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Intelligent Process Automation

Building the bridge between Robotic Process Automation and Artificial Intelligence

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Intelligent Process Automation:
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by

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Master of Science Thesis TRITA-ITM-EX 2019:423
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Intelligent processautomation:

Att bygga bron mellan processautomation och artificiell intelligens

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Abstract

Process Automation has the potential to yield great benefits for companies and organizations, especially in the financial services industry where companies are information-intensive and experience rich data flows. This has mostly been done through Robotic Process Automation (RPA), but the increased maturity of Machine Learning algorithms has increased the viability of combining classic RPA with Artificial Intelligence, leading to Intelligent Process Automation (IPA). However, there is a set of challenges embedded in the transition from RPA to IPA. These challenges need to be dealt with in order to ensure that the benefits of the new technology can be harvested.

The aim of this research was to identify this set of challenges that the companies will face, as well as provide guidance to what preparations that need to be made before IPA can be implemented in full scale.

The research was conducted as a theory building case study at a large Swedish bank. An empirical study was conducted, consisting of interviews with researchers, as well as automation professionals and R&D at the case company. The findings of the empirical study and previous research on the area were combined and condensed into a guiding framework for organizations wanting to adopt IPA.

Keywords: RPA; Robotic Process Automation; Artificial Intelligence; intelligent automation; IPA; cognitive automation; change management; digital transformation

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Sammanfattning

Processautomation har potentialen att ge stora fördelar för företag och organisationer, speciellt i finansbranschen där företag är informationsintensiva och har stora dataflöden. Detta har huvudsakligen gjorts med Robotic Process Automation (RPA) men den ökade mognadsgraden av maskininlärning har snabbt förbättrat möjligheten att kombinera RPA med Artificiell Intelligens (AI) för att därmed möjliggöra Intelligent Process Automation (IPA). I övergången från RPA till IPA uppkommer däremot en del utmaningar och problem som företag måste hanteras innan potentialen med dessa nya tekniker kan förverkligas.

Den här forskningen ämnar att identifiera de utmaningar som företagen kommer ställas inför samt ge vägledning för vilka förberedelser som företagen måste genomföra innan IPA kan implementeras fullskaligt i organisationen.

Forskningen genomfördes som en teoribyggande fallstudie på en stor svensk bank. Den teoretiska grunden samlades in genom en omfattande litteraturstudie och en empirisk studie bestående av intervjuer med forskare samt automationsutvecklare och FoU på banken. Resultaten från litteraturstudien och empirin kombinerades och kondenserades till ett vägvisande ramverk för organisationer som vill implementera IPA.

Nyckelord: RPA; robotic process automation; processautomation; automation; artificiell intelligens; intelligent automation; IPA; kognitiv automation; förändringshantering; digitalisering

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Markus Bellman

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1 Introduction

1.1 Background

Some claim that we are on the verge of a major digital disruption caused by Artificial Intelligence, and enabled by the increasing availability of data in combination with improved processing power. This paper aims to dissect what real opportunities these new techniques present within automation and how organizations should prepare to efficiently implement the technology in their current processes. This research will be conducted in cooperation with the *Automation department* at a large Swedish bank. The Automation department of *the bank* is a great fit for this research as they have rigorous experience from dealing with *Robotic Process Automation* (RPA) development at a large scale. Furthermore, cooperating with a large player in the financial services industry should enable generalizability among the emerging theories from the research. Additionally, *the bank's* Automation department is currently in a phase where they have obtained comprehensive knowledge of RPA, and in order to take their automation efforts to the next level they are in need of new technology, such as AI. However, there are a couple of challenges that need to be dealt with, which implies that a case study with the purpose to develop a guiding framework for *Intelligent Process Automation* (IPA) implementation is highly relevant for *the bank* today.

RPA is software that automates computer programs to carry out tasks according to a set of rules that are in line with the business processes. With the addition of emerging technologies within *Artificial Intelligence* (AI), RPA can be further developed to also carry out tasks requiring human cognition by learning from experience. This combination of techniques is commonly referred to as IPA, and the implementation of these methods have the potential to entirely replace several functions in both front, middle and back office. With advancements like these comes several challenges, both regarding the technical feasibility and human resources. This area of research is very new, and from an implementation point of view, many companies are yet to implement RPA. This makes a disquisition of the bridge to the next level of intelligent robotics particularly interesting. AI and *Machine Learning* (ML) are some of the most prominent buzz-words of this decade. Almost every updated firm throughout all industries have at least heard about the concepts. However, many of the companies are far from actually employing it in their organization, and a reason for that is that the relationship with AI often does not progress beyond the point of hearing about it. In order to make efficient use of the technology, and to not waste money and time trying to implement something that just conceptually sounds great, it is vital to build a sufficient foundation of knowledge from which successful AI implementation can arise (Mohanty and Vyas, 2018).

As of today, large technology companies such as Google, IBM and Amazon, have come far in the development of accessible AI technology through cloud based ML platforms, which has made the technology more available. Although some of the technology is in place, there is still a huge portion of work left to do for organizations that want to implement the functionality, as the technological advancements within AI is on the verge of a complete digital disruption of the market (McKinsey, 2017b). In order to stay competitive in this rapidly changing environment, it is vital for organizations to be well prepared for the disruption, both regarding organizational structure and human capital, but also technical feasibility within the firm. There are many changes that have to be made, and decisions that have to be taken, when planning for AI implementation. Furthermore, the alternatives are plenty, which can delay the process, as companies simply do not know where to begin to realize the transformation optimally. Hence, organizations throughout all industries that employ RPA in their business model could indeed benefit from having a clearly defined path in place before initiating the implementation process.

1.2 Problematization

For RPA in general, and *the bank's* Automation department in particular, AI and ML is the natural next step to take in order to further optimize the functionality and width of services of the robots. As previously explained, there are certain preparations that have to be conducted as a part of the implementation, and in order to proceed with these efficiently, there is a need of a guiding framework. Every aspect of the transition needs to be developed and employed with precise timing, and in order to mitigate the risk of unnecessary spending on insufficient solutions it is vital to have this plan in place before the work is initiated.

1.3 Purpose

The purpose of this paper is to enhance the understanding of how to enable AI to contribute to automation in the financial services industry. This will be done by presenting a framework covering what organizations should do to prepare for an efficient implementation of AI into their existing automation efforts.

1.4 Research Question

The research question was formulated as follows:

How can organizations prepare for an efficient implementation of AI in the field of Robotic Process Automation for financial services?

This research question was split into the three sub-questions below:

- How should the automation department prepare the workforce for new technology such as AI?

- What strategic and technical preparations are necessary for an efficient implementation of AI into automation?
- What pitfalls should be avoided in order to get a seamless transition from automation to intelligent automation?

Relating to the last sub-question, two hypotheses have been formulated that draw on previous experiences from research on RPA and AI.

- Measurability will be an even more prevalent challenge within IPA compared to RPA.
- The issue of hype and unreasonable expectations on AI will spill over to IPA.

1.5 Delimitations

As touched upon in the Purpose section, the main topic of this thesis is the preparation of fitting AI into automation efforts, but not to go in-depth regarding technical aspects of the AI algorithms and techniques that are subjects of interest. As AI platforms are becoming more of a tailored service package offered by tech giants, the challenges in AI implementation today are not limited to developing algorithms, but also include preparing the organization to make use of these services efficiently. Consequently, important aspects will be explained, but mathematical background, algorithm structure or code, will not be included in this thesis. It is not radical to state that obstacles for implementing AI is not only that someone has to write the code, but rather that the concepts and its applications need a broader understanding in the organizations. As more thoroughly reviewed in the literature section, more companies offer solutions that require less and less coding done by the customer. This implies that future key questions, for the majority of people dealing with AI, could be more regarding *How can we use it?* rather than *How does it work exactly?*. Burgess (2018) suggests in his book about implementation of AI, that there is a "Goldilocks" (just right) level of AI understanding.

This thesis is focused on companies that have already implemented RPA in their organization, and want to take their automation to the next level. There are companies that aim to implement AI technology with other purposes than process automation, and there are companies that still have not initiated any effort in automation at all. These companies will not be covered by this research, as the end goal is to build the case regarding connecting the technologies rather than developing any of them separately.

The exploratory interview format also sets its limitations on the number of interviews that were conducted. Since the questions in the interviews were rather complex, they were also time-consuming. In an optimal case, the topic would have been researched by interviewing professionals from several companies that work with RPA. This would have been very difficult due to confidentiality agreements, especially since focus is on the financial services industry.

It would also have been interesting to do an extensive interview session with process owners to try and map AI demand from the customer side of RPA.

1.5.1 Using the term Artificial Intelligence

In this thesis, the term Artificial Intelligence (AI) is commonly used. During the work, there was an extensive discussion whether this term is suitable, since there is a large disparity among interpretations of what AI is, and what it includes. In most cases, the term Machine Learning (ML) would have provided a more precise description of the concepts referred to in this thesis. However, as will be presented, the concept of Intelligent Process Automation (IPA) has been established among professionals, and the "Intelligent" part originates from the term Artificial Intelligence. The final conclusion was therefore that in this thesis, Artificial Intelligence should be used instead of Machine Learning when referring to the concepts that that make up the I (Intelligent) in IPA.

1.6 Contribution

Our expected outcome is a guiding framework for implementing AI in existing automation capabilities. The development of such a framework would contribute to the now popular RPA research that is being conducted worldwide. Research from the near past have identified the possibility of the interaction between RPA and AI. However, few articles make attempts at exploring what factors that affect the feasibility and the level of appropriateness of IPA, in relation to the processes that are being automated. Even fewer articles make an attempt to survey what AI techniques and algorithms that could be relevant in RPA initiatives. The implication of this is that in order to examine what AI techniques that are suitable for RPA initiatives, a large number of articles and books would have to be evaluated. We hope that this thesis can provide a better oversight in that area. A majority of research see RPA and AI as separate subjects, and there is a gap to fill in the interaction between RPA and AI. By combining this theoretically guided study with a case study at the bank, this thesis should provide IPA research that is tangible and applicable in organizations today. The financial services industry is in many ways ideal for implementing IPA, and the results are generalizable for many industries since information flows and data are not very dependant on the underlying industry. Another aspect that makes financial services, especially banks, highly interesting in this field, is its direct access to real data. Regulatory compliance has assured that banks have had to store data since many years back. This data is a potential gold mine in the field of advanced analytics.

This primary focus of this thesis was on the financial services industry, but as mentioned, the results should be highly generalizable. This industry is suitable for this research because it is at the forefront of automation efforts. The results can be generalizable across industries that experience rich data flows and similar business models. The results are relevant for functions of companies that are active in similar processes as the financial services industry, for example finance and insurance departments, customer service departments, analytics departments and sales departments. Since these departments exist across all industries, the findings should be generalizable.

1.7 Disposition

The *Introduction* part covers the background and motivation for the research and presents the scope. In the *Literature review*, key concepts and prior research are presented as a knowledge foundation for the thesis. The *Method* section describes the research design, and presents how the stated problematization is framed for researchability. Continuing with *Empirical research*, which presents the findings collected from the interviews conducted. In *Results: The Bridge*, the findings from the literature review and empirical research have been merged to build the guiding framework for preparing organizations for IPA implementation. Building on the result, the *Discussion* presents an evaluation of the precision of the framework, as well as critique and reflections. The thesis is finalized with *Conclusion*, and this section will present the conclusive answers to the research questions. In addition to that, contribution to the academia and industry will be discussed together with potential further research.

1.8 Glossary

Below is a glossary for technical abbreviations that are used throughout the paper. To find more detailed explanations of terms related to AI, please visit section 2.3.2.

RPA	Robotic Process Automation
IPA	Intelligent Process Automation
CA	Cognitive Automation
API	Application Programming Interface
AI	Artificial Intelligence
ML	Machine Learning
ERP	Enterprise Resource Planning
PoC	Proof of Concept
FinTech	Financial Technology
FTE	Full Time Equivalents

2 Literature review

The topics of RPA and AI are interesting at this point of time, since both are within a relatively young era of research. In particular, the borderland between RPA and AI is specifically interesting, considering that emerging research in AI could have a great impact on RPA.

Performing a thorough literature review is highly necessary, and arguably it is particularly important for this research question. RPA and AI is time consuming to implement, hence studying earlier research and example cases to avoid fallacies that have already been discovered, is crucial in order for the implementation process to be efficient.

2.1 Workforce and macroeconomic implications

Technological advancement does not only affect the operational efficiency for companies, but also affects the human resource landscape as human workers' roles are altered in order to fit the current technological paradigms. So while the technical details of RPA and AI are particularly interesting, one must not forget the potential implications its evolvement might have for the workforce and how it can rewrite the roles of many employees. Parallels can be drawn to the impact of industrial automation on factory workers, where employment in lower-cost countries decreased as a consequence (Targowski and Modrák, 2011).

2.1.1 Impact of automation

Automation has gained increased attention for its great possibilities in cost reductions. It is however, very important to be cautious and critical towards estimates regarding the number of jobs or man-hours, that will be replaced by machines. Arntz, Gregory, and Zierahn (2016) highlight this by repeating the research conducted by Frey and Osborne (2013). Frey and Osborne (2013) conclude that 47 % of total jobs in the U.S could be replaced by machines in the following 10-20 years. Arntz, Gregory, and Zierahn (2016) followed the same methodology and conclude that 9 % of OECD jobs can be replaced by machines, a significant difference. They also highlight the importance of the consideration whether to measure share of job occupations or share of tasks, since a job occupation that is deemed automatable by Frey and Osborne (2013) might still contain its share of tasks that are not automatable.

In various industry reports, the potential impact of automation, especially RPA, is considered to show great promise. Some consulting companies forecast that RPA, fully implemented, can reduce costs by 40 % to 75 % for a function in a company (Infosys, 2017). Overall, the popularity of RPA also seem to be attributed to the fast and often immediate cost savings, with relatively small investments and inputs (Rutaganda et al., 2017). According to McKinsey Global Institute, 16 % of available working hours in the U.S are spent on data processing and

17 % in data collection(McKinsey, 2017a). Out of these, they estimate that the automation potential is 69 % in data processing and 64 % in data collection. In aggregate, this means that 1/3 of the total working hours show an automation potential higher than 60 % according to them.

2.1.2 Outsourcing

A commonly overlooked aspect of increased automation is the impact on offshore outsourcing. In their industry report, Armstrong (2019) claims that in some cases, a RPA robot in the United States can now be four times more cost efficient than outsourcing the task to a lower-cost country. Although the exact cost ratio between robot and outsourcing can be disputed, the essence is that increased automation could bring disruptions to the global trend of offshore outsourcing. This insight is also backed by Wright and Schultz (2018), who suggests that cheap labor providing countries like India and China will experience increased hardships as the need of cheap labor decreases with the increased accessibility of efficient automation. According to Manyika et al. (2017), some economists are worried about a ”premature industrialization” in developing countries as a result of the advancements in automation. On the other hand, for more developed countries such as Japan, automation could be essential to offset the decreasing labor supply which comes as a result of their aging population (Manyika et al., 2017). For countries with a shrinking workforce, the future economic growth is dependent on an increase in productivity and efficiency, while developing countries such as India expects higher future GDP growth from a rapidly growing workforce. Automation increases efficiency and mitigates the issues of an aging workforce, while it challenges job creation in developing countries. This further strengthens the argument that automation benefits developed countries and restricts the economic growth in developing countries that are dependent on outsourcing tasks (Wright and Schultz, 2018).

2.1.3 Labor market polarization

It is argued that automation leads to job polarization as the supply of middle-skilled jobs such as clerical work is declining while low-skilled and high-skilled jobs are increasing (Goose, Manning, and Salomons, 2014). The polarization of the labor market could induce a mass migration of middle-skilled workers towards more low-skilled jobs, while high-skilled workers with little or no routine work will benefit from the automation. In a study by Goose, Manning, and Salomons (2014), they found increased job polarization in all 16 developed countries studied. The polarization is thought to further depress the earnings of people with little or no education, hence increase the wage gap in developed countries (Wright and Schultz, 2018). Other researchers argue that automation done right could very well transform manual routine jobs into high-skilled positions allowing employees to stay on as robot co-developers by maintaining and supervising the AI algorithms through pseudo-code, for example. This is thought to empower the employees as well as maximize operational flexibility, and at the same time provide cost-efficiency (Kopec et al., 2018). To further build on this collaboratory hybrid approach, it is suggested that the transition of these routine jobs could occur through employing the algorithm as a learning apprentice, in which the program observes the human's decisions and captures these as training data. This could result in a reciprocal education where the program learns the human's manual work and the employee obtains an understanding of the program in order to take care of future maintenance (Brynjolfsson and Mitchell, 2017)(Kopec et al., 2018). Hence, according to these theories the increasing need and use of intelligent automation should not necessarily eliminate work, but could instead change the nature of the tasks and make middle-skilled workers move towards high-skilled jobs, rather than the opposite way. Regardless of direction, both perspectives strengthen the theory of automated intelligence inducing labor market polarization.

Burgess (2018) suggests that while implications for the labor market are still not crystal clear, AI is going to heavily disrupt some of the job roles that we know today. He also points out that the software and hardware that is needed for these automation initiatives is not going to maintain itself. When the PC was introduced, some predicted a major job loss, but it turned out that PCs also paved way for a new set of industries that created jobs themselves (e.g. computer games and movie streaming). Lacity and Willcocks (2018) also suggest that a commonly overlooked factor in this context is the job creation from automation that is often in the same magnitude as the job loss.

2.1.4 AI: substitute or complement?

Following the wave of automation and AI comes a wave of concern from the workers whose tasks potentially are to be replaced by machines. While computers have already transformed almost every industry over the past fifty years, the major overhaul is still to come as the rapid advancements within ML is accelerating the development of automation itself (Brynjolfsson and Mitchell, 2017). A study in cooperation between Oxford and Deloitte suggested that from now until 2033, 47 % of jobs in the US are at high risk of being computerized (Frey and Osborne, 2013). However, the fear of machines taking over is not a newly shaped concern, but rather a returning one as the same concerns were raised almost two centuries ago during the industrialization in Britain. Already in 1839, Thomas Carlyle raised his voice against the "demons of mechanics" that would be "the end of workmen" (The Economist, 2016). It is vital to emphasize that technological advancements that aim to automate processes previously carried out by humans does not necessarily delete jobs. It could rather complement the workers so that humans can thrive by focusing their time on development and creative tasks (Lacity and Willcocks, 2018). Because, although many parts of a job could be automated and replaced by AI, there are still tasks that do not fit the template of these algorithms. Therefore, the workforce implications that come with development of AI are far more complex than the simple substitution story that is being broadcasted globally (Brynjolfsson and Mitchell, 2017). Armstrong (2019) states, in their industry report, that Intelligent Automation helps organizations to find a healthy balance between machine and human tasks. Professors Lacity and Willcocks (2018), have throughout their extensive automation research concluded that the major impact on employees is that they have been freed from dreary and repetitive work in order to focus more on value-adding tasks.

2.1.5 Human thinking still needed

In order to give any credible analysis of workforce implications of AI and automation, one must determine what is actually feasible or not. Today we are not yet close to *Artificial General Intelligence* (AGI), which is the term for the scenario where computers can perform any intellectual task as good as a human (McKinsey, 2017b). At this moment, successfully implemented AI rather present solutions for a set of business operation tasks and problems, which is sometimes referred to as ”narrow” AI, in contrast to the fulfilling AGI. Thus, there is for now no reason to worry about computers eliminating the need of human thinking. Despite this, the AI technology available today is still a foundation for a digital disruption (McKinsey, 2017b). The technological advancements in automation and AI will continuously disrupt labor markets affecting its main stakeholders such as laborers, organizations, government and society (Wright and Schultz, 2018). Indeed, for companies to sustain its competitiveness they will rely on automation to a greater extent in order to improve efficiency. However, with the urge of staying competitive in efficiency comes a risk of ignoring long-term macro effects of automation, such as fading reciprocal goodwill between company and stakeholders in favor of short-term financial winnings (Wright and Schultz, 2018). In order to succeed in the long run, it is vital for firms to find a balance between automation and human resourcing.

2.2 Robotics Process Automation (RPA)

2.2.1 RPA basics

Robotics Process Automation (RPA) is a term that describes automation through letting computer programs perform tasks that are usually executed by humans. The ”robots”, in this sense, are not physical robots such as assembly line robots, but they consist purely of code. What distinguishes RPA from other process automation, is the fact that the underlying information systems remains unchanged (Aalst, Bichler, and Heinzl, 2018). Consequently, if a human should be reinstated to execute the task, no problems would occur since user interface and information systems are intact (Asatiani and Penttinen, 2016). RPA code was initially based on simple [if, then, else] statements, although more and more firms and researchers identify emerging business opportunities by continuously extending the available code library to facilitate more advanced task automation.

A central part of RPA is that input, and process rules for input and output, must be clearly defined in advance (Mohanty and Vyas, 2018). This practice facilitates modular robots, enables easy reprogramming of existing robots and the communication between them. Fung (2014) lists some criteria for tasks suitable for Information Technology Process Automation (a synonym for RPA):

- Low cognitive requirements. Tasks that do not require subjective judgment, creativity or interpretation skills
- High volume. Tasks that are performed frequently
- Access to multiple systems. Process that requires access to multiples applications and systems to perform the job
- Limited exception handling. Tasks that are highly standardized with limited or no exceptions to handle
- Human error. Tasks that are prone to human error due to manual labor

2.2.2 RPA software

The software in which these robots are developed, are being sold by an increasing amount of vendors(Aalst, Bichler, and Heinzl, 2018). Many new vendors of RPA software have emerged during he last three years since demand has surged. This software is custom made to handle the kind of tasks that RPA robots usually perform. In other programming languages, such as Python or VBA, the developer has to follow a syntax to develop for-loops and if-statements [1]. RPA software can implement these operations through a simple selection of the desired operation, instead of having to write the code and following the syntax. The threshold to being able to develop an RPA robot is therefore not dependent on programming language proficiency, but rather on general understanding of coding structure (Asatiani and Penttinen, 2016).

There are many ways for organizations to utilize RPA in their work. Lacity and Willcocks (2016) describe some of the ways that organizations can structure their RPA initiatives:

- Insourcing: buying service automation software licenses directly from a service automation provider. This requires the organization to arrange all development and coding of the robots on the software that has been purchased.
- Insourcing and consulting: buying licenses directly from a service automation provider and engage a consulting firm for services and configuration.
- Outsourcing with a traditional business process outsourcing provider: buying service

[1] For-loops and if-statements are main components when coding, to enable rule-based operations from the program

automation as part of an integrated service delivered by a traditional provider.

- Outsourcing with a new provider: buying service automation from a new outsourcing provider that specializes in service automation.
- Cloudsourcing: buying service automation as a cloud service (still emerging).

2.2.3 Weaknesses and challenges of RPA

The market's belief in RPA is quite strong, considering the vast number of industry and market outlook reports that have been produced during recent years (Lowes et al., 2015) (McKinsey, 2017a) (Infosys, 2017) (Rajan, 2016). From academia, the potential of RPA is also seen, with a large number of articles and books related to examining the power of RPA-implementation (Asatiani and Penttinen, 2016) (Kedziora and Kivaranta, 2018) (Lacity and Willcocks, 2016).

However, there is also critique against RPA. The revolution of RPA somewhat reflects earlier automation initiatives, for example Straight Through Processing (STP)(Aalst, Bichler, and Heinzl, 2018). STP was, just as RPA, a tool to automate tasks without human interference, but STP turned out to be too expensive for many firms to implement. The critical difference between STP and RPA is the fact that STP used an inside-out approach, remodelling existing IT-systems. As mentioned earlier, RPA addressed this issue by using the outside-in approach, hence not altering any IT-systems in a significant way.

Rutaganda et al. (2017) states that RPA will neither solve all automation challenges nor will it replace existing applications in an organization. RPA is a powerful tool that enables systems that do not normally communicate automatically, to do so. However, if companies would adopt larger business systems, described by Burgess (2018) as an all-encompassing IT-system, the necessity of RPA would be questioned since these systems provide larger integration and communication between different functions in the program. The implementation of all-encompassing IT systems in certain industries or companies has been hindered since many rely heavily on legacy systems that are hard to replace (Rutaganda et al., 2017). It is important to point out that an all-encompassing IT-system, a system that can take care of every stream of data in a company, does not really exist yet, at least not on companies with non-trivial data streams. An example of something that could resemble an all-encompassing IT-system is the Enterprise Resource Planning (ERP) system. ERP-systems can offer easier built-in automation compared to dealing with different legacy systems. However, it still requires someone to build the automation within the ERP-system. This means that RPA is still relevant for automating ERP-systems (Aguirre and Rodriguez, 2017). An example of this in the market is that one of the largest RPA-system providers; UiPath, offers custom made software to automate one of the most dominant ERP-softwares; SAP (UiPath, 2019[b]), even though SAP has its own service for automation; SAP Test Acceleration and Optimization (SAP, 2019). Lacity and Willcocks

(2018) bring up Siemens as an example of a company that has implemented RPA in order to manage its ERP-systems globally.

Although a tool for cost reductions, it is important to have in mind that RPA does not come for free. Mohanty and Vyas (2018) state that even though cost reductions occur, the overhead cost of managing the RPA initiatives could potentially lead to a net loss in the beginning. It is therefore important to account for all costs when evaluating whether to adopt RPA or not.

The hype around RPA has not been purely positive for the industry during recent years. Headlines such as; "Robots to steal X million jobs in the coming years", has both fueled public opinion against the implementation of automation software, but also delivered promises to businesses that would be extremely difficult to live up to (Rutaganda et al., 2017).

Lacity and Willcocks (2018) state that after the initial hype of RPA, the challenges of successful RPA implementation has been highlighted during the recent years (2017-). They identify that one factor of dissatisfaction is that organizations do accept the complexity of RPA in the same way as with other business challenges and opportunities. The technology research and advisory firm, ISG Group Group (2017), reported in 2017 that about one-third of organizations implementing RPA, experienced challenges such as underfunding, organizational resistance to change, lack of governance and concerns with risk, compliance and security. Lacity and Willcocks (2018) list a number of reports that conclude that the share of unsuccessful or complicated RPA implementations is not as low as what seem to be prevailing market consensus.

Rutaganda et al. (2017) lists some of the most common fallacies in the implementation of RPA:

- Selecting incorrect RPA use cases and lack of clear KPIs
- Incorrect RPA leadership at the top level
- No long-term RPA vision or road-map
- Dated project delivery approach for RPA
- Trying to deliver RPA benefits on shifting sands

2.2.4 RPA in the financial services industry

The financial services industry has been one of the fastest and most aggressive adopters of RPA. This is partly because of the cost pressure, regulatory challenges and rigid legacy systems that banks face, but also due to the potential benefits that RPA has shown. Some of the possibilities within the financial services industry are presented below, as formulated by Rutaganda et al.

(2017).

Capital Markets

Reduced costs, improved controls, and increased speed for processes such as:

- Reconciling trade/account data
- Correcting reference data
- Transaction reporting
- Corporate Action processing
- Client on/off-boarding

Retail Banking

- Increased transaction volumes processed
- Improved accuracy and data analytics
- Sample use cases: Card management, Mortgage processing, Fraud detection and Risk monitoring

Wealth & Asset Management

- Access, gather, move, validate, remediate and update data across multiple systems
- Sample use cases: Know your customer processing, Payments, Asset transfers, Corporate Action processing and Debit balance clearing

2.3 Artificial Intelligence (AI)

Artificial Intelligence (AI) is the umbrella term for making computers think and act like humans (Lacity and Willcocks, 2018). One of the most distinct qualities of humans is the ability to make decisions and take action based on previous experience. While computers for a long time have been quicker than humans when it comes to performing calculations or tasks following a set of rules, the lack of cognition has been an obstacle for computers to approach tasks without predetermined rules of action.

2.3.1 The development of AI

The last couple of years have shown great advancements within the area of AI which has made computers increasingly suitable for carrying out tasks that previously required humans. These advancements have mainly been made possible through the development of Neural Networks, which in essence tries to resemble a computational replica of the human brain, where information is processed through a network of neurons connected by weights. Attached to that structure are training and recall algorithms which, all put together, tries to recreate the key concepts of the human brain such as memory, and the ability to learn from experience (Shanmuganathan and Samarasinghe, 2016). While the idea of a neural networks has been around since the 1940s, as presented by McCulloch and Pitts (1943), it was not until the last decades that the technology really reached its breakthrough point. The breakthrough was made possible through the development of large data storage devices and increasing computational power, which indeed has enabled *data mining* and processing of heavy data sets through complex ML algorithms (Shanmuganathan and Samarasinghe, 2016). Other external factors that have enabled the recent AI advancements are for example cloud computing, and the innovation to execute operations with the Graphics Processing Unit (GPU) instead of the Central Processing Unit (CPU) (Burgess, 2018). When the computational power of supercomputers are combined with analytical and learning qualities of these algorithms, AI arises. The result is a machine, inspired by the human brain, that can process huge amounts of data in a fraction of the time that it would take a human to process it. Furthermore, the algorithm can find patterns in the data unknown to humans, act rationally, avoid mistakes, and take action based on this large and complex input.-

The development of AI is still ongoing. Burgess (2018) states that "AI is in the arena of conscious unknown", meaning that we know that we do not know enough about it. The results of AI applications are however rapidly improving. For example, image recognition algorithms based on *Deep Neural Networks* (DNN) has decreased the error rate of labelling images from 30% in 2010, to less than 3% today. Furthermore, DNNs decreased the error in voice recognition from 8% in 2016, to under 5% in 2017. The 5% threshold was an important number since that is the comparative error rate for a human when given similar data for speech and image recognition (Brynjolfsson and Mitchell, 2017).

2.3.2 Key concepts of AI

AI is a broad field of science and there are many concepts and techniques used. Below is a table that encapsulates the most common concepts of AI that are relevant for this paper.

Artificial Intelligence (AI)	The umbrella term for machines that attempt to behave more human-like.
Machine Learning (ML)	Subset of AI which uses statistical methods to enable machines to learn from experience.
Neural Networks (NN)	Subset of ML which adds complexity to the statistical methods through the use of multi-layer networks. Neural Networks is inspired by the human Neural Networks in the brain and consists of several layers of nodes that together form a model that can be trained (Shanmuganathan and Samarasinghe, 2016).
Natural Language Processing (NLP)	Umbrella term for the interaction between human language and computers. Historically, it has been done through rule-based programming, but today it is most commonly done through the use of ML methods, for example Neural Networks (Deng and Liu, 2017).
Natural Language Understanding (NLU)	Not the be confused with its umbrella term NLP. NLU refers to the specific task of transforming unstructured data into structured data. NLU is the technique for a machine to interpret human language (Deng and Liu, 2017) and is for example used when Apple's Siri or Amazon's Alexa tries to understand user requests.
Natural Language Generation (NLG)	Not to be confused with its umbrella term NLP. NLG is the technique for machines to generate human language based on available data and can be seen as the reverse process of NLU (Deng and Liu, 2017). NLG is for example used when Siri or Alexa answers user requests.
Optical Character Recognition (OCR)	Umbrella term for techniques that enable an input image to be interpreted by a computer. Modern OCR techniques include ML algorithms, such as Neural Networks, in the recognition process (Phangtriastu, Harefa, and Tanoto, 2017).
Supervised learning	Supervised learning is the area within machine learning where the machine is provided an input and an output with the objective to find patterns to connect these. In supervised learning, the classification of data is known, so the objective is to find a function that corresponds to the correct classification (Hudson and Cohen, 2012a).

Unsupervised learning	In contrary to supervised learning, unsupervised learning is where the machine during training is just provided with input data. In unsupervised learning, the classification of data is unknown and it is often unknown how many classes that should be considered (Hudson and Cohen, 2012b). One technique that makes use of unsupervised learning is clustering.
Clustering	Clustering is a technique that looks for pattern and sequences in data (Hudson and Cohen, 2012b). These patterns are often undetectable by humans, commonly because the sheer amount of data or because the patterns might not be logically intuitive. Clustering techniques could be used in a similar way to regression analysis, with the advantage that variables and their interactions do not have to be defined in advance since the computer itself can find relevant patterns in the variables. The outcome of a clustering algorithm is a grouping of subjects depending on their (almost) undetectable characteristics.
Classification	A classification problem is aimed at categorizing an object based on certain attributes (Amezcua, Melin, and Castillo, 2018). This can for example be done through a Neural Network, where the final layer represents the category for the object. Classification can also be done without AI algorithms, but would then only take naive considerations to defined parameters and not see patterns that are not detectable by humans.
Automatic speech recognition	Automatic speech recognition, or as more popularly referred to, Speech recognition, is the operation of transforming spoken words into written text (Renal and Hain, 2010). Note that speech recognition does not interpret the meaning of the content, just as OCR does not analyze its input. To interpret speech, NLP can be utilized after the speech recognition process is done.

2.3.3 Limitations of AI

Knowledge about the possibilities of AI opens up great opportunities, however equally important is to know the limitations of AI. Lacity and Willcocks (2018) states that historically, there have been periods where AI development has frozen, called AI winters. Similar to the impact of the automation hype mentioned in the RPA section, AI hype also has negative effects since expectations are set so high that the technology simply cannot live up to them. They also state that all of the previous AI winters have been preceded by AI hype. Insufficient knowledge about the limitations of AI may be relatively manageable by better education, but there are obstacles that could be harder to climb, one of them being regulatory challenges. They argue that regulatory problems are one of the major possible hinders for the development of AI. This challenge becomes especially relevant for the applications in the financial services industry, which involves a lot of personal data. A concrete example that is introduced, is the issue of training a Neural Network. Can customer data be used to train the Neural Network or do we have to use generated data, and if we use generated data that is not ”real”, how is that discrepancy handled in the Neural Network?

Continuing on the previous notes, it is clear that the regulatory aspect of AI should not be underestimated. Burgess (2018) identifies that a rising problem within this field is that regulators tend to fall behind, and there is a risk that regulations will be deployed that make some applications fall into the gray-zone of the legal landscape. He argues that in time, AI will be more accepted and then regulators will follow, but in the meantime, companies must be ready to provide answers and transparency regarding their AI and data practices. Lacity and Willcocks (2018) also identify the risk of delayed regulatory interventions, that has potential to surprise and disrupt the industry. Taddeo and Floridi (2018) states that the European Parliament formed AI4People, which is an effort to orient AI towards the good for the people. The European commission also has an expert group of AI that can assist legislators on relevant matters (European Commission, 2018). Taddeo and Floridi (2018) argues that the moral responsibility must be distributed between designers, regulators and users.

Most techniques of AI requires a lot of data. Plastino and Purdy (2018) argues that the efficiency of AI directly depends on the quality and the amount of data available. In some cases, the algorithms may be in place, the organization might be ready, but the data is either not existing, not accessible, or very unstructured.

2.3.4 Cloud capabilities

As mentioned, cloud capabilities has been an important factor in the rise of AI during recent years.Burgess (2018) states that organizations have the possibility to utilize cloud capabilities on different levels of difficulty and customization. For organizations that want to build their own cloud capability, frameworks can be coded and trained in-house. Organizations that want more help and less freedom can use platforms, that have pre-developed algorithms, but still need data and training. The highest level of simplicity is to use cloud as a service, where the organization does not necessarily have to provide neither data nor code in order to utilize cloud capabilities. He argues that understanding these different levels of how cloud capabilities can be offered are vital for organizations that want to incorporate AI. For example, an organization without any experienced developers should probably use a cloud-AI as a service, and not code their own framework, as described above.

2.4 RPA + AI = IPA

2.4.1 Addressing the limitations of RPA

RPA robots will do exactly what you tell them, that is their greatest strength, but also their greatest weakness (Mohanty and Vyas, 2018). The user can rely on the robot to execute a well defined code as long as it covers all possible events. Problems arise if the robot encounters situations or data patterns that are unfamiliar or undefined for the robot. An example of unstructured data could be a case where relevant data points are embedded in a body of text instead of formatted in cells.

The rule based algorithms for RPA robots therefore sets its limitations on the tasks that are subject to automation. It seems like this issue has been identified by both academia and the market, which has enabled the rise of Intelligent Process Automation (IPA). IPA is the combination of RPA and AI (Mohanty and Vyas, 2018) (UiPath, 2019[b]). By utilizing ML algorithms and approaches, there has been a broadening of tasks that can be carried out by machines in order to mitigate the human error factor, and speed up the process (Lamberton, Brigo, and Hoy, 2017). This potential has significantly increased the interest for automation as the broader area of possible applications attracts a wider range of users and areas of usage. In the book by Burgess (2018), Dr. Will Venters, from the Information Systems department at LSE, suggests that: "Robotic Process Automation is great for dealing with processes that are clean and structured – as soon as it [the data] becomes messier, then AI can step in and overcome that". LeClair (2018) highlights the importance of maturing RPA to IPA, by arguing that the most important parameter of RPA software success will be integration of AI analytics in their platforms. Lacity and Willcocks (2018) highlight a problem of the addition of AI analytics to RPA software, namely that some vendors make too bold claims regarding their software's AI capabilities (they use the phrase cognitive capabilities), which they refer to as automation washing. They claim that it is highly important to assess the software's true capabilities through tests and evaluations, and to keep a critical standpoint to this kind of claims.

IPA addresses two major constraints of RPA robots as stated by Mohanty and Vyas (2018). Firstly, that unstructured data cannot be processed by regular RPA robots. And secondly, that higher-order decision making is impossible in regular RPA-robots. Both of these can be handled by methods within the field of AI, for example through the use of Neural Networks. Mohanty and Vyas (2018) further argue that RPA is a good initial step in the quest for full IPA implementation. Before an organization attempts to fully deploy IPA, it should have simplified the processes in a way consistent with RPA to avoid having to implement costly techniques on a process that needs to be reworked. Preparing a process with RPA techniques before implementing AI, is a way to avoid having to redo complex steps because the necessary rework was not done in time. The experience and knowledge from RPA automation is a strong foundation in using AI-based concepts in Intelligent Automation. Treating RPA and AI separately in automation would therefore be a developmental setback for practitioners, since many companies and institutions now have functioning RPA departments.

2.4.2 Applicable concepts of IPA

The range of applications of RPA has been established and implemented during the last years. The applications for IPA though, are still in an emerging phase. As pointed out by Mohanty and Vyas (2018), AI is today not on the level that it understands the task by itself and adapts its available toolbox. This means that the developer has to "stitch" together a system that fits for the task at hand.

These solutions vary in how much they need to be configured before they can be deployed. However, there is a difference between having to configure a solution and having to code it (Google, 2019) (IBM, 2019). One of the largest RPA software providers; UiPath, now claims to offer seamless integration of third party AI developers such as Google IBM and Microsoft (UiPath, 2019a). Remember though, that these claims should be thoroughly examined before accepted as truth (Lacity and Willcocks, 2018). Through recent advancements in cloud computing and modular Neural Networks, it is possible to train and utilize a Neural Network without actually writing the associated code. For example, IBM Watson now offers NeuNetS; "Train a neural network without code"(IBM, 2019), and Google Cloud AI offers Building Blocks, which both has pre-trained models in areas such as OCR and NLP but, more interestingly also has custom made "AutoML" products that Google claims require low previous ML experience to adapt (Google, 2019). Again, one should not take these statements for granted, but to some extent, a democratization of AI is happening.

There is a list of the applicable concepts of IPA in the Appendix section. The list is presented in the Appendix because it does not contribute to the theoretical background for this research to a high extent, but rather serves as an information base when driving the IPA development by assessing relevant techniques available.

2.5 Strategy and change management for automation

A reoccurring theme in the literature on automation and IPA, is that in order to utilize IPA to the fullest, organizations must have a long-term strategic plan for their automation initiatives (Lacity and Willcocks, 2018) (Burgess, 2018). It is very easy to fail in the automation journey, but it is also common to perceive the journey as a failure simply because the organization does not know what a success would be in terms of their automation journey (Lacity and Willcocks, 2018). Mohanty and Vyas (2018) argue that Change Management is a critical step of overcoming some of the hardest challenges in implementing Intelligent Automation. Dal

Pont (2016) argues that efficient Change Management requires knowing the business processes, assessing its expertise and its core competences. He also highlights the human aspect of change and argues that "creating a feeling of trust" is at the center of Change Management.

2.5.1 Strategic frameworks

As mentioned, a common factor in the literature is the emphasized significance of having a thorough strategy in place ahead of the IPA journey. However, these strategic frameworks are presented on different levels on the scale between practical implementation and general strategy. To represent this, three strategic frameworks that represent the two extremes and the midpoint respectively, will be presented.

Burgess (2018) writes about the importance of a strategic road-map to support the implementation process, and argues about the significance of aligning the Intelligent Automation journey with the business strategy. This idea is further backed by Mohanty and Vyas (2018) and Lacity and Willcocks (2018). In essence, organizations need to be strategic in order to succeed with implementation of the technology.

Burgess (2018) presents his idea of general strategy for AI implementation with the following aspects:

1. Understanding your ambitions
2. Assessing your maturity
3. Creating a heatmap
4. Developing the business case
5. Understanding change management
6. Developing your road-map

Lacity and Willcocks (2018) present a list of what they believe that being strategic could mean, which is the example of the midpoint level of strategy, consisting of the following six factors:

1. Understanding and planning for mid-term and long-term
2. Aiming for "triple-wins", i.e wins for shareholders, customers and employees
3. Resourcing automation as a strategic business project
4. Ensuring the C-suite is on board with the vision
5. Identifying and managing change and implementation challenges from the start
6. Centralizing the automation capability

Mohanty and Vyas (2018) present a more practically anchored framework, that they call "15 key essentials for a sucessful IPA journey":

1. Start with a proof of concept
2. Set the right expectations: Promise less, deliver more.
3. Have a robust solution focus: Invest efforts in building the right solution to address majority of the variations.
4. Identify and bring evangelizers on board: Change is often resisted even if it is for common and individual good.
5. Leverage complementing tools: Be alert to new tools that open new business opportunities.
6. Follow the quick win delivery methodology: Chances of success increase with smaller manageable sets of automations.
7. Choose processes wisely: The success of first steps will have a significant bearing on the outcome.
8. Make IT an integral part of the journey: Value from RPA has to be co-created by the business and IT teams.
9. Track and reap benefits simultaneously.
10. Plan for sustainability: Institutionalize structure and governance to productively manage automation.
11. Operating model: Guidelines and policies required to execute tasks across the intelligent automation lifecycle.
12. Standards and practices: Standards and practices to consistently manage intelligent automation activities.
13. KPIs and metrics: Measures to cover different aspects of the intelligent automation solution.
14. Methods: Use frameworks to ensure a consistent approach across functions.
15. Governance: Clear segregation of responsibilities and review mechanism.

2.5.2 Getting everyone on board

Lacity and Willcocks (2018) argues that automation journeys are not usually popular in the beginning, and that resistance to this journey is a challenge that must be dealt with by convincing the organization of the benefits for everyone. Mohanty and Vyas (2018) list "Identifying and bringing evangelizers on board" as a key essential for Intelligent Automation success. They argue that change is often resisted, even if it is for common and individual good. This can for example be countered by identifying functional leaders and opinion makers in the organization, and make sure that they are on board. The framework constructed by Mohanty and Vyas (2018) brings up several points on how to get everyone in the organization on board and convinced. "Setting the right expectations", "following the quick win methodology" as well as "tracking and reaping benefits simultaneously", are all aspects that are important to ensure support for the automation journey.

2.5.3 Measuring progress and managing expectations

An important part of the change management aspect is to measure progress correctly in order to gain organization-wide acceptance for the automation journey. IPA has the long-term potential to save costs in organizations, according to Lacity and Willcocks (2018). However, according to their research, it is hard to find applications of IPA that yield fast return on investments like RPA did. As a matter of fact, they argue that at the current state of technology (2018), the most important results from IPA applications are more qualitative than quantitative. IPA initiatives today, can for example increase customer and employee satisfaction, ensure regulatory compliance, and prepare for further steps of the automation journey. Burgess (2018) lists a couple of hard and soft factors that could be relevant for measurement in organizations.

Hard factors; Cost reduction, Cost avoidance, Customer satisfaction, Compliance, Risk mitigation, Loss mitigation, Revenue leakage mitigation and Revenue generation.

Soft factors; Culture change, Competitive advantage, Halo effect (marketing with buzzwords), Enabling digital transformation and other factors such as moving employees to higher value added tasks.

Lacity and Willcocks (2018) emphasize the importance that organizations must not expect the same from IPA as they did from RPA, at least in short term. An important consequence from this, according to them, is that organizations must adapt their KPIs for automation before taking the step from RPA to IPA. Organizations cannot measure short term return on investment anymore in the IPA phase, they must incorporate more sophisticated KPIs. On the same note, they argue that another problem regarding the performance measurement of robots, is that robots are often not compared to humans, but rather to our vision of how robots should be in the future. In one example in their book, an organization reacted quite negatively when it became clear that the NLP tool Amelia would need a couple of months to learn Swedish to an extent that it was able to perform customer service. The key question to consider here is; how long does it take to train a human to master this level of customer service in Swedish? Suddenly, a couple of months does not seem like such a bad performance. Lacity and Willcocks (2018) argue that by considering this, the true potential of IPA and AI can be glimpsed upon, because in the future, emerging business roles that do not exist yet might take years for an educated professional to learn, whereas it could take months or shorter for a robot to learn.

2.5.4 The business case should drive automation

Understanding how to use IPA is not trivial. Mohanty and Vyas (2018) describe the confusion that can arise when directing the automation efforts, but they also propose a remedy.

Organizations should investigate the business processes they possess and thereafter create a heatmap in what processes where IPA could be implemented. Factors that should be taken into considerations are for example created business value, and cost or time of implementation. In the book by Burgess (2018), Dr. Will Venters at LSE, argues that a key factor for businesses to be able to exploit AI to the fullest, is to look at the business case and not at the technology itself. In addition, Mohanty and Vyas (2018) suggest that organizations should assess their capabilities and technology changes required to complete the adoption of IPA in a business process. It can be dangerous, but at the same time appealing, for the organization to take on a challenge that they might not be ready for. Lacity and Willcocks (2018) also give another advice when deciding what business cases that should be automated, focus more on functions and workflows, and much less on automating roles and people. Studies have shown that less than 10 % of roles, sometimes as low as 5 %, can be replaced in its entirety by robots in the following few years. In the meantime, studies estimate that a much larger portion of man-hours can be automated (Lacity and Willcocks, 2018). Although these estimates vary, the lowest that was found in this study was around 30 %, which is a strong argument for focusing on functions and not on roles, as explained by Lacity and Willcocks (2018).

2.5.5 Managing data

As previously brought up in the AI section, one of the strongest limitations of AI implementations is the access to data that is suitable for the task at hand (Plastino and Purdy, 2018). To manage the automation journey, it is of essence that organizations have a structured way of handling its data and everything that comes with it. **A˙Lacity˙2018** argue that data, and access to it, is one of the three most serious obstacles for implementing IPA. Many large organizations are adding a Chief Data Officer (CDO) to their C-Suite management, and according to Gartner (2016), 90 % of large companies will have that in place by 2019. However, according to Plastino and Purdy (2018), the CDOs are mostly concerned with regulations, data security and governance. They argue that in order to fully exploit the advantages of data in AI, companies need to introduce a Chief Data Supply Chain Officer, who can construct a seamless end-to-end data supply chain.

2.6 Summary of literature review

Researchers observe a fear among workers that automation and RPA will make their skills obsolete. Although, most agree that automation will cause job loss, more nuanced research also highlights job creation from technological advancements, and that the net effect is more interesting than the loss factor itself. Another aspect that is brought up is the fact that jobs have historically been destroyed and subsequently recreated somewhere else, and that the rise of AI could for example be compared to the industrial revolution in that way. Macroeconomic implications from RPA has contributed by decreasing need of outsourcing since cost of robots has lowered during recent years relative to increasing emerging market wage rates. Automation also seem to create a polarization on the job market, since the jobs most susceptible to automation belong to the middle-skilled worker segment, according to the research.

RPA research has focused on the potential applications that could have great impact on business. RPA has a strong track record of applications where cost-cutting, operational security and compliance seem to be key effects of the efforts. The track record seem to be especially strong within the financial services industry. The weaknesses and challenges is also a popular topic, where lack of cognitive and intelligent abilities is something that is considered to hinder efficient automation. RPA is a software that is applied on top of system architectures to stitch systems together, and can be described as a band-aid made necessary by old and large legacy systems. Today there are large ERP-systems with built in automation functions, but even with these, RPA softwares can be useful, and some RPA manufacturers offer custom made solutions to automate these ERP-systems. When a company begins its automation journey, there are some common fallacies in the implementation of RPA, one of them being that the large initial investment often brings unreasonable expectations and hype. Furthermore, lack of clear KPIs, incorrect RPA leadership, and lack of a long term RPA vision often confines the RPA journey.

The rise of AI is what enable computers to carry out tasks that previously required human intelligence and decision making. The idea behind the algorithms has been around for some time, but in later years the main enablers for the rapid development and commercialization has been increased data storage and computational power. This in turn has naturally enabled the development of the actual algorithms.

IPA emerged to address the shortcomings of RPA, namely handling more subjective tasks. The effect of this is that the range of processes that are automatable has been increased. However, since RPA and IPA are different, it also means that there are differences in how RPA and IPA can be treated, for example how to measure results and how to create a strategic plan. Noticing these differences is important to avoid costly mistakes in the implementation process.

Many potential applications of IPA has been presented, with a big variety of usage areas. These applications have mainly been examined by the industry rather than research so far, but there are some that have caught the interest of academia. Researchers seem to unite around the fact that the financial services industry might be the industry most suitable for pilot projects in applications, partly due to its rich access to data, and pioneering efforts in digital transformation.

To create a powerful automation initiative, it is of essence to implement an automation strategy, and work with change management. There are a number of strategic road maps available that describe how to create this change. Some of the key factors to success are; getting everyone on board, managing expectations and hype, and adapting KPIs. It is important that there is a long-term vision that the automation initiatives aim to achieve, and that the business value is in focus when creating this vision and strategy.

3 Method

This section provides information regarding the process of planning and conducting the research correctly to fulfill the purpose of the research, and to efficiently tackle the research questions presented.

3.1 Research design

In order to cope with the problematization and to fulfill the purpose of the research, an inductive approach was taken by way of a case study at *the bank*. According to Eisenhardt and Graebner (2007), this type of inductive theory building approach responds very well to understanding *how* and *why*, but is less sufficient when it comes to answering *how often* or *how many*. Therefore, as Eisenhardt and Graebner (2007) also argue, a case study is a good fit for complex research questions which require thorough qualitative data to offer new understandings of social and organizational processes that quantitative data cannot reveal. Although the end goal was to produce generalizable results, the research could still benefit from this inductive approach as the empirics should guide the potential theory contribution to be relevant as it is deemed applicable to *the bank*. Additionally, a case study enables preservation of the holistic nature of real life events which also aligns well with the purpose and research questions.

Conclusively, an inductive case study approach was deemed most suitable, as it enabled the research to emerge from empirical material, hence giving a thorough understanding of *the bank*. Ultimately it also provided generalizability when combined with available theory and research on the subject.

The research was carried out from *the bank's* office in Stockholm, more specifically from the *Automation* department. This position has enabled a thorough immersion in the operational processes at the Automation department, as well as provided contact to other stakeholders in the organization that touches IPA development in different ways. Given this position, it has been possible to gain detailed insights in the current development of RPA, as well as to cover several perspectives on the potential future development towards IPA within the organization.

3.2 Information gathering

The information gathering was partly structured as a participant observation process. A participant observation involves social interaction, as well as both formal and informal interviews with subjects, and direct observation of relevant events (McCall and Simmons, 1969). Participant observation also includes collection of documents, and some flexibility in the direction where the study takes. The participant observation method suited this study well since there is a lot of knowledge to be absorbed through unstructured interaction apart from the interviews conducted and literature reviewed.

3.2.1 Literature study

The literature study was conducted to gather data of both researchers' and industry experts' views on IPA and its potential. Information regarding RPA and IPA implementation was also gathered to build on the understanding of previous initiatives and the challenges that were faced. In addition to this, there was a need to cover literature about more general change management theories, as well as implications for the workers, both on an organizational level and on a macro level.

When searching for literature, KTH's PRIMO search and Google Scholar were the main platforms used. The search was first limited to well-cited articles in reviewed journals, in which more relevant articles could be found in the reference lists. However, as the literature available turned out to be quite limited, the scope was broadened to also accept industry reports. The industry reports were very limited in amount and were primarily used to overview the Automation market characteristics. Keywords included in the search strings were for example RPA; Robotic Process Automation; Machine Learning; Automation Implementation; Business Automation; Financial services; Artificial Intelligence; Intelligent Process Automation; Business Process Automation.

The literature study helped to shape the approach to solving the problem, and was also used to position this research within existing research in order to create an insightful and contributing research question. It was further used to build a deeper foundation of knowledge regarding RPA in general and the idea of IPA in particular. Introducing new technology into departments or organizations has an impact on a wide spectrum of aspects, hence the literature study needed to correspond to that wide picture, as well as covering both technical theory and human resource theory.

3.2.2 Earlier research

Previous research in the field of IPA was examined in the Literature review, and condensed in the appurtenant summary. Rynes and Gephart Jr (2004) states that the relationship between theory and methodology is important, and that the researcher's methodologies should be consistent with assumptions of the theoretical view being expressed. In this research, the aim was to consistently align the methods with existing theories to ensure unity and consistency in the thesis.

3.2.3 Interviews

Interviews often become the primary source of data when conducting case studies. In this research specifically, the interviews were deemed most contributing if carried out in an exploratory manner. Critics claim that data collected from interviews are at high risk of being biased. However this risk can be mitigated by using data collection strategies that limit bias. For example, as Eisenhardt and Graebner (2007) describe in their article, that one can use a wide range of interviewees on different hierarchical levels, functional areas or geographies. Furthermore, one can also interview outside observers such as market analysts or researchers. A final important aspect is to discuss both retrospective and real-time as the interviewee's comprehension of a challenge could indeed have changed over time (Eisenhardt and Graebner, 2007).

In order to cope with above presented challenge, a wide range of interviews were conducted in order to cover many perspectives of the topic. It was important to capture the views of developers, management, internal functions and outside observers as they all provided different comprehension, and have experienced different aspects of similar problems. It could have been desirable to interview people from more companies, but the consequences of confidentiality agreements would be too complicated, and would likely have lead to dubious ethical situations. In the analysis, it is therefore important to consider that the empirical research from the interview section mostly comprises a view from a single company. The process of crafting generalizable conclusions should therefore be guided by insights from the part of the empirical research that was not tied to this single company, but rather by the researchers and external observers.

The interviews were of semi-structured form. Wilson (2012) states that semi-structured is a form of interview that allows for more flexibility than structured interviews. A set of guiding questions is pre-defined to keep the interview on track, but the semi-structured setting involves some flexibility where the interviewer has possibilities to explore possible areas that seem interesting. The interview guiding questions can be found in the appendix.

Test interview

In order to ensure quality and efficiency in the interviews, a test round was conducted. Through this approach, the questions could be tested and evaluated so that all questions were clear and understandable. It was vital to generate interview material that enabled depth of analysis, while not ending up being too informal and therefore hard to extract relevance from. Conclusions from the test round was that more questions should be less specified, and instead more open than previously formulated. This was due to the fact that several questions were not adapted for the wide range of roles among the interviewees. If interviewees had trouble understanding a question, it was possible to slightly clarify the question or to ask a follow-up question instead, but ideally, clarifications should be kept to a minimum. Clarifications and follow-up questions do not necessarily violate the rules of a semi-structured interview (Kallio et al., 2016), but with every clarification, the risk is that bias from the interviewers pollute the answers. By this adjustment, a balance was found before the primary interview round.

3.3 Data analysis

The data analysis was conducted through a rigorous mapping of the gathered qualitative data. The main tactic for this research was to connect the dots between theory and empirics in order to be able to create a comprehensive framework for the bridge between classic RPA and IPA. To make this possible, the data from the semi-structured interviews had to be organized in a perspicuous manner, and presented as such. The data analysis was conducted iteratively, where the literature could provide new insights for upcoming interviews, and interviews could present new thoughts to be delved further into in theory. However, the interview guiding questions remained constant throughout the process. Conducting these parts in conjunction enabled synergies between theoretical material and empirical insights throughout the research process.

3.4 Quality of research

The responsibility of the researchers in qualitative research is high. Van Maanen (1998) suggests that qualitative research is often designed at the same time it is being done, and therefore requires "highly contextualized individual judgements". This was also to some extent true for this study, especially since semi-structured interviews were used.

3.4.1 Research ethics

This research is to some extent based on internal processes and intellectual property of *the bank*. Furthermore, these internal processes at *the bank* did in some cases contain confidential information. At the start of the research, a non-disclosure agreement was signed to ensure that the confidentiality of this information should not be threatened as a result of this research. To cope with this, there has been minor alterations to the data in order to respect the confidentiality, without erasing the validity of the research.

In these sorts of studies, there is often a risk of confirmation bias since researchers might want to find evidence that their ideas and hypotheses are correct. In this study specifically, it had to be ensured that central theory from the literature review would not taint the interview process, since the combination of them would eventually produce the results (the framework). Powell, Hughes-Scholes, and Sharman (2012), showed in their study, that confirmation bias was more prevalent among inexperienced and bad interviewers. In order to avoid common fallacies such as the confirmation bias, it was therefore important to study guiding literature for interviews, to seek experience from more knowledgeable interviewers at KTH, and to test our interviews before deploying them at full scale at *the bank* and external observers.

The result of this thesis is a framework based on the previous research and empirical interviews. It is important that the framework is a product with a strong fundament in the previous research and empirical interviews, and not purely a collection of factors that the authors thought would please the intended audience. Therefore, in the beginning of each section in the framework, there is a condensed guide that points to what research and empirics that stand as foundation for that particular section. As a consequence of this, it is also possible for the reader to find additional information regarding a section, in case it is of special interest to them.

3.4.2 Sources

Since this field of research is so young, in some cases, external information sources apart from peer reviewed journal articles had to be utilized. This demanded a specially high integrity in the navigation among these sources. A strong reason why a wide variety of sources were included, is because this field is driven by business rather than research. Hence there are some highly relevant insights presented by industry reports that have not yet gotten a foothold in the research realm.

It is important to separate research sources such as peer reviewed journals, or published books, from technology reports. Especially in the field of IPA applications, one must have a cautious approach to accepting conclusions. For example, some more visionary technology reports claim that Cognitive Agents (see Appendix section 9.2) is something that should be considered in the near future. However, examining the research done in this area, it is quite clear that Cognitive Agents is more of a futuristic concept rather than an application in the near future.

As previously discussed in the interview section, the majority of interviewees were all employees at *the bank*. This empirical data from the interviews will naturally be biased, and that had to be considered when producing generalizable conclusions. However, since the thesis consists of an in-depth case analysis of a specific company, bias in the data is a direct consequence of the chosen research method. Luckily, this research had access to four external observers, including 3 researchers, which enabled relatively unbiased sources to be the main influencers of the generalizable framework from the empirical section. The empirical interviews with employees at *the bank* were therefore primarily used to provide insights for applying the framework, as well as providing support from practitioners to the literature and unbiased sources. Insights from the employees at *the bank* could therefore not give rise to factors in the framework on their own, but they could to some extent confirm that a factor carries relevance also in practice.

4 Empirical research

4.1 Interviews

The first part of the empirical research consisted of 15 interviews. They were conducted to obtain insights, not only from researchers or industry reports, but also from employees that work hands-on with the techniques. This was important to enable cross-comparisons between real-life cases and theory. Implementing advanced techniques is often presented as a very simple plug-and-play process by the providers of the services, while in reality it is usually very challenging to seamlessly integrate new techniques in existing processes. Hence, it was crucial to capture the views on the subject from the personnel that is set to conduct the actual implementation, and not only cover fancy concepts, and ignore the complexity it comes with.

Below, we present the key takeaways from the interviews, categorized by competence/function. Full interview transliterations, apart from confidential information, are available on demand.

4.1.1 RPA developer interviews

Four RPA developers from the Automation department were interviewed. The primary focus for the developers is robot programming, but some of them also have tasks such as; platform controlling, team leading and strategic initiatives.

Generally, developers have a positive outlook, and see potential with AI technologies. Most have sound expectations, and feel that they are not falling for the hype of AI. A specific application example that was mentioned several times is the OCR technology, and there is an active OCR project at the Automation department. Furthermore, it was mentioned that some previously built RPA processes have only been partly robotized because some aspects of the process requires human intervention. The developers stated that these parts of the robot have potential to be taken over by AI algorithms and most of these parts were concerning error and exception handling.

As for limitations, the developers identify that potential AI cases are overlooked today in favor of standard rule-based automation cases. This is because the AI technology is not present today. They believe that a change in mindset is necessary going forward to address this, as they suspect that people perceive AI to be too abstract to yield any practical applications in the near future.

Regarding challenges, developers pointed out a variety of important aspects such as; data security and access, competence, training algorithms, KPIs, cross-functional cooperation and responsibility for robot actions. These will be further described below.

The silo-structure of data pools in *the bank* enables clear ownership of data at the cost of accessibility. Developers identified both pros and cons with this structure. They also mentioned that this data governance structure could be hard to challenge since it is deeply rooted in *the bank*.

The developers' automation competence and skill is generally high at the department with some developers having a background in software development, and some trained specifically to handle RPA software. The developers felt that AI knowledge could be higher among themselves, achieved for example by training. They said that this training could be a challenge since the backgrounds are so varied. However, almost more important than developer training, general knowledge about AI-techniques in the organization is a tougher challenge. One developer mentioned that different stakeholders have very differing opinions about digital transformation and AI. Some see potential whereas some see it as an abstract concept that does not concern their work. They mentioned that this could be a big limitation if the vision for digital transformation is not aligned.

The developers themselves also have differing opinions about how progressive the RPA department should be. Some developers felt that there was a risk of lagging behind technology-wise, whereas one developer felt that it was most important to deliver efficient solutions now, and not to focus too much on what lies ahead.

One potential overlooked aspect of adopting AI is the time and effort it takes to train the algorithm. Training an algorithm is very time consuming and might not be aligned with RPA goals of quickly reducing workload from robots. Training of algorithms might also have to be redone and thus robots might require maintenance, whereas traditional RPA robots requires less maintenance.

One aspect that developers felt hindered strategic AI initiatives was that the KPIs for the department put a lot of pressure on delivering quick cost-saving RPA robots. It was hard to prioritize strategic efforts, at least during the beginning of the year before the teams were on track to reaching the set goals.

Developers identified a need to further improve cross-functional communication within *the bank* to benefit IPA efforts. *The bank* has an AI department that is separate from the Automation department today, and while the communication between these is present today, a closer and more frequent communication could benefit both departments in the future.

One consideration brought up by the developers is that RPA software can set its limitations on the capabilities at the department. Some functionalities might enable cases, and lack of functionalities might hinder cases. They stressed the importance if properly evaluating software before buying it.

One highly relevant topic is how to handle responsibility for robot actions. Today, robots must be connected to a user and the user is indirectly responsible for the robot actions. When IPA robots will do more sophisticated tasks, how should this be handled? The bank is currently exploring how to use digital coworkers that have accountability on their own. The developers identified this as an important question to answer going forward.

The developers were well aware of data rules and had good knowledge of how to approach cases with uncertainties regarding data. For example, there is a GDPR group in *the bank* ready to handle this sort of questions.

4.1.2 AI department interview

Three employees from the AI department were interviewed, one covering more strategic aspects, and two working directly with R&D and Proof of Concepts.

The AI department truly sees the potential of both AI generally, and intelligent automation specifically. They believe that the financial services industry has plenty of interesting cases which is basically most limited by IT-security factors. The financial industry is also especially suitable because of its rich access to AI training data, which is important. One mentioned example of IPA being a chatbot that triggers robots which in turn could employ AI to produce answers to the customers. The AI department believe that there are AI techniques today that are ready, as long as the cross-system communication works.

When it comes to limitations, the most prominent one is, as previously mentioned, IT-security. AI is new territory for old and large companies who have a large focus on security. One of the limitations regarding security is the ability to map responsibility for actions by a robot. When you incorporate intelligence, it is even more tricky to map responsibility. In regular RPA you can often derive responsibility from the set of rules or the one who triggered the robot.

It is believed that the main challenges with implementing new technology is on the organizational part rather than the technical. This is also connected with the clear focus on security which is affected by the size and reputation of the company. It is suggested that the IT-structure that is in place might not be dynamic enough to handle new techniques that require data from different sources within the IT architecture. Another limitation that is mentioned is the financial services industry itself. It is one of the most mature and regulated industries which require transparent contact with governmental authorities. Additionally, a mentioned challenge is to get the entirety of the organization on board and accept the technology.

The key factors for a successful AI journey is pointed out as having a progressive and prepared organization as well as sufficient, but not too preventing, regulations.

4.1.3 Automation management

The backlog owner at the Automation department was interviewed. The backlog owner manages the case portfolio and leads the work of prioritizing among the robot cases. Furthermore, the manager for the Automation department was interviewed.

The backlog owner started to see the potential for IPA quite recently. Before, he was quite skeptical. Not necessarily about the technology, but rather about the challenges of getting everyone on board, which is vital to succeed. There needs to be a common goal all the way from top management to the target user, which implies that there needs to be a strategy in place that all levels of the organization believes in. He recognizes that IPA is not the solution to all problems, but that it can be a great supportive tool, especially where the IT architecture is not optimal. The backlog owner points out that RPA has been a band-aid to deal with complex legacy systems and layers upon layers of additional systems. However, he wishes to point out that RPA should not only be seen as a band-aid, but rather that its main benefit is improving *time to market* substantially.

For newer companies, he points out that the need of automation might be lower due to the absence of older legacy systems, but that in the financial services industry, it is extremely hard to avoid adding layers of new IT systems eventually. Therefore, even newer FinTech companies might find themselves in need of automation (like RPA) because they simply can't avoid it. The automation manager stated that he sees huge potential in IPA and believe strongly in the new technologies. Building IT solutions in huge systems is too expensive, but adding automation on top of the system is cheaper than hiring people for the tasks. He believes that the question is the pace of the development. The automation manager believes in exploring opportunities by learning through experimenting.

As for limitations, the backlog owner sees some risks with evolving RPA to IPA. Becoming better and better at automating and creating connections between a web of IT systems means that organizations might be less inclined to establish a good IT architecture in the first place. Theoretically, the more skilled the automation department is, the less they have to think about how well functioning the IT architecture is. The backlog owner also highlights that robots require maintenance, especially if systems change.

Another limitation that the backlog owner sees for IPA is that bad processes sometimes hinder automation. Processes might require extensive redesigning before automation can happen. Old processes might include manual tasks such as phone calls, and even though it might be possible to eliminate those aspects, it has to be considered as a serious obstacle for the work.

The backlog owner states that RPA software can also set its limit on the work with automation. It is very hard to choose the right software, and what could seem as a good choice because of one factor might be a bad choice because of another factor. He argues that it is not fun to later discover discrepancies between the expectations on the software and how it actually performs.

The backlog owner points out a couple of challenges that he believes have to be dealt with in order to be successful at IPA. First, he feels that innovation initiatives at the department can be hindered by their target KPI, saved workhours. Before the department is well on track with this KPI, innovation cases are usually deprioritized in favor of more standard cases. He thinks that measuring benefits of automation in a fair way is a very tough challenge because it requires an organization-wide change of mindset, especially for key stakeholders such as managers. The backlog owner sees that apart from saved workhours, RPA robots already contribute by increasing compliance in the processes. As for IPA, he recognizes that more robots will be augmenting, value-adding and also increasing compliance levels. He states that it is really difficult to measure these factors, and that there is no clear way of how to do it today. The automation manager further builds on this idea as he sees challenges in the requirements of measuring impact. In order to achieve change, you need hard numbers to support the solution. Providing this for a solution that is supposed to improve quality or mitigate risk could be difficult as those could be quite soft values.

The backlog owner says that *the bank's* system of internal charging for internal services also affects how the department works. With less of a baseline budget, it is harder to find financial space for innovation since innovation cases can be hard to attribute to a specific customer.

The automation manager mentions challenges regarding the width and complexity of AI initiatives compared to RPA initiatives. Employing a robot can take about 2 weeks and the expectations are altered based on that. However, when implementing advanced technology, the implementation can be very time-consuming and complex which entirely changes the expectations on what it needs to achieve. Furthermore the introduction of AI techniques has the potential to not only increase efficiency in processes but actually change the core of the processes. In that sense, AI is closer to traditional system development in contrast to RPA.

The backlog owner believes that key factors in order to create a successful IPA department, is to establish a Centre of Excellence with a variety of competences, have a long term strategic plan in place, and make sure that customers are on board with the new capabilities that the robots will have. The automation manager states that one important factor for a successful IPA journey is change management, including selling the idea to the organization to make sure everyone is on board. Attracting competence is another factor, as developing technology requires sufficient competence. Finally, measuring and showing value is important, meaning employing the right KPIs to show that the efforts are valuable. This should preferably be done incrementally to make the message clear.

4.1.4 Automation software engineer

The Automation software engineer also agrees on the potential of AI. He states that the most important aspect of bringing in AI into automation is to understand and clearly define the purpose of the new techniques. He further mentions that AI techniques does not only work as an analyzing step in an automation process, but could also improve the foundation of the robot software itself. This can be done for example by giving the robot "virtual vision" to see and learn from its own mistakes. He points out a limitation in unreasonable expectations, and strongly rejects the common binary view on AI, where it is thought to be either too abstract to trust, or able to do everything instantly. Identifying a clear purpose, and employing a fitting solution is the key to success. He further acknowledges a limitation regarding the transfer of data. Today, AI engines are commonly working on cloud-based solutions where the actual servers are placed in the United States. This can cause complications in practice due to regulations on data traffic, with one example being that health care data is not allowed to be transferred outside of EU.

He believes that the greatest challenges are not necessarily technical, but rather organizational, and coping with expectations. However, on a technical note the biggest challenge is training the algorithms with relevant data, and trusting the trained algorithm.

4.1.5 IT security and Architecture

This section includes interviews with one IT security specialist and one IT architect. One mentions that the IPA potential is great for *the bank*, in particular since there are a lot of manual assessments today where machine learning can be helpful. Here he quickly mentions the importance of being certain of how much responsibility you dare to give the machine. The question of responsibility is a recurring challenge. One interviewee mentions that AI could be employed to analyze the performance of the robots to find areas of improvement. By this, the robots could also teach themselves to identify buttons that are moved or reshaped to continue the process without force quitting. Another potential application mentioned is the surveillance aspect. A software can monitor the actions on a computer to identify potential automation cases. There are of course problems with monitoring employees on this level, but it has potential for the future.

When it comes to challenges and limitations, the main theme was regarding data. Challenges identified was both regarding generation of test data, and anonymizing real data for training algorithms, as well as the question of secure storage and processing in cloud platforms. Also, as touched upon before, the issue with traceability and responsibility was in focus. Within big financial organizations, risk awareness is really important, and therefore it is important to be able to assess *why* and *how* if money is lost due to a certain decision. This is particularly difficult with AI that enables subjectivity. All in all, it is deemed that AI has big potential, but for a company strictly moderated by risk awareness and security there are a lot of challenges that arise.

Organizational challenges mentioned are essentially to get the organization to trust the machine, and to understand that it is a mean of supporting employees by taking over some aspects of the work, and not replacing the human worker per se. A more broad challenge is also mentioned when it comes to changing the organization's general view on big changes and disruptive technology such as cloud platforms, and rethinking the foundations of the IT structure and protocols. Once again, it is a challenge to maintaining security and secure environments while still trying to develop for the future.

4.1.6 Researchers

Jan Gulliksen, PhD

As a Professor in Human Computer Interaction at KTH since 2009, and Vice President for Digital transformation at KTH, Jan Gulliksen has been involved in many projects in digital transformation. He sees great potential in digital transformation and AI as it enables us to automate many tasks, and instead let humans focus on future development and value-creation. He states that there is a common view that technology is erasing job positions, but argues that new jobs as a result of the technological advancements are created at the same pace. This is not a new phenomenon in the labor market, but has rather been going on for decades. Gulliksen sees a lot of potential for intelligent technologies within the financial services industry, since the extensive access to data enables good training for ML algorithms.

Gulliksen believes that the biggest challenges and limitations are regarding competence and data security. Competence development is key, and we need to close the competence gaps if we want to continue the development. For example, he mentions that within AI/machine learning there is now more positions open than there are qualified candidates. On an internal note, within companies, he believes that that there has to be an eager to learn and keep filling the knowledge bank which is related to having an innovative and progressive culture. Everything is becoming more and more data-intensive which means a change in responsibility for accessibility, security and integrity. He understands that regulations are a limiting factor for data-intensive technology and questions the reason for geographical boundaries when it comes to processing data. If the data is encrypted and the line is secure, why could you not run a process on a server outside of the office?

Gulliksen concludes that the most important factors for a future with AI are; competence, infrastructure, security, integrity and an innovative climate.

Joakim Wernberg, PhD

Joakim Wernberg is a research leader for digital transformation and technological development at the Swedish Entrepreneurship Forum. Wernberg's research is mainly focused around the complexity and interaction between technological development and society.

Wernberg sees a great potential for intelligent tools to automate monotone or calculation heavy tasks. He highlights that this change will impact people differently depending on their role and competence. He argues that there is a high probability of polarization because of this and that research seem to point out that middle-skilled jobs are most susceptible. However, he also states that intelligent tools show great promise in augmenting humans and that this can move people up the skill-ladder. Wernberg emphasizes that technology itself does not destroy jobs but rather changes the division of labor between human and machine, where the human's capability to work with cognitive tasks will be increasingly important. Wernberg thinks that one serious limitation with AI is that the traceability in ML algorithms are so low, which could yield regulatory complications as an example.

Wernberg states the importance of understanding that buying technology, and actually implementing technology are two very different things with the latter being a lot harder. Lack of competence is usually an obstacle here, and the risk is that organizations miss out great potential with poor implementation. To that, he adds that one of the biggest obstacles is suboptimal implementation of AI or ML. Utilizing new technology is not limited to absorbing the technology itself, but to adapt the organization and its processes to fit the tools that new technology brings.

Regarding data access, Wernberg states that lack of access to data between departments and systems can hinder efficient and accurate ML algorithm training. He highlights that pooling large quantities of data is positive from an algorithm training perspective, and that silo structures can be a problem on this topic. He also states that integrity regulations of course has an important part to play here, and that regulations are subject to change. Wernberg states that organizations usually have well established structures regarding financial flows, but not for data flows, and that organizations need to see that data flows are really important as well, and therefore structure them properly.

Jens Ohlsson, PhD

Jens Ohlsson is an affiliated researcher at Stockholm University with extensive practical experience of employing his models in organizations. Ohlsson claims that he belongs to the group of people that believe that radical changes are prominent and will challenge today's structures both on a macro level and organizational level. He recalls earlier technological disruptions such as the internet in the late 90's, and believes that we are now getting closer to a tipping point with intelligent machines, where radical change is inevitable. He believes that the tech giants such as Amazon, Google, Tencent and Alibaba will lead the disruption and chooses to see IPA as a sort of middle-solution before these giants provide all-encompassing solutions.

Ohlsson believes that the biggest challenges in the near future is the heavy economic structure that is in place after the third industrial revolution. The mass production system, like all paradigms, will be defended by major stakeholders that strive against radical change in fear of becoming obsolete. He further develops that this macro view is applicable also on an organizational level where the structure of processes is set, and that the mindset in many large organizations is not about rethinking the actual processes, but rather trying to streamline the processes that has been in place for a very long time. He concludes that developing and improving existing structures and processes is the easy way out, but what we actually should want to do is to change on a deeper level. He mentions Henry Ford who stated that if he would have asked the people what they wanted, they would have answered "faster horses", and instead he built the first commercialized car.

Ohlsson further discusses that business development should be technological and information driven. He believes that change should not be done top-down but rather in an experimental manner where trial-and-error is applied in the bottom layers of the organization. Trying things out that shows promise can potentially create momentum and create an innovation organization within the organization. He suggests that this bottom-up approach has better odds for development in contrast to deploying a general strategy from top management that is hard to follow up. This way of thinking about innovation requires management that dares to bet on hidden potential and take some risks. Generally speaking, he thinks that large corporations are too planning and controlling, and they want to see a business plan for every action with a clear process which eliminates the space for trial-and-error innovation. Furthermore, he mentions that KPIs could hinder innovation by attracting all focus to existing business and not leaving any thought for development.

5 Results: the bridge

With the literature review as a foundation, and key takeaways from the interviews, a framework for managing the transition to IPA was created. First, a condensed figure of the framework is presented to show the general structure and core areas it covers. It is then followed by a substantial walkthrough of each area and/or initiative that the framework treats.

The framework for transitioning from RPA to IPA is presented in the shape of a bridge, connecting today with tomorrow through the fundamental pillars. The general idea with the framework is to cover both the cores and fundamentals of the transition, as well as going into details of challenges and possible solutions. By incorporating both the general and detailed scope in the framework, it gives prerequisites for an organizational-wide preparation as well as a more focused perspective for the automation department in particular.

As for fundamentals, three core areas have been identified as the pillars of the bridge; *technological factors*, *workforce factors* and *strategic factors*. Each of the three core areas contains several subcategories that need attention in order to prepare the organization for an efficient and valuable implementation process. Every subcategory is furnished with a preface containing theoretical and empirical connections to provide clear reasoning behind the suggested initiatives.

5.1 Visualization of the bridge

Figure 1: The bridge with the fundamental pillars and their respective building blocks

5.2 Technological factors

Technological factors are what the name suggests, namely factors of transitioning to IPA that are enabled or limited by technological matters. It covers everything from managing data storage to choosing the right softwares for the purpose.

5.2.1 Data

Data is probably the most central piece of AI since every outcome and decision is directly dependent on the quantity and quality of data that the algorithm has learned from. Given this, important factors for enabling intelligent automation is directly related to data whether it be storing, accessing or processing it. Wernberg stated that companies in the financial services industry, for example banks, are very competent at handling various flows of money, both internally and externally, but that flows of data are not treated with the same respect. Wernberg argues that banks could benefit from respecting the importance of data flows, just as they do with money flows.

The data aspect draws on section 2.3.3, with Plastino & Purdy's argument that AI effectiveness depends on data accessibility. In section 2.5.5, this is discussed by Burgess, who focuses on why managing data supply chains in a serious way is essential. In section 2.5.5, Lacity & Willcocks state that data is one of the three most significant obstacles for IPA. Researchers Gulliksen and Wernberg stress the importance of data access in accelerating automation efforts. Several professionals from the Bank identified data access as a key enabler, namely; IT security and Architecture, AI department as well as developers.

In Mohanty & Vyas framework (2.4.1), one of their 15 key essentials is to leverage complementing tools that open new opportunities within IPA, cloud solutions can be identified as a complementing tool with great potential. In section 9.2, Kehoe argues that cloud solutions will be a useful tool in future ways to utilize IPA. Cloud solutions specifically, is not a topic commonly discussed by researchers, but is a practical solution to important problems within data management that has emerged from the industry side. The automation software engineer, IT security and Architecture all identify cloud solutions as an opportunity, but acknowledge that there are some obstacles before they can be fully utilized.

Lacity & Willcocks (section 2.3.3) and Wernberg both identify the issue of training data as a hinder across many industries for implementing AI algorithms. Gulliksen highlights that banks can have an advantage in the digital area due to its access to algorithm training data. Several interviewees at the Bank identified training data as key; the AI department, IT security and Architecture. The automation software engineer argued that training data was the most important technical factor for IPA.

Data access

Compared to RPA, IPA robots will generally be more dependent on data. In order to facilitate smooth robot development, organizations have to ensure that the data is accessible across the organization. This is a complicated matter since the financial services industry handles extensive amounts of sensitive data. If departments are responsible for granting access to their specific data, in a so-called silo structure, that risks to hinder efficiency for a future IPA department. However, full data sharing might not be desirable due to problems with confidentiality. No matter what data accessibility structure that is in place, it is important that there is a standardized and systematized way of accessing relevant data for robot development.

Conclusively, what seems to be important is to have a data access strategy that enables and facilitates a safe data storage service where IPA developers have easy access to data needed to build robots.

Cloud solutions

With IPA comes increased demands on data storage and computational flexibility. Cloud solutions have the potential to answer this call, but there are regulatory issues to overcome. One of them is that confidential data cannot always be transferred to cloud services due to regulations. An example of a suboptimal workaround that might have to be used, is local installations of cloud computing software. That means running offline computations on a platform that is built to be online, which is far from perfect. It is important that companies adopt a modern set of data rules. However, as previously mentioned, some of the rules are regulated by national laws, and therefore not up to individual company policies to handle.

Data security regulations is something that is lagging behind business today. A limitation is that many regulations are tied to jurisdictions based on geography, such as countries or the EU, whereas the internet is not that concerned with geography. An example is that it might be illegal to send data to a highly secure cloud storage service in one country, but legal to send it to a much less secure cloud storage service in another country. The list of what is considered secure countries is in the EU decided by the General Data Protection Regulation (GDPR). An interesting consideration is that the location of servers can have legal implications. A server located in the United States is subject to their laws and if there is misconduct, the server might be seized by U.S. authorities and subject to investigation there.

Obviously, data protection laws are harder to change than organizational rules and policy, so there is sometimes no quick-fix to counter these kinds of issues. It is however important to be aware of these challenges, especially when choosing cloud solutions for IPA, and data storage initiatives.

Conclusively, the journey to IPA can be possible without utilizing cloud solutions, since the ultimate goal is to have well structured data that is easily accessible, regardless of how its done. Nonetheless, instead of entirely changing the data structure in existing system architecture, it could be beneficial to create and implement a cloud strategy which will force a data structuring that can be done right from the beginning. As mentioned, employing a cloud solution is therefore not the end goal itself, but possibly the most viable option to reach this goal. A progressive and open approach to cloud solutions should greatly facilitate the IPA journey.

Training data

RPA algorithms are rule-based and might have required certain data for testing the robot before deployment. With several of the AI-technologies comes the aspect of training the algorithm. It does not suffice to just have test data, but training data might be required to build the robot. Depending on the robot case, the requirements on the data will be very different. One of the rather important differences from RPA is that the number of data points required for training is vastly greater for IPA.

This data either has to exist in the organization or has to be supplied from the outside. Two examples could illustrate this well, one from insurance and one from banking.

The first example is to identify damages to a car in an insurance claim, it is highly possible to buy external data to train an image recognition algorithm in case the insurance company does not have access to this data themselves.

The other example is anti-money laundering detection algorithms. In this case, it could maybe be possible to buy data on illegal and legal transactions to train the algorithm with. It is however quite likely that this data is not representative for the customers, and it is hard to obtain.

Conclusively, IPA robots will require training data that has not been needed before in the same way, and organizations have to understand and allocate resources for this. It is important to assess if this data exists at all and then to understand if the data is available in the organization or if it has to be bought.

Organizations that discard a lot of data regularly should also consider the possibility of saving the data instead as it could prove useful in robot training. This could require new agreements with customers, but as long as the data is properly anonymized, it should be possible.

5.2.2 Choice of software

Without good software, automation efforts will go from being a tough challenge to being almost impossible. Choosing automation software is not like buying a Microsoft Office license, it is a larger commitment, and therefore requires more work. RPA software is discussed in section 2.2.2, where for example Asatiani & Penttinen discusses the special characteristics of this software, and Lacity & Willcocks try to bring clarity to different approaches for buying software services. In section 2.4.2, Mohanty & Vyas discuss that organizations must "stitch" together the software portfolio. Developers at the bank asserted the importance of properly evaluating software before investing. Automation Management stated that software can both hinder and enable automation efforts and that it is hard to select software.

Choice of software

The software that is selected must be chosen with great care. It is highly important not to blindly trust software salesmen, but instead to undergo thorough testing, preferably regarding algorithms closely related to the relevant business cases. However, committing to a software purchase is not only about buying software, it also means investing in a relationship with the software provider. Analyzing the software provider can be equally important as analyzing the software itself since there is usually a high degree of interaction with the provider after the purchase. It is also possible that the software provider acts as a gatekeeper to some areas of application since they are in some cases responsible for implementing new techniques and functionalities in the software.

The first step is the make or buy choice. The available solutions range from pre-packaged and pre-trained algorithms, to a platform for writing own code. It is important to consider that the more software development that the organization undertakes on its own, the higher demands on the programming competence in the organization. There is a wide variety of solutions available, from a blank sheet of coding software, to more or less plug and play programs with support from the software provider.

The make or buy choice should be put in context to what technologies that are interesting. For example, if the organization wants to work with NLP in customer service, a buy strategy might be more relevant since NLP software is usually quite well-performing after a shorter time of training. With NLP software, the basics are usually implemented in the capabilities already and the additional training could be specific languages or addition of technical terms. NLP in customer service is relatively similar from company to company and even from industry to industry and that is why the software will require relatively little customization. The more peculiar the task, the bigger reason to look at more customized software or maybe even building it in-house. OCR is another technology where there is usually no reason to build anything in-house. The sole purpose of OCR is to identify text and arrange it in a desired way, and since this task is relatively simple and general, the software available is very good at it.

If the choice is to buy a more developed software and not to build something from scratch, a number of considerations arise. Softwares perform differently depending on the task. For example, one provider might offer an all-inclusive package with NLP capabilities, OCR and advanced analytics. The NLP might be cutting-edge, but the rest might be bad or outdated. In this case, it could be relevant to cherry-pick several softwares at the cost of having to buy from more than one provider. A choice that could depend on the financial muscles of the organization, as well as importance of the different cases.

AI-RPA software connection

The choice of AI software also has to depend on the RPA software. The point of IPA is to integrate AI technologies in automation, and it is therefore crucial that the software can communicate seamlessly.

Some RPA software have integrated AI capabilities and other have implemented good connections to third-party software providers. As in the previous section, it is of essence to thoroughly dissect, or at least test the communication between softwares before investing. If RPA software providers claim to have integrated AI capabilities, then they must also be tested, as is the case for AI software.

5.2.3 Assessment of available techniques

One bottom line to go by, is that techniques that are not understood will not be valuable. This does not necessarily imply understanding the mathematics behind or build-up of each algorithm, but rather to have an idea about what the techniques are ready to do, and for what type of case each technique can be useful. In section 9.2, various applicable techniques are discussed by several sources, for example Renal & Hain, Riikkinen et al., Stigerud et al., and Phangtriastu et al. In this section, there are also examples of analyzing why certain techniques are especially suitable in the financial services industry, for example by Mittal. Wernberg states the importance of understanding, as well as implementing, technology and techniques and not just buying anything to have something. The automation software engineer argues that all new technology that is brought in must have a purpose, and that it is essential to not adopt different technologies without planning.

Pointing out the relevant IPA techniques

Initiatives in new technology could be costly if a clear purpose is lacking. To have a clear purpose for each initiative, the different techniques available need to be assessed in terms of suitability. With a thorough understanding of what techniques are suitable for what type of case, the IPA department enhances the probability of focusing their efforts in the right direction from the beginning.

This assessment could be done through a workshop together with people with AI competence. By letting them present their catalogue of techniques that are deemed ready to use and combine that with automation knowledge and experience it should crystallize the needs and suitable solutions going forward. At the same time, this will also affect the knowledge spread throughout the automation department. As a support to this assessment, section 9.2 presents different IPA techniques and their area of usage.

Developing a timeline for IPA techniques

Relevance of the functionality is not everything when scoping the initiatives. It also needs to be technologically feasible. Given that, it is vital to understand the timeline for the techniques. It could very well be that a solution that seems relevant is not ready for production yet or is delayed by other factors such as shortage of training data or regulatory matters. For example, there might be a fantastic application for implementing a certain function based on clustering techniques, but policies might not allow this to happen. To be able to implement this, X years might be needed to make these changes in policies, and the technique is therefore placed X years into the future on this timeline. Focusing on solutions that are too far down the line could risk neglecting the short-term winnings which means that the idea of *when* to initiate efforts needs to be clear.

The prioritization of the initiatives could be assessed using an impact-feasibility matrix. By giving IPA initiatives an impact rating of 1-5, and feasibility rating of 1-5 one can rank the initiatives and get a good picture of how to prioritize between them.

5.3 Workforce factors

New technology most often implies changes for the workforce. For employees to cope well with technological advancements, certain areas have to be assessed and preparations have to be conducted.

5.3.1 Competence

A key component of advancements is competence development. Changing ways of working, and adding new tasks naturally require adapted competence levels. Whether this is achieved through hiring or educating existing employees is less relevant as long as the competence is sufficient to cope with the development. The question about competence was brought up by several inter-

viewees in the empirical studies. Automation management stated that hiring the right people is an important factor as technological development enables new and more advanced techniques. They also stated that it is not simply a matter of hiring, but also a matter of developing existing resources. Researchers Gulliksen and Wernberg shares the common view that finding, developing and capitalizing on competence is one important factor of the digital transformation process. They both have identified that there is a general lack of competence within these developing areas such as ML. In section 2.5, Dal Pont's research is presented, which says that a vital part of efficient Change Management requires assessing the organization's expertise and its core competences.

The strategic frameworks in 2.5.1 mention centralizing the automation capability, and co-creation between automation, business and IT. Empirical studies showed an explicit wish from the Automation department to have closer collaboration with stakeholders, such as data scientists and robot case clients. The automation management stated that establishing an IPA Centre of Excellence with mixed competences could be a key enabler. In 2.4.1, Mohanty & Vyas' viewpoint is presented, which says that treating RPA and AI separately when transitioning to IPA, would be a developmental setback.

AI knowledge and education

The problem with advanced topics like AI, is that people commonly avoid trying to learn more about it, as it is out of their comfort zone. It is simply a fear of the unknown and that they will not be able to understand it. Therefore, it is important to try to simplify the knowledge, and distribute it in the automation department. For example, this challenge can be coped with by bringing in external lecturers. While deeper knowledge within the subject could of course be valuable, it is more important that everyone has a conceptual grasp of what it is. To further build the competence in the department, a next step is to either hire or educate one or more designated specialists in the developer team, to cover the depth of knowledge. This specialist will inevitably spread the knowledge over time when working with IPA cases.

Cooperation

Isolation of the future IPA department is a threat to developing efficient robots. Robot developers need to have access and cooperation with relevant departments. This is something less critical in small organizations, since the organizational structure is organically less divisionalized. However, in larger organizations, these other departments that the future IPA department will depend on, can be hard to communicate and cooperate with. Examples of relevant departments and partners are; IT-security, data scientists and of course, robot case customers. In some cases, the knowledge that exists in these departments could be injected into the new IPA department by recruitment or education, but if that is not the case, the IPA department must collaborate more closely with them. A solution could be to make sure that the departments have close physical proximity, regular meetings or workshops. Employees could also temporarily switch departments to spread local knowledge through the organization.

Change in robot case characteristics

RPA developers are trained to look for rule-based executions, which is not always applicable to AI. While RPA is mainly used to build robots that automate straightforward workflow, AI can be used for advanced analysis, which is going to put much higher demands on developers. Suddenly, processes and actions that were non-automatable due to subjective decisions are now automatable, and in order to not neglect these processes, employees have to know this change. To make use of new techniques, there needs to be a change in approach, mindset and knowledge in the case selection process. While the case selection and prioritization should remain business-driven, it will now require a more open and exploratory mindset, rather than a binary possible/not possible judgement.

5.3.2 Organization-wide knowledge

To create successful change, it is of essence that the people who are subject to change are willing to accept and understand it. Since IPA aims to improve the organization broadly, the knowledge needs to be widespread. Not taking this into account might hinder the automation efforts. Common knowledge of IPA in the organization is mentioned as a key factor in the strategic frameworks presented in 2.5.1. It is also present in section 2.5.2 where several researcher's opinions on the subject is presented. Furthermore the empirical studies showed that both developers and automation management felt that the RPA case requests got bigger, better and more relevant over time as the organization got more knowledge about the capabilities of RPA. Managing hype is commonly referred to as one of the main challenges of implementing AI. In section 2.5.3, one aspect of managing expectations is presented; the organization should not expect the same type of effects from IPA as they did from RPA. Furthermore in the strategic framework by Mohanty & Vyas in 2.5.1, it is suggested by them to promise less and deliver more. Managing expectations is also a recurring theme as hype was an initial cause of dissatisfaction for early RPA implementations as presented in 2.2.3. From the empirical study, the mere insight that the perception and expectation differed vastly among interviewees suggests that expectations must be managed in some way to avoid a potentially harmful hype. On top of that, the automation software engineer suggested that coping with expectations throughout the organization was the greatest challenge of them all.

Common knowledge of IPA

In order to find suitable IPA cases and serve the organization, stakeholders throughout the organization need to have a "Goldilocks" level of knowledge of the capabilities in the future IPA department. One obvious, yet reasonable, way to contribute to this is to prepare pedagogical material that appeal to the other employees to present the ideas and reasoning behind the initiative, as well as the potential it brings. Employees in the organization could for example get an introduction by an information folder which cover previous cases, present capabilities and some examples of near-future proof of concepts.

On the same note, it is important to get top management on board so that IPA initiatives become a central and interesting development area in the eyes of management, and information spreading could contribute to this as well. Since digital transformation in general is a hot topic today, it is reasonable to believe that top management is receptive to this kind of information, but must still be assured.

The goal of these efforts is to both find promising automation cases by including more and more employees in an automation mindset, but also to create opinion for IPA initiatives to get stakeholders on board.

Expectations and hype

A key to IPA success is to have a positive framing of automation efforts, but also not to induce AI-hype.

When communicating regarding automation efforts, it is recommended not to state that automation will be the key to reducing manpower and saving costs. First of all, because many automation efforts, especially IPA, are augmenting and value-adding but not necessarily cost-cutting. Secondly, this communication risks to create powerful opinion against automation that could hinder organizations from adopting new technologies. If an organization is inefficient, manpower will most likely have to be reduced sooner or later anyway, regardless of automation efforts. The message that needs to be communicated is that automation is not what causes layoffs, but a way to decrease inefficient, dull and non-value adding tasks for employees.

AI-hype is potentially one of the most challenging threats to IPA initiatives. Previous AI-hype has eventually led to big disappointments and general disbelief in emerging technology. There are however ways to tackle this.

Make sure not to over-promise what IPA efforts will lead to. It is better to under-promise and over-deliver than to do the opposite. When convincing an organization to invest in IPA, it could be viable to display successful Proof of Concepts or previous RPA cases, instead of forecasting how well IPA cases will do, and then make promises based on that.

On the contrary to what is done in this thesis, avoid using the word Artificial Intelligence. Too many people have already formed their own opinion about what AI is and what it is not. If the relevant technology is OCR and clustering, use those words specifically instead of referring to them as AI. This will steer away AI-hype as well as bringing more accuracy into the expectations.

5.3.3 Changed workload and tasks

IPA initiatives will alter some roles, both for the organization as a whole and at the automation department. One interesting topic, by Kopec et al. (section 9.2) is the Hybrid Approach that envisions a new duality between human and robot. This approach handles the topic of robot trainers, that could be seen as a future role for some employees. In section 2.3.3, Lacity & Willcocks and Plastino & Purdy discuss the issue with finding proper training data for AI algorithms. Armstrong (section 2.1.4) argues that IPA helps organizations to find a healthy balance between machine and human. The automation software engineer argued that the biggest technical challenge for IPA is training the algorithms. The issue of training the robots was also brought up by IT security and architecture as well as Wernberg. Maintenance of the robots is also something that is easily overlooked, Brynjolfsson & Mitchell has one proposed remedy for this in section 2.1.3, which is similar to the Hybrid Approach. Maintenance of the robots has also been a topic for developers and automation management, where a central question is who is going to be responsible for the training task that does not exist in RPA development.

Training of robots

RPA robots are to a very large extent done and finished when they leave production. For some IPA robots, this will not be the case. Many of the relevant AI techniques require extensive training when the code for the robot is completed. Robot training could be done purely by a data set, but for some robots where data is scarce, it could be relevant to let the process owner train the robot. This could for example be especially relevant in exception handling, where the rule-based robot might be able to handle 90 % of cases well, but the last 10 % requires subjective judgement. The process owner could work parallel to the robot with the process and take over operations when the robot fails. In a longer perspective, robot trainer roles might be relevant to consider as an addition to the organization.

Maintenance of robots

Some IPA robots that utilize AI techniques that require training will also need a higher degree of maintenance than RPA robots. This is due to the fact that the rules that the robot learns by training, might have to change from time to time. For example, if an RPA robot requires a change, it might suffice to alter an if-statement. For a trained IPA robot, it might have to be entirely retrained if the old data set is obsolete. Imagine a robot that has been trained to detect suspicious transactions in a bank. If the bank establishes operations in a new country, the pattern of illegal transactions might change because money can be routed in new ways compared to the training data set. This means that the robot has been trained on outdated data and has to be retrained. To conclude, the developer force will probably in the long run have to spend more time on questions such as these, and the new IPA department needs to have the capabilities to deal with these matters.

5.4 Strategic factors

The strategic aspect is the core pillar that ties it all together. Technological initiatives and workforce changes are meaningless and hard to carry out without an all-embracing awareness of why it is done, and what end goal that is aimed for. This is where the strategic factors become relevant. With a clear long-term vision, means to measure the created progress, as well as a relevant business focus, Automation potential can be maximized.

5.4.1 Adapted KPIs

In section 2.5.3, both Burgess' and Lacity & Willcocks' views on adapted KPIs is presented. The need for adapted KPIs is also backed by the empirical studies, where Ohlsson stated that KPIs that are totally focused on past or current business can obstruct innovation and development. Rutaganda et al. describes lack of clear KPIs as one of the most common fallacies for implementing RPA (section 2.2.3). Section 2.5.3 also presents Burgess' list of factors that could be relevant as a foundation for metrics for IPA. The empirical studies further showed that the strict focus on hard KPIs leaves little space for innovation as there needs to be constant focus on reaching set targets, as described by both developers and automation management at the Bank. Automation management further mentioned that showing and proving results and progress is a vital part of every development process, which makes finding relevant adapted KPIs a true key factor to gain trust and momentum.

Technological advancements imply that new KPIs are needed to assess performance. Basic RPA brings immediate cost savings by taking over repeated and simple tasks from humans. However, this is not the case for IPA. Since intelligent techniques are designed to handle more advanced tasks relative to RPA, one cannot presume cost savings from the beginning. To adapt to this, it is more suitable to find KPIs that capture long-term value-adding from these initiatives. As IPA changes the workload and tasks for the workforce towards being more focused on maintaining and developing performance over time, the KPIs have to be altered in the same manner. Hence initially, KPIs can not be set to *saved man-hours* (Usually formulated as Full Time Equivalents, FTE) but rather more focused on the performance itself. Naturally, this will change over time as the technology matures, and in the long-term cost savings could be a result of IPA as well. However, initially IPA is more focused on value-adding rather than cost-cutting.

The risk with utilizing RPA KPIs focused around cost-cutting and time-saving is that IPA initiatives become limited to cases that are very similar to RPA. This might force the future IPA department to focus on short-term gains and not actually create long-term value.

Another issue with how automation efforts are being measured, is that the expectations of the capability is compared to a human, but the time it takes to learn is compared to a standard computer. A robot that requires 3 months training to perform like a human for a specific task is considered slow. But it is expected to perform as good, or better, than a human with much longer training than 3 months.

Conclusively, as IPA becomes more and more advanced, the contribution will be more about value-adding and less about cost-cutting. Organizations might not be ready to adopt new KPIs immediately, but will likely have to do so in a longer perspective.

Instead of measuring FTE for all robots across different functions, the KPIs could focus on specific areas where they bring value, for example compliance or customer service. In compliance, number of transactions or persons controlled due to increased automation, could be measured. In customer service, online waiting times could be measured. Customer satisfaction is also something that could potentially be interesting.

5.4.2 Business focus

It is important to understand that business is the core, and technology is simply a mean to drive the business forward. Hence, it is vital to have a sound business focus when conducting technological development in an organization. This includes having a long-term plan in place, in terms of planning for where in the business the technology should be applied, and also to let business opportunities set the direction of the technological initiatives. All of the strategic frameworks presented in 2.5.3 suggest that a long-term plan and vision needs to be in place. Lack of a long-term plan is mentioned in 2.2.3 by Rutaganda et al., as one of the common factors for failed RPA implementation, which suggests that this is a recurring theme that needs to be coped with. This thought is further backed by the automation management who identified that they could have benefited from a more developed long-term strategy when they first introduced RPA, and stated that having a long-term strategy in place will be crucial when aiming for IPA. Section 2.5.4 presents the ideas of several researchers who point out the importance of letting the business case drive automation. This is emphasized by Mohanty & Vyas, Venters, as well as Lacity & Willcocks.

Long-term planning

IPA initiatives should be guided by a long-term vision of how it will contribute to the overall business strategy. IPA could have general goals, such as generating revenue and cost-cutting, or more specific goals such as having a fully automated customer service. The goal could also be more visionary, for example that no employee should feel that a large portion of their work is repetitive and boring, or maybe that all employees should be augmented by technology in their decision-making processes.

The IPA road ahead, should then be shaped by this strategy. For example, if the goal is a fully automated customer service, the IPA department should focus on NLP capabilities and PoCs in customer interactions. This goal for automation will contribute to a thought overall business goal of having the most satisfied customers in the industry.

The long-term planning in essence contributes to direct focus, create meaning for employees involved, and make sense of each initiative's connection to the overall business targets of the company. Paving this way will not only make the journey clearer and more meaningful for employees on the department, but will also contribute to making the organization as a whole understand the value of the efforts.

Business-driven approach

A business-driven approach to adopting IPA is recommended. Being business-driven means that choices of techniques should be based on how good of a fit they are for the business, rather than trying to force a technique to fit a certain purpose. It does not have to be the most advanced technology, because there might be greater benefits with a more simple technology. It is neither necessary to utilize the most advanced packages from the software vendors just because it is said to be the latest and greatest.

This approach implies identifying the business case, and then using the knowledge of the techniques to deem what is the most suitable way to tackle the case, rather than using the available techniques as the starting-point and then forcing business cases on the techniques.

A business-driven approach to IPA also means that the processes of the cases should be simplified and evaluated before starting the robot development process. By simplifying and perfecting the process means that the robot can be cheaper to develop, and performing better in the end. When evaluating the process, it is also possible to find more radical process improvements, potentially even realizing that a robot might not have to be developed, the process can be handled differently.

5.4.3 Accountability

The empirical research showed that tracing responsibility for actions is vital, not least within the financial services industry. Deriving responsibility for decisions was pointed out by a vast majority of interviewees, both internal employees and external researchers, as a challenge with these new intelligent techniques. Gulliksen specifically highlights integrity and responsibility, and Wernberg points to integrity and traceability as points that organizations have to review. Responsibility is a point of discussion within the field of AI, for example brought up in section 2.3.2 by Tadeo and Floridi, who discuss the distribution of moral responsibility among stakeholders. Hence, this factor could not be ignored when constructing the framework.

Traceability

In the long term, responsibility will probably have to be partly attached to robots in several of the decision-making processes. Human responsibility over robot actions could be held by the robot developer, the employee who starts the robot (process owner), or maybe by department managers. Neither of these options seem to be a crystal clear choice and eventually it is likely that organizations will have to realize that robots to some extent will be accountable for their own actions. For RPA robots, this has been a relevant issue for long since they usually operate human user accounts. Organizations should consider using robot accounts instead for IPA robots, since traceability is not enabled by robots operating a human user account. It could in some situations be directly confusing to not be able to distinguish between human and robot operations.

As for why a robot is taking a certain decision, the level of traceability is very dependant on the sort of underlying algorithm. One of the major problems with Neural Networks is that it is essentially a "black-box" algorithm. There are certain financial services that are incompatible with untraceable decisions and this could have impact on whether Neural Networks can be used or not. This is an aspect that has to be considered when using Neural Networks as an engine for decisions in IPA robots.

The demand for traceability actually encourages augmentation instead of replacement of humans since many organizations are not ready to entirely hand over responsibility to robots.

Trust

The question of trusting an intelligent machine is rather philosophical. Do we trust a machine taking decisions by its own? Do we trust a human taking decision based on the input from a machine? It might sound trivial, but in a larger perspective this is probably one of the biggest questions going forward. Letting go of control over a process or decision that has been conducted by humans for several decades is hard, both for the workers directly connected to the process as well as for management and other stakeholders.

As mentioned in above section, one of the main factors that implies a lack of trust for intelligent techniques is that the process leading to a certain decision is a "black-box". It can be shown that such algorithm has been correct X% of the time, but as of today we cannot derive how or why it came to its conclusion. Few would (hopefully) trust a human who suggests buying shares in a company, if the person cannot argue for the case, so why would someone trust a machine doing the same? On the other hand, the person showing a track record of picking well-performing stocks could most likely use that statistic to build trust for future suggestions.

5.5 Applying the framework

The above presented framework was applied to *the Bank*. Applying the framework meant using the above presented factors for success to generate concrete recommendations for the company. Due to matters of confidentiality this section cannot be presented in its entirety. The application of the framework does not affect the emerging theories of this research. However, applying the framework certainly contributed to an assessment of the goodness of fit of the framework. Without including details of the actual application, the performance of the framework will be treated in the discussion sections 6.1 and 6.2.

6 Discussion

In this section critique towards the framework will be presented. Both in terms of content and how well it fulfills its purpose. Furthermore there will be some other reflections, including automation in the macroeconomic perspective for example.

6.1 The framework

The framework is an attempt at condensing the key factors from available literature and empirical interviews into a comprehensive guide to shed light on some key challenges. It is hard to validate the applicability since a majority of the challenges lies in the near future. The framework should also be seen as a manual to start IPA initiatives from RPA.

It is hard to evaluate the performance of employing the framework since the framework in essence is a starting point for changes that takes time to implement. Many of the challenges and changes presented require years of work before the end result can be deemed succesful or not.

The framework covers a wide variety of important factors that will be vital for the IPA journey. This perspective means that the framework is comprehensive in width, but not in depth. Data and other IT-strategy aspects are deemed crucial for the IPA journey but digging deeper within those specific areas would constitute an entire report on its own. Hence, the details of creating and employing an IT-strategy to face the challenges presented in this thesis, is outside the scope of this report. This could be a reasonable area of further research to support intelligent automation and digital transformation.

6.1.1 Application on *the bank*

When applying the framework at *the bank*, there were some areas that were identified as critical while some were deemed more mature. This is a reasonable insight as the framework in its origin should be generalizable regardless of size of the business. The bank has passed many growing pains but is instead affected by some challenges that mainly large and old organizations face, such as huge and complex IT-structures. An interesting observation is that *the bank* throughout this thesis work have launched initiatives that is very much in line with the recommendations in the framework. This thesis does not seek to claim any credit for that since it was released during the creation of the report, but at least it points out aspects in the framework being relevant which strengthens the validity of the research.

6.2 Critique

One potential issue is that the presented framework has been applied on the same company that was examined as one step in the process of constructing it. It is therefore important to highlight that the application of the framework on *the bank* cannot be regarded as a confirmation of the validity of the framework. However, building the theory through a case study at *the bank* enabled insights in details from hands-on work that is hard to replace solely by theory. Furthermore, it must be emphasized that all main aspects of the framework were inspired by previous research and interviews with researchers on the topic. Under ideal circumstances, the framework would have been tested on another company in the financial services industry. Two aspects stopped this approach: Firstly, it is time consuming to understand a company enough to apply the framework, and secondly, this would have caused problems regarding confidentiality.

One possible problem with the presented framework, it that it primarily sheds light on challenges rather than solving them. Hence, it is required that the user of the framework has the ability to generate an appropriate action plan to counter the challenges. This is however quite natural, since the problems that companies face are similar, but the solutions have to be tailor-made for each company. Generating every possible solution to the above mentioned challenges is simply an impossible task. Identifying and defining the problem can however be one of the hardest aspects of solving it and therefore the framework still contributes. As an example, the framework points out that cloud solutions is a suitable way forward and explains why, but does not give concrete guidance in how these solutions should be implemented in detail. Setting a cloud strategy and an action plan for implementation is in itself a project requiring an entirely different scope of research.

The framework presented in this thesis assumes that companies have started an RPA journey and want to transition into an IPA journey. There are of course some companies that will want to leap over the RPA phase and go straight to the IPA phase. In the future, when a higher maturity has been reached within this field, going straight to IPA might be strategically viable. However, as presented in this thesis, there are several arguments to why it is very beneficial to have a mature RPA journey before starting the IPA journey.

6.3 Reflections

The standpoint that IPA techniques will be augmenting rather than replacing in the financial services industry seems to be more and more backed by arguments the deeper the research goes. This could be due to the fact that responsibility and traceability are such vital characteristics of the industry, meaning that companies might be a little less inclined to replacing instead of augmenting. It shall however be mentioned that these industry characteristics are not the main reason why augmentation instead of replacement is more likely. The main reasons are because techniques rarely can do even close to 100 % of a job role better than a human, and the optimal combination is therefore human with support from a robot.

The macroeconomic implications of automation are highly interesting. The topic of decreased outsourcing as a consequence of automation is something that carries interest of macroeconomics, but could also be of interest for companies where outsourcing of manual repetitive tasks constitute a significant part of expenditures. An interesting topic for further research in a couple of years could therefore be outsourcing and automation, connected to implications for outsourcing firms.

7 Conclusions

This section will dissect how well the produced results answers the stated research questions and hypotheses. Furthermore, suggestions for further research in the field will be presented.

7.1 Answers to the research questions and hypotheses

How can organizations prepare for an efficient implementation of AI in the field of Robotic Process Automation for financial services?

This research question was split into the three sub-questions:

How should the automation department prepare the workforce for new technology such as AI? What strategic and technical preparations are necessary for an efficient implementation of AI into automation? What pitfalls should be avoided in order to get a seamless transition from automation to intelligent automation?

All of the sub-questions are answered by providing the framework presented in the results section. The framework is shaped in a way that it naturally addresses the two first research questions with its division of technological factors, workforce factors and strategic factors.

Integrated into the framework is also the answer to sub-question three where pitfalls, both previous and future, are addressed throughout a wide spectrum of areas that need action.

H1: *Measurability will be an even more prevalent challenge within IPA compared to RPA*

Based on theory which suggests that difficulties in measuring performance of RPA exists, a hypothesis that these difficulties will increase with IPA was produced. This is supported by empirical evidence that suggests that IPA techniques will move automation efforts toward being more augmenting rather than replacing. This change increases the need of new measurements of performance, and these measurements will be a lot harder to define than before since performance measurement for new techniques will be more of a subjective judgement. It will no longer be sufficient to judge an automation effort by the amount of man-hours it saves. This conforms with the point that the impact of RPA that is measurable today is time-saving, and the empirical study indicates that for IPA, the time-saving will not be the central benefit. Conclusively, based on this research, the hypothesis can be confirmed.

H2: *The issue of hype and unreasonable expectations on AI will spill over to IPA*

By reviewing the previous research and empirical study, it is possible to see that some hype is already present in IPA, since sporadic elements of hype has been encountered. The conclusion must be that there is a risk that unrealistic expectations and hype may spill over to IPA. However, since the topic of IPA has been less commercially exposed than the topic of AI, there is a possibility to counter this phenomenon before it becomes a problem. As the empirical study has indicated, the key to doing this is through knowledge, education and spreading the word without over-promising. On that note, it is reasonable to conclude that while there is some hype tendencies present, the hypothesis cannot be either confirmed or rejected with confidence at this stage.

7.2 Suggestions for further research

The research within the subject of IPA is currently in an emerging phase. The scope of the framework presented in this thesis is quite broad. A suggestion for further research could therefore be to examine one of the three factors in the framework more thoroughly.

One example would be to examine the educational part of Competence; What people in the organization need to have in-depth knowledge of AI, and what level of education is suitable for the rest of the employees? How do you efficiently educate these different groups to achieve the desired level of knowledge?

Another interesting subject to examine is how unrealistic expectations and hype can impact digital transformation in general and AI efforts in particular.

8 References

Aalst, P van der, M Bichler, and A Heinzl (2018). “Robotic Process Automation”. In: *Bus Inf Sys Eng* 60.4, pp. 269–272.

Aguirre, S and A Rodriguez (2017). “Applied Computer Sciences in Engineering”. In: Springer. Chap. Automation of a Business Process Using Robotic Process Automation (RPA): A Case Study, pp. 1–7.

Amezcua, J, P Melin, and O Castillo (2018). *New Classification Method Based on Modular Neural Networks with the LVQ Algorithm and Type-2 Fuzzy Logic*. Springer.

Armstrong, D (2019). *Accelerating Business Value With Intelligent Automation*. Tech. rep. https://forbes.com/forbes-insights/: Forbes Insights.

Arntz, M, T Gregory, and U Zierahn (2016). *The Risk of Automation for Jobs in OECD Countries: A Comparative Analysis*. OECD Publishing.

Asatiani, A and E Penttinen (2016). “Turning robotic process automation into commercial success”. In: *Journal of Information Technology Cases* 6, pp. 67–74.

Brynjolfsson, E and T Mitchell (2017). “What can machine learning do? Workforce implications”. In: *Science* 358.6370, pp. 1530–1534.

Burgess, A (2018). *The executive guide to artificial intelligence*. palgrave macmillan.

Business Insider Nordic (2018). *A Swedish bank has fired its world-famous AI assistant, Amelia*. URL: `https://nordic.businessinsider.com/a-swedish-bank-just-fired-its-top-ranked-ai-colleague--heres-why--` (visited on 02/27/2019).

Dal Pont, J-P (2016). *Process Engineering and Industrial Management*. Wiley. Chap. Change Management.

Deng, L and Y Liu (2017). *Deep Learning in Natural Language Processing*. Springer. Chap. Natural Language Processing: The Basics.

Eisenhardt, K and M Graebner (2007). “Theory Building from Cases: Opportunities and Challenges”. In: *The Academy of Management Journal* 50, pp. 25–32.

European Commission (2018). *High-Level Expert Group on Artificial Intelligence*. URL: `https://ec.europa.eu/digital-single-market/en/high-level-expert-group-artificial-intelligence` (visited on 02/27/2019).

Evreinov, G (2006). “Computers Helping People with Special Needs - 2006 10th International Conference”. In: ed. by Miesenberger K et al. Springer. Chap. 150.

Frey, C and A Osborne (2013). “The future of employment: how susceptible are jobs to computerisation?” In: *Oxford Martin*.

Fung, H (2014). “Criteria, Use Cases and Effects of Information Technology Process Automation (ITPA)”. In: *Advances in Robotics & Automation* 3.3, pp. 1–10.

Gartner (2016). *Gartner Estimates that 90 Percent of Large Organizations Will Have a Chief Data Officer by 2019*. Tech. rep. https://www.gartner.com.

Google (2019). *Google Cloud AI Building Blocks*. URL: `https://cloud.google.com/products/ai/building-%20locks/` (visited on 02/04/2019).

Goose, M, A Manning, and A Salomons (2014). "Explaining Job Polarization: Routine-Biased Technological Change and Offshoring". In: *The American Economic Review* 104.8, pp. 2509–2526.

Group, ISG (2017). *RPA and AI Survey Report*. Tech. rep. IS Group.

Hudson, D and M Cohen (2012a). *Neural Networks and Artificial Intelligence for Biomedical Engineering*. Wiley. Chap. Supervised Learning.

— (2012b). *Neural Networks and Artificial Intelligence for Biomedical Engineering*. Wiley. Chap. Unsupervised Learning.

IBM (2019). *IBM Watson AI OpenScale NeuNetS*. URL: `https://www.ibm.com/cloud/ai-openscale` (visited on 02/04/2019).

Infosys (2017). *Robotic Process Automation*. Tech. rep. Market outlook. https://www.infosys.com/.

Kallio, H et al. (2016). "Systematic methodological review: developing a framework for a qualitative semi-structured interview guide". In: *Journal of Advanced Nursing* 72.12, pp. 2954–2965.

Kedziora, D and H-M Kivaranta (2018). "Digital Business Value Creation with Robotic Process Automation (RPA) in Northern and Central Europe". In: *Management* 13.2, pp. 161–174.

Kehoe, B et al. (2015). "A Survey of Research on Cloud Robotics and Automation". In: *IEEE Transactions on Automation Science and Engineering* 12.2.

Khandani, A, A Kim, and A Lo (2010). "Consumer credit-risk models via machine-learning algorithms". In: *Journal of Banking & Finance* 34, pp. 2767–2787.

Kopec, W et al. (2018). "Hybrid Approach to Automation, RPA and Machine Learning: a Method for the Human-centered Design of Software Robots". In: *arXiv* 1811.

Kulinich, A (2018). "Architecture of a Qualitative Cognitive Agent". In: *Artificial Intelligence*. Ed. by S.O Kuznetsov, G.S Osipov, and L.S Stefanuk. Vol. 16. RCAI. http://2018.rncai.ru/: Springer, pp. 102–111.

Lacity, M and L Willcocks (2016). "A new approach to automating services". In: *MIT Sloan Management Review* Fall.

— (2018). *Robotic Process and Cognitive Automation: The Next Phase*. SB Publishing.

Lamberton, C, D Brigo, and D Hoy (2017). "Impact of Robotics, RPA and AI on the insurance industry: challenges and opportunities". In: *The Journal of Financial Perspectives: Insurance* 4.

LeClair, C (2018). *The Forrester Wave^{TM}: Robotic Process Automation*. Tech. rep. https://go.forrester.com/: Forrester.

Lowes, P et al. (2015). *Automate this: The business leader's guide to robotic and intelligent automation*. Tech. rep. https://www.deloitte.com/.

Manyika, J et al. (2017). *Jobs lost, jobs gained: What the future of work will mean for jobs, skills, and wages*. Tech. rep. https://www.mckinsey.com.

McCall, G and J Simmons (1969). *Issues in participant observation: A text and reader*. Addison-Wesley.

McCulloch, W and W Pitts (1943). *The bulletin of mathematical biophysics*. Springer. Chap. A logical calculus of the ideas immanent in nervous activity.

McKinsey, Global Institute (2017a). *A future that works: automation, employment, and productivity*. Tech. rep. https://www.mckinsey.com/.

— (2017b). *Artificial Intelligence: The Next Digital Frontier?* Tech. rep. https://www.mckinsey.com/.

Mittal, V (2019). *RPA and AI in banking*. URL: `https://medium.com/@vratulmittal/rpa-and-ai-in-banking-the-next-step-in-the-efficiency-game-for-banks-to-deliver-better-customer-f2aa60dffbf0` (visited on 02/04/2019).

Mohanty, S and S Vyas (2018). *How to compete in the age of artificial intelligence*. Apress.

Nash, K (2017). *Deutsche Bank Deploys Artificial Intelligence to Help Meet Demands of Regulatory Compliance*. URL: `https://blogs.wsj.com/cio/2017/04/18/deutsche-bank-deploys-artificial-intelligence-to-help-meet-demands-of-regulatory-compliance/e` (visited on 06/08/2019).

Phangtriastu, M, J Harefa, and D Tanoto (2017). "Comparison Between Neural Netwrosks and Support Vector Machine in Optical Character Recognition". In: *Procedia Computer Science* 116, pp. 351–357.

Plastino, E and M Purdy (2018). "Game changing value from Artificial Intelligence: eight strategies". In: *Strategy & Leadership* 46.1, pp. 16–22.

Powell, M, C Hughes-Scholes, and S Sharman (2012). "Skill in Interviewing Reduces Confirmation Bias". In: *Journal of Investigative Psychology and Offender Profiling* 9, pp. 126–134.

Rajan, Zeeshan (2016). *Robotic Process Automation (RPA) within Danske Bank*. Tech. rep. Company Report. https://www.danskebank.com/.

Renal, S and T Hain (2010). *The Handbook of Computational Linguistics and Natural Language Processing*. Blackwell Publishing Ltd.

Rich, B (2018). *Harvard Business Review: How AI is changing contracts*. URL: `https://hbr.org/2018/02/how-ai-is-changing-contracts` (visited on 02/04/2019).

Riikkinen, M, H Saarijärvi, and P Sarlin (2018). "Using artificial intelligence to create value in insurance". In: *International Journal of Bank Marketing* 36.6, pp. 1145–168.

Rutaganda, L et al. (2017). "Avoiding pitfalls and unlocking real business value with RPA". In: *The CAPCO Institute Journal of Financial Transformation* 46, pp. 104–115.

Rynes, S and R Gephart Jr (2004). "From the Editors: Qualitative Research and the "Academy of Management Journal". In: *The Academy of Management Journal,* 47.4, pp. 454–462.

SAP (2019). *SAP TAO*. URL: https://wiki.scn.sap.com/wiki/pages/viewpage.action?pageId=442631301 (visited on 02/01/2019).

Shanmuganathan, S and S Samarasinghe (2016). *Artificial Neural Network Modelling*. Springer.

Stigerud, F, F Andrén, and M Kihlberg (2018). *Skandia Investment Management (SIM) i en digital värld*. Tech. rep. EY.

Taddeo, M and L Floridi (2018). "How AI can be a force for good". In: *Science Magazine* 361, pp. 751–752.

Targowski, A and V Modrák (2011). "Is Advanced Automation Consistent with Sustainable Economic Growth in Developed World?" In: *ENTERprise Information Systems*. Ed. by M Cruz-Cunha et al. Vol. 219. Springer, pp. 63–72.

The Economist, S (2016). *The Return of the Machinery Question*. URL: https://www.economist.com/special-report/2016/06/25/the-return-of-the-machinery-question (visited on 01/28/2019).

UiPath (2019a). *UiPath - Intelligent Process Automation*. URL: https://www.uipath.com/rpa/intelligent-process-automation (visited on 02/07/2019).

— (2019[b]). *Reliable SAP Automation software*. URL: https://www.uipath.com/solutions/technology/sap-gui-automation (visited on 02/01/2019).

Vagen, T (2018). *HSBC set to launch cloud-based AML system next year, says senior official*. URL: https://www.reuters.com/article/bc-finreg-hsbc-data-cloud-aml/hsbc-set-to-launch-cloud-based-aml-system-next-year-says-senior-official-idUSKCN1NX1KU (visited on 06/08/2019).

Van Maanen, J (1998). "Different strokes: Qualitative research in the Administrative Science Quarterly from 1956 to 1996". In: *Qualitative studies of organizations*, pp. 9–32.

Wilson, V (2012). "Research Methods: Interviews". In: *Evidence Based Library and Information Practice* 7.2, pp. 96–98.

Wright, S and A Schultz (2018). "The rising tide of artificial intelligence and business automation: Developing an ethical framework". In: *Business Horizons* 61, pp. 823–832.

9 Appendix

9.1 Interview questionnaire

Do you encounter AI in your daily work? If yes, in what way?

What opportunities do you see for AI in general and AI for automation in particular?

What are the biggest limitations for AI in general and AI for automation in particular?

What challenges do you think that an implementation of AI implies for an organization?

What factors do you believe are the most important before a future with AI?

How do you handle uncertainty regarding access and usage of data?

9.2 Applicable concepts of IPA

Below is the section of the Literature review that was deemed to be more important for practitioners to examine, and less important for the research conducted.

Here, several applications and areas of applications are presented. This list should not be seen as a catalogue of all IPA techniques, but rather as inspiration and initial guidance. Apart from the more popular techniques, The Hybrid Approach will be described, which is a way of working with AI in general, rather than a set of algorithms or techniques. Cognitive Agents will also be presented, although it is more of a futuristic concept rather than a reasonable application at this time.

Natural Language Processing and Speech Recognition

Mohanty and Vyas (2018) state that Natural Language Processing (NLP) certainly could be utilized as a complement to RPA. NLP can standardize information from several input sources, among them; emails, databases, websites, logs and transcripts. As stated before, a significant drawback with RPA is that it requires perfectly defined input data. NLP has a potential to limit this drawback quite significantly, since it can structure unstructured language data. This implies that the addition of NLP can increase the range of applications to processes where unstructured data previously was an obstacle. Armstrong (2019), in their industry report, suggests that NLP can be a useful addition to RPA, by for example handling incoming communication and classifying them, and therefore decreasing manual workload. LeClair (2018), in their industry report, claim that text analytics, which NLP enables, enhances the strategic value of RPA.

Speech recognition could be utilized to enhance they way people can communicate with computers and systems (Renal and Hain, 2010). Through for example Apple's Siri and Google's Alexa, this technique is already enhancing people's everyday life. With increasing precision in the algorithms of speech recognition, the business case for this technique becomes stronger and stronger.

User interface through text

An interesting application of NLP, especially in processes regarding customer service, is the implementation of chatbots (Riikkinen, Saarijärvi, and Sarlin, 2018). The chatbots are in essential a combination of NLU and NLG. The chatbots can be implemented both for external and internal use, as described by Stigerud, Andrén, and Kihlberg (2018), and a connection with RPA software enables automated communication with great possibilities. Mohanty and Vyas (2018), also identify chatbots as a great extension of RPA, where the chatbot can act as a window to the user to extract information that the rest of the RPA-program can retrieve for them. There are several pre-developed and pre-trained NLU softwares in the market today that can be used to build a chatbot, for example; Amazon's Lex, Microsoft Linguistics Analysis or Google's Parsey McParseFace. Benefits of these solutions include that they are very cheap and API based [2] (Burgess, 2018). Lacity and Willcocks (2018) highlight the fact that different chatbot softwares are on extremely different cognitive levels. Available in the market, there are many rule based chatbots that are very naive, but there are some more refined options available. An example of a more refined software is IPSoft's Amelia, that uses algorithms that enables the bot to use memory from previous conversational exchanges as well as perception of mood. The memory aspect is quite significant, for example Siri and Alexa cannot put a question asked to them into a context, they do not even draw connections between two questions asked in sequence.

The Swedish corporate bank SEB, has tried one of the most progressive applications of chatbots within customer service (Lacity and Willcocks, 2018). They let IPSoft's Amelia handle several of its customer service interactions, for example credit card blocking, password change, instructions for setting up accounts and other general questions that deemed suitable for an AI. The results have been promising so far and according to SEB, the solution is saving time for customer service professionals, but most importantly, it will prepare SEB for future IPA implementations that can truly have an impact on costs and revenues. The implementation of Amelia is not a simple task though. Business Insider Nordic reported in 2018 that the internet bank Nordnet "fired" its Amelia system as it could not live up to its expectations (Business Insider Nordic, 2018).

Automated contract review

[2] API based means that they can be called with input and will then provide output that can be used for example by an RPA robot

The Digital transformation leader of Barclays Bank, Mittal (2019) identifies the concept of Automated contract review as a viable IPA application in the financial services industry. Banks and insurance companies deal with several different types of contracts, and the review process are in many cases good candidates for automation by AI systems.

Automated contract review is not a new concept, and there are a vast number of AI services for this application available in the market. Rich (2018) describes that Automated contract review can both help to identify errors in contracts, but also ensure that contracts are consistent and easy to interpret. He states that automated contract review has mostly been cost efficient for firms that handle a large number of contracts. However, as pointed out by Mittal (2019), the financial services industry does handle a large amount of different types of contracts, and could therefore be a suitable candidate.

User interface through speech recognition

One possible approach, that is quite straightforward, is to simply attach speech recognition software to existing NLP software. As in the example with chatbots, it does not really matter if the input is written or in speech, as long as the algorithms are precise enough. Mohanty and Vyas (2018) bring up speech recognition as a good addition to chatbots. Speech recognition could be used in customer service, but also in more general applications as it sometimes can be faster or even essential, for example in the case where the user is visually impaired (Evreinov, 2006).

Compliant customer interactions

One interesting application, suggested by Burgess (2018), is to let a speech recognition system, that is connected to a NLP-program, monitor interactions with customers. This could for example be done in asset management advisory to ensure that all recommendations are compliant, but also reasonable. A version of this has been implemented by Deutsche Bank, and has now replaced auditors who previously had to transcribe conversations and review them (Nash, 2017).

Automated report drafting

Burgess (2018) states that NLP has been implemented to draft earnings reports, for example at the news agency, The Associated Press. NLG, the subset of NLP that focuses on generating text, can be used to draft data-focused reports where the content to some extent follows a pre-defined pattern.

Auditing of financial instruments

Lacity and Willcocks (2018) tell the automation story of the global auditing firm KPMG. KPMG uses IBM Watson to assist finance professionals in the auditing process of financial instruments. The NLP robot examines the material for the audit and highlights parts that are subjects of interest or questionable. This has enabled the auditors to spend more time on value adding tasks instead of reading through all the material. IBM Watson is here used as a complement and not replacement for these auditors.

Optical Character Recognition

In their industry report, Stigerud, Andrén, and Kihlberg (2018) identifiy OCR-tools as a natural stage in the journey to what they refer to as Intelligent Automation; from RPA to AI. Mohanty and Vyas (2018) mentions OCR as an example of "leveraging complementing tools", which is one of their 15 key essential steps for a successful IPA journey (see section 2.4.1 Strategic frameworks). OCR enables processes that include handling of physical documents and previously non-readable documents (for a computer), to be automated by RPA. OCR is not something that lies in the future, but is relatively simple to integrate in the RPA process due to the maturity of OCR software. In their industry report, Armstrong (2019) surveyed more than 300 large companies (revenue > \$1B) and found that 13 % had fully implemented OCR systems in the automation process. OCR enables smart document reading that is not limited by fonts or handwriting. Before OCR, these documents would have to be manually handled by a human.

Advanced document scanning

The applications of OCR are very straightforward. Documents that were previously unreadable by computers can now be read (Phangtriastu, Harefa, and Tanoto, 2017). It could be a contract, a report or a handwritten note.

Clustering and classification

Credit risk modelling

A generic example of a data analysis application in the financial services industry is a consumer credit risk model, as showed by Khandani, Kim, and Lo (2010). A clustering approach to a credit risk model, is to let the clustering algorithm divide consumers into a specified amount of groups, called clusters (Burgess, 2018). The underlying characteristics and their interactions (often not observable by a human) will be the foundation for the group fragmentation. If a high number of consumers in a specific group starts to default, one could assume that other group members are at risk of defaulting. An addition to clustering is to combine it with classifiers, for example a binary response variable for *default* or *no default*, to be able to point out good and bad applicants.

Insurance risk modelling

Very similar to the previous application, clustering and classification modelling can be applied to identifying individuals that should pay higher insurance premiums. Burgess (2018) brings up the idea to classify people based on these techniques and the insurance industry has seen great development in this field during the recent years. It should however be mentioned, that this application is ethically questionable.

Identifying identity theft

As previously stated, these techniques are very efficient at finding patterns, but also interruptions in patterns. The insurance company USAA is using pattern recognition to identify transaction behaviours that deviate too much from previous patterns, and that match with fraudulent behaviour (Burgess, 2018).

Detection of fraudulent transactions

For detection of criminal activities, an account can be classified by a trained neural network by analyzing and classifying the transaction flows. Detection of fraudulent behaviour has been conducted for quite some time, but with the introduction of Neural Networks this can be done at a higher pace, covering more accounts and their transactions simultaneously. HSBC is currently investigating the use of these techniques in their money laundering detection unit (Vagen, 2018). The bank claims to have decreased the number of investigations by 20 %, without decreasing the number of cases sent to further investigation, implying that it can be used as a viable support system for investigators (Burgess, 2018).

The Hybrid Approach

Learning from errors with the Hybrid Approach

Kopec et al. (2018) suggest the concept of Hybrid Approach to automation as a new way of viewing the automation journey. By letting the process owner, i.e. the target for automation, be a part of the development process, the robot can be co-developed and co-maintained by the process owner.

A possible area of application of the Hybrid Approach is exception handling (Kopec et al., 2018). If a robot has some known error encounters, where it is impossible to setup proper rule-based handling, the robot could allow a user to handle the exception through manual correction. The robot can then record input data and the action for every exception, and thus learn to handle events that would be impossible by employing classic RPA methods. This approach also ensures less downtime for robots since process owners would be able to correct errors themselves instead of having to consult with the robot developer.

Training the robot with the Hybrid Approach

An example that Kopec et al. (2018) bring up is that a Neural Network could be implemented in the RPA system, for example in image recognition. An obstacle with Neural Networks is that the network requires proper data training to be able to function. A way to tackle this, is by using the process owner as a trainer of the Neural Network. The process owner would ensure that input and output of the robot are correct and by doing so, training the Neural Network. This would enable Neural Networks without proper training data to be trained live in the RPA development process. However, it is important to remember that training a Neural Network is very time consuming (requires many data points) and depending on the task, could even be impossible to do by humans.

Training the robot with cloudsourcing

A similar approach to the recently described Hybrid Approach to automation is described by Kehoe et al. (2015). Through the increased capabilities of cloud computing, training robots by outsourcing handling of input and output data is now a possibility. Cloud solutions in general has a possibility to increase the set of available operations and task handling, since solutions no longer have to be developed in-house.

Cognitive Agents

Mohanty and Vyas (2018) envision one of the bolder suggestions, that Cognitive Agents would oversee entire IPA systems, communicate with humans and machines, and identify optimization possibilities for IPA systems. The Cognitive Agent is something that lies in the future, and none of the industry reports that were examined mentions concepts such as Cognitive Agents. The Cognitive Agent would be a robot that acts like a system manager, that continuously evaluates possible improvements in the system. The architecture of such Cognitive Agents would resemble the human mind and features of the Cognitive Agent would include; perception, memory, beliefs and goal-settings(Kulinich, 2018).