).

One business process outsourcing provider automated a business process for generating a customer-requested payment receipt, and concluded that a team with an RPA solution could handle 21 % more customer requests than a team without RPA (Aguirre & Rodriguez, 2017, 5). A case study by Willcocks et al. (2015, 4-5) of Xchanging, an international provider of technology-enabled business processing, technology and procurement services, reported typical cost saving per process to be 30 %. They emphasized that the savings were not from replacing existing employees with robotics, but from doing more work with the same workforce.

Besides instant cost savings, Moffitt et al. (2018, 8) state that there can also be indirect benefits from customer and supplier satisfaction through simple time savings such as the time spent between receiving an invoice and the payment made. The largest positive effects from RPA such as cost reductions, quality, innovation, and reduction of routine tasks are experienced with long time usage (Eikebrokk & Olsen, 2020, 124).

When moving the scope of benefits from RPA and AI to accounting, one thing where RPA and AI can make a difference in shortening the time to prepare financial statements for companies. Some of the timetables are set by authorities, but in today's fast-paced economy delays in forming of information could be detrimental to the company also in internal reporting. (Petkov, 2020, 101) Besides answering the time pressure needs by regulators and businesses, saving working time is generating clear cost savings in salaries (Lacity, Wilcocks, 2016a, 47). To give context for the cost savings that saving employee time and reducing manual labor that ultimately is affecting the needed workforce, we can do a rough estimate of the costs of labor in the accounting sector in Finland by calculating the hourly salary from the median salary of employee working at accounting office (2 844 € / month in 2020) with employee side costs multiplier (1,2032 in 2020), divided by daily working time of 7,5 hours with 21 working days in a month (ERTO, 2020; Elinkeinoelämän Keskusliitto, 2021). This would give the price of a worker to be per hour 2 844 € * 1,25 / (7,5 * 21) = 22,57 €, when no additional costs are considered.

Many software companies have made claims for the time and labor savings their solutions could gain. CGI (2016) estimated that a municipality with 100 000 invoices a year may save up to 135 000 € by implementing their RPA solution, by shortening the lead times of invoice processing and therefore freeing working time to more productive activities. Capgemini Consulting (2017) reports, that their in-house robots have processed 1,5 million transactions in the year 2015, which was equivalent to 200 employees. Their best-performing RPA solutions had made a cost reduction of 80 % per process, but the results varied widely from one process to another. According to them, the average robot of theirs replaces 4 FTE's and returns ROI in 3-6 months. (Capgemini Consulting, 2017)

In their interviews with the Big 4 public accounting firms, (PwC, Deloitte, EY, and KPMG), Cooper et al. (2019, 16) had one of them reporting over one million human work hours saved from RPA in 2017, and one of them described turning a 16-hour task into a 17-second one. They also shared an accuracy increase to 99,9 %, whereas earlier human performance was able to reach 90 % accuracy with the same task. The respondents however did not report plans of reducing headcounts from the time save the RPA was enabling and were able to allocate the displayed individuals to other productive tasks.

2.2.3 Challenges of RPA

The RPA technology and its deployments are not without problems, and the success of an RPA project has proven not to be a foregone conclusion. Even 30-50 % of RPA projects are reported to fail due to reasons like problems with sourcing, the fitness of selected tools, long project time estimates, challenges in operations and execution, and change management. (Moffitt et al., 2018, 9) Also, the lack of stakeholder buy-in is hindering the success of the projects, as well as unrealistically positive expectations from management. (Eikebrokk & Olsen, 2020, 123) Figure 2 presents the risks of a PRA project in the different stages of the project.

A major part of an RPA implementation and its successful outcome is in its opportunity identification to focus on the processes most benefitting from RPA, and further solution design phases to have effective technological architecture. Identification and classification of the processes and furthermore their immaculate documentation can be a work heavy process in itself. Very rarely an organization's processes are documented on the level, that could be used as it is for automation purposes. (Smith, 2020, 103; Matthews & Greenspan, 2020, 91) Besides being clearly defined and documented, the processes that can be automated profitably should have the characteristics of being tedious, time-consuming, repetitive, frequent, rule-based, high-volume, prone to error, and not available for API. Constructing an RPA solution for a task that needs to be done only once a year, might easily prove to be unprofitable (Taulli, 2020, 88).

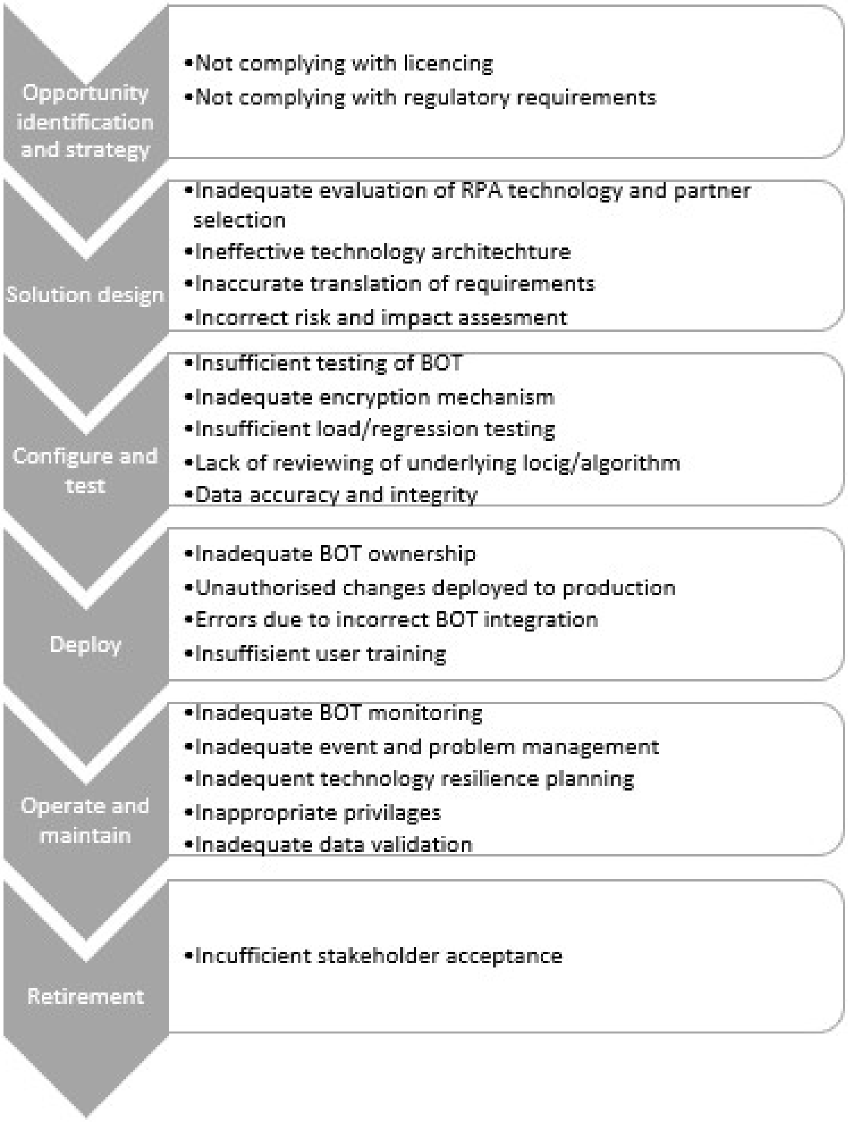

Figure 2 RPA risk universe (KPMG, 2018).

Information needs to be shared openly between the provider and the end-users, to ensure especially that opportunity identification and strategy, and solution designing phases are focused on relevant processes, translating the processes correctly and meeting all the requirements. Proper user training is essential for the successful implementation of RPA, and adequate controls throughout the lifecycle of the robot prevent incorrect data from being distributed or unauthorized changes being deployed to the process. (Smith, 2020, 147) One common mistake in the solution design phase is that after a short training period most users are able to form a solution for simple processes but keeping the bigger picture of RPA processes scalable and resilient needs skill and throughout planning (Lamberton, Brigo & Hoy, 2017, 14).

It should be taken into notice, that many employees are concerned about the impacts of automation. (Lacity, Wilcocks, 2016a, 47, Matthews, Greenspan, 2020, 91) Some of them are plainly afraid of software robots taking on human jobs (Moffitt et al., 2018, 9). There are some mixed results on how the RPA has affected the workforce. In case studies by Lacity and Wilcocks (2016a, 47) they found that the jobs affected were tedious and repetitive, and automating them resulted in higher employee satisfaction, and a rise in productivity resulted in reductions in hiring, but not layoffs of full-time employees. However, a study by Eikebrokk and Olsen (2020,121) concluded that even though RPA did generate positive consequences through more efficient work processes and fewer routine tasks, it did actually result in a reduction in hiring and layoffs for knowledge workers, especially in the finance industry. Because of these fears of losing one’s job, there is resistance to change. The workers whose primary tasks are about to be automatized are not the most open to being part of the developing process of RPA implementation. (Eikebrokk & Olsen, 2020, 120)

The cost ownership structures are somewhat inconsistent between different service providers of RPA, varying from yearly licenses to charge by bots. Besides the actual robots being provided, there are also costs from training the users and ongoing maintenance. If there are changes applied to the underlying software, the RPA solutions need also to be updated. (Taulli, 2020, 14) The issues in deploying, as well as in the operating and maintaining state, boil down to the neglections of bot ownership. With strong ownership and allocated responsibility, the problems of inadequate BOT monitoring, problem management, and inadequate data validation can be avoided (Lamberton et al., 2017, 14). The bots should be assigned to the business departments they will be active at, to reach the required ownership (Schmitz et al., 2018).

2.3 RPA combined with AI for Intelligent Process Automation

AI is a computational technology that is able to perform tasks that would normally require human intelligence such as sensing, learning, reasoning, and taking actions. In general, AI is used widely in different parts of society, from statistical forecasting, engineering, language translations, and video games to self-driving cars (Marttinen, 2018, 247). With process automation, computational AI aims to reduce or remove human engagement and supervision. AI builds on general automation and standardization and RPA, as can be seen illustrated in Figure 3. (Smith, 2020, 84-85)

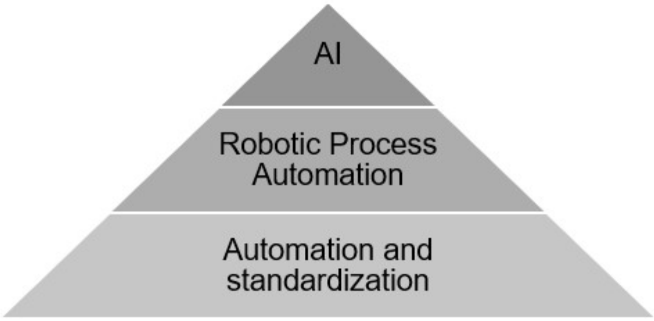

Figure 3 Automation to AI pyramid (Smith, 2020, 84)

The more advanced version of RPA also utilizes AI to improve the automated processes with more intelligent solutions. This next phase of RPA is referred to in literature and business field by several terms and varying levels of artificial intelligence; “RPA 2.0.”, Intelligent Process Automation (IPA), Intelligent Automation (IA), cognitive automation or cognitive RPA (CRPA), Smart Process Automation (SPA) and Augmented Intelligent Process Automation (AIPA) (Taulli, 2020, 6; Matthews & Greenspan, 2020, 97, Ng et al., 2021, 5). Ng et al. (2021, 6) present the term Intelligent Automation to be the roof term for the automation that is grounded in RPA technology, and adding different levels of artificial intelligence to it. Illustrations of this are shown in Figure 4. This presentation is a spectrum where RPA has no intelligence, and in the other end are Autonomous agent applications, which have self-learning capabilities and zero human interference. In practice, well-functioning AA has yet not been commercially deployed due to limitations in technological advancements, so the available solutions fall more likely to IPA-category. (Ng et al., 2021, 5-6)

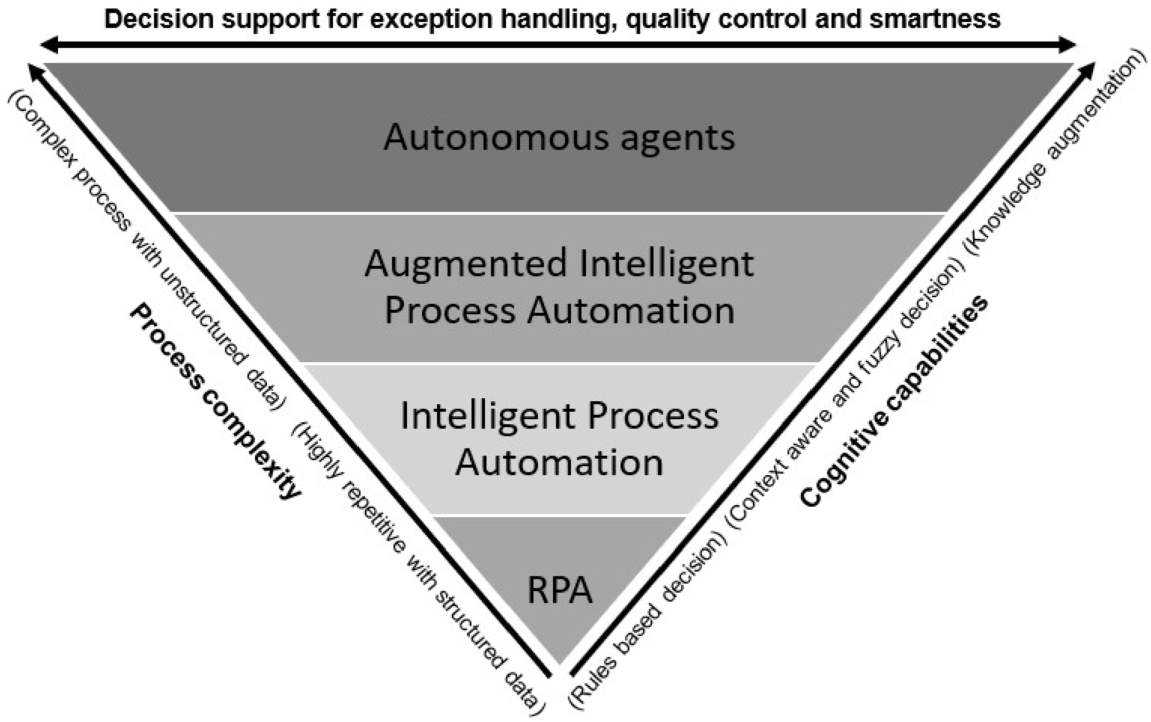

Figure 4 An overview of IA applications by NG et al. (2021,6)

With RPA technology, Artificial Intelligence is used to tackle the difficulties of being able to use unstructured data and making decisions. RPA needs structured and defined data to work, such as a database, spreadsheet, or web form, since it uses a predefined set of rules for actions. Unstructured or semi-structured data can however be transformed into structured data for robots to process with the help of AI and especially its search capability. Invoices are a typical example of semi-structured data, as they generally include the same information (supplier, invoice date, product and prices, VAT amount, etc.), but the data can come in different forms and orders. AI can create its own rules and tasks to search for meta-data in the invoices, and transform it to a standard form to be used in robotic automated processing. (Burgess, 2018, 62-63; Taulli, 202, 43) The recognizing patterns or rules can be done with the AI branch of Machine Learning (ML) to do predictions or decisions for the data structure, and document handling can be supported by Optical Character Recognition (OCR) and Natural Language Processing (NLP) (Cockcroft & Russell, 2018, 324).

Optical Character Recognition OCR was developed for text extraction from scanned documents, PDF files, or images taken by a digital camera. With business automation, OCR is widely used in interpreting non-electrical invoices and receipts and extracting the text from them for further processing. Receipt camera apps for mobile phones are offered by multiple accounting software providers, to make it easy to provide the necessary documentation to the bookkeeping of a business. (Rajeswari & Magapu, 2018, 766)

Whereas OCR interprets visual elements, Natural Language Processing NLP helps machines to understand, interpret and generate human languages. The technique uses a linguistic-based approach with a range of computational techniques for analyzing and representing naturally occurring texts. (Kamath, Liu & Whitaker, 2019, 7) The applications of NLP with RPA include for example classification of financial statements, fraud prediction, risk assessments, and predicting stock prices and market activity. (Fisher, Garnsey & Hughes, 2016, 163-166)

Besides restructuring data, the second application of AI for RPA is decision-making inside the processes. Simple decisions based on scoring or such are still manageable for RPA itself, but when a more refined judgment or predictions are needed, AI can be applied in form of a cognitive reasoning engine or machine learning. (Burgess, 2018, 64) The ability of machines to evaluate and choose strategies accordingly in decision-making scenarios might turn out to be the most notable impact of AI in the support role of human task performance (Kokina, Davenport, 2017, 117).

Machine learning is a system that is given a training set of data and based on that it will learn to predict outcomes on similar cases. Machine learning can be divided into supervised and unsupervised learning, where the first consists of human interference by confirming and correcting the predicted outcomes whereas the latter operates on its own and finds possible hidden patterns in the data. (Bell, 2020, 3-4) Machine learning utilizes traditional statistical methods such as k-nearest neighbor and the naïve Bayes classifier (Taulli, 2020, 39). The detected correlations or patterns are used with self-informing regression algorithms for the determination of successful operation, which can be used for predictions (Kaya et al., 2019, 238). However, it should be pointed out, that the quality of the predictions relies on the original dataset's quality and inherent bias (Cockcroft, Russell, 2018, 329).

Machine learning has changed programming in the last years. Traditionally software engineers have written list of commands that computer has followed and executed. Now, when machines can learn from past examples, programmers are rather teaching them and not writing straightforward commands. For a simple example, to teach a machine to recognize a cat, you will not anymore describe how the cat looks, but show thousands of pictures of cats from which the machine will learn to recognize the species. (Marttinen, 2018, 261-262)

One of the benefits of Machine Learning is, that it can constantly recognize new data and improve the outcome of the learning process with a larger pool of examples and different variations. The Machine Learning models can be divided into online models that use this option of stream of new data to process and consider, and offline models that learn from one teaching set and keep static after that. (Merilehto, 2018, 34) One thing to remember is, that as human actions sometimes lack rationale, the AI trying to interpret it logically does not always yield hoped results, and therefore there should always be upper and lower limits for the decisions the machine is allowed to make on its own (Petkov, 2020, 102).

As with RPA, also AI raises concerns among the employees whose tasks the automation would affect. On top of the worries of job replacement, reluctance to fully embrace AI is increased by fears of it “taking over”, and skepticism that it would not be able to recognize the economic events such as bank statements and contracts correctly as they occur. These concerns should be addressed with properly planned change management and employee training to raise awareness of the possibilities of AI. (Lacity & Wilcocks, 2016a, 47; Petkov, 2020, 104)

2.4 RPA and AI in accounting

2.4.1 The use of RPA and AI in accounting

The presence of PRA is becoming more president by day in the fields of finance and accounting activities especially in large companies and accounting offices (Lacurezeanu, Tiron-Tudor & Bresfelean, 2020, 768). The profession has already long been a target for simpler levels of automatization with evolving accounting software and was listed as one of the most automatable professions overall alongside cashiers, auditors, loan processors, and couriers (Frey & Osbourne, 2017, 71). Frey and Osborne (2017, 71) go as far as predicting that 94% of accounting professional occupations could be replaced by AI within the next 10 years, but that has been contradicted by other literature in the field with implications that the occupation will be directed to AI-based tasks (Pettersen, 2019, 1065).

Emerging technologies such as RPA, AI, and blockchain will most definitely have a profound impact on the profession, such as restructuring accounting procedures, improving efficiency and reducing accounting information errors, and changes in accounting career paths. (Smith, 2020, 22; Kaya et al., 2019, 244, Zhang et al., 2020, 12; Leitner-Hanetseder, Lehner, Eisl & Forstenlechner, 2021, 539). Automation by RPA and AI are indeed becoming part of the accountant profession at an accelerating pace. (Kokina, Gilleran & Blanchette, 2020, 12) According to Smith (2020, 91), nearly all existing accounting software providers are implementing some form of AI tools and processes. Several big accounting firms have also already shifted from attended RPA to IPA to enable more sophisticated solutions that overcome the limitations of explicit rules that RPA has (Kokina & Davenport, 2017, 117; Cooper et al., 2019, 32).

The benefits that these technologies can bring to the profession include the timeliness of the information that is used in decision-making. AI's capability to analyze and interpret data much faster than a human worker would lead to the possibility of more timely and accurate financial statements. Accuracy should also increase when RPA and AI are performing the tasks by the rules that they have been given, and are not able to deviate from them, unlike the human workers. (Petkov, 2020, 102) However, there has been a substantial gap in the accounting firms' understanding of the possibilities and means of using RPA for moving the profession forward (Cooper et al. 2019, 16).

RPA for areas of accounting and audit has high potential with the profession-specific tasks which are usually characterized by interacting with multiple systems, having high manual transaction processing volume, and requiring real-time decision making. (Kokina, Blanchette, 2019, 2) Representatives from the Big 4 accounting firms named the biggest cost-saving potential from RPA in administrative functions to be with human resources (60-80 %), purchase-to-pay (50-70 %), and order-to-cash (40-60 %). The least cost-save potential they saw with supply chain (10-15 %) and general accounting (10-15 %) which consists of for example of closing and reporting and local tax accounting. (Cooper et al., 2019, 19)

To write an example out, the order-to-cash process could include the following automated steps: a sales order PDF approved by the customer could be read by OCR to electrical format, and RPA would add it to multiple software used by the supplier. A bot could send out an invoice on receiving the order information. Payment reminders and collection of the invoice could be scheduled to be done by another bot if the payment is not yet received, as well as allocating the payment in the bank statement for a journal entry when it does arrive. (Schmitz et al., 2018, 353)

Even though the end goal of automation is the same as RPA and AI, the specific processes, or problems that they solve are partly different. Where RPA is tackling repetitive, rule-based tasks (Lacity, Wilcocks, 2016a, 47), AI can replace tasks that require restructuring unstructured data or decision-making (Taulli, 202, 43). For AI, Petkov (2020, 103) has formed an extensive framework for possible AI implementations in accounting, to show that there are several points where there is potential for intelligent automation. The framework is presented in Table 2.

Petkov's (2020, 103) framework has multiple suggestions on automating journal entries with predictions and scanning receipts with OCR. AI capabilities of OCR and NLP techniques are especially used to interpret different kinds of documents in accounting. OCR can be used to transform scanned invoices or receipts to electronic format for further processing with RPA, and NLP can help with analyzing documents for example for investment decisions or classifying financial statement contents. After the OCR and NLP have digitalized the documents, they are categorized and interpreted by machine learning, which allocates the accounts and other necessary accounting information in the accounting system. (Rajeswari & Magapu, 2018, 766; Kamath et al., 2019, 175, Leitner-Hanetseder et al., 547)

Table 2 Part of Petkov's (2020, 103) framework of Potential Accounting Functions to Delegate to an AI

	Human function	AI function
Cash	- Manual Input of Cash Receipts and Payments (use of Journal Entries). - Bank Reconciliation is performed by individuals reconciling outstanding checks, deposits, errors, interest, etc.	- To scan cash payments/receipts into the general ledger - To train AI to perform this reconciliation by analyzing reconciling inputs and generating bank rec report for reviews by humans
Accounts Receivable	- Journal entry prepared based on contractual obligation (be it oral or verbal, followed by invoice). - Journal entry for collection based on receipt of payment. - Journal entry for allowance for doubtful accounts, based on estimations and assumptions.	- These tasks could be delegated to AI. Specifically, the receipt of cash payments via wire transfers or checks at the point of scanning could result in Journal entry in the system (similar to Bank Deposits/Withdrawals).
Inventory	- Journal entry for purchases and sales.	- AI is capable of identifying the movement of inventory (ins and outs) and prepare automatic Journal entries.
Accounts Payable	- Journal entry prepared based on contractual obligation (be it oral or verbal, followed by receipt invoice from vendor). - Journal entry for payment to a vendor.	- These tasks could be delegated to AI. Specifically, the payment of cash payments via wire transfers or checks at the point of scanning could result in J/E in the system (similar to Bank Deposits/Withdrawals).
Unearned revenue	- Journal entry to record an initial liability. - Journal Entry to recognize revenue based on the use	- Delegate to AI by training to analyze budgets and tie the budgets to actual revenue order and its performance.
Prepaid, Investments, PPE	- Journal entry for an initial asset, recording.	- Delegate to AI by training it to scan bank statements and identify such transactions.

As for advantages, there are also some challenges specific to the field. Accounting has still some processes and persistent clients where paper input is used, and these are harder to automate than electric processes. Also, fragmented processes are seen as difficult for automation, e.g., processing invoices differ from one country to another. (Kokina, Blanchette, 2019, 5) Another issue to take into consideration with specifically accounting and finance applications is governance issues, when robots are handling accounting records that would otherwise be restricted to certain personnel (Harrast, 2020, 211). To have full auditability of AI implementations, the performance of the algorithms needs to be transparent and explainable instead of black-box models. Understanding the reasoning behind the AI, also the usability and the confidence of the users increases besides transparency. (Gotthardt, Koivulaakso, Paksoy, Saramo, Martikainen & Lehner, 2020, 99)

2.4.2 The effects of RPA and AI for accounting professionals

As accounting, auditing and taxation are highly regulated fields, it is important to include professionals from that field to work with the more technical personnel when automating the accounting processes to meet all the necessary requirements (Cooper et al., 2019, 21). The accountants however do not need to become professional in coding to be able to form implementations for their customers, since the interfaces and user functionality of the RPA solutions are becoming more sophisticated as the technology becomes more widely used (Smith, 2020, 90). Even though accountants should be trained not necessarily to code, but they should be trained to understand the possibilities of RPA and AI, to be able to identify the processes in their work that have potential benefits from automation for their clients. (Cooper et al., 2019, 21)

In the daily work, accountants will more likely need skills related to data management and security to manage the bots, but also develop expertise on higher value-added work such as data analysis and counseling. (Kokina et al., 2020, 13, Lacurezeanu et al., 2020, 769) Since data-driven decision-making is also very much on the surface at this moment, accountants are expected to produce easily interpretable reports and deeper analysis than before, and this is where they should leverage the technology of RPA and AI. This development will remove job descriptions especially from entry- and lower-level jobs, such as reconciliations, sales and purchase ledger, bookkeeping and income tax reporting. However, at the same time, there will emerge a need for workers who are able to understand the logic behind the algorithms and evaluate the outputs. (Smith, 2020, 17, 27, 94) The skills of technical computing and data analytics have become a standard requirement in accounting education courses (Andiola, Masters & Norman, 2020, 100655).

With RPA and AI, the role of an accountant is moving from traditional accounting skills, such as bookkeeping and information processing, closer to the company's management functions, and soft skills are required to be able to succeed in an advisory role (Meena, 2020, 141; Melnyk et al., 2020, 2414). In a conference proceeding by Peng & Chang (2019, 381) 32 % of the accounting practitioners interviewed said that they have a sense of crisis of the thought of their work being replaced by AI. Contradictory results have been found in studies regarding the effects of RPA on reducing the workforce (Lacity & Wilcocks 201a6, 47; Eikebrokk & Olsen, 2020, 120). Automating economy and accounting tasks with RPA however has led to fewer downsizing of the human workforce than using RPA automation in other functions (Eikebrokk & Olsen, 2020, 117).

2.4.3 Accounting offices as providers of automation

RPA platforms and software are often bought from third-party vendors for the public accounting companies rather than developing the RPA software internally and coding individual bots to suit their client's tasks (Cooper et al., 2019, 6-7). Deloitte (2020) found in their annual global survey on RPA and automation that 64 % of their respondents used AaaS (Automation-as-a-service) in some form. Multiple companies are offering RPA solutions that are already tested and used by other firms and can be delivered almost with "plug and play" (Smith, 2020, 102). On top of the strictly RPA and AI-focused providers, most of the major accounting software vendors (e.g., Xero, OneUp, Intuit, QuickBooks Online, and Sage) are offering AI and machine learning supported automation capabilities for data entry, reconciliations, and more (Su, 2018).

For accounting offices to stay on top of the evolving industry, they need to be able to offer their clients effective automation solutions (Cooper et al., 2019, 28). For monetizing RPA, a Finnish case of OpusCapita Oy names four different business models; License seller, Value-added consultant/reseller, SaaS-provider, and RPA-enabled outsourcing partner (Asatiani, Penttinen, 2016, 73). For smaller accounting offices the value-added consulting and reseller role is relevant, whereas the large multinational firms such as the big 4 of accounting are already providing the RPA and AI as a whole service as SaaS-providers with consulting (Cooper et al., 2019, 28). In

Finnish markets, most of the largest accounting software providers have implemented RPA and AI solutions to ease the repetitive processes in accounting (Accountor Finago 2021; Heeros 2021; Visma Solutions 2021).

For accounting firms, the most profitable angle to approach RPA is to program robots that are adaptable for multiple customers, requiring minimal modifications for customer-specific tasks (Cooper et al., 2019, 22). One interviewed professional by Cooper et al. (2019, 22) stated that realistically 60 % of the RPA solution to a client could be standard tasks and 40 % customer customized tasks. Lacity & Wilcocks (2016a, 45) state that for scalability the most viable option is to place the software robots in the cloud so that they can be copied easily to be deployed across the networks.

Cooper et al., (2019, 16) interviewed the leaders of Big 4 accounting firms about the potential impacts of RPA on the accounting profession. They found that the accounting firms were implementing RPA in all their service areas. However, the RPA had not affected the costs or fees of the services they charge customers, since they all were still in the initial phase with the projects. They were also concerned that the use of RPA and the benefits it brings could drive the competition to “race to the bottom”. (Cooper et al., 2019, 16) As the level of direct labor will decrease in time with more automation, the cost structure of the accounting services will change (Kaya et al., 2019).

3 DATA AND METHODOLOGY

3.1 Research methodology

This research is formed of theoretical and empirical parts. The first one, presented in chapter two, consists of an academic literature review and creates a baseline for the latter discussed in chapter four. The aim of this part is to describe comprehensively the state of the RPA and IPA in accounting scope and form comparison for the results from the empirical part.

The empirical part is a single quantitative study, that consists of analyzing secondary, partly compiled data collected by the case company of the usage records of their software. A quantitative study is defined as a study that presents phenomena through numeric data. The characteristics of quantitative study are large sample size, relations between different mattes, and studying change. The method is especially suitable to measure a current status of a phenomenon. (Heikkilä, 2014, 15-16) In quantitative research, the researcher states a hypothesis, gathers empirical evidence, and tests it against the hypothesis, which is then either accepted or rejected (Blair, 2016, 52). This study aims to examine the measurable effects of IPA implementation through a hypothesis of automation reducing time and manual labor, and therefore the quantitative method was chosen to be a suitable one.

The data for the study is provided by a case company and consisted initially of 71 accounting office customers that use the case company's accounting software. The sample group had a separate IPA solution implemented for their accounting software, and this study examined the usage data of the software before and after the implementation. The end customer companies to take part in the implementation were chosen by the accounting office that does their bookkeeping, and the researcher did not affect the sample participants. All the companies taking part in the IPA solution implementation were considered in the sample before data cleansing.

Analyzing the data is done on data visualization software Tableau and part of data analysis is done in Microsoft Excel. In this study, variables of time used to work on one accounting office customer company and manual labor made are constructed from the raw data. The total time used to work on a single customer is determined by time logged into the customer's account in the cloud-based accounting software and on different sites of it, and manual labor done is calculated as the different site loadings and event actions made in the software while logged into the accounting customer's account. Both variables are also divided into accounting processes, to be able to examine the automated processes separately.

Statistical analysis is done for the data, to study if there is a significant difference between the values on time points of before implementing the IPA solution and after implementing it. Descriptive statistics are used to examine the measures of location and spread of the results on differences between the years, and paired sample t-tests are done to determine if there is a significant difference. Descriptive statistics are quantitative summarized statistics, that are used to describe a pattern in data of a single variable or to explore the relationship between multiple variables (Geher & Hall, 2014, 7). A T-test is usually used on hypothesis testing, to determine how probable it is that the results have occurred by chance alone by comparing the difference between the means of samples. Paired t-test is used for evaluating change in one sample group, whereas an independent t-test is used between groups. (Saunders, Lewis & Thornhill, 2015, 543) A paired t-test is used in this study to measure the change in the sample group for its suitability to the comparison of the same sample group at different times, as well as its robustness for non-normal data when there are at least 20 observations in the sampled groups.

The differences are also compared to a control group's difference in the values at the same time frame. The control group has not had the studied IPA solution implemented, and it was chosen from the overall customer data based on similar parameters with the sample group accounting office such as size and customer count. The difference of the control group's time spent on vouchers and records made per voucher between Q1/2020 and Q1/2021 is also calculated, and after that independent two-sample t-tests are done to determine if there is a significant difference between the two groups in both variables.

The t-tests are used as hypothesis testing, and the results are analyzed and compared to the previous findings from the scientific literature in the following chapters, where analysis, discussion, and conclusions are presented.

3.2 Data collection

The data is collected from a case company, which is a Finnish SaaS provider of accounting software. Their customer base consists of small and medium-sized companies as direct customers, and accounting offices that have multiple companies as end customers. The IPA solution that is studied in this thesis, is especially made for the public accounting companies, to create generalizable automation, so that the accounting offices can utilize the same automation rules for several end customers of theirs.

The IPA solution of the case company is at the time of this study on soft launch phase with one accounting office as the first to use it on their end customers. The hierarchical structure of the affiliated companies is illustrated in Figure 5. The solution is planned to use IPA for automating several processes of accounting. At the time of this study, the processes included were purchase-to-pay and handling bank statements (allocating accounts for events in them and creating journal entries), and other processes were under development. RPA is used in the implementation for creating sets of rules for the processes to fill in information for accounting and create flows for the purchase invoices. Machine learning from the end customers' past data is used for predictions of the accounts and VAT codes. The information from the IPA implementation is then transferred to the accounting software for further processing.

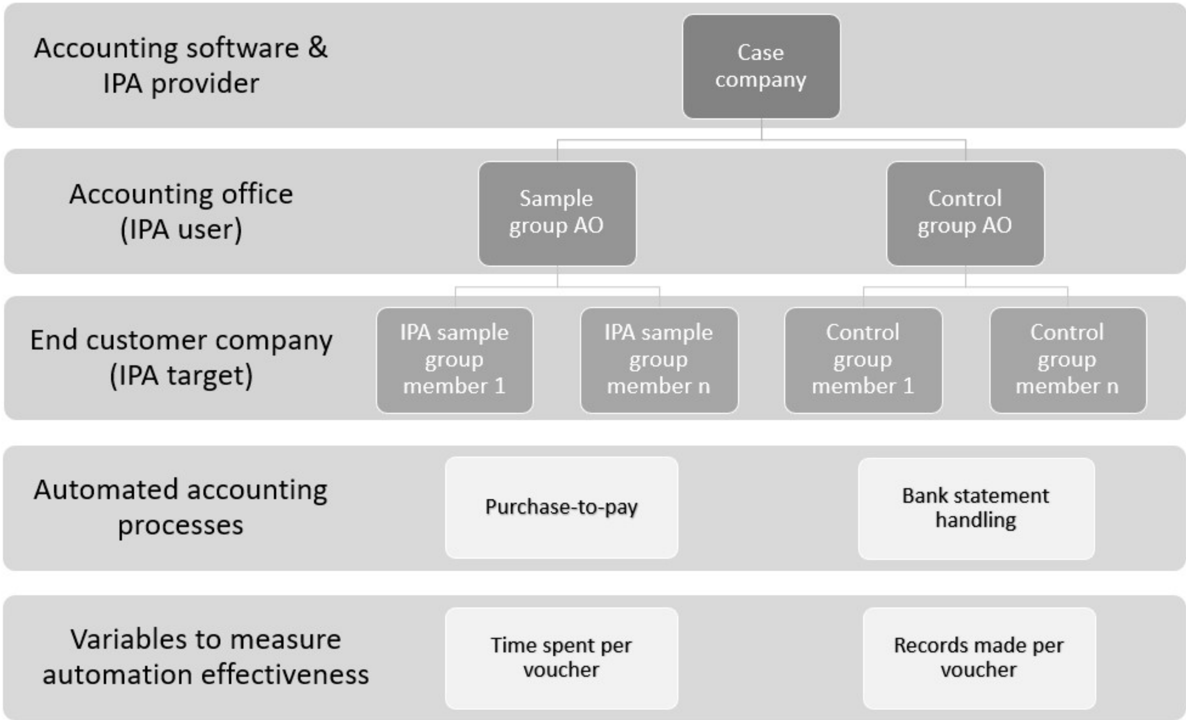

Figure 5 Case company's IPA implementation participants and measures used in this research for automation effectiveness

The data sample for this study was collected from the three first months of the use of the IPA solution, which was Q1/2021. Since accounting has yearly tasks that often occur at the beginning of the year, the comparison period chosen was Q1/2020. For determining the most time-consuming and manual labor-heavy processes, the period was set to be the year 2020 in whole to have a broader scope, but to restrict it to a recent time period, and still include the typical year span that accounting has.

The actual data used in this research is software usage data on the end customer company level. For the time spent and manual actions made on accounting related to the automated processes, the data was recorded by users entering certain sites inside the browser-based software in the end customer company environment, timestamps for the entries, and certain event actions such as saving, or updating. The site loadings and event actions are calculated to present the manual work done in the software and these actions are called further in the study as the number of records. The usage records of the IPA implementations robot user were excluded from the data.

To have a scale for these metrics, a count of vouchers in the end customers accounting was used, so the final variables examined are time spent per voucher, and records per voucher. This will eliminate the normal deviations in the two metrics, so that for example general growth of the end customer company, leading also to more time spent in accounting, is not seen as a failure of the automation.

First, the recorded site addresses which represent different views in the accounting software were examined and categorized for main accounting processes. The same was done for the voucher counts, which had a record of voucher type. From these the time spent and records made in the IPA automated processes are calculated as variables. Simple data perturbation was conducted to the values of the two variables, for corporate confidentiality reasons. The perturbation was done in a way, that left the relationships between the variables, and their variances intact.

The sample data consists of 71 end customers of a single accounting office. The end customers are small and medium-sized businesses, with a median turnover of 400.000 euros in the year 2020. An exploratory data analysis was done on the variables time spent, records made and voucher count per customer was done. The data points that had no sufficient data for both the 2020 and 2021 periods, were excluded from the sample which reduced the group to 58. The missing values were due to the fact that the end customer company might not have been using the software or the studied part of it for one whole year.

3.3 Exploratory data analysis

Exploratory data analysis was conducted on the sample data with Tableau software, which was also used for further analysis to answer the research questions. In the scatterplot in Figure 6 Time spent and Number of vouchers are plotted together, and they seem to have a loose linear relationship with one another. The same applies to the number of records and the number of vouchers, which are plotted in Figure 7. This is intuitive; the more vouchers there are, the more time and records in total will be spent handling them. In general, the bank statement handling is generating fewer vouchers, and therefore taking also less time and creating less records, but staying in the same linear pattern as the pay-to-purchase vouchers. Outliers are not identified in this point, since the measured variable will be the time spent per voucher and the records made per voucher, and the difference between the compared time points.

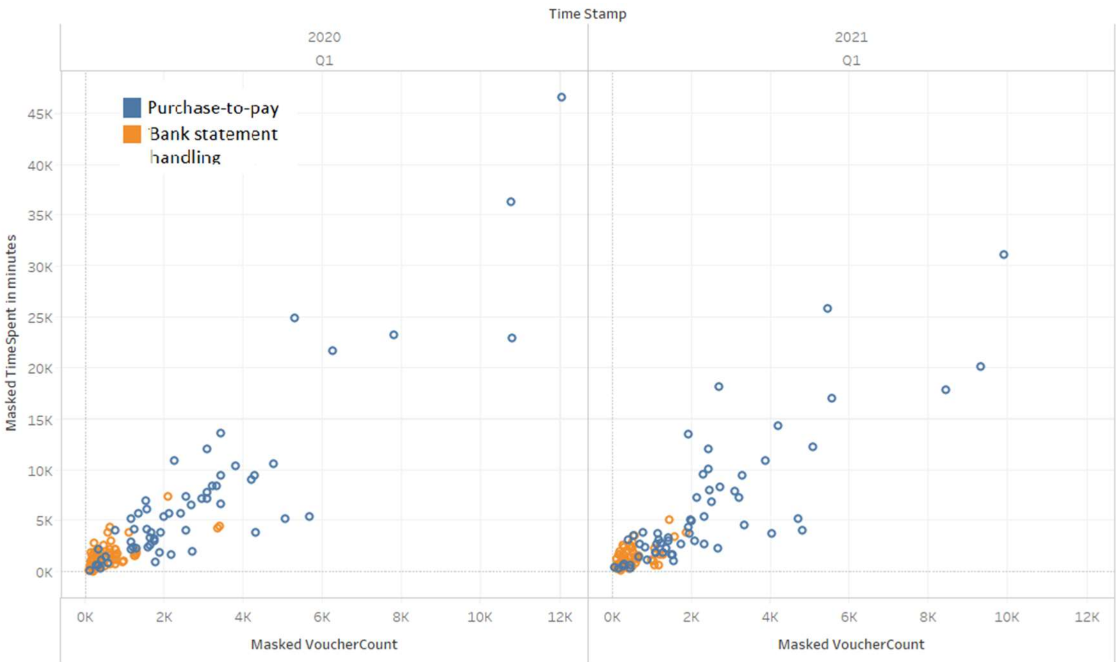

Figure 6 Scatterplot of Time spent and Number of vouchers for Q1/2020 and Q1/2021 of the sample group

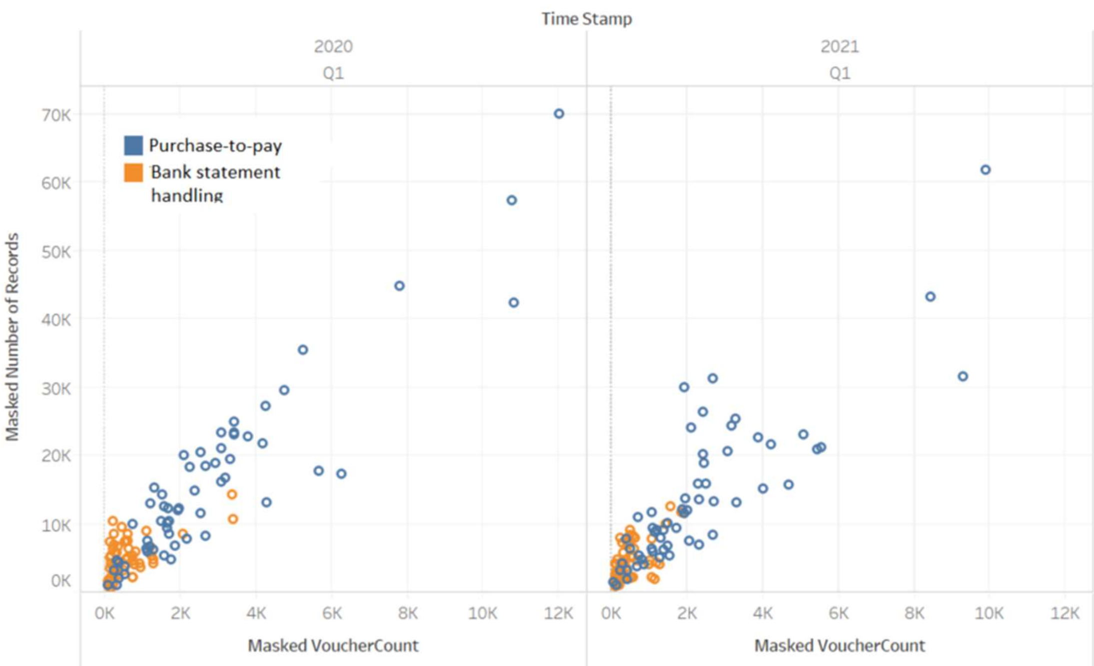

Figure 7 Scatterplots of Number of records and Number of vouchers for Q1/2020 and Q1/2021 of the sample group

Table 3 presents the descriptive statistics of the time spent and vouchers made. There is a general declination on both variables for the year 2021. An explaining factor for the overall lowered number of vouchers could be the global COVID-19 pandemic affecting most of the areas of business from Q2/2020 up to the moment of writing this thesis in Q2/2021. In general, there is a large scale between the minimum and the maximum values, which means that in the sample there are companies that utilize the accounting software at very different levels.

Table 3 Descriptive statistics of the base variables in the sample group after missing values, n= 58

No. of Vouchers	***Min***	***25th percentile***	***Mean***	***Median***	***75th percentile***	***Max***
2020	*343*	*1,771*	*3,554*	*2,849*	*3,934*	*15,442*
2021	*273*	*1,424.5*	*2,919*	*2,184*	*3,766*	*11,494*
TimeSpent						
2020	*428*	*3,758*	*9,314*	*6,307*	*10,577*	*51,047*
2021	*660*	*3,091*	*7,723*	*5,469*	*10,162*	*34,543*
No. of Records						
2020	*4277*	*12,680*	*22,044*	*19,149*	*25,810*	*80,647*
2021	*3913*	*10,270*	*18,705*	*15,498*	*24,253*	*74,256*

After examining the values of the variables in general, the variables time spent, and records made were divided on company level by the vouchers made, to have a scale to the general size of the company's businesses and the growth or reductions in there. The varying levels of the base variables are also taken into account by comparing them to the voucher count. The values of variables time per voucher and records per voucher were then compared for Q1/2020 and Q1/2021, to have a percentage difference between the two time periods. Figure 8 shows the distributions by variable in boxplots. Outliers were identified of the data points that were beyond the boxplot's whiskers, and therefore being outside 1.5 times the interquartile range above the upper quartile and below the lower quartile. As the above side exceeds 100 % change, the data points over that were also called outliers, reasoned with the assumption that over 100 %

change in these variables is more likely caused by external reasons besides the IPA automation added.

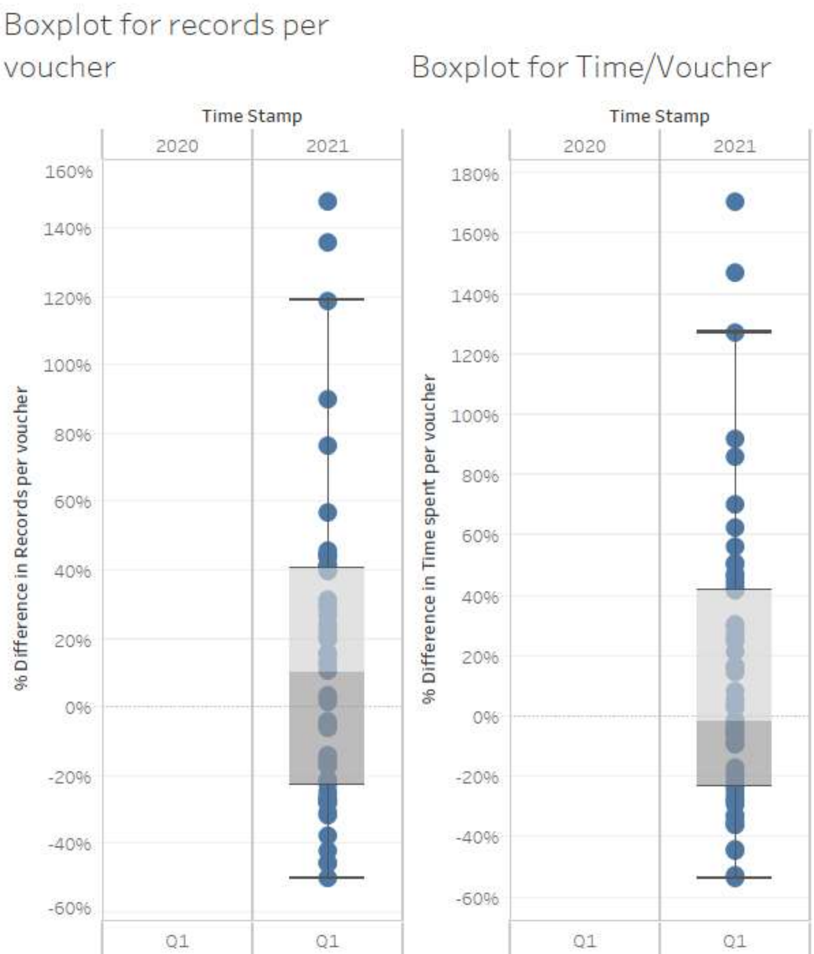

Figure 8 Boxplots of percentage difference from Q1/2020 and Q1/2021 of the variables on the sample group before removing outliers

The automated processes were also examined separately. There were few extreme values of over 300 % in the Time per voucher in bank statement handling which were removed from the sample, as was done also for other outliers based on boxplots' whiskers. Otherwise, the data points exceeding 100 % in the separate processes were left in the sample, since the intention was not to cut too many values that represent the population.

The control group of the accounting office and its customers, which has not implemented the IPA solution examined, was chosen to be equal size before the data cleaning and ended up as n= 45. The control group is chosen to include end-customer companies similar in size and received a similar excluding of missing value data points and outliers than the sample group. The boxplots for the difference in variables can be found in Appendix 1.

4 EMPIRICAL RESULTS AND ANALYSIS

First to study the research question of what are the most time-consuming and the most manual work-heavy processes, the variables Time spent, and Number of event actions were categorized for different accounting processes. The sample used includes data from the sample group for the year 2020. The sectioning was done by going through all the usage links in the software usage data and allocating them to the correct accounting process. The structure chosen follows the partitioning of the processes used in the accounting software. Purchase-to-pay consists of purchase orders, receiving of purchase invoices, allocating accounts and other information, circulation of the invoice, and payments. Order-to-cash consists of sales orders, creating invoices, sending them, and management of receivables. Bookkeeping holds in tasks such as tax-reporting, reconciliation of main ledger, deferrals, closing the periods, and reporting. Payroll consists of salaries, marking working hours, and travel and expense invoices. Bank statement handling is in this study the process of allocating accounts, creating journal entries, and a reconciliation of the bank accounts.

The results are visualized in Figure 9. From the figure's left side we can see that the purchase-to-pay process is the most time-consuming in accounting software, followed by the order-to-cash process. In the histogram, the bank statement handling is differentiated from bookkeeping, since the bank statement process is automized in the case company's IPA implementation, but in a more traditional partition of the processes, those could be combined, making it the second most time-consuming section.

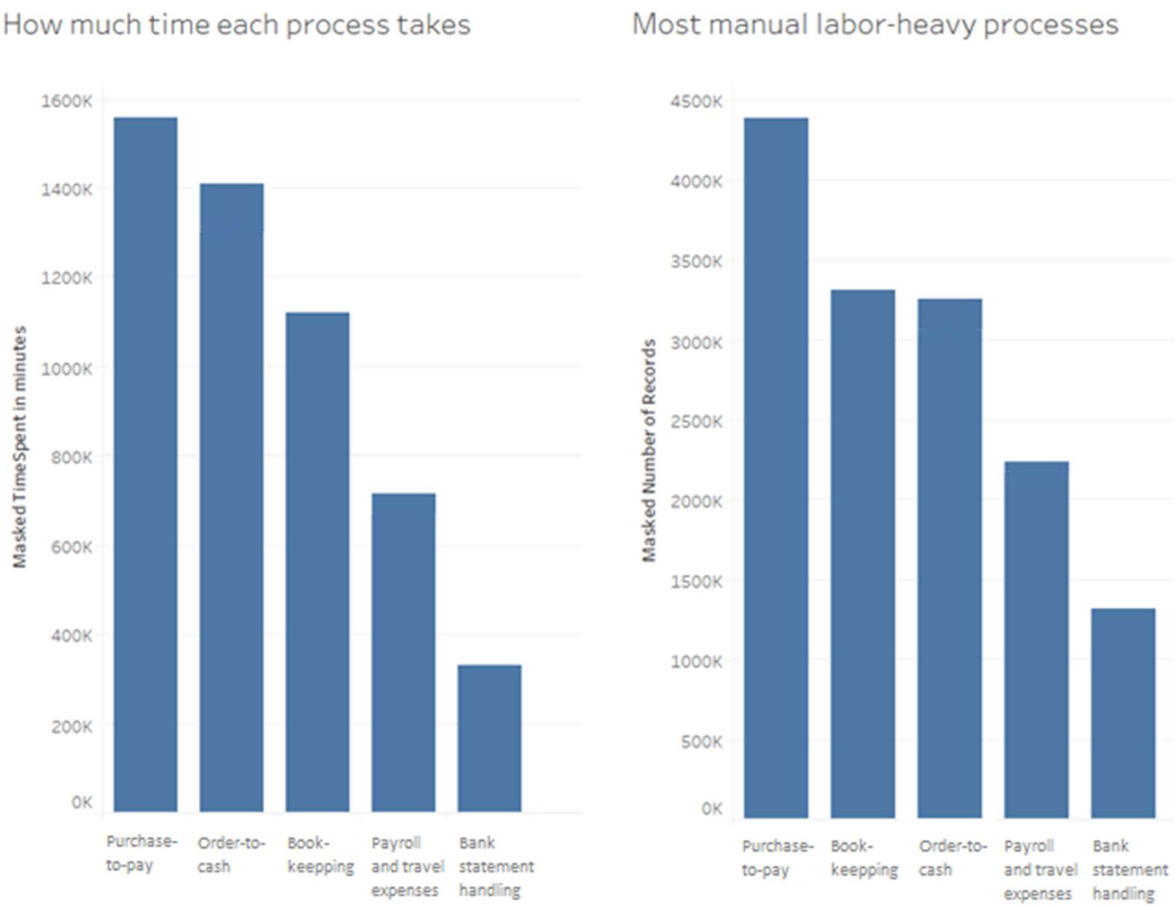

Figure 9 Time spent and records made in different accounting processes in accounting software by sample group in 2020

The manual work done in the accounting software in the different processes is presented on the right side of Figure 9. Based on the data, the purchase-to-pay process and bookkeeping seem to require the most manual work. If we would combine the bank statement handling with the bookkeeping process, it would be in total the most manual labor heavy one. Bank statement handling on itself is lower than the main processes in both variables.

4.1 Time per voucher

The percentage difference of the time spent per voucher from 2020 to 2021 was chosen to be one of the two measures to indicate the effects of the IPA implementation. Figure 10 shows the percentage difference of the values between the years for the whole implementation, and the purchase-to-pay process and bank statement handling process separately. Both of the separate processes are skewed to the higher end, but the end customer companies having high growth in the other process, have slower growth or even decrease on the other one evening the difference for the processes combined lowering the total difference in the processes combined.

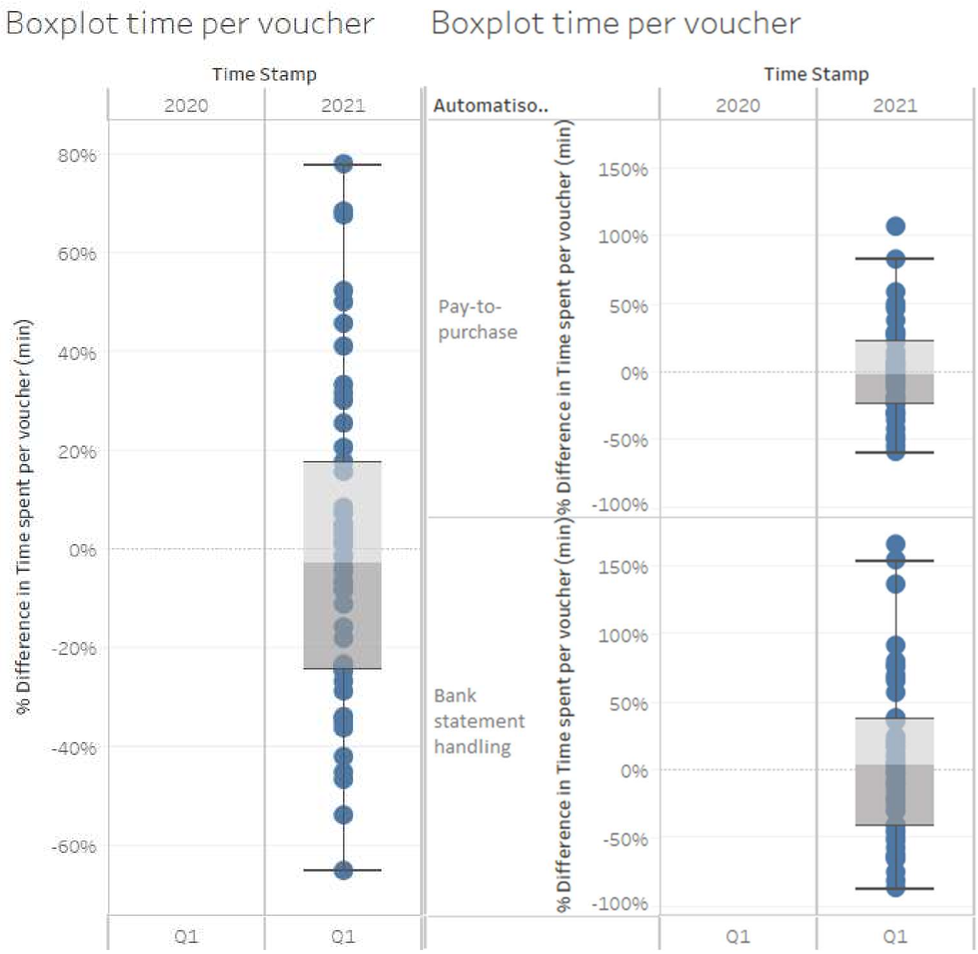

Figure 10 Percentage difference in time spent per voucher on sample group between Q1/2020 and Q1/202.

To look at the values more closely, Tables 4 and 5 show descriptive statistics of the time spent per voucher. In Table 4 the measures of location show some differences in the 75th quartile, where bank statement handling has a higher value than the pay-to-purchase process. This indicates that the pay-to-purchase process has less high growth percentages in the change in time spent per voucher. For both processes separately, the average percentage difference between the Q1/2020 and Q1/2021 stays above zero. The mean of the processes combines is slightly on the negative side, being -0.10 records per voucher, and the numerical difference is below zero on the processes separately and combined.

Table 4 Descriptive statistics, measures of location, n = 50

Time per voucher	**Min**	**25th percentile**	**Mean**	**Median**	**75th percentile**	**Max**
Pay-to-Purchase	-57.64 % -1.80	-24.15 % -0.44	0.82 % -0.08	-0.32 % -0.01	24.16 % 0.45	113.65 % 1.38
Bank statement	-84.73 % -7.02	-38,69 % -0.67	5.05 % -0.48	-3.35 % 0.18	85.38 % 0.85	169.21 % 3.58
Processes together	-64.88 % -2.32	-23.42 % -0.53	-0.14 % -0.10	-3.71 % -0.02	15.92 % 0.31	72.14 % 1.29

Table 5 presents the measures of spread for the percentage difference of time spent per voucher between before and after the IPA implementation. According to the values, the distribution of the data is moderately skewed and slightly platykurtic.

Table 5 Descriptive statistics, measures of spread, n = 50

N	50
Standard deviation	0.3595
Skewness	0.5
Kurtosis	-0.1

The frequency of distribution divided into bins is plotted with a normal distribution curve in Figure 11. Visibly the distribution is somewhat normal. Anderson-Darling test of normality was done for the percentage difference in time spent per voucher values to confirm the normality, with the null hypothesis being that the distribution is normal. The results presented A_2 statistic as 0.46 and a p-value of .2522, which is higher than the 0.1 critical value. Therefore, with a significance level of 10 %, the null hypothesis is not rejected, and we can conclude that the data is normally distributed.

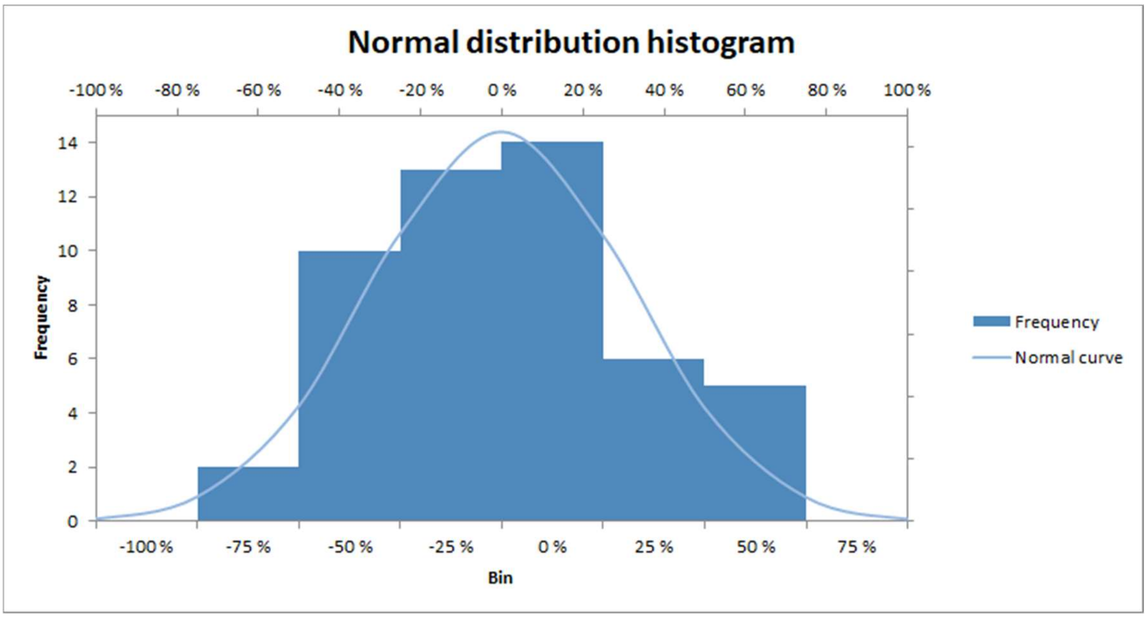

Figure 11 Frequency histogram with normal distribution line of the percentage difference of records made per voucher

For determining the statistical significance, a paired two-sample t-test for means was performed for the values of time spent per voucher on the combined processes before and after the IPA implementation, which measures the overall effect on time spent with the IPA implementation for the accounting office. Paired sample t-test was chosen, since it can be used to compare means from the same group at different times, and for being robust also to non-normal data when the sample size is over 20. The null hypothesis for the t-test is, that the true mean difference is equal to zero. The resulting p-value for two-tailed test is t(49) = 2.02, p = .004321, which is below critical value of .05. From this, we can state, that the null hypothesis is rejected, and there is a statistically significant difference between the values before and after the IPA implementation.

An independent two-sample t-test was done between the sample group and the control group. The results for time spent t(94) = -1.31, p = .1932964, indicate that with the time spent variable the results do not significantly differ from another. The values from the comparison group showed however higher values in the first quartile in the time spent per voucher, wherein the sample group it is -23.42 % and for the control group it is -0.10 %.

When looking at the processes individually, they have higher variances and means than the processes as a whole. The purchase-to-pay process has 49.02 % of its values with negative growth, and bank statement handling has respectfully 56.86 %. The proportion of the negative value indicates that there is a signicant group of companies that have had advantages from the IPA implementation. For identifying these companies, a correlation was run between the results of the variables and few metrics. These are presented in Table 6. However, there were no significant correlations found in these metrics, and therefore it would require more research, to identify the end customers, which had success in reducing time spent and manual work done in the pilot phase of the IPA implementation.

Table 6 Correlation between the change in studied variables and chosen metrics

	Personnel count	**Company turnover**	**Number of accounting dimensions**	**Number of e-invoices**
Change in time spent per voucher	0.035235	-0.01198	-0.18177	-0.12718
Change in records per voucher	0.030598	-0.04455	-0.01851	-0.06688

4.2 Records per voucher

The percentage difference of the records per voucher from 2020 to 2021 was chosen to be the second of the two measures to indicate the effects of the IPA implementation. The variable describes the manual labor made in the accounting software, as it is composed of the site loadings and events made inside the software, the “clicks” made so to say. Figure 12 shows the percentage difference of the values between the years for the implementation as a whole, and the purchase-to-pay process and bank statement handling process separately. Both of the separate processes have more growth values than decrease values in the distribution of percentage difference.

Figure 12 Boxplots percentage difference of records per voucher between Q1/2020 and Q1/2021 on the sample group

The descriptive statistics for records per voucher are shown in Table 7. For both processes, as well as the processes together the mean stays above zero, which means that the general null hypothesis of the change being zero or over, is not rejected. The majority of the end customer companies have not had a decrease in the manual labor with the IPA implementation in the first three months of the usage, even though there is a notable portion of the data points with negative differences also. Bank statement handling had an average of numerical -1.71 fewer records made per voucher, whereas the other values are above zero.

Table 7 Descriptive statistics, measures of location, n = 50, percentage difference between and the numeric difference Q1/2020 and Q1/2021

Records per voucher	**Min**	**25th percentile**	**Mean**	**Median**	**75th percentile**	**Max**
Pay-to-Purchase	-55.09 % -4,97	-18.99 % -1.02	9.36 % 0.53	8.48 % 0.53	31.98 % 1.52	129.53 % 1.30
Bank statement	-81.34 % -36.26	-40.90 % -3.13	11.59 % -1.71	13.52 % 1.21	28.89 % 3.82	154.14 % 1.54
Processes together	-49.98 % -8.5	-24.53 % -1.49	4.71 % 0.13	3.29 % 0.21	38.34 % 1.54	89.82 % 4.83

Table 8 presents the measures of spread for the percentage difference in records made per voucher between before and after the IPA implementation. The skewness of 0.3 would suggest that the distribution is approximately symmetric, whereas -0.63 kurtosis suggests that it is platykurtic.

Table 8 Descriptive statistics, measures of spread, n = 50

N	50
Standard deviation	0.3345
Skewness	0.3
Kurtosis	-0.63

The frequency is plotted with a normal distribution curve in Figure 13. As for visually observing that the distribution is not necessarily normal, the Anderson-Darling test of normality was conducted for its abilities to be robust for non-normal data. The test was done on the percentage difference in records made per voucher values, and the results showed A_2 statistic as 0.66 and a p-value of .0807. With a significance level of 10 %, the null hypothesis of normally distributed data is rejected. This can be caused partly by the limited sample size of 50. This level of non-normality is however tolerable in real-life data when choosing further tests with reasonable robustness to non-normality.

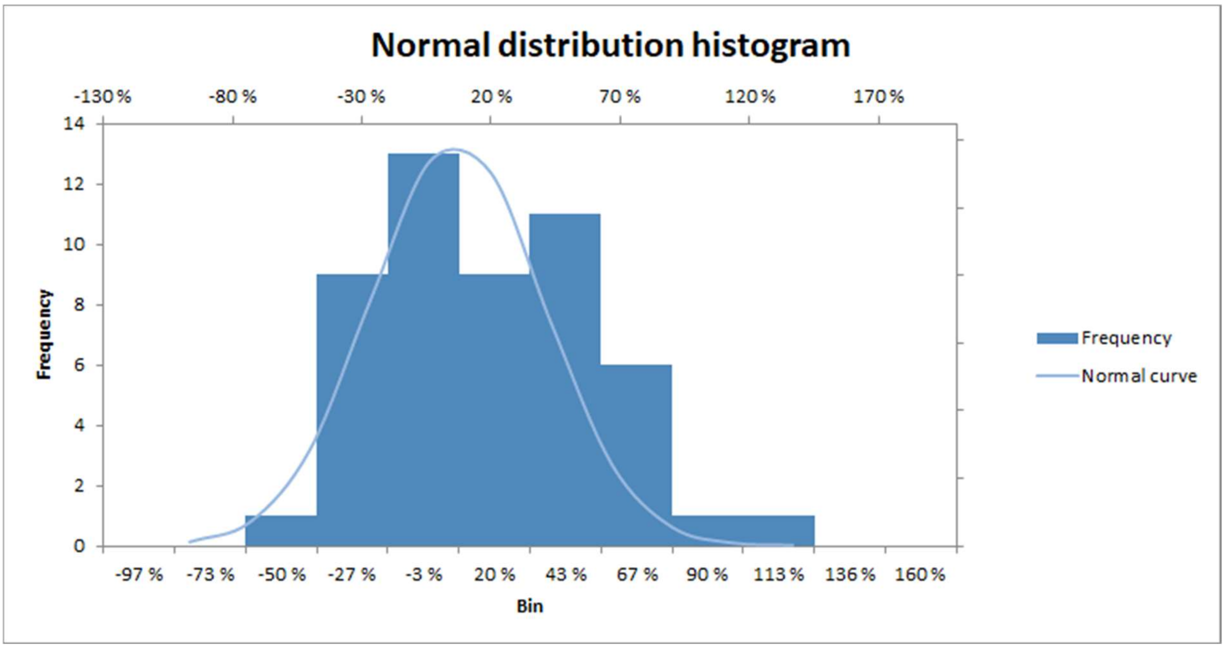

Figure 13 Frequency histogram with normal distribution line of the percentage difference of records made per voucher

A paired two-sample for means t-test was conducted to find the statistical significance of the change in values of records made per voucher on the combined processes before and after the IPA implementation. The hypothesis for the t-test is, that the true mean difference is equal to zero. The resulting p-value for two-tailed test is $t(49) = 2.9$, $p = .7169747$, which has the p-value over critical value .05. The null hypothesis is not rejected, and the difference between the years is not statistically significant.

The amount of manual labor through site loadings and events made in the accounting software on the average per customer rose 0.13 units in quarter, which is not practically significant. As for processes, the purchase-to-pay process had 37.25 % of the values with desirable negative growth, whereas the bank statement handling had 44.23 %. Bank statement handling's mean and median were higher than in the purchase-to-pay process.

Boxplots for distributions and descriptive statistics for the control group can be found in Appendix 1. For comparing the sample group and control group, an independent two-sample t-test was run. The results for the difference in records made had $t(94) = 1.51$, $p = .135532$, indicate with a critical value of 0.05 that with the records made the means of the results do not significantly differ from another.

4.3 Analysis and discussion

As selecting the processes that benefit the most from the automation, is one of the most important things for the successful implementation of RPA, it is beneficial to be able to identify them. (Matthews & Greenspan, 2020, 91). The most suitable tasks for RPA according to the literature are tedious, time-consuming, repetitive, frequent, rule-based, high-volume, prone to error, and not available for API (Anagnoste, 2013, 307; Leshob, Bourgouin & Renard, 2018, 53; Taulli, 2020, 88). The frequency and the volume are measured in this study as the records made per voucher in the accounting software, whereas the amount of time spent per voucher is measuring if the process is time-consuming.

The most time-consuming and manual work requiring processes according to this study are the purchase-to-pay process and bookkeeping. In the results, the bank statement handling has been presented as its own since it is one of the two automated processes studied further in the thesis, but in general, it would be considered to be part of the general accounting. Also, the order-to-cash process is one of the highest in both time spent per voucher and the records made per voucher, whereas the payroll is notably lower in both metrics. According to previous literature, the most advantage from RPA and AI could be gained in human resources, purchase-to-pay and order-to-cash, journal entries, and bank reconciliation. General ledger was interestingly named to be one of the least automatable, which could be reasoned for its fragmented processes. In the studied accounting software, human resources processes are limited to payroll and work hour entries, so that process is not fully comparable, but otherwise the processes automated with the studied IPA implementation are similar to the ones mentioned. (Cooper et al., 2019, 19)

To mirror the AI part of the case company’s IPA solution to earlier publications, Petkov's study (2020, 103) name’s both bank reconciliations and journal entries based on the purchase-to-pay process on the framework as a potential ground for automation, as well as the similar journal entries for the order-to-cash process. Payroll is not mentioned in the AI framework, and based on benefit potential with time spent and manual labor done in the software, it should not be the first to be automatized.

Order-to-cash has a lower time spent and manual labor made in the accounting software than the two automated processes in the IPA implementation, but would also have the potential for automation compared to payroll. The other criteria of the suitability of the task to be automated with IPA, such as if it is rule-based or prone to error, should be considered too when making plans for automation.

The time and work savings generated with process automation had very versatile estimates on the previous literature, but they did all state having such benefits from the successful implementations of RPA or IPA solutions (Aguirre & Rodriguez, 2017, 5; Burgess, 2018, 57; Cooper et al. 2019, 16; Lacity & Willcocks 2016b, 18; Moffitt et al., 2018, 8; Osman, 2019, 71; Petkov, 2020, 102; Suri et al. 2017, 90; Willcocks et al. 2015, 4-5). The results from this study, visible summarized in Table 9, did not show overall similar benefits when comparing the results of the same sample group before and after the IPA implementation.

Table 9 Effectiveness of case company's IPA implementation on first three months

<table>
<tr><th></th><th>Average difference between Q1/2020 and Q1/2021</th><th>T-test p-value (95 % confidence level)</th><th>Significance</th></tr>
<tr><td rowspan="2">Time per voucher</td><td>-0.14 %</td><td rowspan="2">.004321</td><td>Statistically significant</td></tr>
<tr><td>-0.1 minutes</td><td>Practically not significant</td></tr>
<tr><td rowspan="2">Records per voucher</td><td>6.59 %</td><td rowspan="2">.7169747</td><td>Statistically not significant</td></tr>
<tr><td>0.13 units</td><td>Practically not significant</td></tr>
</table>

The results for time saved with the IPA implementation show average of -0.14 % difference between the Q1/2020 and Q1/2021, and difference of -0.1 minutes. The difference between the years is statistically significant, but on the other hand, the difference between the sample group and the control group was not. As for practical significance, the time used on accounting software per quarter reduced on average 0.04 minutes per voucher per end customer company. The average number of vouchers per customer in the sample group was 416.98 in the Q1/2021, which would make the time saved per average accounting office customer in the case 43.78 minutes (0.73 hours) in a quarter. Using the hourly pay for an accountant calculated in the theory section, the per end-customer value of the IPA implementation would be 0.73 hours x 22.57 € = 16,47 € per quarter. This might have practical significance if the number of customers is high, but the sum itself is relatively low.

As for the manual labor, the percentage change in the difference for records per voucher was 6.59 %, and the average difference in records made was 0.13. For the average of 416.98 vouchers per end customer, that would make 54.2 records more in quarter. The percentage difference is not statistically significant, and neither is the reduction in the number of records. There was growth in the records per voucher in the control group also (16.35 %), so even though the t-test regarding the difference between the sample and the control groups results were insignificant, it could be deducted that the growth in the records made is not probably caused by the IPA implementation, but is generated by other reasons.

Compared to the average of 3 FTE's saved on a yearly basis or the that the earlier research suggests, the results in this study, therefore, do not overall correspond. There was statistical significance in the difference of time spent on Q1/2020 and Q2/2021, and the mean of the results is a negative one, but the amount of the reduction is relatively small. One noteworthy point is, that the data was gathered from the first three months of the implementation, which still include checking the results of machine learning predicted data and creating the rules for RPA. The automation solution itself had a build, that might lessen the reduction of time recorded and records made, as the accounts and VAT codes were automated, but the accounting dimensions (such as cost pools) were not. This means that if the end customer is using some accounting dimensions, the accountant needs to open the purchase invoice or bank statement journal entry and add the dimensions there manually. This can also explain the slight difference between the time spent per voucher and the manual work done per voucher, as the time will be saved when part of the information on the purchase invoice has been filled automatically, but opening, filling in the rest of the information and saving the invoice creates nearly the same amount of “clicks” as without the IPA implementation.

The research period might have been too early on the implementation’s usage cycle in general, since the greatest benefits from RPA are experienced with long-time usage (Eikebrokk & Olsen, 2020, 124). The study by Willcocks et al. (2015, 10) presented their case company Xchanging to take nearly a year to automate the first four processes. In this study’s case, it should be noted however that developing the IPA implementation’s functions and the UI has already been done before the scope of this study, and the studied results are measured of the mere effects of the implementation’s automated filling of information (the accounts, VAT-codes, and voucher flow), on the usage of the accounting software. The creation and management of the RPA rules and predictions with AI were done in separate UI, and the time spent on those was not considered in this study.

The differences to the control group were not statistically significant on either of the variables, even though the difference in the percentage differences were around 7 % in both variables. The results of t-tests could be explained with high variability on the results, that varied from +94.07 % to -64.88 %. Overall, the control group had more increase in the change between 2020 to 2021 in both variables than the sample group, and especially the 25^{th} quarter having notably lower values in the sample group.

The bank statement handling seems to have relatively more advantages from the IPA solution than the purchase-to-pay process. The mean in percentage differences between Q1/2020 and Q1/2021 is higher in the purchase-to-pay process in both variables, but the proportion of the companies that had a declination on the examined variables as well as the actual effect on minutes or records made had better results in the bank statement handling. A slightly greater difference was found in the time spent variable, than in the records made.

In the data at the end customer company level, the differences had wide variation between the processes. Where a company had reduced time per voucher in bank statement handling, the same company could have grown in manual events made per voucher. This would indicate that the different processes are suitable for automation in different companies.

4.4 Reliability and validity

To assess the validity of a study, the results and studied material, and therefore the whole study needs to be taken under consideration to be valid. The validity of a study is based on how comprehensively the used research method is able to measure the subject that is being researched. In addition, validity is affected by how well the gathered material corresponds to the studied phenomenon. Reliability measures the quality of handling and analyzing the data. Reliability also describes the repeatability of the results, and if would most of the evaluators end up with similar results. (Anttila 2014; Hirsjärvi et al. 2009)

The timing of the study (Q1/2020 - Q1/2021) could have some effects from the global pandemic of Covid-19, which had a generally noticeable impact on many areas of business. However, the study is measuring the time spent and work made in accounting software in relation to the number of accounting vouchers made, so the impacts on the size of the end customer companies' revenues should be phased out.

The collecting of the data should be repeatable since it is comprised of user data derived straight from the case company's software. The data itself should not, therefore, have any errors in measurement since it is withdrawn from the system. There should not be any effect of the data being distorted for the reasons of gathering the data for the study. The end customer companies chosen to take part in the IPA implementation, have been chosen by the customer, for being suitable for such automation in the first place. The customers have been using the studied accounting software also before the implementation, and have therefore already very digital accounting and possibly had prior automation.

The data for this study was gathered in a very early stage of the IPA implementation, which includes still a lot of evaluating the results and teaching the IPA implementation correct automation rules. This may affect the results in a way, that time spent and especially the records made on the accounting software has not reduced, since the evaluation of the results is still done in there, even though the automation would allocate part of the accounting information in the IPA implementation app.

5 CONCLUSIONS

5.1 Summary and conclusions

RPA and AI are a hot topic in the business world and especially among the accounting and financial management fields. The market segment of RPA has been growing rapidly in the last few years and is just starting to reach the masses. The research around the topics of RPA and IPA has also risen alongside the interest around it, most of it relying on qualitative interviews of the users and implementers of the technology. This study aimed to examine the subject through quantitative data.

To create a foundation for the results from the data analysis, the first research question however was about the benefits and time savings that were gained from IPA implementations according to previous literature. Most of the found literature was regarding RPA-solutions but they were also applicable for IPA since the former is used as a base for the latter. The most obvious benefits from RPA and IPA come from time and human labor savings when the robots free workers from time-consuming, repetitive, and mundane tasks for more strategic or analytical work. RPA helps to automatize the repetitive processes and tasks that are seen as lower value work, and adding AI to the automation solution, decision-making and handling unstructured data are also possible.

The current scientific literature suggests varying levels of time savings gained, with 3 FTE's per implementation mentioned several times and the general statement being that successful RPA implementation will lead to time savings on automated processes. Apart from plain costs savings through saved labor costs, RPA can help also to improve employee satisfaction and productivity. When the robots perform the tasks, they are done promptly and in the same way, every time, which improves accuracy, consistency, and reliability. Automation also creates flexibility in the workforce, being easier and quicker to scale once set up, than hiring and training new staff.

To close on the second research question, the supporting question of "Which of the accounting processes seem to be the most time consuming and manual work-heavy according to case company data?" was answered first. For this study, the usage data from the case company's accounting software was analyzed. The usage links generated from cloud-based accounting software were categorized as different accounting processes so that the time spent on them and manual labor ("clicks") made on them could be compared to one another. The sample group's data on the year 2020 shows, that the pay-to-purchase process is the most time-consuming as well as most manual labor heavy of the differentiated accounting processes, followed by general bookkeeping, and order-to-cash process. Payroll is distinctively lower on the comparison with both variables than the first three. These results mirror the previous literature and would implicate that a good place to start considering robotic process automation for a company is the pay-to-purchase process.

The second supporting research question was about which processes had the highest advantages from the case company's IPA implementation. To answer this and the main research question, two variables of time spent per voucher, and records made per voucher (representing the manual labor done) were constructed from the usage data, and the difference between time before implementing the automation and time after it was compared. The comparison was done on a sample group of 50 end customer companies' data. The results show that the bank statement handling had more time saved, and less records made on average, with the IPA implementation than the purchase-to-pay process. In relation to the total time spent and records made per process, the bank statement handling is over three times smaller process than purchase-to-pay, but the relative benefits are greater.

As the various type of automation solutions are becoming part of everyday work in accounting through being more accessible in the accounting software and external integrations, the struggle for accounting firms is creating and maintaining RPA rules for multiple customers. Therefore, an RPA solution that has generalizability in the rule sets could be the most profitable solution for the sector (Cooper et al., 2019, 22). In the case company's IPA implementation, one of the goals was to provide the accounting office solution to this. When studying the processes' data on the whole sample group, the benefits gained can be examined at the accounting office level.

Therefore, the main research question sought to answer what time and manual work savings were gained from IPA implementation on accounting based on the data of 50 public accounting customer companies. The results for time spent per voucher showed a decrease of 0.14 % as the mean percentual difference per end customer between the years. In minutes the average difference per customer was -0.1 minutes per quarter, which is not a practically significant amount of time, even though the differences in the means were statistically significant. For the records made, that represented the amount of the manual labor, the mean percentual difference was an increase of 6.59 %, and in numerical terms 0.13 records more in Q1/2021 than in Q1/2020. These values are not significant either. The control group faced a greater increase in the records per voucher variable. Based on the results the null hypothesis of the difference in time spent and manual labor done per voucher being zero or greater is not rejected. The hypothesis of RPA with machine learning applications reducing the time and manual work required for accounting was not fully supported, even though there were end companies that had desired results. This disagrees with the results from previous literature for successful RPA and IPA projects.

Implementing the RPA or IPA solutions can have its difficulties, and according to Moffitt et al. (2018, 9), even 30-50 % of the projects do end unsuccessfully. According to the previous literature, the difficulties can be caused by unrealistic expectations, insufficient resourcing of the project, long project time estimates, challenges in operations and execution, and poor change management. (Moffitt et al., 2018, 9; Eikebrokk & Olsen, 2020, 123) In this case, the main stumbling block however might have been the timing of the study, the research period being too early on the implementation's usage cycle. The data was collected from the three first months of the implementation being in the production for the sample group members. This period involved still a lot of checking and proofing of the results of the implementation and forming a accountants' trust in the automation to perform reliably without human intervention. Since the effects were measured through the clicks made and time spent, these check-ups might distort the interpretation of the automation results. The companies chosen for the case company's IPA process were also most likely suitable for automation to start with and probably also had some previous automation in use, which also can fade out the gained benefits shown in the results obtained in this research.

The conclusion from the results could be, that the first three months of using the case company IPA implementation did not generate yet the hoped effects. There were also great differences inside the variable on the differences between the time points. If the studied group had been more homogenous the results might have been more supportive of the hypothesis. Identification of the characteristics of the companies that had the most benefits from the automation would be the recommended next step with the case-company data.

To sum it all up, the most automatable processes in this study were similar to previous literature. The purchase-to-pay process and general accounting processes, followed by order-to-cash were the most time-consuming and manual labor heavy in the accounting software. From the automated processes of the case company implementation, the bank statement handling had more benefits, but in the comparison of all processes, it holds a relatively small role. The time savings and reduced manual labor suggested by the previous literature were not detected in this study.

5.2 Limitations and further research

The most considerable limitation of this research is its generalizability since it is a case study on a single IPA implementation. However, the automated processes in this project are the most common ones for RPA solutions in accounting (Cooper et al., 2019, 19). In addition to being a single IPA implementation, the sample consists of end customers of one public accounting firm, which could have some company-specific working habits. This study considers only the Finnish accounting environment, and the results are therefore not necessarily directly applicable to other markets.

This study was done as a quantitative study and with numeric data. Further quantitative research could be enhanced by gathering qualitative material on the accountants' experiences regarding the IPA application under study. The limitations of this study could be addressed by conducting a similar study with more time between the implementation phase and the data collection. In general, even though the studies of RPA have increased, there are still very few on IPA. As the automation method increases in popularity, there could be more opportunities also to conduct research on it. Comparing the effects generated from RPA and IPA could also be an interesting angle for research in the future.

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APPENDICES

Appendix 1 Distribution and descriptive statistics of the control group

Table 10 Descriptive statistics of the control group of differences between Q1/2020 and Q1/2021

	Min	***25th percentile***	***Mean***	***Median***	***75th percentile***	***Max***
Records per voucher	*-32.81 %* *-6.34*	*-4.40 %* *-0.56*	*16.35 %* *1.8*	*11.03 %* *1.35*	*30.77 %* *3.07*	*85.82 %* *15.96*
Time per voucher	*-55.63 %* *-3.75*	*-13.80 %* *-0.44*	*8.38 %* *0.09*	*7.41 %* *0.14*	*24.42 %* *0.74*	*87.67 %* *4.33*

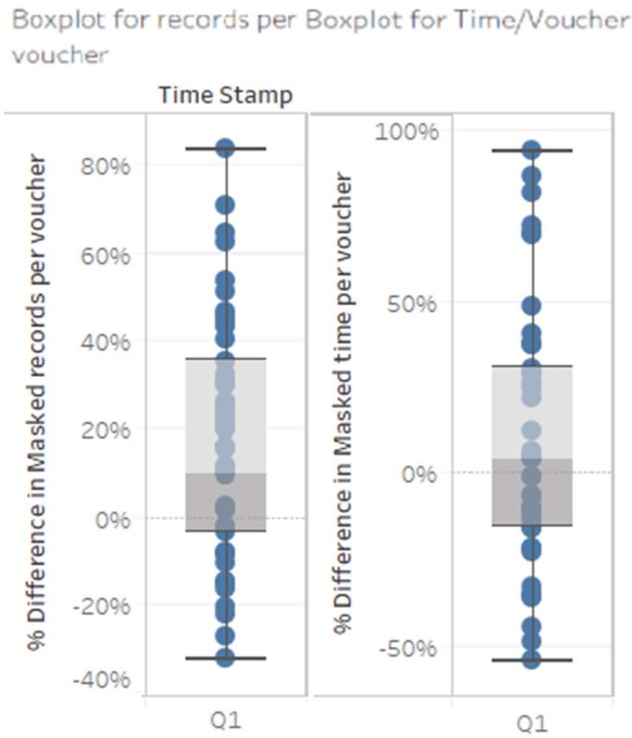

Figure 14 Boxplots of the control group's percentage difference in records per voucher between Q1/2020 and Q1/2021