Czech University of Life Sciences Prague

Faculty of Economics and Management

Department of Information Technologies

Diploma Thesis

Artificial Intelligence in finance shared services

Nazira Beisenbekova

DIPLOMA THESIS ASSIGNMENT

Bc. Nazira Beisenbekova

Economics and Management
European Agrarian Diplomacy

Thesis title

Artificial Intelligence in finance shared services

Objectives of thesis

The main aim of this thesis is to analyse the impact of AI on performance of finance shared services operations in SAP Services s.r.o. and explain it through a relevant theory.
The partial objectives are such as:
-To conduct a comprehensive literature review, studying the relevant theories on current usage and prospects of AI in finance shared services.
-To study challenges, opportunities, benefits and implications of AI in finance-related job functions.
-To examine the impact of AI on entry-level and mid-level employees of finance shared services.
-To evaluate the proposed ideas, formulate recommendations and make conclusions.

Methodology

The theoretical part of this thesis is based on the author's own research and study of relevant information resources, using qualitative document analysis and external desk research. The practical part will use both qualitative and quantitative methods. Based on an interpretation of the survey through a selected theory the conclusions and implications both for theory and practice will be formulated.

The proposed extent of the thesis

60-80 pages

Keywords

Artificial Intelligence, Machine Learning, Analytics, Financial operations, Digitalization, Future technology.

Recommended information sources

Bonnie G. Buchanan, PhD, FRSA. 2019. Artificial intelligence in finance. [https://www.turing.ac.uk/sites/default/files/2019-04/artificial_intelligence_in_finance_-_turing_report_0.pdf] s.l. : The Alan Turing Institute, 2019.

BUTLER, Tom; O'BRIEN, Leona. Artificial intelligence for regulatory compliance: Are we there yet?. Journal of Financial Compliance, 2019, 3.1: 44-59.

Mélanie Claudé, Dorian Combe. 2018. THE ROLES OF ARTIFICIAL INTELLIGENCE AND HUMANS IN DECISION MAKING: TOWARDS AUGMENTED HUMANS? [http://www.diva-portal.org/smash/get/diva2:1230135/FULLTEXT01.pdf] 2018.

Services, Tata Consultancy. 2017. Getting Smarter by the Day: How AI is Elevating the Performance of Global Companies. [http://sites.tcs.com/artificial-intelligence/wp-content/uploads/TCS-GTS-how-AI-elevating-performance-global-companies.pdf] 2017.

Stephen Jones, Craig Wellman. 2019. Artificial Intelligence in Financial Services. [https://www.ukfinance.org.uk/system/files/AI-2019_FINAL_ONLINE.pdf] s.l. : UK Finance and Microsoft, 2019.

Expected date of thesis defence

2020/21 SS – FEM

The Diploma Thesis Supervisor

Ing. Miloš Ulman, Ph.D.

Supervising department

Department of Information Technologies

Electronic approval: 20. 7. 2020	Electronic approval: 19. 10. 2020
Ing. Jiří Vaněk, Ph.D.	**Ing. Martin Pelikán, Ph.D.**
Head of department	Dean

Prague on 31. 03. 2021

Declaration

I declare that I have worked on my diploma thesis titled "Artificial Intelligence in finance shared services" by myself and I have used only the sources mentioned at the end of the thesis. As the author of the diploma thesis, I declare that the thesis does not break copyrights of any their person.

In Prague on 31.3.2021

Acknowledgement

I want to firstly thank my supervisor Ing. Miloš Ulman, Ph.D., for his guidance and feedback, which were crucial for completing this thesis. Secondly, I want to thank all the respondents who were kind enough to share their time and thoughts to contribute to this study.

Artificial Intelligence in finance shared services

Abstract

This study was conducted to understand how AI / RPA affects employees' performance in finance shared services and employment. RPA and AI work in tandem to expand automation into all sorts of new areas, allowing more complex tasks to be automated. The finance shared services are one of the most influenced by automation due to the sheer number of standard routines that accountants perform every day. The theoretical part is based on the literature on artificial intelligence and robotic process automation. The practical part includes quantitative and qualitative research. An attempt has been made to use the UTAUT model's construction, which helps identify influencing factors for technology adoption. In this context, one factor, the expected performance, was tested. The findings of the study demonstrated that the expected performance significantly affects the motivation of employees to work with AI / RPA systems. Moreover, concerning the issue of employment, fears of employees losing their jobs were identified. However, this study showed that AI/RPA is not currently replacing financial employees entirely but inviting them to interact with AI/RPA systems to work more efficiently.

Keywords: Artificial Intelligence, RPA, Finance Shared Services, Accountants, Performance Expectancy, UTAUT.

Table of content

1 Introduction

In today's world, many technological advances are rapidly evolving, exacerbating the need for companies to invest in artificial intelligence (AI) and automation. This is reflected in the global RPA and AI markets, which are growing rapidly and are expected to grow even more in the coming years. This area is profitable and has a lot to offer both to a wide range of companies and their clients.

Talking about these markets, we see a huge and progressive development in robotic process automation (RPA). RPA is mainly responsible for the higher efficiency of simple, repetitive, and time-consuming tasks. At the same time, we see that (AI), which improves decision making in very complex processes, is compatible to work in close tandem with (RPA). The result is a relatively new trend that has taken automation to a whole new level. At the moment, it is penetrating all sorts of new areas of the market. By combining (AI) and (RPA), many companies have been transformed and their decision-making and operational efficiency have improved significantly.

Of the many industries currently affected by the (AI) / (RPA) tandem, the finance industry is one of the most thriving. The reason for this is the huge number of standard routine operations in this area, which have the potential to be automated. According to a study by Frey & Osborne (2017), 702 workplaces are at risk of automation. Among these professions, accounting ranks first on the list with a 94% chance of being computerized over the next two decades. (Nagaraja, 2016).

More specifically, (AI) is rapidly changing the way financial services operate and is expected to increasingly take over core functions through cost savings and operational efficiencies. As a result, accountants will perform fewer repetitive number-related tasks and focus more and more on the added value tasks. However, given such rapid change and the human factor, it is not difficult to imagine the potential problems and limitations of such innovation. History taught us many times that innovations that were too progressive could strike fear into the hearts of people. And since no innovation is possible without considering the people who form the backbone of any company, it is important to make sure they are prepared for such rapid change. Among the most common negative moments among employees are stereotypes, fear, and misunderstanding of new trends and innovations. The main key to this problem lies in the hands of management, who must be able to work with their subordinates and ensure that the innovation process runs smoothly.

Therefore, this dissertation focuses on the impact of AI / RPA on the productivity and employment of GFSS financial operations employees in SAP Services s.r.o. The company that develops enterprise software for business operations and customer relationship management was chosen for its enormous innovative potential. GFSS is SAP's core business unit, where financial processes are led by global teams of more than 1,200 employees, whose main strategic agenda is continuous improvement and automation. Moreover, the author of this master's thesis has worked for the company for a year and therefore has personal experience with it, as well as access to the necessary sources.

2 Objectives and Methodology

2.1 Objectives

The main aim of this thesis is to analyse the impact of AI on performance of finance shared services operations in SAP Services s.r.o. and explain it through a relevant theory.
The partial objectives are such as:

- To conduct a comprehensive literature review, studying the relevant theories on current usage and prospects of AI in finance shared services.
- To study challenges, opportunities, benefits, and implications of AI in finance shared services job functions.
- To examine the impact of AI on entry-level and mid-level employees of finance shared services.
- To evaluate the proposed ideas, formulate recommendations and make conclusions.

2.2 Methodology

The theoretical part of this thesis is based on the author's own research and study of relevant information resources, using qualitative document analysis and external desk research. The practical part will use both qualitative and quantitative methods. Based on an interpretation of the survey through a selected theory the conclusions and implications both for theory and practice will be formulated.

3 Literature Review

3.1 Artificial Intelligence

Despite all attempts to give an exact definition of the term “*Artificial Intelligence*”, one concrete definition does not exist. Every day, we hear that artificial intelligence will solve all our problems - from self-driving cars to cancer treatment. At the same time, some scientists and industry captains, such Stephen Hawking, theoretical physicist, and Elon Musk, the founder of Tesla believe that Artificial Intelligence poses an existential threat to humanity (Griffin, 2015) (Sulleyman, 2017). Where is the truth and what is hidden under this term?

The name of Artificial Intelligence was coined by the American scientist John McCarthy in 1956, one of the few pioneers of Artificial Intelligence, who firmly stated that Artificial Intelligence should mainly be aimed at forcing computers to do what people do easily and without thoughts, for example, to see and talk, drive and manipulate objects, and plan daily lives (Wilks, 2019). Modern dictionary definitions focus on Artificial Intelligence, which is a sub-branch of computer science, and how machines can imitate human intelligence, that is, to be like a human rather than becoming human. The Oxford English Dictionary defines AI as “*The theory and development of computer systems able to perform tasks normally requiring human intelligence, such as visual perception, speech recognition, decision-making and translation between languages.”*

The definitions of artificial intelligence begin to change depending on the goals that people are trying to achieve using the Artificial Intelligence:

- *Strong AI*. Some people tend to create systems that think just like people do. Work aimed at authentic modeling of human thinking is usually called “Strong AI”, also known as Artificial General Intelligence (AGI). Any result can be used not only to create systems that think, but also to explain how people think as well. Joseph Weizenbaum, of the MIT AI Laboratory, has described the ultimate goal of strong AI as being "*nothing less than to build a machine on the model of man, a robot that is to have its childhood, to learn language as a child does, to gain its knowledge of the world by sensing the world through its own organs, and ultimately to contemplate* *the whole domain of human thought*" (Copeland, 2000). However, we have yet to see a real model of strong AI or systems, which are real simulations of human cognition, since this is a very complex problem that needs to be solved (Hammond, 2015). A strong AI has attracted the attention of the media, but not all AI researchers believe that a strong AI is worth pursuing. Some critics doubt whether research in the next few decades will lead to the creation of a system with the overall intellectual abilities of an ant. (Copeland, 2000).

- *Weak AI*. Others simply want systems to work without understanding how human thinking works. Weak AI, also known as Artificial Narrow Intelligence, is about creating systems that can act like people, but the results will not tell us anything about how people think. The current AI program in most cases is a simulation of a cognitive process but is not itself a cognitive process. (Mooney, 2010) Similarly, a meteorological computer simulation of a hurricane is not a hurricane. One vivid example of this is IBM's Deep Blue system, which was programmed to solve the complex, strategic game of chess, a system that was a major chess player but, of course, did not play like people did (IBM, 1997)

- *In the middle of Strong AI and Weak AI.* This category includes systems that are informed or inspired by human reasoning. These systems use human thinking as a guide, but they are not guided by the goal of perfectly modeling it. (Hammond, 2015) It turns out that the main part of the development of AI, which is happening today by industry leaders, falls under the third goal and uses human reasoning as a guide to provide better services or create better products, rather trying to achieve the perfect copy of the human mind (Marr, 2018).

Those who work with Artificial Intelligence today make it a priority to identify the field for the problems it will solve and the benefits the technology can bring to society. For most, it is no longer the main goal to get to AI, which works just like the human brain, but to use its unique capabilities to improve our world. (Marr, 2018)

3.1.1 Four approaches of AI

"Artificial Intelligence, compared with natural human intelligence, aims at imitating, extending and augmenting human intelligence through artificial means and techniques to achieve certain machine intelligence" (Shi, 2011). When thinking about artificial intelligence, we should pay attention to the interaction between finding a goal, processing the data used to achieve the goal, and getting data used to better understand the goal. Artificial intelligence relies on algorithms to achieve a result that may or may not have any relation to human goals or methods to achieve these goals. With this in mind, we can classify AI in four ways:

- *Acting humanly.* Modern methods include the idea of achieving a goal, rather than imitating people completely. For example, the Wright brothers were unable to create an airplane by accurately copying the flight of birds; rather, the birds provided ideas that led to aerodynamics, which ultimately led to human flight. The goal is to fly. Both birds and humans achieve this goal but use different approaches. (Mueller, et al., 2018)
- *Thinking humanly* means trying to understand and model how the human mind works. There are (at least) two possible ways in which people can find the answer to the question: 1) discovering and documenting the methods used to achieve goals by monitoring your own thought processes. 2) observation of human behavior and adding it to the database of similar behavior of other people, considering a similar set of circumstances, goals, resources and environmental conditions. (Sklar, 2010)
  The difference between "*acting humanly*" and "*thinking humanly*" is that the former deals only with the actions, results, or product of a person's thinking process, while the latter deals with modeling human thinking processes (Sklar, 2010).
- *Thinking rationally.* A computer that thinks rationally relies on recorded behavior, providing guidance on how to interact with the environment based on available data. The goal of this approach is to solve problems logically. In many cases, this approach creates a basic method for solving the problem, which is then modified to solve the problem. (Mueller, et al., 2018)
- *Acting rationally.* Studying how people act in certain situations under certain restrictions allows us to determine which methods are effective and efficient. A

computer that acts rationally relies on recorded actions to interact with the environment based on conditions, environmental factors, and existing data. As in the case of rational thinking, rational actions depend on a fundamental decision, which can be useless in practice. Nevertheless, rational actions provide the basis on which the computer can begin negotiations to successfully achieve the goal. (Mueller, et al., 2018)

3.1.2 AI and human intelligence differences

Artificial intelligence and human intelligence delve into cognitive functions such as memory, problem-solving, learning, planning, language, reasoning, and perception. Both played huge roles in improving our society.

AI is an innovation created by human intelligence (Brown, 2019) designed to perform specific tasks much faster and with less effort. On the other hand, human intelligence copes with multitasking better and may include emotional elements, human interaction, and self-awareness in the cognitive process. (Brown, 2019) The following discussions further will explore these differences.

Storing and processing information. People are inferior to computers in the storage and processing of information. For example, a person must listen to a song several times before he can remember it. However, remembering a song is as simple as clicking "Save" in the application or copying the file to your hard drive for a computer. (Dickson, 2018) The human cannot remember everything on a long-term basis and cannot execute complex mathematical and logical calculations. Humans must settle for limited reasoning and memory abilities. (Wallon, 2019)

Speed of AI and human intelligence. The area where machines have the definitive advantage is in the processing speed. A machine can perform 93,000 trillion operations per second. For example, let us say that a doctor can make a diagnosis in ten minutes. An artificial intelligence system would be able to make one million diagnoses in that amount of time. (Watson, 2019) AI solves ten problems in a minute when a human can solve one math problem in 5 minutes (Gene Brown, 2019). Such processing speed and energy that the computers can provide allows them to excel in chess areas since they can calculate hundreds of thousands of moves per second. (Watson, 2019)

Decision Making. AI is very objective in making decisions since it analyzes based on purely collected data. On the other hand, human decisions can be influenced by subjective elements based not only on numbers (Ribiero, 2020) (Balinggan, 2019). Human thinking is, in most cases, not rational. It does not consider all relevant information, unlike what computers do with their statistical models. Besides, most human judgments are based on various mental rules that give reasonable judgments. They are often doubtful due to human feelings and prejudices. (Wallon, 2019)

Accuracy. AI often produces accurate results as it functions based on a set of programmed rules, while human intelligence is usually room for a "human error" since some details may be left out at one point or the other. (Balinggan, 2019)

Adaptation of AI and human intelligence. Human intelligence is flexible in response to the changes to its environment, while AI takes much more time to adapt to new changes. (Balinggan, 2019) For instance, when people play their first video game, they quickly transfer their everyday life knowledge into the game's environment. They know that they must dodge bullets and avoid getting hit by vehicles, for example. For AI, every video game is a new, unknown world. It must learn from scratch. (Dickson, 2018)

General function. Humans can create, collaborate, brainstorm, and implement, while AI is more about optimization and efficient task performance according to how it is programmed (Balinggan, 2019). The scientists who studied the brain found that the human brain consists of two hemispheres. The left half is associated with analytical, quantitative functions and language thinking, and the right half is associated with intuitive, creative, and non-verbal thinking. Both sides interact with each other thanks to the corpus callosum. The most significant difference with the computer is right there. Unlike people, a machine consists only of the left hemisphere and cannot be intuitive and creative. (Wallon, 2019)

3.1.3 AI real-world applications

According to a study by the IBM Institute for Business Value (ibm.com), 82 percent of all businesses and 93 percent of high-performing businesses are currently considering AI or moving forward, driven by technology's ability to increase profits, improve customer service, and reduce costs, and manage risks. (Rossi, 2019)

Currently, scientists are busy creating samples of artificial intelligence of increasing power and complexity. One can find some of the already created AI samples on his computer, in various gadgets, in his smartphone and car. Some of them, developed by organizations such as Google, Facebook, Amazon, IBM. The creators of such AIs hope that their offspring will reach the human level of intelligence, those who believe this will happen in the next 10-15 years. (Barrat, 2015)

Google AI conducts research that advances state of the art in this area, applying AI to products and new areas and developing tools to ensure that everyone can access AI. Jeff Dean, Google Senior Fellow, says that they want to use AI to expand people's abilities to achieve more and devote more time to creative efforts (Google). Google believes that it can make a significant contribution based on the scale of its products and services, investments in AI research, and its commitment to the responsible use and development of AI. They do this with AI for the public good, a program that focuses AI expertise on humanitarian and environmental issues. (Google)
"Keeping people safe with AI-enabled flood forecasting" is one of their recent projects. To increase awareness of impending floods, Google uses AI and significant computing power to forecast model creation that predicts when and where floods will occur and include this information in Google's public alerts. It also generates maps and runs up to hundreds of thousands of simulations in each location. Using this information, they create flood forecasting models that can predict when and where a flood could occur and its severity. (Matias, 2018)

Facebook AI Research is committed to *"advancing the file of machine intelligence and creating new technologies to give people better ways to communicate"* (Marr, 2018). One of the long-term goals of artificial intelligence is developing chatbots that can communicate with people naturally. Existing chatbots can sometimes perform specific independent tasks. However, it is difficult for them to understand more than one sentence or combine subtasks into one task to complete an enormous task. A more complex dialogue, such as booking a restaurant or talking about sports or news, requires understanding a few sentences and then explaining these offers to provide the next part of the conversation. Since dialogs between people are so diverse, chatbots must be experienced in many related tasks that require different skills but use the same input and output format. The Facebook AI Research team has built a ParlAI, a new open-source platform used for training and testing dialog models across multiple tasks to achieve these goals. (Weston, 2017) (Moore, 2017)

IBM Research (IBM, 2018) has been a pioneer in artificial intelligence since its inception and continues to expand its borders with research portfolio focused on three areas: Advancing AI, Scaling AI, and Trusting AI. *"IBM Research AI drives research in core techniques of AI: learning, reasoning, natural language processing, vision, speech recognition and planning"* (IBM, 2018). IBM Research is a leader in the development of reliable AI (IBM, 2019). It identifies aspects of reliable AI for scientific and engineering purposes, identifies various approaches to their achievement, and determine how to integrate them throughout the life cycle of the AI application. IBM Research leads the democratization of AI, making development faster, safer, easier, more comfortable and accessible to non-AI experts. (IBM, 2018)

Project Debater is IBM's next major milestone for AI, following previous achievements such as Deep Blue. Project Debater is the first AI system that can discuss people on complex topics. The system collects relevant facts and opinions, shapes them into structured arguments, and uses the language in clearly and convincingly. Moreover, this system can understand long and spontaneous speech delivered by a human opponent to create a meaningful refutation. (Aharonov, et al., 2019) Debater can be used by a lawyer preparing for a trial. He can review legal precedents and check the strengths and weaknesses of the case using fictitious legal discussions. Debater can identify financial facts that either support or undermine an investment strategy in the financial services industry. It can also be used as a layer of voice interaction for various complex interactions with clients, or even to improve young people's critical thinking and critical writing skills. This system is about language. Mastering the human language is one of the most ambitious goals of AI. Project Debater brings us one step closer on this journey. (Aharonov, et al., 2019) (IBM)

Furthermore, several industry leaders, including Amazon, Apple, Google, IBM, and Microsoft, joined to create a partnership on AI's benefits. This partnership is for people and society to study and formulate best practices on AI technologies, advance the public's understanding of AI, provide an open platform for discussion, and identify aspirational AI for socially beneficial purposes. This partnership establishes a common ground between entities that otherwise may not work together and serves as a uniting force for good in the AI ecosystem by gathering the leading companies and organizations. (PAI Staff, 2021)

3.1.4 AI in workplace

Artificial intelligence is completely changing the way we work. Complex tasks previously performed by humans are increasingly being automated thanks to advances in artificial intelligence technology, the increasing processing power of computers, and the availability of vast amounts of data. (Viehhauser, 2020)

Public concerns about human replacements due to automation and mechanization date back to the Industrial Revolution and even earlier (Martens, et al., 2018). One fear that AI could replace human cognitive functions and lead to the displacement of half of all jobs and lead to polarization, declining skills, and unemployment in the next two decades (Frey, et al., 2017). On the other hand, others argue that automation will not replace personnel but complement it, increasing employee productivity and creating new professions (A.Wright, et al., 2018). Historically, despite the unceasing waves of mechanization after the industrial revolution in all industries, automation has created more jobs for workers than replaced them (Martens, et al., 2018). (McKinsey, 2017b) believes there is no reason to worry about AI destroying jobs. Indeed, the successfully implemented AI has not yet come close to performing intellectual tasks as well as a person (Bughin, et al., 2017).

In the beginning, AI can help make existing processes faster and more efficient by automating and augmenting workers so that people can free themselves from boring and repetitive work and focus their attention on development and creative tasks (Bellman, et al., 2019). However, at some point, the processes may need to be changed entirely. Seizing this tipping point while keeping in mind the human dimension of AI and teams is a crucial challenge for management to adapt. (Kaplan, et al., 2020)

Sheen (2020) argues that as AI rapidly conquers the market, software and application vendors such as SAP must adapt to keep up. However, it looks more like plain a marketing ploy to convince SAP users to switch to systems with artificial intelligence capabilities and spend more money. In reality users do not really see how to integrate AI with human labor and tend to spend less on AI projects. A survey of Boston Consulting Group and MIT executives shows that seven out of ten AI projects had little impact, and AI adoption plans fell from 20% in 2019 to 4% in 2020 (Economist, 2020). Likewise, a study of senior executives working on AI projects (Davenport et al., 2017) reports that 47% of respondents find it challenging to integrate AI with existing people, processes, and systems. Thus, for AI to be successfully implemented, employees must accept, interact, and integrate their behavior with AI systems. Building the organizational infrastructure that will lead organization to success will require a new mindset, learning culture and leadership support. (E. Makarius et al., 2020).

Management and IT support are critical to the successful implementation of new technology. To increase the adoption and implementation of RPA into operational processes, effective change management and communication strategies are needed to ensure that employees understand the facts and benefits of RPA. (Fernandez, et al., 2018)

To find a healthy balance between machine and human tasks, management must engage in open dialogue with employees first and foremost as empathetic mentors and build trust with them. It is important to understand that many employees will be wary of replacing AI, whether that fear is justified or not. (Kaplan et al., 2020) Continuous improvement managers must understand the importance of supporting and educating employees and strive to give them the best (Fernandez, et al., 2018).

Secondly, organizational structures may need the flexibility to accommodate the different proportions of people and machines and the changing distribution of tasks between them. Management needs to identify its employees' skills and find a place for them in an ecosystem in which people and machines work hand in hand, complementing each other. Since AI increasingly performs many analytical and thinking tasks, workers need to pay increased attention to empathy and the emotional aspects. They have an inherent advantage over machines. (Huang, et al., 2019)

Thirdly, it is necessary to involve employees in developing and implementing artificial intelligence systems, combining the capabilities of humans and AI to obtain the best results (Cappelli, et al., 2018) (Rossi, 2019).

3.1.5 AI adoption theory

It is critical to understand how people adopt technology, specifically how people adopt artificial intelligence and what can be done to encourage people to adopt new AI programs. Employee technology adoption is a mature research area with many well-established theories that successfully predict the adoption and use of a wide range of technologies (Venkatesh, 2021). Researchers have developed models based on socio-psychological theories to understand how and why individuals accept and use technology. The most universal, generalizing eight other common theories and models of the adoption and use of technologies, was proposed by Venkatesh (2003). The Unified Theory of Acceptance and Use of Technology (UTAUT) includes Intention to Use as dependent variables. Four constructs are predictors:

- “Effort expectancy” or ease of use is defined as the degree of an individual’s conviction about how easy it is to master a given technology;
- “Social influence” is defined as the degree of conviction of an individual in how significant representatives of his social environment believe that he should use this technology;
- “Facilitating conditions” include training, support, infrastructure, knowledge and means the degree of conviction of the individual that the organization where one works adequately ensures and supports the use of the given technology by the employees;
- “Performance expectancy” is defined as the degree of conviction of an individual that using a given technology will help improve work performance (Venkatesh, 2021).

When the different findings are examined, it is seen that the most important determinant of behavioral intention is performance expectancy, in other words, the effect of expected productivity on the intent of use. That means it is crucial for people that the tool is useful and contributes to improving their performance. For example, perceptions of how practical AI applications are for achieving daily goals are consistent with earlier findings by (Chatterjee et al., 2020) to use the AI integrated CRM system. Similar results were obtained for voting machines (Merhi et al., 2019). A single study was found on AI applications and tools to support operations management. The study by (Cabrera-Sánchez et al., 2021) shows that the revised and expanded UTAUT model is consistent. The behavioral intent for AI applications to support operations management is significantly influenced by performance expectancy.

3.2 Finance Shared Services

Economic globalization has spurred the expansion and diversification of business enterprises, which has led to increased demand for a financial transaction model and operational efficiency. The Shared Financial Services Center has proven to be an effective solution to improve the standardization of financial accounting and its processes and facilitate the integration of business and finance. (Kong, et al.) Today 95% of Fortune 500 companies use Shared Service Centers, while mid-cap companies join this trend. The scope and depth of joint services and outsourcing continue to expand. (Arthur D.Little, 2015) (Kong, et al.)

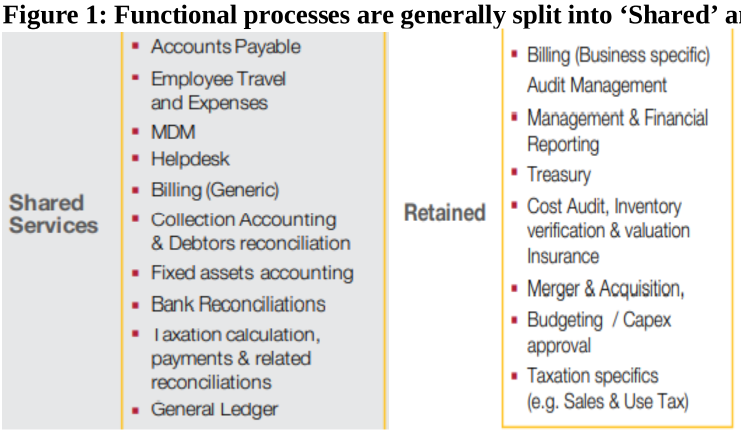
Shared Services is comprised of organizational units that ensure high standards of quality and efficiency while performing tasks to support business units and corporate headquarters. Shared Services can be divided into three focus areas:

1. Administrative support covers all transactional and rule-based tasks and should include automation experts as it holds the most potential for automation. Master data management is a typical example of activity within administrative support.
2. The monitoring of automated processes still has to be monitored to cover non-automated transactions and prevent misuse.

3. Centers of excellence are specialized teams that are self-contained and responsible for the entire function or process. (Suska, et al., 2019)

They are firmly entrenched in the corporate realm of large global companies. Shared Services focuses on providing support in the areas of finance, HR, procurement, and IT. Within these functions, only those actions with enormous potential for efficiency potential are outsourced to Shared Services Centers. In (Figure 1) below, we can see that, as a rule, general actions are those that are transactional, large-scale, and highly standardized. The rest of the activities are categorized as retained activities supported in local business units. They require more excellent proximity to the business and cannot be replicated with specific knowledge. (Capgemini Consulting, 2015)

Figure 1: Functional processes are generally split into 'Shared' and 'Retained' buckets



Source: (Capgemini Consulting, 2015)

Companies looking to centralize their finance and accounting functions usually want to process standardization and efficiency, cost-saving, and business intelligence. Standardized processes make it easy to design and update the control environment and create consistent reports. Companies with decentralized accounting functions spend a significant amount of time collecting data but not analysing it. When time management information is collected, and reports are available, it may already be outdated. Companies with a centralized function, in turn, can significantly reduce costs, simplify the verification work, and reduce the number of iterations. (Constantin, 2019)

3.2.1 The role of technology in Shared Services

SSC is continually striving to improve its performance by adding new technologies. Their goals are simple: reduce the burden on transactions, centralize and eliminate duplication of processes, create tighter controls, and improve transparency. (Buchanan, 2020)
However, making these goals a reality is not an easy task. Technology can be the solution when it is implemented wisely. Enormous opportunities have indeed already been created by technology.

The PWC (Suska et al., 2019) study shows which emerging digitalization initiatives are currently most widely used in Shared Service Centers to enhance automation's potential. 65% of survey participants indicated that they use RPA, 26% use chatbots, and 9% claimed to use Artificial Intelligence to automate their services. For instance, Artificial Intelligence takes on specific tasks traditionally performed by humans. It can also assist them in their existing tasks, increasing the overall process efficiency using machine learning algorithms. These algorithms transform detailed data into predictive models that provide new insights and accelerate decision making. Chatbots simulate conversation and reproduce automated self-service AI-powered customer interactions. They are increasingly used in Shared Service Centers to bridge language barriers between employees, which improves the overall quality of communication and shortens translation times. (Suska et al., 2019) Another example of what is possible, and is becoming increasingly available, is a technology known as Robotic Process Automation. Automation has enabled organizations of all sizes to reduce manual tasks. (Buchanan, 2020) That is a lot when considering the ever-growing amount of financial data to be processed, the ever-growing expectations of more accurate financial closures, and the inevitability of tightening budget constraints. Transactional tasks have moved to integrated business service solutions using robotics, automating, or eliminating up to 40% of transactions by 2020. (Axson, 2015) (Spanicciati, 2019) RPA is considered a major digital initiative for the near future to improve data standards and quality. It lays the foundations for more advanced intelligent technologies such as artificial intelligence. Today's digital leaders are combining RPA with Artificial Intelligence to automate any process that can be automated in Shared Services. This combination of RPA and AI provides shared service centers with the ability to process varying amounts of data. Adopting an automation-centric approach to RPA enables the Shared Services Center to move from cost reduction to value creation. One can identify the parts of the optimal process for automation and use them to change the way employees and software robots work together. This approach to RPA allows reevaluating how processes run from start to finish, remove the chore while freeing up employees for more critical activities, and increase the breadth and depth of the workload that can be handled without increasing its headcount staff or budget. (McDaniel, 2019)

3.2.2 Next generation Shared Services

As valuable as these achievements are (previous chapter), they are only a starting point. The next generation of Shared Services must be more agile, collaborative, and technologically savvy (Postma).

Corporate leaders need to rethink their organizational structure with a common goal of creating value beyond labor arbitration and efficiency increase (Suska, et al., 2016).

Shared services are now expected to play an increasingly important strategic role in the company's operations, influencing profits through labor cost arbitrage and efficiency benefits and increasing new business-oriented offerings, and increasing productivity (Capgemini Consulting, 2015).

Many aspire to create Global Shared Services by adopting shared services and outsourcing methods that are often first developed in finance, in other areas such as HR, procurement, IT, and equipment management (Lyon, et al., 2012).

In this respect and to reflect these areas, Shared Services is now increasingly referred to as Global Shared Services. (Capgemini Consulting, 2015)

Global Shared Services create value based on intangible factors. Global Shared Services provide highly standardized processes and maintain a constant focus on continuous improvement. The vision requires the organization to develop technological insight and customer focus. The relevance of customer service, cost-effectiveness, and scalability is increasing. (Suska, et al., 2016)

It is important to use technology effectively to meet the demands of global business services. The integration of specialized tools and systems speeds up process flows and significantly reduces errors. Besides, it allows businesses to continuously monitor work processes, which provides improved quality and high transparency. This standardized and technologically

advanced environment allows additional savings, such as automation of robotics processes, which will be discussed in more detail in the following sections. (Suska, et al., 2016)
Moreover, the successful implementation of Global Shared Services implies essential shifts in terms of talent management. Shared Services implementation and outsourcing often shift the rest of the finance group's responsibility away from performing financial processes to managing financial processes and managing service delivery relationships. The shift means that new skills are needed, including management, problem- solving, and communication skills. Influence skills are also essential to ensure key stakeholders' engagement in the business by demonstrating added value. (Lyon, et al., 2012)
Talented Shared Services professionals have the potential to become in-house consultants, best-in-class thinkers capable of quitting challenge the status quo by drawing on a wide range (Postma). It requires close coordination and integration, which can only be managed by developing healthy results-oriented thinking (Consulting, 2015).
Global Shared Services is a coalition of employees, business managers, technology professionals, suppliers, vendors, government officials, and customers that focus on the same goals. In the new world order, the ability to quickly adapt to changing industry dynamics will differentiate business leaders from laggards. (Postma)

3.3 SAP SE

There are many essential elements needed to run a company nowadays, so it needs something that becomes a management tool that is easy to use but can manage all the issues related to its sustainability (Sterling, 2020). One such tool for managing various business affairs of a company is SAP, which stands for System Applications and Products.

In 1972, five German entrepreneurs had a vision of the business potential of technology. Starting with one client and several employees, SAP has taken a path that changed the way companies do business. (SAP SE)

SAP is the leader and most used enterprise software on the market, with hundreds of fully integrated modules covering every aspect of business management. Its machine learning, IoT, and advanced analytics technologies are transforming customer businesses into smart businesses. SAP offers an integrated set of applications that support end-to-end business processes. This suite helps manage every part of the organization - people, customers, products, expenses, finance, and IT. (SAP SE) Using SAP creates a centralized system for enterprises that allows each department to access and share data to create the best working environment for every employee. (Indeed.com, 2020)

3.3.1 SAP GFSS

Global Finance Shared Services (GFSS) is a key SAP department (Raelson, 2017). It creates value for business partners and internal colleague around the world by executing financial processes led by global teams of over 1,200 employees of over 65 nationalities, located in offices in Singapore, Dublin (Ireland), Prague (Czech Republic), Manila (Philippines) and Buenos Aires (Argentina) (Raelson, 2017). SAP GFSS provides standardized services, optimizes processes, and emphasizes employee development in its departments. (portal.wdf.sap.corp)

3.3.2 SAP and AI

SAP has always been a data-driven company. SAP is known for transactional data - transactions, customers, products, points of sale, structured data (Bloomberg, 2019). This data forms the basis of what SAP calls the smart enterprise. SAP understands that as the volume of data grows, it needs to increase productivity and innovate at unrelenting clock rates to accelerate value creation. (Bloomberg, 2019)

The Intelligent Enterprise Campaign represents a shift in SAP investment in AI. SAP launched the SAP Leonardo toolset in 2017, which consists of services in areas such as the Internet of Things, Machine Learning, Analytics, Big Data (Press) that are often applied in tandem with AI (Duin, et al., 2018). In 2019, rather than focusing its efforts on Leonardo as a standalone product, the company decided to integrate AI across its entire product line. They make up the bulk of SAP's current smart technology suite of products. (Press) Research to date has shown that AI capabilities are most robust when used in tandem with other technologies. Many AI applications use a combination of automation and enhancement of existing processes. (Zhang, et al., 2020) For example, SAP Analytics Cloud expands access to over 150 cloud data sources, and enhancements to SAP Analytics Cloud include prebuilt content and business logic for over 20 SAP products, including SAP SuccessFactors, SAP S

/ 4HANA, and others (SAP News, 2018). What's especially interesting about how SAP integrates AI into many of its products is how pragmatic the company is. SAP is destroying this misconception that AI is for new things and uses AI for the same purposes for which they used business intelligence, but faster, cheaper, more reliable, and with much more data. (Bloomberg, 2019)

3.3.3 SAP Analytics Cloud

SAP offers a variety of products that implement various AI concepts. One of them is the SAP Analytics Cloud (SAC) tool. SAC was designed to provide a one-stop approach to analytics that brings people, data, and ideas from multiple sources to make decisions quickly and confidently. (Penner, 2019) Data preparation functions and analytics in one product enable users to plan and forecast more efficiently by switching freely between data management and visualization creation. (Penner, 2019) (Sheen, 2020)

SAC covers many of the AI concepts included in the tool, and people are often confused as SAP does not directly call these AI concepts. Instead, they have their terms for various AI functions, including concepts such as machine learning (ML) and natural language processing (NLP). (Sheen, 2020) Below we will look at what opportunities these concepts offer us:

Modelling helps improve the data for our more profound understanding. Machine learning technology can automatically cleanse data, alerting us to potential errors and categorizing measures and dimensions. (Sheen, 2020) (saphanajourney.com, 2020)

SAP Analytics Cloud automatically suggests intelligent transformations based selected column’s context and provides data preparation recommendations. To better prepare the data for advanced visualization, we can update the values and sort, delete, merge, and split columns. (Sheen, 2020) (saphanajourney.com, 2020)

SAP Analytics Cloud machine learning technology complements the analytics process by enabling to move from insight to action in a short timeframe. Automated technology avoids agenda-driven decision making and bias by uncovering the story behind what drives business. (Ivain, 2019)

Natural language query instantly creates visualizations to answer questions. Machine learning technology helps to identify significant trends at the click of a button. (Sheen, 2020) (saphanajourney.com, 2020)

Smart Insights allows seeing more information about the received data on the chart or variances in the visualization. We can identify the area that contributes the most as well as the customer segment. We can also use the results to drill down to the different details for each one. (Hilgefort, 2020)

Smart Discovery automatically creates an extensive four-page story “Overview, Key Influences, Surprising Values, and Simulation” in just a few minutes. These pages contain ready-to-use complex information. Discovery in SAP Analytics Cloud creates a story by highlighting key influencers and enabling different simulations. This feature is essential when finding information and preparing for what might come next is vital. (Ivain, 2019)

Smart Predict functionality in SAP Analytics Cloud allows to create predictions of future events, values, and trends using historical data (Moser, 2020).

3.4 Robotic Process Automation

The trend towards Artificial Intelligence has also reached the Robotic Process System. Various researchers indicate that complex RPA solutions are starting to become smart and include of Artificial Intelligence and Machine Learning (ML) capabilities to recognize and process unstructured data or learn in collaboration with humans. (Viehhauser, 2020)
RPA is a software-based process automation technology that involves robotic assistant’s customization that mimic human activity by performing routine office work tasks based on customized rules. The main goal of RPA is to automate everyday tasks to improve efficiency, provide better services and reduce costs. (Dias, et al., 2019)

Many organizations have been keen to adopt RPA technology to improve their operational efficiency, quality of work produced, simplify, and accelerate implementation and integration with other systems, and improve risk management and compliance (Syed, et al., 2020).

RPA focuses on time-consuming tasks that are large in volume and require many manual steps, usually associated with shared service centers (Suska, et al., 2016). A typical use case is invoice creation. To create an invoice, the bot can be instructed to extract data from an Excel sheet and enter the invoice data from that sheet into the correct fields on the SAP form. When all data is inserted into SAP, the bot creates an invoice by performing all transactions. This example highlights the considerable power of RPA, which is to connect different applications without human intervention. (Noppen, et al., 2020)

Without human validation, RPA can get things done faster and better, but it can also make mistakes due to low data quality or inadequate definition of business rules (Kirchmer, 2020). However, these risks can be minimized if tasks being automated are expected to have the following characteristics:

High volume: With bots that perform routine, repetitive, high-volume tasks, employees can focus on more valuable tasks that require higher-order thinking (Griffiths, 2016). Desktop applications and workflows that require information gathering from multiple sources or high-volume bulk processing functions within tools such as enterprise resource planning systems are ideal candidates for RPA (Suri, et al., 2017).

Repetitive: One can quickly identify clerical, repetitive work that does not need reasoning, creativity, emotional intelligence, or interaction with other people to be performed (Zaharia-Radulescu, et al., 2017).

Rules-driven: Data entry, account validation, maintenance, creating online credentials for new employees and customers, issuing purchase orders, maintaining a general ledger account and other back-office processes that do not require human intervention or complex exception handling are ready to be automated by RPA (Slaby, 2012).

Structured inputs: Well-defined and structured tasks and processes are ideal candidates for automation. A high degree of standardization is required prior to automation to reduce process and output variations. Decisions do not require subjective judgment or interpretation skills as the process follows a rule-based flow. Mundane, simple, and monotonous tasks work well for standardized procedures. (Griffiths, 2016) (Wellmann, et al., 2020)

Mature: Repetitive processes executed over multiple periods are the most likely candidates. Management usually has in-depth knowledge and ample experience in performing these processes. They also have process summaries or control descriptions that document activities and results. New activities with little performance history or documentation are less attractive. (Seasongood, 2016)

After selecting a process and completing the process documentation, including all involved systems and applications, requirements, and exclusions, the next step is to decide which RPA vendor to choose. Different RPA solution providers are offering a wide range of features. In keeping with the idea of automating a company, a robot can be programmed in a complex way using code or built using a visual drag and drop method that looks like a flowchart of a process. This uncomplicated programming method has become part of most major vendor offerings. In the next chapter, we will look at the three RPA leaders - Blue Prism, Automation Anywhere, UiPath, and the niche player SAP RPA. (Hanna, 2020)

3.4.1 UIPath

UiPath software aims to eliminate repetitive and tedious tasks, allowing users to reduce costs and increase business profitability. UIPath has three modules available: UiPath Robot, UiPath Orchestrator, and UiPath Studio. (Gill, 2020)

UiPath Studio has three profiles available for business users and developers. The first profile is Studio, which offers many tools for developing complex automated and maintainable automation processes for experienced RPA developers (uipath.com). With built-in registrars and integrations with Microsoft Office, Gmail, and file manager, no code drag-and-drop operations, pre-designed templates, and scripting, the second StudioX profile is designed for business users to automate daily tasks efficiently. It does not require any high-level programming skills. (uipath.com) (Bornegrim, et al., 2020) The third is Studio Pro profile, the most advanced Studio, containing testing tools, advanced RPA features, and advanced encoding services intended for specialized developers(uipath.com).

UIPath Studio can also be used to run a complete recorder to record a sequence of steps. With the recording and playback function, the user can record actions and create them as an automated sequence of processes. There are four recording options available in UiPath: basic recording used for a single activity, desktop recording used to record multiple activities that can occur between different applications, web recording used to record web and browser activities, Citrix recoding used for virtual environments, and image recording for image, text and keyboard automation. (Khan, 2020)

UiPath Orchestrator manages and monitors the robotic workforce. This web application allows the user to implement, plan, control, and manage robots and processes in Studio. (Tripathi, 2018)

UiPath Robots are attended and unattended robots that interact with various applications, including web and desktop applications. Influenced by advanced computer technology, it accelerates the precise automation of SAP, Citrix, and Mainframe processes. (Sureka, 2020) Automated robots work independently in the background and handle lengthy processes with heavy tasks. Automated robots communicate with employees for review, or questions, or exceptions via UiPath Action Center. Attendant robots work side-by-side with humans at their desks and act as personal assistants to help carry out daily tasks. Users access, schedule, and run automation in UiPath Assistant. (uipath.com) These robots can be controlled using the orchestrator, which is part of the UIPath Enterprise Edition. This version is suitable for large companies starting their RPA projects and looking to scale their robot deployments in the future. It is possible to disconnect these robots from the orchestrator during installation and work independently on the desktop. There is no orchestrator in the Community Edition, and the installed robot will operate independently in user mode. The Community Edition is suitable for individual developers and smaller organizations with fewer employees. It can be used to learn UIPath for free of charge. (Tripathi, 2018)

3.4.2 Automation Anywhere

Automation Anywhere, available in the server version, allows users to design automation processes with centralized security, user management, collaboration, and deployment. Automation Anywhere consists of 3 core components – Bot Creator, Control Room, and Bot Runner. (Isaac, et al., 2017) (Locke, 2019)

Bot Creator serves as a development environment. Using drag-and-drop, powerful writing, and editing capabilities, developers create and test rule-based automation that will be sent to the Control Room and then to deployment (Locke, 2019). To quickly create bots, built-in screen recorders can capture the keystrokes and mouse clicks that the bot should replay. Bots can also be manually created and edited using the task editor, which offers hundreds of commands that allow non-technical users to create automated tasks and technical users to create more complex integrated tasks. (ibm.com)

Control Room is the hub for all RPA robots, where users can start, pause, stop, track, check and schedule robots in real-time for reliable and safe execution (ibm.com). It can also store credentials and audit logs. (Locke, 2019) Control Room can be managed so that users can submit hundreds of issues to Bot Runner with a single click. The intuitive visual interface ensures a smooth experience on all devices, includes built-in predictive analytics dashboards and a notification area with the ability to configure alerts to prompt for action. (ibm.com)
Bot Runner is a software machine that runs a bot or several bots in parallel, created by the Bot Creator. (Gill, 2020) When Bot Creator creates a bot, members can launch that bot at any scale. Bots mostly run unattended using schedules or triggers. After Bot Creator loads the bot, the Control Room user can schedule and run the bot on an authorized bot executor server. Users can also run bots served on local computers. In this case, the attended Bot Runner runs the bot script through human intervention rather than through the Control Room scheduler. (ibm.com)

We can say that the main advantage of Automation Anywhere is the ease of use. New users require little or no programming language to start building robots. Automation Anywhere is designed for users and businesses with no programming experience or even basic programming knowledge. Automation Anywhere can be used by any user. However, it can be limited from a developer's point of view as coding is not supported, and the developer may prefer the advanced features of other RPA vendors. (Bornegrim, et al., 2020)

In addition to the Automation Anywhere Enterprise RPA platform, the company offers IQ Bot for AI capabilities, Bot Insight for operational and business intelligence, and Bot Farm for cloud RPA on-demand as a service (Muscolino, 2018). Companies need a market advantage, and cognitive adaptability is essential for that. Automate Anywhere takes part in intelligent cognitive abilities. While Blue Prism and UiPath have reliable insights, Automate Anywhere learns and applies this knowledge over time. (Data Semantics Staff, 2020)

3.4.3 Blue Prism

Robotic process automation was invented by Blue Prism, which process automation experts founded to develop technologies that could improve the effectiveness of organizations. Initially, their focus was on the back office, where they realized a massive demand for automation. Blue Prism provides a drag-and-drop flowchart for step-by-step automation of manual, repetitive back-office processes. It aims to improve the accuracy of operations through the development of a digital workforce. (Isaac, et al., 2017)

Blue Prism focuses on running fully automatic unattended automation (Noble, 2019). Rather than helping current employees automate some of their work on their desktops, Blue Prism RPA aims to eliminate full-time jobs, allowing organizations to reallocate workers to more value-added tasks. The software is balanced to handle different types of data. From load balancing to end-to-end encryption, everything is verified and communicated with the user. (Data Semantics Staff, 2020)

The Blue Prism process model is designed to handle complex logic that includes exception handling and automatically recovering from failures. For example, a robot can create a support ticket or email an administrator when a problem occurs. The product can also restart the failed robot and mark all the queue items it was working on when the failure occurred. It allows the Blue Prism administrator to examine these elements to determine how to handle them. (Chappell, 2016)

Unlike many other RPA tools, Blue Prism's does not offer a process recorder (Ray, et al., 2020). Instead, IT pros and business people use the Object Studio graphical tool to create a solution design document that includes multiple processes and business objects. These business objects handle the low-level details of interacting with application user interfaces. Once they are ready, IT or business people use Process Studio to define the process's steps. Since it will be used to create a software robot that can work independently, the draft decision document should indicate the complete business process, what exceptions can happen, what to do for each exception, and much more. (Chappell, 2016)

Blue Prism is designed to automate software development for mainframe, Windows applications, web applications, Java, SAP, Exchange, custom applications, and Citrix. (Blue Prism, 2016) (Gill, 2020) It differs from other RPA tools in that it requires at least an intermediate level of knowledge from the developer in order for the user to understand what to do and how to manage objects. (Data Semantics Staff, 2020)

Blue Prism provides advanced features for developers or users with experience writing code in .NET programming languages such as C #. Some processes can be implemented partially or entirely without code. However, the possibilities for implementation without code are limited, and some programming experience is still recommended for any implementation. (Bornegrim, et al., 2020)

3.4.4 SAP RPA

SAP RPA has three main components: Cloud Factory, Desktop Agent, and Desktop Studio. *Cloud Factory* is a cloud solution based on the SAP cloud platform. Users can manage sets of virtual machines for workstation unattended bots or desktops for attended bots, control jobs, and agents. Attended bots are triggered by custom events and work together with a human on the same workstation. In contrast, unattended bots operate unattended in a virtual environment and can automate any number of processes. (Gill, 2020)

Desktop Agent allows the user to capture the applications that the bot interacts with to perform the necessary automation tasks, create scripts and workflows, and test and debug various scripts to ensure bot’s efficiency and speed (Vannier, 2020).

Desktop Studio allows the user to automate build processes. It contains four main components:

- an application capture tool
- a workflow designer
- a code editor
- a built-in debugger (Arora, 2019)

As far as the pricing model is concerned, it is entirely consumer-driven, which is one of SAP's strengths. The user does not pay for what he develops or customizes but only pays for what he uses. Transaction-based pricing is triggered when the bot is launched, regardless of the bot size or robotic task's duration, with no design or control function fees. (Clair, 2019) Automation can be scaled flexibly or automatically using a single model pricing by paying the same price for attended and unattended bots. (Hurtebize, et al., 2019)

SAP Intelligent RPA enables citizen developers and business process experts and developers to create bots quickly and easily (SAP Community). With a Low-Code approach, developers and business users can build and run their application bots using hand-coding JavaScript knowledge. Easy-to-use bot creation capabilities offered in the cloud studio enable experienced developers and business users to build and edit cloud projects without writing a code line. (SAP SE, 2021) A no-code approach combined with detailed user documentation and an active developer community offers users an intuitive workflow design (SAP Community). Moreover, SAP RPA provides ready-to-use templates to accelerate implementation that can be imported into the bot design studio and personalized according to the user's unique needs (Chen, 2020).

In general, SAP has a clear vision of ERP-centric automation with built-in core iBPMS capabilities and built-in connectors for SAP S / 4HANA, ABAP, and UI5, as well as non-SAP applications like any Windows-based application. Customers with SAP-heavy ecosystems can benefit from this, especially if they plan to migrate to SAP S / 4HANA. (Ray, et al., 2020)

3.4.5 Comparison of RPA tools core functionalities

As a niche player, SAP is distinguished by its clear vision of ERP-centric automation, with end-to-end capabilities spanning a wide range of technologies, including process discovery, iBPMS, machine learning, and cloud delivery. AA, UiPath, Blue Prism are distinguished by their artificial intelligence and best-in-class automated machine learning and NLP capabilities. Blue Prism boasts a robust vertical market strategy resulting in 42 industry solutions with many clients across most industries. UiPath has earned the most vital ability to perform. Its rich partner ecosystem includes over 250 technology partners and support for integrations with most enterprise products and applications. Automation Anywhere offers an intuitive multi-user interface, guided navigation, reusable machine learning libraries, and robust built-in security. (Hanna, 2020)

Table 1 Comparison table of SAP RPA with RPA leaders (adopted from Khan (2020))

Features	SAP RPA	UIPath	Automation Anywhere	Blue Prism
Architecture type	Cloud based	Cloud based	Server based	Server based
Main components	Cloud studio, Desktop agent, Desktop studio	Studio, Orchestrator and Robots	Bot creator, Control room and Bot runner	Process diagram, Process studio, Object studio and Application modeller
Robots	Attended and unattended	Attended, unattended	Attended and unattended	Unattended, back office automation only
Usability	No coding skills or IT involvement is required.	Code-free development, with the possibility of writing code.	Usable for any user but limited from a developer standpoint, code writing is not supported.	Code-free implementation is limited, suited for developers or users with knowledge in .NET programming languages such as C#.
Recording	YES	YES	YES	NO
Application	Third party tools, non-SAP systems, web applications, Windows applications, Java applications.	Desktop and mobile versions. It can work with any applications, for example, with "1C" or SAP.	The platform is web-based and cloud- and SaaS-ready and allows full web-based robot composition.	Browser-based interface, windows interface, mainframe applications via terminals, and interfaces using java.
Free versions	Limited period free self-service trial	Free community edition	Free trial up to 30 days, free community edition	Free trial up to 30 days, free learning edition up to 180 days
Price	Transaction based pricing model	Charges per Bot	Costs according to the number of processes	Charges per Bot

4 Practical Part

In the practical part, we will find answers to questions that arise from theoretical research. We will learn what GFSS employees perceive and experience when working with artificial intelligence. After all, employees currently working in this field may have a different perspective on what AI / RPA entails. Their views may be similar or radically different depending on work experience and their position within the company. Specifically, this study analyzes the relationship between various individual characteristics (such as academic degree, work experience, and job title) and their perceptions of AI and RPA's impact on their job prospects. This study aimed to find answers to the following questions:

RQ1: How do GFSS employees perceive the use of AI/RPA in their workplace?
RQ2: What is the impact of AI/RPA on the future of jobs at GFSS from the employees' perspective?

Concerning these questions, four hypotheses were formulated:
H1: There are statistically significant differences in the level of agreement among employees regarding the impact of AI/RPA on their performance.
H2: There are statistically significant differences in employees' intentions to work with AI/RPA.
H3: There are statistically significant differences in employees' responses regarding the number of jobs at GFSS in the future.
H4: There are statistically significant differences in different groups of employees regarding fear of losing their jobs due to AI / RPA.

4.1 Mixed method approach

During the survey, primary data were obtained, which were subjected to quantitative analysis. Deductive approach was applied by deriving hypotheses from literature and testing them by collected data, either rejecting or accepting the hypotheses.

Using a survey alone can lead to conflicting results with conflicting answers that can make the data difficult to interpret. Therefore, the study also uses semi-structured interviews conducted with two respondents at different times to provide a more detailed and objective presentation of the data. Thus, a mixed methods approach that combines quantitative and qualitative research techniques has been applied. (Molina-Azorin, 2016)

When analyzing the results, the survey results are presented first, and then the interviewees' corresponding comments. Fundamental questions have been pre-agreed with the GFSS R2R Center of Excellence Manager to ensure that the questions comply with business and data security regulations.

4.2 Survey population and sample

An online survey was emailed to existing SAP GFSS employees. Thus, any GFSS user could fill out the form voluntarily. The study population included all SAP GFSS employees, 1200 employees in total. At the end of the survey, a sample of 208 employees was interviewed. The corresponding sample size was found using a simple random sampling technique (Taherdoost, 2016).

4.2.1 Survey questions

The final questionnaire consisted of two main parts. The first part included a set of demographic questions to determine the degree, job title, and years of experience. The second part of the questionnaire consisted of three sections that aim to determine the validity of hypotheses and answer the research questions.

The first section included the following set of questions in the form of seven statements (positive influence of AI / RPA) to find an answer to the first research question: “AI / RPA can replace routine tasks and complement non-routine tasks.”, “AI / RPA can eliminate inconsistencies in my performance and deliver accurate results.”, “Using AI/RPA can decrease the stress and the need for over-work hours during the hectic month-end closing time.” “Using AI / RPA allows me to shift my focus to higher value-added tasks, which increases my job satisfaction.”, “Using AI / RPA can improve the efficiency of accounting processes by quickly delivering results.”, “Using AI / RPA frees me from my day-to-day drudgery and allows me to define my relationship with work in a more positive and socially beneficial way.", "Using AI / RPA can boost my intellectual, innovative, and productive energy."

The second section (motivation to work with AI / RPA) included two statements: "I am motivated to work with AI / RPA as it creates new opportunities for me, combined with higher responsibilities.", "I am willing to participate in AI/RPA based projects to contribute to accounting systems design."

The last section (impact of AI / RPA on employment) included two questions: "What will be the impact of AI / RPA on employment in GFSS in the future?" and "Are you afraid of losing your job due to AI / RPA?". Each section's questions were combined to measure the respondents' collective stance towards the three research questions.

Respondents were asked to indicate their degree of agreement or disagreement with each presented statement. Participants were asked to rate items in the first and second section on a 5-point Likert scale ranging from 1 = strongly disagree to 5 = strongly agree, items in the third section on a 5-point Likert scale ranging from 1 = much less jobs to 5 = much more jobs and a 3-point scale, where 1 = yes, 2 =slightly, and 3 = no.

4.2.2 Data analysis

The data was collected using Google Forms and then encoded and analysed using the Statistical Package for Social Sciences (IBM SPSS). Descriptive statistics such as the mode and median for central tendency and frequency of variability were first calculated for each question to analyse ordinal data. As we know, mean and standard deviation are invalid parameters for descriptive statistics when data are presented on ordinal scales, like any parametric analysis based on a normal distribution. Therefore, the author focused on non-parametric procedures, calculations based on rank, median, or mode that are more relevant. (Allen, et al., 2007)

Non-parametric Kruskal-Wallis and Mann-Whitney tests were used to measure significant differences between the different demographic variables. The Kruskal-Wallis test is an extension of the two-group Mann-Whitney U test. Thus, Kruskal-Wallis is a more generalized form of the Mann-Whitney U test and a non-parametric version of one-way ANOVA (McKight, et al., 2010). Data with an abnormal distribution, such as ordinal in our case, are suitable for the Kruskal-Wallis test. Kruskal-Wallis models can provide the same type of results as an analysis of variance but based on the ranks and not the means of the responses. (Allen, et al., 2007)

Statistical analysis adhered to Spearman’s correlation coefficient that produces a score ranging between -1 and +1 and was used to answer the research questions and hypotheses. Spearman's correlation assumptions are that the data should be at least ordinal and estimates for one variable should be monotonically related to another variable. (Schober, et al., 2018)

4.2.3 Survey respondents

Table 1: Frequency distribution of employees according to education, job title and years of experience

	Bachelor		**Master**		**Other**		**PhD**		**Total**	**Total**
	N	**%**	**N**	**%**	**N**	**%**	**N**	**%**	**N**	%
Associate	**66.00**	**32%**	**33.00**	**16%**	**7.00**	**3%**		**0%**	**106.00**	**51%**
From 10 to less than 15	4.00	2%		0%		0%		0%	4.00	2%
From 5 to less than 10	8.00	4%	13.00	6%		0%		0%	21.00	10%
Less than 5	54.00	26%	20.00	10%	7.00	3%		0%	81.00	39%
Expert		**0%**	**6.00**	**3%**	**2.00**	**1%**	**6.00**	**3%**	**14.00**	**7%**
From 10 to less than 15		0%		0%	2.00	1%	2.00	1%	4.00	2%
From 15 and over		0%	6.00	3%		0%	4.00	2%	10.00	5%
Manager	**3.00**	**1%**	**5.00**	**2%**	**2.00**	**1%**		**0%**	**10.00**	**5%**
From 10 to less than 15	3.00	1%	4.00	2%		0%		0%	7.00	3%
From 15 and over		0%		0%	2.00	1%		0%	2.00	1%
From 5 to less than 10		0%	1.00	0%		0%		0%	1.00	0%
Specialist	**40.00**	**19%**	**37.00**	**18%**	**1.00**	**0%**		**0%**	**78.00**	**38%**
From 10 to less than 15	10.00	5%	11.00	5%	1.00	0%		0%	22.00	11%
From 15 and over	12.00	6%	1.00	0%		0%		0%	13.00	6%
From 5 to less than 10	18.00	9%	25.00	12%		0%		0%	43.00	21%
Grand Total	**109.00**	**52%**	**81.00**	**39%**	**12.00**	**6%**	**6.00**	**3%**	**208.00**	**100%**

As mentioned above, the number of respondents whose answers are presented here is 208. First three questions in the survey aimed at finding out more about the respondents - how long they have worked in finance-related field, what kind of education they have and what kind of position they hold within GFSS.

For the purpose of descriptive analytics, the respondents were asked to identify their education as bachelor, master, PhD and other, job title as associate, specialist, manager and expert and year of experience as less than 5, from 5 to less than 10, from 10 to less than 15 and from 15 and over. Such information was relevant for the purpose of data analysis and comparison of mean ranks among groups.

A minor part of the surveyed sample of respondents are experts- 7% (14 out of total 208 respondents) and managers- 5% (10 out of 208), while most of the respondents are associates- 51% (106 out of 208) and specialists- 37% (78 out of 208). This indicates that half of the respondents are GFSS employees directly responsible for administrative and transactional tasks. The other half consists of managers and experts with extensive knowledge and experience, who are responsible for the entire process of financial transactions.

Proportion of respondents with a PhD degree is 3% (6 out of 208), with a master's degree- 39% (81 out of 208), with a bachelor's degree- 52% (109 out of 208). Consequently, the survey sample that responded to the questionnaire is educated people with high and medium academic qualifications.

81 out of 208 respondents (39%) are relatively new to accounting with less than 5 years of work experience, 127 out of 208 respondents (62%) are people with more than 5 years of work experience in finance related field, 30% with work experience from 5 to 10 years, 20% with work experience from 10 to 15 years, the remaining 12% has work experience of 15 years and over. It is important to note that this question does not reflect the respondent's age in any way, as the respondent may have had another job before starting a career in finance-related field.

4.2.4 Hypothesis 1

In this part, we will look at the first seven statements that were provided to employees to rate their agreement level to assess if the AI/RPA positively affects employees' performance at work regardless of their background.

The respondents were asked to rate the extent to which they agree with the statements which state "AI/RPA can substitute in routine tasks and complement in non-routine tasks" (Table

2), "AI/RPA can eliminate inconsistencies in performance and deliver accurate results" (Table 3), "The use of AI/RPA can decrease the stress and the need for over-work hours during the hectic closing time" (Table 4), "The use of AI/RPA enables me to shift my focus to higher value-added tasks, which improves my job satisfaction" (Table 5), "The use of AI/RPA can improve the efficiency of the accounting processes by providing the results promptly" (Table 6), "The use of AI/RPA frees me from the day-to-day drudgery and allows me to define my relationship with work in a more positive and socially beneficial way" (Table 7), "The use of AI/RPA can increase my intellectual, innovative, and productive energy" (Table 8).

Each statement's level of agreement was similar to one another. The statements were rated by the majority of the participants towards the agreement side (on average 70% out of total 208 respondents), the minority of participants towards the disagreement side (on average 17% out of total 208) and the rest preferred to stay neutral (on average 12,6 % out of total 208). The distribution of responses is presented below in Tables 2-8.

Table 2: AI/RPA can substitute in routine tasks and complement in non-routine tasks.

Statement 1		**1. Strongly Disagree**	**2. Disagree**	**3. Neutral**	**4. Agree**	**5. Strongly Agree**	**Total N**	**Total %**	**Mean rank**	**Mode**	**P-value**
Degree	Bachelor	8 (7%)	10 (9%)	14 (13%)	51 (47%)	26 (24%)	109	52%	104.07	4	0.636
	Master	8 (10%)	7 (9%)	11 (14%)	35 (43%)	20 (25%)	81	39%	103.29		
	PhD	0	0	0	4 (67%)	2 (33%)	6	3%	134.17		
	Other	1 (8%)	2 (17%)	1 (8%)	5 (42%)	3 (25%)	12	6%	101.75		
Total							208	100%			
Job Title	Associate	14 (13%)	6 (6%)	13 (12%)	45 (43%)	28 (26%)	106	51%	104.41	4	0.847
	Specialist	7 (9%)	8 (10%)	9 (12%)	35 (45%)	19 (24%)	78	38%	103.86		
	Manager	0	1 (10%)	1 (10%)	5 (50%)	3 (30%)	10	5%	117.90		
	Expert	1 (7%)	1 (7%)	2 (14%)	8 (57%)	2 (14%)	14	7%	99.21		
Total							208	100%			
Years of experience	Less than 5	9 (11%)	4 (5%)	13 (16%)	33 (41%)	22 (27%)	81	39%	105.35	4	0.954
	From 5 to less than 10	7 (10%)	5 (8%)	5 (8%)	32 (49%)	16 (25%)	65	31%	106.58		
	From 10 to less than 15	6 (16%)	3 (8%)	2 (5%)	17 (46%)	9 (24%)	37	18%	102.03		
	From 15 and over	0	4 (16%)	5 (20%)	11 (44%)	5 (20%)	25	12%	99.98		
Total		**22 (10%)**	**16 (8%)**	**25 (12%)**	**93 (45%)**	**52 (25%)**	**208**	**100%**			

The author of this study examined in detail the difference of the acceptance scores for each level of the variable "degree", "job title" and "years of experience" for significance. The

Kruskal-Wallis test compares mean ranks and determines if there are statistically significant differences in employees' perceptions of *AI/RPA being able to substitute in routine tasks and complement in non-routine tasks* on their performance at work due to demographic factors. The null hypothesis of the Kruskal-Wallis test is that the mean ranks of the groups (i.e., Associate, Specialist, Manager, Expert) are the same. At first glance, it may appear that the mean rank of employees with a PhD degree is different from employees with a bachelor's or master's degree. Even if the mean ranks are not similar, the differences are not significant. For each tested group (Table 2) there is insufficient evidence to reject the null hypothesis that the mean ranks of the groups (i.e., Associate, Specialist, Manager, Expert) are the same at the 5% significance level (p-values are 0.636, 0.847 and 0.954, thus p-value >0,05). Therefore, it can be concluded that the distribution of the general level of agreement is the same across the groups of employees with different degree, job title and year of experience.

The same conclusion can be applied to the rest six statements, the tables (Table 3-8) for each statement and short comments are presented under each table below. One can only notice small differences in the answers of employees, for example, those who agreed with the first statement strongly agreed with the second statement or remained in a neutral position, but these differences are insignificant.

Table 3:AI/RPA can eliminate inconsistencies in my performance and deliver accurate results.

Statement 2		**1. Strongly Disagree**	**2. Disagree**	**3. Neutral**	**4. Agree**	**5. Strongly Agree**	**Total N**	**Total %**	**Mean rank**	**Mode**	**P-value**
Degree	Bachelor	6 (16%)	13 (12%)	12 (11%)	48 (44%)	30 (27%)	109	52%	105.38	4	0.622
	Master	7 (9%)	6 (7%)	9 (11%)	40 (49%)	19 (23%)	81	39%	102.79		
	PhD	0	0	0	4 (67%)	2 (33%)	6	3%	131.00		
	Other	2 (17%)	3 (25%)	0	3 (25%)	4 (33%)	12	6%	94.79		
Total							208	100%			
Job Title	Associate	9 (8%)	13 (12%)	10 (9%)	47 (44%)	27 (26%)	106	51%	101.56	4	0.851
	Specialist	5 (6%)	7 (9%)	7 (9%)	37 (47%)	22 (29%)	78	38%	108.53		
	Manager	0	1 (10%)	2 (20%)	4 (40%)	3 (30%)	10	5%	108.95		
	Expert	1 (7%)	1 (7%)	2 (15%)	7 (50%)	3 (21%)	14	7%	101.11		
Total							208	100%			
Years of experience	Less than 5	5 (7%)	10 (12%)	9 (11%)	37 (45%)	20 (25%)	81	39%	102.21	4	0.873
	From 5 to less than 10	5 (8%)	5 (8%)	4 (6%)	34 (52%)	17 (26%)	65	31%	108.39		
	From 10 to less than 15	3 (8%)	6 (16%)	2 (5%)	14 (38%)	12 (33%)	37	18%	106.35		
	From 15 and over	2 (8%)	1 (4%)	6 (24%)	10 (40%)	6 (24%)	25	12%	99.06		

Total		**15 (7%)**	**22 (11%)**	**21 (10%)**	**95 (46%)**	**55 (26%)**	**208**	**100%**			

The mean ranks of all three groups regarding the level of agreement that *AI/RPA's eliminate inconsistencies in their performance and deliver accurate results*, are very similar. The Kruskal-Wallis test results show p-values (0.62, 0.85, 0.87, thus p-value>0.05) at the 5% significance level, which means differences in answers are not statistically significant (Table 3).

Table 4: The use of AI/RPA can decrease the stress and the need for over-work hours during the hectic closing time.

Statement 3		**1. Strongly Disagree**	**2. Disagree**	**3. Neutral**	**4. Agree**	**5. Strongly Agree**	**Total N**	**Total %**	**Mean rank**	**Mode**	**P-value**
Degree	Bachelor	10 (9%)	10 (9%)	12 (11%)	53 (49%)	24 (22%)	109	52%	101.14	4	0.245
	Master	5 (6%)	8 (10%)	11 (14%)	33 (41%)	24 (29%)	81	39%	107.65		
	PhD	0	0	0	3 (50%)	3 (50%)	6	3%	145.00		
	Other	1 (8%)	2 (17%)	1 (8%)	6 (50%)	2 (17%)	12	6%	93.50		
Total							208	100%			
Job Title	Associate	7 (7%)	13 (12%)	12 (11%)	48 (45%)	26 (25%)	106	51%	102.85	4	0.884
	Specialist	9 (12%)	5 (6%)	6 (8%)	39 (50%)	19 (24%)	78	38%	104.74		
	Manager	0	1 (10%)	3 (30%)	3 (30%)	3 (30%)	10	5%	104.20		
	Expert	0	1 (7%)	3 (21%)	5 (36%)	5 (36%)	14	7%	115.86		
Total							208	100%			
Years of experience	Less than 5	3 (4%)	10 (12%)	11 (14%)	38 (47%)	19 (23%)	81	39%	103.53	4	0.572
	From 5 to less than 10	7 (11%)	4 (6%)	4 (6%)	30 (46%)	20 (31%)	65	31%	111.38		
	From 10 to less than 15	4 (11%)	4 (11%)	4 (11%)	15 (41%)	10 (26%)	37	18%	102.00		
	From 15 and over	2 (8%)	2 (8%)	5 (20%)	12 (48%)	4 (16%)	25	12%	93.46		
Total		**16 (8%)**	**20 (10%)**	**24 (12%)**	**95 (46%)**	**53 (24%)**	**208**	**100%**			

The Kruskal-Wallis test results (Table 4) show p-values (0.24, 0.88, 0.57) greater than 0.05 at the 5% significance level, which means that there is no statistically significant difference between the mean ranks of different demographic groups when assessing employees' level of agreement on *AI/RPA's ability* to *decrease the stress and the need for over-work hours during the hectic closing time.*

Table 5: The use of AI/RPA enables me to shift my focus to higher value-added tasks, which improves my job satisfaction.

Statement 4		**1. Strongly Disagree**	**2. Disagree**	**3. Neutral**	**4. Agree**	**5. Strongly Agree**	**Total N**	**Total %**	**Mean rank**	**Mode**	**P-value**
Degree	Bachelor	6 (5%)	9 (8%)	15 (14%)	52 (48%)	27 (25%)	109	52%	104.69	4	0.661

	Master	7 (9%)	6 (8%)	10 (12%)	39 (48%)	19 (23%)	81	39%	102.17		
	PhD	0	0	0	4(67%)	2 (33%)	6	3%	132.17		
	Other	1 (8%)	2 (16%)	1 (8%)	4 (34%)	4 (34%)	12	6%	104.67		
Total							208	100%			
Job Title	Associate	10 (9%)	7 (7%)	14 (13%)	48 (45%)	17 (25%)	106	51%	103.04	4	0.979
	Specialist	4 (5%)	8 (10%)	7 (9%)	40 (51%)	19 (25%)	78	38%	106.06		
	Manager	0	1 (10%)	2 (20%)	4 (40%)	3 (30%)	10	5%	108.75		
	Expert	0	1 (8%)	3 (21%)	7 (50%)	3 (21%)	14	7%	103.79		
Total							208	100%			
Years of experience	Less than 5	6 (7%)	4 (5%)	13 (16%)	36 (44%)	22 (27%)	81	39%	105.96	4	0.63
	From 5 to less than 10	5 (8%)	6 (9%)	3 (5%)	35 (51%)	18 (27%)	65	31%	109.62		
	From 10 to less than 15	3 (8%)	4 (11%)	4 (11%)	20 (54%)	6 (16%)	37	18%	95.34		
	From 15 and over	0	3 (12%)	6 (24%)	10 (40%)	6 (24%)	25	12%	100.04		
Total		**14 (7%)**	**17 (8%)**	**26 (13%)**	**99 (47%)**	**52 (25%)**	**208**	**100%**			

The Kruskal-Wallis test results (Table 5) show p-values (0.66, 0.98, 0.63) greater than 0.05 at the 5% significance level, which means that there is no statistically significant difference between the mean ranks of different demographic groups when assessing employees' agreement on *AI/RPA's ability to shift employees' focus to higher value-added tasks, which improves their job satisfaction.*

Table 6: The use of AI/RPA can improve the efficiency of the accounting processes by providing the results promptly.

Statement 5		**1. Strongly Disagree**	**2. Disagree**	**3. Neutral**	**4. Agree**	**5. Strongly Agree**	**Total N**	**Total %**	**Mean rank**	**Mode**	**P-value**
Degree	Bachelor	7 (6%)	11 (10%)	15 (14%)	43 (40%)	33 (30%)	109	52%	104.56	4	0.456
	Master	7 (9%)	5 (6%)	13 (16%)	34 (42%)	22 (27%)	81	39%	101.98		
	PhD	0	0	0	3 (50%)	3 (50%)	6	3%	141.00		
	Other	1 (8%)	2 (16%)	1 (8%)	4 (34%)	4 (34%)	12	6%	102.75		
Total							208	100%			
Job Title	Associate	8 (7%)	11 (10%)	14 (13%)	39 (37%)	34 (32%)	106	51%	104.87	4	0.683
	Specialist	7 (9%)	5 (7%)	10 (12%)	38 (49%)	18 (23%)	78	38%	100.31		
	Manager	0	1 (10%)	2 (20%)	3 (30%)	4 (40%)	10	5%	114.40		
	Expert	0	1 (7%)	3 (21%)	4 (29%)	6 (43%)	14	7%	117.96		
Total							208	100%			
Years of experience	Less than 5	3 (4%)	9 (11%)	13 (15%)	28 (35%)	28 (35%)	81	39%	108.20	4	0.844
	From 5 to less than 10	6 (9%)	5 (8%)	6 (9%)	31 (48%)	17 (26%)	65	31%	103.32		
	From 10 to less than 15	5 (14%)	3 (8%)	3 (8%)	17 (46%)	9 (24%)	37	18%	98.15		
	From 15 and over	1 (4%)	1 (4%)	7 (28%)	8 (32%)	8 (32%)	25	12%	104.98		
Total		**15 (7%)**	**18 (9%)**	**29 (14%)**	**84 (40%)**	**62 (30%)**	**208**	**100%**			

The Kruskal-Wallis test results (Table 6) show p-values (0.45, 0.68, 0.84) greater than 0.05 at the 5% significance level, which means that there is no statistically significant difference between the mean ranks of different demographic groups when assessing employees' agreement on *AI/RPA's ability* to *improve the efficiency of the accounting processes by providing the results promptly*.

Table 7: The use of AI/RPA frees me from the day-to-day drudgery and allows me to define my relationship with work in a more positive and socially beneficial way.

Statement 6		**1. Strongly Disagree**	**2. Disagree**	**3. Neutral**	**4. Agree**	**5. Strongly Agree**	**Total N**	**Total %**	**Mean rank**	**Mode**	**P-value**
Degree	Bachelor	8 (7%)	10 (9%)	13 (12%)	57 (53%)	21 (19%)	109	52%	103.56	4	0.068
	Master	7 (9%)	7 (9%)	11 (14%)	38 (47%)	18 (23%)	81	39%	103.79		
	PhD	0	0	0	2 (33%)	4 (67%)	6	3%	161.50		
	Other	1 (8%)	3 (25%)	1 (8%)	5 (42%)	2 (17%)	12	6%	89.29		
Total							208	100%			
Job Title	Associate	10 (9%)	9 (8%)	14 (13%)	53 (50%)	20 (19%)	106	51%	100.87	4	0.748
	Specialist	5 (6%)	9 (11%)	6 (8%)	41 (53%)	17 (22%)	78	38%	107.04		
	Manager	0	1 (10%)	3 (30%)	3 (30%)	3 (30%)	10	5%	106.90		
	Expert	1 (7%)	1 (7%)	2 (14%)	5 (36%)	5 (36%)	14	7%	116.11		
Total							208	100%			
Years of experience	Less than 5	4 (5%)	8 (10%)	13 (16%)	41 (51%)	15 (18%)	81	39%	102.29	4	0.799
	From 5 to less than 10	7 (11%)	4 (6%)	4 (6%)	34 (52%)	16 (25%)	65	31%	110.19		
	From 10 to less than 15	4 (11%)	5 (14%)	3 (8%)	16 (43%)	9 (24%)	37	18%	102.36		
	From 15 and over	1 (4%)	3 (12%)	5 (20%)	11 (44%)	5 (20%)	25	12%	100.02		
Total		**16 (8%)**	**20 (10%)**	**25 (12%)**	**102 (48%)**	**45 (22%)**	**208**	**100%**			

The Kruskal-Wallis test results (Table 7) show p-values (0.068, 0.75, 0.80) greater than 0.05 at the 5% significance level, which means that there is no statistically significant difference between the mean ranks of different demographic groups when assessing employees' agreement on *AI/RPA's ability to free them from the day-to-day drudgery and allow to define their relationship with work in a more positive and socially beneficial way.*

Table 8: The use of AI/RPA can increase my intellectual, innovative, and productive energy.

Statement 7		**1. Strongly Disagree**	**2. Disagree**	**3. Neutral**	**4. Agree**	**5. Strongly Agree**	**Total N**	**Total %**	**Mean rank**	**Mode**	**P-value**
Degree	Bachelor	9 (8%)	10 (9%)	19 (17%)	52 (49%)	19 (17%)	109	52%	100.59	4	0.19
	Master	7 (9%)	7 (9%)	11 (14%)	39 (48%)	17 (20%)	81	39%	105.59		

	PhD	0	0	0	3 (50%)	3 (50%)	6	3%	151.50		
	Other	1 (8%)	3 (25%)	1 (8%)	2 (17%)	5 (42%)	12	6%	109.17		
Total							208	100%			
Job Title	Associate	7 (7%)	12 (11%)	15 (14%)	59 (56%)	13 (12%)	106	51%	98.92	4	0.362
	Specialist	9 (11%)	6 (8%)	11 (14%)	31 (40%)	21 (27%)	78	38%	107.14		
	Manager	0	1 (10%)	3 (30%)	2 (20%)	4(40%)	10	5%	116.55		
	Expert	1 (7%)	1 (7%)	2 (14%)	4 (29%)	6 (43%)	14	7%	123.39		
Total							208	100%			
Years of experience	Less than 5	5 (6%)	8 (9%)	13 (16%)	46 (57%)	9 (12%)	81	39%	98.66	4	0.702
	From 5 to less than 10	5 (7%)	6 (9%)	9 (14%)	29 (45%)	16 (25%)	65	31%	108.45		
	From 10 to less than 15	4 (11%)	4 (11%)	5 (13%)	13 (35%)	11 (30%)	37	18%	107.49		
	From 15 and over	3 (12%)	2 (8%)	4 (16%)	8 (32%)	8 (32%)	25	12%	108.72		
Total		**17 (8%)**	**20 (10%)**	**31 (15%)**	**96 (46%)**	**44 (21%)**	**208**	**100%**			

The Kruskal-Wallis test results (Table 8) show p-values (0.19, 0.36, 0.70) greater than 0.05 at the 5% significance level, which means that there is no statistically significant difference between the mean ranks of different demographic groups when assessing employees' agreement on *AI / RPA's ability to increase intellectual, innovative and productive energy of employees.*

Table 9: Reliability Statistics

Reliability Statistics		
Cronbach's Alpha	Cronbach's Alpha based on standardized items	N of items
0.972	0.973	7

The seven statements were assessed by the same rating scale with 5-point answering mode from "1=strongly disagree" to "5=strongly agree" to measure the level of agreement towards the first hypothesis, which states AI/RPA has a positive impact on employee's work performance regardless of employees' education, job title and work experience. The appropriateness of combining each of the seven statements to a joint scale was ensured by sufficient scale reliability Cronbach Alpha. It measures the tightness of the multiple correlation of all items on a scale. The closer alpha is to its maximum value of 1, the more consistent and reliable the scale is. By small scales like this, the contingency coefficient should exceed 0.7 which is probably the most "acceptable" in most social science research situations. (Taber, 2018) The Cronbach coefficient equals 0.97 (Table 9), which means that the variance's reliability is high and statistically significant. The survey's reliability is understood as the degree of consistency and continuity when repeated at different times.

Table 10: Item internal consistency

Spearman's rho		Statement 1	Statement 2	Statement 3	Statement 4	Statement 5	Statement 6	Statement 7
Statement 1	Correlation Coefficient	1.000	,709**	,718**	,747**	,684**	,712**	,663**
	Sig. (2-tailed)		0.000	0.000	0.000	0.000	0.000	0.000
	N	208	208	208	208	208	208	208
Statement 2	Correlation Coefficient	,709**	1.000	,726**	,792**	,691**	,749**	,732**
	Sig. (2-tailed)	0.000		0.000	0.000	0.000	0.000	0.000
	N	208	208	208	208	208	208	208
Statement 3	Correlation Coefficient	,718**	,726**	1.000	,741**	,751**	,757**	,751**
	Sig. (2-tailed)	0.000	0.000		0.000	0.000	0.000	0.000
	N	208	208	208	208	208	208	208
Statement 4	Correlation Coefficient	,747**	,792**	,741**	1.000	,755**	,803**	,739**
	Sig. (2-tailed)	0.000	0.000	0.000		0.000	0.000	0.000
	N	208	208	208	208	208	208	208
Statement 5	Correlation Coefficient	,684**	,691**	,751**	,755**	1.000	,753**	,752**
	Sig. (2-tailed)	0.000	0.000	0.000	0.000		0.000	0.000
	N	208	208	208	208	208	208	208
Statement 6	Correlation Coefficient	,712**	,749**	,757**	,803**	,753**	1.000	,798**
	Sig. (2-tailed)	0.000	0.000	0.000	0.000	0.000		0.000
	N	208	208	208	208	208	208	208
Statement 7	Correlation Coefficient	,663**	,732**	,751**	,739**	,752**	,798**	1.000
	Sig. (2-taled)	0.000	0.000	0.000	0.000	0.000	0.000	
	N	208	208	208	208	208	208	208

The internal consistency of the table refers to the extent to which its items can be said to be measuring the same attitude if those who agree with one item tend to agree with the other- that is, if responses to those items are closely correlated (Johns, 2010). The Spearman's rank correlation (.663-.803) indicates a strong correlation between the groups with a p-value <.001, which proves that the rank correlation is statistically significant (Table 10). The p-value <.001 is to be understood that this value is rounded off up to four decimal places. The actual value is not zero. It is greater than zero though may be very small and close to zero. It would be not proper to conclude that the impact of the respective variable is absolutely significant, but one can simply conclude that the impact of the respective variables is significant or highly significant according to the prefixed level of significance.

In general, all Likert scale items are subject to the tendency to agree with statements and no significant differences in evaluation was caused by a singled group factor. With high internal reliability and significant correlation, we conclude that the hypothesis "there are statistically significant differences in the level of agreement among employees regarding the impact of AI/RPA on their performance" is proved to be untrue.

4.2.5 Hypothesis 2

In order to determine employees' attitude towards working with AI/RPA, statements "I am motivated to work with AI/RPA as it creates new opportunities for me combined with higher responsibilities." and "I am willing to participate in AI/RPA based projects to contribute to accounting systems design." were rated on a 5-point Likert scale with 1 representing strongly disagree and 5 representing strongly agree.

The frequency distributions on tables below show the similar level of agreement regarding the statement 8 and 9 in (Tables 11 and 13). The statements were rated by the majority of the participants towards the agreement side, accepting the statements and confirming their motivation to work with AI/RPA and contribute to accounting systems design. On average, most respondents (67,5 % out of 208) agreed or strongly agreed with the statement, while the minority of participants (17,5% out of 208) disagreed or strongly disagreed and the rest (15% out of 208) preferred to stay neutral. High summary scores are indicative of positive perceptions towards AI/RPA. The distribution of responses is presented below in Tables 11 and 13.

Table 11: I am motivated to work with AI/RPA as it creates new opportunities for me combined with higher responsibilities.

Statement 8		1. Strongly Disagree	2. Disagree	3. Neutral	4. Agree	5. Strongly Agree	Total N	Total %	Mean rank	Mode	P-value
Degree	Bachelor	8 (7%)	13 (12%)	21 (19%)	30 (28%)	37 (34%)	109	52%	101.35	4	0.231
	Master	4 (5%)	6 (7%)	11 (14%)	38 (47%)	22 (27%)	81	39%	105.58		
	PhD	0	0	0	2 (33%)	4 (67%)	6	3%	151.17		
	Other	1 (8%)	3 (25%)	1 (8%)	2 (17%)	5 (42%)	12	6%	102.46		
Total							208	100%			
Job Title	Associate	6 (6%)	19 (18%)	23 (22%)	28 (26%)	30 (28%)	106	51%	92.94	4	0.028
	Specialist	6 (8%)	4 (5%)	6 (8%)	33 (42%)	29 (37%)	78	38%	114.82		
	Manager	0	0	1 (10%)	5 (50%)	4(40%)	10	5%	127.25		
	Expert	0	0	3 (21%)	6 (43%)	5 (36%)	14	7%	118.25		
Total							208	100%			
Years of experience	Less than 5	5 (6%)	13 (16%)	18 (22%)	24 (30%)	21 (26%)	81	39%	92.01	4	0.038
	From 5 to less than 10	5 (8%)	6 (9%)	7 (11%)	26 (40%)	21 (32%)	65	31%	106.49		

	From 10 to less than 15	2 (5%)	3 (8%)	4 (11%)	14 (38%)	14 (38%)	37	18%	113.49		
	From 15 and over	0	1 (4%)	4 (16%)	8 (32%)	12 (48%)	25	12%	126.48		
Total		**12 (6%)**	**23 (11%)**	**33 (15%)**	**72 (35%)**	**68 (33%)**	**208**	**100%**			

Relationships between demographic characteristics and participants' attitude towards working with AI/RPA at GFSS were explored using Kruskal-Wallis non-parametric test with further post hoc assessments where appropriate and Spearman correlation was performed for internal consistency check.

The results of the Kruskal test (Table 11) show no contradiction in rejecting the null hypothesis of equal mean ranks for the variable job title and years of experience at the p-value <0.05. Statistically significant differences were found in respondents with different job titles and years of experience, where p-value= 0.028 and p= 0.038, thus p<0.05. We can see that these variables affect the result, but we cannot say how. However, we can take this as a hint and look for additional data on a pair of groups in question. For this, the Mann-Whitney test was carried out, which shows us the differences between a particular pair of groups (Table 12). Whitney test analysis reveals that respondents working as managers have significantly higher positive attitude scores towards working with AI/RPA than associates. Table 11 shows 90% of managers is motivated to work with AI/RPA as it creates new opportunities for them combined with higher responsibilities, while 10% of managers is being neutral. It significantly differs from associate's perspective, where 58% of associates is motivated, 22% is neutral and the rest 24% does not find working with AI as an opportunity to get higher responsibilities.

Table 12: Mann-Whitney U test results

Mann-Whitney U		**P- value**
Job Title	Associate- Manager	0.01
Years of experience	Less than 5- From 15 and over	0.01

Moreover, Mann-Whitney test analysis shows a high statistical probability (p-value=0.01. thus <0.05) with confidence level over 95% that there is a difference between employees with 5 years of experience and over 15 years of work experience in the finance-related field (Table 12). Table 11 shows 56% of employees with 5 years of experience is motivated to work with AI/RPA, 22% of employees is not motivated and the rest 22% is staying neutral. On the other hand, 80% of employees with over 15 years of experience believes in AI/RPA bringing them new opportunities with higher responsibilities, while 16% is neutral and only 4% does not show any motivation.

Table 13: I am willing to participate in AI/RPA based projects to contribute to accounting systems design.

Statement 9		1. Strongly Disagree	2. Disagree	3. Neutral	4. Agree	5. Strongly Agree	Total N	Total %	Mean rank	Mode	P-value
Degree	Bachelor	9 (8%)	13 (12%)	20 (18%)	34 (32%)	33 (30%)	109	52%	99.44	4	0.10
	Master	3 (4%)	7 (9%)	11 (13%)	35 (43%)	25 (31%)	81	39%	109.61		
	PhD	0	0	0	2 (33%)	4 (67%)	6	3%	152.67		
	Other	0	4 (33%)	1 (8%)	4 (33%)	3 (26%)	12	6%	91.88		
Total							208	100%			
Job Title	Associate	6 (6%)	20 (20%)	22 (21%)	34 (32%)	24 (23%)	106	51%	89.74	4	0.002
	Specialist	6 (8%)	4 (5%)	6 (8%)	31 (41%)	30 (38%)	78	38%	116.97		
	Manager	0	0	1 (10%)	5 (50%)	4(40%)	10	5%	128.65		
	Expert	0	0	3 (21%)	4 (29%)	7 (50%)	14	7%	129.54		
Total							208	100%			
Years of experience	Less than 5	4 (5%)	15 (19%)	17 (21%)	28 (34%)	17 (21%)	81	39%	89.46	4	0.038
	From 5 to less than 10	6 (9%)	5 (8%)	7 (11%)	24 (37%)	23 (35%)	65	31%	109.55		
	From 10 to less than 15	2 (6%)	3 (8%)	4 (11%)	16 (43%)	12 (32%)	37	18%	110.93		
	From 15 and over	0	1 (4%)	4 (16%)	7 (28%)	13 (52%)	25	12%	130.58		
Total		**12 (6%)**	**24 (12%)**	**32 (15%)**	**75 (36%)**	**65 (31%)**	**208**	**100%**			

The results of the Kruskal test revealed statistically significant differences in respondents' levels of agreement towards the willingness to work with AI/RPA based project to contribute to accounting systems design due to different job titles and years of experience. There is no contradiction in rejecting the null hypothesis of equal mean ranks for the variable job title and years of experience at p-value <0.05 (0.0002, 0.038).

Moreover, Mann-Whitney test analysis shows a high statistical probability (p-value<0,05) with confidence level over 95% that there is a difference between employees with less than 5 years of experience and over 15 years of work experience in the finance-related field. (Table 14). Out of total 25 employees with over 15 years of experience, 80% are willing to participate in AI/RPA based project to contribute to accounting systems design,16% are neutral and only 4% is not willing to participate in AI/RPA based projects. This percentage distribution differs significantly from the distribution of answers of employees with less than 5 years of experience. Out of 81 employees with less than 5 years of working experience, 55% are willing to participate, 21% are neutral and 24% are not willing to contribute to AI/RPA based projects regarding accounting system designs.

Overall, it can be noted that the assessment of the consent of employees with more than 15 years of experience is 25% higher compared to employees with less than 5 years of experience, which tells us about the greater interest of employees with more than 15 years of experience.

Table 14: Mann-Whitney test results

Mann-Whitney U		P-value
Job Title	Associate- Specialist	0.002
	Associate- Manager	0.034
	Associate- Expert	0.015
Years of experience	Less than 5- From 15 and over	0.01

The motivation of specialists, experts, and managers to work with AI/RPA based projects contributing to accounting systems design is 24-35 % higher compared to associates. Table 13 shows that out of total 208 employees, 79% of specialists, 90% of managers and 79% of experts are motivated to work with AI/RPA based project to contribute to accounting systems design, while 13% of specialists shows no motivation to work with AI/RPA based project. No disagreement responses were recorded from managers and experts. Overall, it is statistically proven that associates with less than 5 years of experience are less motivated to contribute to AI/RPA based projects contributing to accounting systems design compared to more experienced employees.

Table 15: Reliability Statistics

Reliability Statistics		
Cronbach's Alpha	Cronbach's Alpha based on standardized items	N of items
0.959	0.959	2

Table 16: Spearman's correlation

Spearman's rho		Statement 8	Statement 9
Statement 8	Correlation Coefficient	1.000	,846
	Sig. (2-tailed)		0.000
	N	208	208
Statement 9	Correlation Coefficient	,846	1.000

	Sig. (2-tailed)	0.000	
	N	208	208

The amount of acceptance was measured by a rating scale with 5-point answering mode from "1=strongly disagree" to "5=strongly agree". The appropriateness of using the sum of the items as a scale was ensured by demonstrating sufficient scale reliability Cronbach's Alpha 0.96 (Table 15). In addition, the Spearman's rank correlation (.846) indicates a strong correlation between the groups with a p-value of <.001, which proves that the rank correlation is statistically significant (Table 16). Overall, based on the statistical analysis above, the hypothesis "there are statistically significant differences in the perceptions of employees of different groups regarding working on projects related to AI / RPA" is proved to be true.

4.2.6 Hypothesis 3 and 4.

There is limited information about how employees perceive AI/RPA within the scope of their own careers. The next two questions were created as a new measure for this research, capturing the degree to which employees feel their jobs at GFSS might be impacted by AI/RPA.

Additional information on expectations in GFSS in terms of employment shows a large contrast in responses among employees. Only 8% of employees foresee a positive impact of AI/RPA on employment in GFSS, with 0% betting on a big positive impact. However, 74% of employees believe that the impact on employment of AI/RPA will be negative at GFSS, with 36% of them expecting this impact to be very negative. (Table 17).

Table 17: What will be the impact of AI/RPA on employment at GFSS in the next 5 years?

Statement 10		**1. Much less jobs**	**2. Somewhat less jobs**	**3. About the same**	**4. Somewhat more jobs**	**5. Much more jobs**	**Total N**	**Total %**	**Mean rank**	**Mode**	**P-value**
Degree	Bachelor	42 (38%)	40 (37%)	21 (20%)	6 (5%)	0	109	52%	113.54	2	0.007
	Master	27 (33%)	33 (41%)	12 (15%)	9 (11%)	0	81	39%	91.37		
	PhD	1 (17%)	3 (50%)	2 (33%)	0	0	6	3%	109.50		
	Other	6 (50%)	3 (25%)	2 (17%)	1 (8%)	0	12	6%	108.50		
Total							208	100%			
Job Title	Associate	43 (41%)	39 (37%)	19 (18%)	5 (4%)	0	106	51%	102.38	2	0.52
	Specialist	30 (39%)	33 (42%)	8 (10%)	7 (9%)	0	78	38%	109.81		

	Manager	1 (10%)	3 (30%)	5 (50%)	1 (10%)	0	10	5%	83.05		
	Expert	2 (14%)	4 (29%)	5 (36%)	3 (21%)	0	14	7%	106.29		
Total							208	100%			
Years of experience	Less than 5	22 (27%)	38 (47%)	15 (19%)	6 (7%)	0	81	39%	103.10	2	0.305
	From 5 to less than 10	30 (47%)	20 (31%)	10 (15%)	5 (9%)	0	65	31%	96.15		
	From 10 to less than 15	15 (41%)	14 (38%)	5 (13%)	3 (8%)	0	37	18%	114.31		
	From 15 and over	9 (36%)	7 (28%)	7 (28%)	2 (8%)	0	25	12%	116.24		
Total		**76 (36%)**	**79 (38%)**	**37 (18%)**	**16 (8%)**	**0**	**208**	**100%**			

The Kruskal-Wallis test compares mean ranks and determines if there are statistically significant differences in employees' perceptions of *AI/RPA having impact on employment at GFSS in the future* due to demographic factors. For each tested group, there is insufficient evidence to reject the null hypothesis that the mean ranks of the groups are the same at the 5% significance level (p-value>0,05). The distribution of the general level of agreement is the same across different degree, job title and year of experience groups. Therefore, based on the statistics above, the hypothesis "there are statistically significant differences in employees' responses regarding the number of jobs at GFSS in the future" is proved to be untrue.

Table 18: Are you afraid to lose your job due to AI in the future?

Statement 11		**1. Yes**	**2. Slightly**	**3. No**	**Total N**	**Total %**	**Mean rank**	**Mode**	**P-value**
Degree	Bachelor	27 (25%)	47 (43%)	35 (32%)	109	52%	111.59	2	0.24
	Master	18 (22%)	35 (43%)	28 (35%)	81	39%	94.77		
	PhD	1 (16%)	2 (33%)	3 (50%)	6	3%	103.17		
	Other	4 (33%)	5 (42%)	3 (25%)	12	6%	109.75		
Total					208	100%			
Job Title	Associate	33 (31%)	47 (44%)	26 (25%)	106	51%	88.24	2	0.001
	Specialist	15 (19%)	32 (41%)	31 (40%)	78	38%	119.15		
	Manager	0	5 (50%)	5 (50%)	10	5%	150.30		
	Expert	2 (14%)	5 (36%)	7 (50%)	14	7%	113.29		
Total					208	100%			
Years of experience	Less than 5	35 (43%)	38 (47%)	8 (10%)	81	39%	88.88	2	0.001
	From 5 to less than 10	13 (20%)	33 (51%)	19 (29%)	65	31%	105.41		
	From 10 to less than 15	2 (5%)	11 (30%)	24 (65%)	37	18%	115.24		
	From 15 and over	0	7 (28%)	18 (72%)	25	12%	136.84		
Total		**50 (24%)**	**89 (43%)**	**69 (33%)**	**208**	**100%**			

Table 19: Mann-Whitney U test results

Mann-Whitney U		P-value
Job Title	Associate- Specialist	0.01
	Associate- Manager	0.02
Years of experience	Less than 5- From 10 to less than 15	0.016
	From 5 to less that 10- From 15 and over	0.012
	Less than 5- From 15 and over	0.001

The Kruskal-Wallis test compares mean ranks and determines if there are statistically significant differences in employees' responses regarding *the fear of losing their jobs due to AI / RPA.* Out of total 208 employees, only 33 % are not afraid to lose their jobs and 43% are slightly afraid. It only leaves 24% of the surveyed employees to be actually afraid. (Table 18).

The results of the Kruskal test show that there is no contradiction in rejecting the null hypothesis of equal mean ranks for the variable job title and years of experience at the p-value <0.05. Statistically significant differences were found in respondents with different job titles and years of experience (p-value=0.001). In addition, Mann-Whitney test shows a high statistical probability (p-value<0,05) with confidence level over 95% that there are statistically significant differences in responses of associates compared to specialists and managers (p-value=0.01, p-value=0.02), while no statistically significant differences compared to experts exist (Table 19). We can see that 31% out of total 106 associates are afraid or slightly afraid to lose the job, while 25% is not afraid to lose the job. Which is almost opposite to specialists, 40% out of 78 specialists are not afraid and 19% are afraid to lose their jobs due to AI/RPA. However, the percentage of associates and specialists who are a little afraid of losing their jobs due to AI/RPA is almost comparable (41-44%). Responses of associates are opposite to managers, where 50% of managers are not afraid and 50% are slightly afraid. When it comes to the years of experience, mean ranks of employees with less than 5 years of experience are significantly differ from employees with more than 10 years of experience. More than a half of employees with more than 10 years of experience are tend to not afraid of losing job due to AI/RPA (65% with 10-15 years of experience, 72% with over 15 years of experience). Also, 71% of employees with 5-10 years of working experience are tend to have a fear of losing their jobs (51% are slightly afraid, while 20% are afraid), which is completely opposite to employees with more than 15 years of experience, where 72% have no fear to lose the job. It can be said that employees with more experience have less fear of losing their jobs compared to less experienced employees. Therefore, based on the statistics above, the hypothesis “there are statistically significant differences in the responses of different groups of employees regarding fear of losing their jobs due to AI / RPA” is proved to be true.

4.3 Interview

In addition to the survey, two short 15-20-minute interviews were conducted via MS Teams with two middle-level managers to provide a more detailed context for the survey results. Semi-structured interviews were conducted, which offer a more flexible approach to the interview process. During the interview, the author wanted to clarify if there is a justified fear of associates (entry-level accountants) being replaced by AI/RPA and any measures to encourage employees to participate in AI/RPA related projects. Since the interviewees are more experienced than the interviewer, they could express their thoughts and ideas to provide a realistic dialogue, allowing for unexpected answers and problems that arise during the interview. (Frances, et al., 2009) The results of the conversation present the following:

Regarding the managers' actions encouraging employees to participate in AI/RPA related projects, Manager 1 conducts one-on-one conversations and team meetings with employees every two weeks and asks them to think about which processes have the potential to be improved. New joiners or young specialists are especially encouraged to share their thoughts or ideas on how the processes can be improved, as they can look at the processes from a different angle and possibly notice the processes that, in their opinion, do not make sense. Manager 2 strives to encourage their cooperation with IT and entrust projects to accountants, so they work together. They understand that they free up time for more exciting tasks, personal development, or learning new skills thanks to automated tasks. It is essential to show them what they can do in the future when RPA frees up their time for more exciting tasks, show them a new role that they can fulfill, or how to grow up the career ladder.

When it comes to half of the employees being afraid of losing their jobs, Manager 1 believes that if employees start to update their skills and competencies right now following the current technology trends, the risks of being replaced by AI/RPA are low. She says that the repetitive, rule-based processing tasks are being replaced by AI/RPA, but not the jobs being removed. Instead, the jobs are changing, allowing employees to work on more value-added tasks. Associates can do more complex tasks migrating from CoEs, while accounting specialists and managers can expect a shift towards more strategic roles. She mentions one of her colleagues moving from a finance operations manager position to a new position to work on strategic finance projects. She believes that accountants skilled at observing, evaluating, and utilizing AI/RPA systems will be needed. Accountants must act and evaluate the potential to automate tasks. The company provides employees with all the necessary training to advance their knowledge, and employees, in turn, should be technology-friendly, open-minded, and ready for change.

Manager 2 believes that there is no shortage of work in any business environment today. The company is growing and with it the number of processes. Constant changes and process improvements are going on. The processes that they have today will look completely different next year. Accountants with basic IT skills and adaptability, who are always ready to integrate more efficient tools into existing processes will always be required. Moreover, he believes that there is a growing need for finance and accounting professionals who combine educational qualifications, professional skills, and skill sets that include data analysis and business analytics.

5 Results and Discussion

This thesis has provided a new perspective on the use and perception of artificial intelligence and RPA by employees of financial operations when automation of finance processes becomes more critical. This chapter summarizes the observations from the previous chapter and presents reflections on the research findings, theoretical and practical contribution, limitations, and future research.

5.1 Key findings

The final section of this master thesis provides a discussion in which literature is compared to a survey and interview analysis. During the practical part, it was important to find out how employees of different groups of the GFSS perceive the use of artificial intelligence at their workplace and whether there are concerns about the employment from the employees' perspective.

Conclusions of the research questions are as follows:

1. <u>How do GFSS employees perceive the use of AI / RPA in their workplace?</u>

In order to provide more coherent answer to this question, two perspectives are discussed. On the one hand, we found out if the benefits of AI / RPA, which were often discussed in the literature, improve the quality of performance of the GFSS employees. On the other hand, we find out if employees are motivated and willing to work with AI / RPA.

Previous studies of Suska et al.,(2019) and Buchanan (2020) argued the introduction of AI / RPA leads to an increase in the quality of accounting processes within organizations. It is supported by employees within SAP Services s.r.o in this study. The survey results showed that employees are aware of artificial intelligence capabilities and believe that, with its help, it is possible to achieve productivity in performing their work. Seventy percent of those surveyed say they already enjoy the benefits of automation. They responded by agreeing that AI / RPA can replace routine tasks and complement non-routine tasks, eliminate work inconsistencies, and deliver accurate results. It allows workers to reduce stress and focus on higher value-added tasks, which increases their job satisfaction, allowing them to define their relationships with work in a more positive and socially beneficial way. Differences in work experience, education, and position did not affect this result, meaning that all employees, regardless of their level of position, experience the benefits of AI's at their workplace.

Regarding the second perspective of the answer to the research question, about 67% of participants showed their motivation and willingness to work with AI-based systems and contribute to accounting systems development. It was statistically proven that variable job title and years of work experience had the most significant impact. In particular, employees with more than 10 years of work experience were generally more interested in working with AI than less experienced employees. Also, managers and experts are more optimistic about working with AI / RPA when compared to employees. In short, 90% of managers, 79% of specialists, and the same number of experts are ready to work with AI / RPA systems because this can create new opportunities for them when only 58% of associates see new opportunities in working with AI / RPA. As a rule, managers and experts have extensive experience of more than 10 years. The associates' experience varies from less than 5 years, rare from 5 and more.

In conclusion, the author of the thesis decided to check whether workers' motivation and willingness to work with AI is related to its positive capabilities that improve their work productivity. Research into UTAUT's theory shows that expected performance is significantly related to employees' intention to use technology. To the intention of employees to use AI / RPA, we attributed the motivation of employees to work with AI / RPA systems and the willingness to contribute to the system's design. Moreover, to the expected performance, we attributed all those seven features provided by AI / RPA (Hypothesis 1 chapter). Our study confirmed this belief, showing a statistically significant correlation between AI's positive effects and the motivation to work with AI systems (p-value <0.05, correlation coefficient = 0.79). Roughly similar results can be seen in a study of Cabrera-Sánchez et al., (2021). The study concludes that the behavioral intention to use AI applications to support operations management is highly dependent on expected performance (p-value <0.05, correlation coefficient = 0.65). No other similar studies that tested the effect of expected performance on intentions to use AI / RPA systems were found.

2. What is the impact of AI / RPA on the future of jobs in GFSS from the point of view of employees?

The answer presented here is connected to two survey questions in chapter 4.2.6. The results to the second research question showed that the impact of RPA / AI could be viewed from both positive and negative sides. The main findings of our study can be summarized as follows. According to an analysis, 74% of employees think that the number of jobs will decrease significantly in the future. Only 8% believe in creating new jobs. The remaining 18% think that the number of jobs will remain about the same. These results are consistent with a Deloitte study that suggests automation can be of tremendous strategic value to the profession, especially in general financial services. It is clear that automation, even if it has not yet been widely adopted in the industry, is strategic priority number two right after a process improvement. Particularly in finance operations, perhaps up to 56% of roles may have a high likelihood of automation (Nagarajah, 2016).

On the other hand, talking with managers shows us a different perspective: it is not about the jobs that will be cut, but tasks performed manually by accountants that will be modified or removed due to automation. The tasks will be modified but not destroyed. Even if the amount of work is reduced, other more exciting positions will be created. The company is growing, and with them, the number of processes. As predicted by the Bureau of Labor Statistics (2021), by 2026, accountants' employment rate will increase by 4% from 2019 to 2029. As the economy grows, more workers should be required to prepare and audit financial statements.

Moreover, 67% of employees are slightly fearful of being replaced by robots and losing their jobs, 33% do not fear losing their jobs. In particular, employees with less than 5 years of work experience tend to perceive higher personal risk. In contrast, managers and experts with more than 10 years of work experience tend to be more confident and lower job loss risk. The most pessimistic view of the future of accounting comes from Deloitte and the University of Oxford, which predicts the likelihood that when a robot takes over as a data science and number processing accountant, accountants have a 95% chance of losing their jobs (Chukwudi, et al., 2018). Managers in interviews urge employees to look at this from a positive side, prompting them to take actions that can minimize the likelihood of replacing them with artificial intelligence. According to them, it can be noted that good changes await accountants. As technology becomes advanced, roles are expected to shift, and professionals can expect to shift towards more strategic and analytical roles.

It can be concluded that the impact may not be as inevitable and severe as predicted if accountants do not continue to spend a lot of time keeping accounts, but instead try to provide decision support services to managers by constantly analyzing processes and suggesting new ideas. their improvements, taking advantage of new opportunities on the wave of artificial intelligence.

5.2 Implications and limitations

This thesis contributed to research on AI / RPA on financial operations employees in finance shared services. Observations were made on the expected performance variable of the UTAUT model. The study of the effect of expected performance on intention to use AI / RPA complements previous research on similar topics regarding the use of AI applications and at the same time contributes to subsequent research, as no research regarding the effect of AI/RPA on finance operations personnel could be found. This part is limited to identifying only one factor, expected performance, that influences the intentions of employees to work with AI / RPA-based systems, rather than measuring all four factors, including social impact, contributing factors, and expected effort. These factors need to be considered in future research for a complete picture of technology adoption by financial operations personnel.

Moreover, using data from an original survey of people, new data are presented on the impact of artificial intelligence (AI) and robotics on employment. This study's partial interest was which employees are concerned about losing their jobs and whether the employees justify these concerns in the opinion of the managers of these employees. Several characteristics of GFSS employees have been identified in terms of their work experience and title, the study of which is also limited in academia. It would be worthy to conduct in-depth interviews with employees to gain a better overview of their intentions and concerns.

This research can help accounting practitioners and their managers in other companies planning or just starting to adopt AI/RPA to see the trends, implications, and concerns. It might also help AI/RPA solution providers who would like to provide their automation solutions to SAP employees to see employee concerns and reach employees and help them learn more about AI/RPA.

6 Conclusion

The main purpose of this thesis was to investigate the impact of AI on the performance of GFSS employees at SAP Services s.r.o.

The first partial objective of this research was to explore relevant theories about the current trends and prospects of artificial intelligence in finance shared services. Chapter 3.1. covered a wide range of topics. Specifically, it was the history, approaches, and detailed definition of AI, human intelligence differences and AI, real-world applications of AI, and finally workplace and AI. Chapter 3.2. deals with the role and importance of technologies such as AI, RPA in financial shares services.

The second partial objective was to explore the challenges, opportunities, benefits, and implications of AI in the financial shared services. According to the literature, one of the main concerns is public concern about automation (Chapter 3.1.4.). The author has researched from trusted and reliable sources (mainly Scopus and Science direct database) on this topic (again chapter 3.1.4.) and concluded how important the role of management is and what actions from the side of middle management are needed to cope with employees concerns.

In addition to these literature studies, short conversations were held in MS Teams with SAP GFSS managers, during which we learned about their perceptions of employees being replaced due to automation. We also learned about calls to employees, encouraging them to learn and use AI / RPA (chapter 4.3.). Before the interviews, an online survey of SAP employees was also conducted. Here, answers were found to questions about the perception of the main AI / RPA capabilities by employees, their positive intentions to use and work with AI / RPA (see more in chapters 4.2.4. and 4.2.5.). Other answers were connected to the fear of losing a job. In this case, 67 % percent of respondents had concerns about being replaced due to the automation (see more in chapter 4.2.6.).

The third partial objective was to examine the impact of AI on entry-level and mid-level employees. By Mann-Whitney's testing, it was generally determined that there are statistically significant differences among entry-level employees and mid-level employees (associates, managers, and experts). Specifically, employees with less than 5 years of work experience, show more fears about their employment compared to mid-level employees. Fully detailed results can be found in chapters 4.2.5 and 4.2.6.

Finally, the results of this master thesis not only provided the answers to the research questions but also suggested the possible ways in which this topic could be further developed (chapter 5.2.).

7 References

A.Wright, Scott and E.Schultz, Ainslie. 2018. The rising tide of artificial intelligence and business automation: Developing an ethical framework. *Business Horizons.* [Online] 2018. https://www.sciencedirect.com/science/article/abs/pii/S0007681318301046?casa_token=Ds3-JNv3V9kAAAAA:Ii9KVBV73rMS3wt_iEEvv6yJD9xOwX4LzVA5nBylifREc53pQkdjvTQtRcMWy0xfFUYOSNU5FOE.

Aalst, Wil M. P. van der, Bichler , Martin and Heinzl , Armin . 2018. Robotic Process Automation. *Business & Information Systems Engineering.* [Online] 2018. https://link.springer.com/article/10.1007/s12599-018-0542-4.

Adams, William. 2015. Conducting Semi-Structured Interviews . [Online] 2015. https://www.researchgate.net/publication/301738442_Conducting_Semi-Structured_Interviews.

Aharonov and Slonin. 2019. Watch IBM's AI System Debate a Human Champion Live at Think 2019. [Online] IBM, 2019. https://www.ibm.com/blogs/research/2019/02/ai-debate-think-2019/.

Akimbekova, G., Horska, E. and Yegizbayeva, G. 2018. Advantages of formation and perspective models of agricultural cooperatives in the Republic of Kazakhstan. [Online] 2018. http://www.revistaespacios.com/a18v39n18/a18v39n18p06.pdf.

Akimbekova, Galiya, Horská, Elena and Yegizbayeva, Gulnur . 2017. Evaluation of the development of various forms of agriculture cooperation in the Republic of Kazakhstan. *1) LLP "Kazakh Research Institute of Economy Agribusiness and Rural Development" Almaty, Republic of Kazakhstan. 2) Slovak University of Agriculture in Nitra, Slovak Republic* . [Online] 2017. https://www.researchgate.net/publication/318184230_Evaluation_of_the_Development_pf_Various_Forms_of_Agriculture_Cooperation_in_the_Republic_of_Kazakhstan.

Allen, I. Elaine and Seaman, Christopher A. 2007. Likert Scales and Data Analyses. [Online] July 2007. http://rube.asq.org/quality-progress/2007/07/statistics/likert-scales-and-data-analyses.html.

Arora, Paras. 2019. RPA: SAP Robotic Process Automation Architecture & Use Cases. [Online] November 2019. https://www.linkedin.com/pulse/rpa-sap-robotic-process-automation-architecture-use-cases-paras-arora?trk=related_artice_RPA%3A%20SAP%20Robotic%20Process%20Automation%20Architecture%20%26amp%3Bamp%3Bamp%3B%20Use%20Cases_article-card_title.

Axson, David. 2015. Death by Digital: Good-Bye to Finance as You Know It. [Online] 27 October 2015. https://www.cfo.com/analytics/2015/10/death-digital-good-bye-finance-know/.

Balinggan, Gene. 2019. Difference Between Artificial Intelligence and Human Intelligence. [Online] DifferenceBetween.net., 2019. http://www.differencebetween.net/science/difference-between-artificial-intelligence-and-human-intelligence/.

Barrat, James. 2015. *OUR FINAL INVENTION: Artificial Intelligence and the End of the Human Era.* [https://kniga.biz.ua/pdf/5433-poslednee-izobretenie.pdf] New York : Thomas Dunne Books, St. Martin's Press, 2015.

Bekbosynova, Assel B., et al. 2018. Organization and parametric optimization of agricultural cooperatives in the Republic of Kazakhstan. *Kazakh National Agrarian*

University, Republic of Kazakhstan. [Online] 2018. http://www.revistaespacios.com/a18v39n27/18392711.html.
Bellman, Markus and Göransson, Gustav. 2019. Intelligent Process Automation. *Building the bridge between Robotic Process Automation and Artificial Intelligence.* [Online] 2019. https://www.finansforbundet.se/contentassets/3f53c230bef9402ca72bcd32b3d7bcb0/masteruppsats_markusbellman_gustavgoransson.pdf.
Bloomberg, Jason. 2019. Can artificial intelligence save SAP? [Online] 19 April 2019. https://siliconangle.com/2019/04/19/can-artificial-intelligence-save-sap/.
Bornegrim, Lucas and Holmquist, Gustav. 2020. Robotic process automation - An evaluative model for comparing RPA-tools. *DEPARTMENT OF INFORMATICS AND MEDIA.* [Online] 2020. https://www.diva-portal.org/smash/get/diva2:1442991/FULLTEXT01.pdf.
Brown, Gene. 2019. Difference Between Artificial Intelligence and Human Intelligence. [Online] 1 March 2019. http://www.differencebetween.net/science/difference-between-artificial-intelligence-and-human-intelligence/.
Buchanan, Jim. 2020. SHARED SERVICES IN AN AGE OF FINANCE TRANSFORMATION. [Online] 22 January 2020. https://www.blackline.com/blog/finance-automation/shared-services-finance-transformation/.
Bughin, Jacques, et al. 2017. Artificial Intelligence: The next digital frontier? *Mckinsey Global Institute.* [Online] June 2017. https://www.mckinsey.com/~/media/mckinsey/industries/advanced%20electronics/our%20insights/how%20artificial%20intelligence%20can%20deliver%20real%20value%20to%20companies/mgi-artificial-intelligence-discussion-paper.ashx.
Cabrera-Sánchez, Juan-Pedro, et al. 2021. Identifying relevant segments of AI applications adopters – Expanding the UTAUT2's variables. [Online] 2021. https://www.sciencedirect.com/science/article/pii/S073658532030188X?via%3Dihub.
Cappelli, Peter and Tambe, Prasanna. 2018. Artificial Intelligence in Human Resources Management: Challenges and a Path Forward. [Online] January 2018. https://www.researchgate.net/publication/328798021_Artificial_Intelligence_in_Human_Resources_Management_Challenges_and_a_Path_Forward.
Chappell, David. 2016. Understanding Enterprise RPA: The Blue Prism example. [Online] 2016. https://www.blueprism.com/uploads/resources/white-papers/Understanding-Enterprise-RPA-The-Blue-Prism-Example.pdf.
Chatterjee, Sheshadri, et al. 2020. Employees' Acceptance of AI Integrated CRM System: Development of a Conceptual Model. [Online] 2020. https://link.springer.com/chapter/10.1007%2F978-3-030-64861-9_59.
Chen, Chuck. 2020. New Home for Pre-built Bots – SAP Bot Store. *SAP Community.* [Online] 23 March 2020. https://blogs.sap.com/2020/03/23/new-home-for-pre-built-bots-sap-bot-store/.
Chukwudi, Odoh Longinus, et al. 2018. Effect of Artificial Intelligence on the Performance of Accounting Operations among Accounting Firms in South East Nigeria. [Online] 2018. https://www.journalajeba.com/index.php/AJEBA/article/view/10486.
Clair, Craig Le. 2019. The 15 Providers That Matter Most And How They Stack Up. [Online] 23 October 2019. https://www.quanton.co.nz/wp-content/uploads/2019/12/Forrester-Wave-Robotic-Process-Automation-Q4-2019.pdf.

Community, SAP. SAP Intelligent Robotic Process Automation FAQ. [Online] https://community.sap.com/topics/intelligent-rpa/faq.

Constantin, Emine. 2019. Netherlands: The Pros And Cons Of Shared Service Centres For Finance And Accounting. [Online] 16 September 2019. https://www.mondaq.com/accounting-standards/845004/the-pros-and-cons-of-shared-service-centres-for-finance-and-accounting.

Consulting, Capgemini. 2015. Shared Services: what global companies do. *Key trends and perspectives.* [Online] 2015. https://www.capgemini.com/consulting-fr/wp-content/uploads/sites/31/2017/08/shared_services_what_global_campanies_do.pdf.

Cooperatives"., Law No.372-V ZRK of 29 October 2015 "On Agricultural. 2015. [Online] 2015. http://www.ilo.org/dyn/natlex/natlex4.detail?p_lang=en&p_isn=102050&p_count=1&p_classification=22.

Copeland, B.J. 2000. AlanTuring.net. *What is Artificial Intelligence?* [Online] May 2000. http://www.alanturing.net/turing_archive/pages/reference%20articles/what_is_AI/What%20is%20AI02.html.

Davenport, Thomas H., Loucks, Jeff and Schatsky, David. 2017. Bullish on the business value of cognitive. *The 2017 Deloitte State of Cognitive Survey.* [Online] 2017. https://www2.deloitte.com/content/dam/Deloitte/us/Documents/deloitte-analytics/us-da-2017-deloitte-state-of-cognitive-survey.pdf..

Dias, Malshika, Pan, Shan and Tim, Yenni. 2019. KNOWLEDGE EMBODIMENT OF HUMAN AND MACHINE INTERACTIONS: ROBOTIC-PROCESS-AUTOMATION AT THE FINLAND GOVERNMENT. *In Proceedings of the 27th European Conference on Information Systems (ECIS), Stockholm & Uppsala, Sweden, June 8-14, 2019. ISBN 978-1-7336325-0-8 Research-in-Progress Papers.* [Online] 2019. https://aisel.aisnet.org/cgi/viewcontent.cgi?article=1017&context=ecis2019_rip.

Dickson, Ben. 2018. There's a huge difference between AI and human intelligence—so let's stop comparing them. [Online] TechTalks, 2018. https://bdtechtalks.com/2018/08/21/artificial-intelligence-vs-human-mind-brain/.

Dictionary, The Oxford English. [Online] https://www.lexico.com/definition/artificial_intelligence.

Duin, Stefan van and Bakhshi, Naser. 2018. Artificial Intelligence. [Online] March 2018. https://www2.deloitte.com/content/dam/Deloitte/nl/Documents/deloitte-analytics/deloitte-nl-data-analytics-artificial-intelligence-whitepaper-eng.pdf.

E.Makarius, Erin, et al. 2020. Rising with the machines: A sociotechnical framework for bringing artificial intelligence into the organization. *Journal of Business Research.* [Online] 2020. https://www.sciencedirect.com/science/article/pii/S0148296320305002?casa_token=Y1r5feOge_kAAAAA:J2Q1Ha4Ba8-sQNOJmIz6a_1DYpjJW1uHn_W8wisHEDazXtA2Xe75V1cZPqdP2oM_Ac71JqoyM7Y#b0220.

Economist, The. 2020. Businesses are finding AI hard to adopt. [Online] 2020. https://www.economist.com/technology-quarterly/2020/06/11/businesses-are-finding-ai-hard-to-adopt.

Fernandez, Dahlia and Aman, Aini. 2018. Impacts of Robotic Process Automation on Global Accounting Services. *Asian Journal of Accounting and Governance 9: 123–131* . [Online] 2018. https://pdfs.semanticscholar.org/ddb7/31a4f4f50835e081d2d20ba59b7dca0b027c.pdf.

Frances, Ryan, Coughlan, Michael and Cronin, Patricia. 2009. Interviewing in qualitative research. [Online] 2009. https://www.researchgate.net/publication/261471599_Interviewing_in_qualitative_research.
Frey, Carl Benedikt and A.Osborne, Michael. 2017. The future of employment: How susceptible are jobs to computerisation? *Technological Forecasting and Social Change.* [Online] 2017. https://www.sciencedirect.com/science/article/abs/pii/S0040162516302244.
Gill, Jagreet Kaur. 2020. Getting Started with UiPath – UseCases | Benefits | Features. [Online] 8 May 2020. https://www.xenonstack.com/blog/uipath/.
Google. [https://ai.google/social-good/]
—. *Bringing the benefits of AI to everyone.* [https://ai.google/about/]
Griffin, Andrew. 2015. Independent.co.uk. *STEPHEN HAWKING: ARTIFICIAL INTELLIGENCE COULD WIPE OUT HUMANITY WHEN IT GETS TOO CLEVER AS HUMANS WILL BE LIKE ANTS.* [Online] Independent- UK's largest quality digital news brand, 8 October 2015. https://www.independent.co.uk/life-style/gadgets-and-tech/news/stephen-hawking-artificial-intelligence-could-wipe-out-humanity-when-it-gets-too-clever-as-humans-a6686496.html.
Griffiths, Jordan. 2016. How to avoid the SIX most damaging mistakes. *Accenture Technology Vision 2016.* [Online] 2016. https://www.accenture.com/t00010101T000000Z__w__/au-en/_acnmedia/PDF-41/Accenture-Robotic-Process-Auto-POV.pdf.
Hammond, Kris. 2015. Computerworld.com. *ARTIFICIAL INTELLIGENCE TODAY AND TOMORROW.* [Online] 2015. https://www.computerworld.com/article/2906336/what-is-artificial-intelligence.html.
Hanna, Tess. 2020. Key Takeaways: 2020 Gartner Magic Quadrant for Robotic Process Automation. [Online] 2020. https://solutionsreview.com/business-process-management/key-takeaways-2020-gartner-magic-quadrant-for-robotic-process-automation/.
Hilgefort, Ingo. 2020. Smart Insights for Variances. [Online] 2020. https://saphanajourney.com/sap-analytics-cloud/learning-article/smart-insights-for-variances/.
Holma, Jane. 2020. SAP automation using Robot Process Automation . [Online] 2020. https://www.theseus.fi/bitstream/handle/10024/337433/Holma_Janne.pdf?sequence=2&isAllowed=y.
Huang, Ming-Hui, Rust, Roland and Maksimovic, Vojislav. 2019. The Feeling Economy: Managing in the Next Generation of Artificial Intelligence (AI). [Online] July 2019. https://journals.sagepub.com/doi/abs/10.1177/0008125619863436?journalCode=cmra&.
Hurtebize, Laurent, Gourdin, Thierry and Bhat, Harshavardhan. 2019. SAP Intelligent Robotic Process Automation in a Nutshell. [Online] 2019. https://open.sap.com/courses/rpa1/items/tmdkZb8By6g62SvbXj1vb.
IBM. 2018. [Online] 2018. https://www.research.ibm.com/artificial-intelligence/publications/2018/scaling-ai/.
—. 2018. Advancing AI. [Online] 2018. https://www.research.ibm.com/artificial-intelligence/publications/2018/advancing-ai/.
—. How does Project Debater work? *AI Research.* [Online] https://www.research.ibm.com/artificial-intelligence/project-debater/how-it-works/.

—. 2019. IBM Spectrum Virtualize. [Online] 2019.
https://www.ibm.com/downloads/cas/BD4AJ0AY.
—. 1997. ibm.com. *Deep Blue.* [Online] 1997.
https://www.ibm.com/ibm/history/ibm100/us/en/icons/deepblue/.
ibm.com. Explore the inner workings of IBM Robotic Process Automation with Automation Anywhere. [Online] https://www.ibm.com/products/rpa-with-automation-anywhere/details.
—. IBM Institute for Business Value. *Shifting toward Enterprise-grade AI.* [Online]
https://www.ibm.com/thought-leadership/institute-business-value/report/enterpriseai.
—. Robotic process automation: A no-hype buyer's guide. [Online]
https://www.ibm.com/cloud/smartpapers/rpa-buyers-guide/#section-2.
ICD. 2019. Worldwide Spending on Artificial Intelligence Systems Will Be Nearly $98 Billion in 2023, According to New IDC Spending Guide. [Online] 2019.
https://www.idc.com/getdoc.jsp?containerId=prUS45481219.
Indeed.com. 2020. What Is SAP and Why Is It Important in the Workplace? [Online] 2020. https://www.indeed.com/career-advice/finding-a-job/what-is-sap.
Isaac, Ruchi, Muni, Riya and Desai, Kenali. 2017. Delineated Analysis of Robotic Process Automation Tools. *First International Conference on Information Technology, Communications and Computing (ICITCC 2017), 24-December-2017, Bhopal, M.P., India | ISBN (Online): 978-81-932623-3-7.* [Online] 2017.
https://zenodo.org/record/1134259#.YB8B1jGg82x.
Ivain, Jérôme. 2019. Augment your Analysis with Smart Discovery. [Online] 7 September 2019. https://saphanajourney.com/sap-analytics-cloud/resources/augment-your-analysis-with-smart-discovery/.
Johns, Ron. 2010. LIKERT ITEMS AND SCALES. [Online] March 2010.
https://ukdataservice.ac.uk/media/262829/discover_likertfactsheet.pdf.
Kaplan, Andreas and MichaelHaenlein. 2020. Rulers of the world, unite! The challenges and opportunities of artificial intelligence. *Business Horizons.* [Online] 2020.
https://www.sciencedirect.com/science/article/abs/pii/S0007681319301260?via%3Dihub.
Khan, Sameera. 2020. COMPARATIVE ANALYSIS OF RPA TOOLS- UIPATH, AUTOMATION ANYWHERE AND BLUEPRISM. *International Journal of Computer Science and Mobile Applications.* [Online] November 2020.
https://www.researchgate.net/publication/347604931_COMPARATIVE_ANALYSIS_OF_RPA_TOOLS-UIPATH_AUTOMATION_ANYWHERE_AND_BLUEPRISM.
Kirchmer, Dr. Mathias. 2020. ROBOTIC PROCESS AUTOMATION – PRAGMATIC SOLUTION OR DANGEROUS ILLUSION? [Online] 10 February 2020.
https://insights.btoes.com/risks-robotic-process-automation-pragmatic-solution-or-dangerous-illusion-1-1.
Kong, Bill and Lee, Edmund. Finanail Shared Service. [Online]
https://www.pwchk.com/en/services/consulting/finance/financial-shared-service.html.
Kurmanalina, Aigul, et al. 2020. *A Swot Analysis of Factors Influencing the Development of Agriculture Sector and Agribusiness Entrepreneurship.* 2020.
https://www.abacademies.org/articles/a-swot-analysis-of-factors-influencing-the-development-of-agriculture-sector-and-agribusiness-entrepreneurship-8969.html.
Little, Arthur D. 2015. Executive Roundtable: Shared Services. [Online] 2015.
https://www.adlittle.com/sites/default/files/viewpoints/24_07_2015_Arthur_D_Little_Roundtable_Shared_Services_Summary.pdf.

Locke, Dallas. 2019. How Does Automation Anywhere Work? [Online] 2019. https://smartbridge.com/how-does-automation-anywhere-work/.
Lyon, Jamie and Kops, Deborah. 2012. Finance transformation: expert insights on shared services and outsourcing. [Online] January 2012. https://www.accaglobal.com/gb/en/technical-activities/technical-resources-search/2012/january/finance-transformation-expert-insights-sso.html.
Marr, Bernard. 2018. The Key Definitions Of Artificial Intelligence (AI) That Explain Its Importance. [Online] Forbes, 14 February 2018. https://www.forbes.com/sites/bernardmarr/2018/02/14/the-key-definitions-of-artificial-intelligence-ai-that-explain-its-importance/#6595a4154f5d.
Martens, Bertin and Tolan, Songül. 2018. Will This Time Be Different? A Review of the Literature on the Impact of Artificial Intelligence on Employment, Incomes and Growth. *JRC Digital Economy Working Paper 2018-08.* [Online] 2018. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3290708.
Matias, Yossi. 2018. *Keeping people safe with AI-enabled flood forecasting.* [https://www.blog.google/products/search/helping-keep-people-safe-ai-enabled-flood-forecasting/] s.l. : Google, 2018.
McDaniel, Kate. 2019. How Can RPA Transform Shared Services and Global Business Services? [Online] July 2019. https://www.uipath.com/solutions/whitepapers-old-feb2020/rpa-transforming-shared-services-and-global-business-services.
McKight, Patrick E. and Najab, Julius. 2010. Kruskal-Wallis Test. [Online] January 2010. https://onlinelibrary.wiley.com/doi/abs/10.1002/9780470479216.corpsy0491.
Merhi, Mohamed, Hone, Kate and Tarhini, Ali. 2019. A cross-cultural study of the intention to use mobile banking between Lebanese and British consumers: Extending UTAUT2 with security, privacy and trust. [Online] 2019. https://www.sciencedirect.com/science/article/pii/S0160791X19300132.
Mohamad, Mimi Mohaffyza, et al. 2015. Measuring the Validity and Reliability of Research Instruments. [Online] 2015. https://pdf.sciencedirectassets.com/277811/1-s2.0-S1877042815X00413/1-s2.0-S1877042815047771/main.pdf?X-Amz-Security-Token=IQoJb3JpZ2luX2VjECoaCXVzLWVhc3QtMSJHMEUCIQCrkI4Nq8H0GiGkviNG%2FJ14T8GDPE6Zrl1OEdtcRurmggIgQoZVb7gslBT1OhEdMeqpiWaPt%2FyxcYHscZ9%2Bl0.
Molina-Azorin, Jose F. 2016. Mixed methods research: An opportunity to improve our studies and our research skills. *European Journal of Management and Business Economics 25(2):37-38.* [Online] 2016. https://www.researchgate.net/publication/303691681_Mixed_methods_research_An_opportunity_to_improve_our_studies_and_our_research_skills#:~:text=ArticlePDF%20Available-,Mixed%20methods%20research%3A%20An%20opportunity%20to%20improve,studies%20and%20our%20r.
Mooney, Raymond J. 2010. The University of Texas at Austin, Department of Computer Science. [Online] 2010. http://www.cs.utexas.edu/~mooney/cs343/slide-handouts/philosophy.4.pdf.
Moore, Madison. 2017. SD Times GitHub project of the week: ParlAI. [Online] May 2017. https://sdtimes.com/sd-times-github-project-week-parlai/.
Moser, Flavia. 2020. Incorporating Predictions in Your Planning Process with Smart Predict. [Online] 2020. https://saphanajourney.com/sap-analytics-cloud/learning-article/incorporating-predictions-in-planning-smart-predict/.

Mueller, John Paul and Massaron, Luca. 2018. [Online] John Wiley & Sons, Inc., , 2018. file:///C:/Users/I535117/Downloads/Artificial%20Intelligence%20for%20Dummies%20by%20John%20Paul%20Mueller,%20Luca%20Massaron%20(z-lib.org).pdf.
Muscolino, Holly. 2018. WorkFusion, Blue Prism, and Automation Anywhere in 2018 Point to Growth in RPA Software. [Online] 2018. https://documentmedia.com/article-2847-WorkFusion-Blue-Prism-and-Automation-Anywhere-in-2018-Point-to-Growth-in-RPA-Software.html.
Nagarajah, Eva. 2016. What does automation mean for the accounting profession? [Online] 2016. https://www.pwc.com/my/en/assets/press/1608-accountants-today-automation-impact-on-accounting-profession.pdf.
Naumov, Mikhail. 2018. 4 Ways Conversational Process Automation Revolutionizes Customer Service Operations. [Online] 2018. https://customerthink.com/4-ways-conversational-process-automation-revolutionizes-customer-service-operations/.
Nazarbayev, N. A. 2012. Srategy Kazakhstan 2050. [Online] 2012. https://kazakhstan2050.com/2050-address.
Nesipbayeva, I., Yerkinbayeva, L.K. and Järvelaid, Peeter M. 2019. Legal problems of development of agricultural cooperation: new approaches and prospects. [Online] 2019. file:///C:/Users/I535117/Downloads/2203-1-4480-1-10-20191203.pdf.
News, SAP. 2018. SAP Galvanizes the Enterprise with Intelligent New Products and Choice. [Online] 2018. https://news.sap.com/2018/06/sapphire-now-sap-intelligent-enterprise-products-choice/.
Noble, Josh. 2019. Blue Prism Attended Automation – How to Configure Desktop Triggers. [Online] 2019. https://www.linkedin.com/pulse/blue-prism-attended-automation-how-configure-desktop-triggers-noble.
Noppen, Philip, et al. 2020. How to Keep RPA Maintainable? *In: Fahland D., Ghidini C., Becker J., Dumas M. (eds) Business Process Management. BPM 2020. Lecture Notes in Computer Science, vol 12168. Springer, Cham.* [Online] 2020. https://link.springer.com/chapter/10.1007%2F978-3-030-58666-9_26#copyrightInformation.
OECD. 2019. Monitoring the Development of Agricultural Co-operatives in Kazakhstan. *OECD publishing.* [Online] 2019. http://www.oecd.org/eurasia/competitiveness-programme/central-asia/Kazakhstan-Monitoring-Agricultural-Co-operatives-2019-EN.pdf.
Partnerhip on AI. [Online] https://www.partnershiponai.org/.
Penner, Terry. 2019. SAP Analytics Cloud Embedded and Enterprise Strategy for SAP Concur, SAP Ariba and SAP Fieldglass. [Online] 22 October 2019. https://blogs.sap.com/2019/10/22/sap-analytics-cloud-embedded-and-enterprise-strategy-for-sap-concur-sap-ariba-and-sap-fieldglass/.
portal.wdf.sap.corp. Global Finance Shared Services. [Online] https://portal.wdf.sap.corp/wcm/ROLES:/portal_content/cp/roles/com.sap.sen.fa.rl_finance_and_administration/finance_and_administration/fd_organization_2/Infocenters/WS%20Finance%20%26%20Administration/Organization/~/Global%20Finance%20Infrastructure/Globa.
Postma, Jeff. Next generation shared services. [Online] https://www.de.kearney.com/leadership-change-organization/article?/a/next-generation-shared-services.
Press, SAP. SAP Intelligent Robotic Process Automation and Business Processes. [Online] https://www.sap-press.com/media/samples/epubs/4998/OEBPS/02_003.html#h2.

—. SAP Intelligent Technologies. [Online] https://learning.sap-press.com/intelligent-technologies.
Prism, Blue. 2016. Blue Prism Software Robots. *Introducing the virtual workforce.* [Online] 2016. https://www.blueprism.com/uploads/resources/white-papers/Blue-Prism-Product-Overview-Enterprise-Edition.pdf.
Raelson, Adam Michael. 2017. Global Finance Shared Services (GFSS) at SAP. [Online] 2017. https://blogs.sap.com/2017/04/12/global-finance-shared-services-gfss-at-sap/.
—. 2017. Global Finance Shared Services (GFSS) at SAP. [Online] 12 April 2017. https://blogs.sap.com/2017/04/12/global-finance-shared-services-gfss-at-sap/.
Ray, Saikat, et al. 2020. Magic Quadrant for Robotic Process Automation. [Online] July 2020. https://www.gartner.com/doc/reprints?id=1-1ZK435W1&ct=200728&st=sb&__hssc=71912524.10.1600949777170&__hstc=71912524.77802b7b71f84de6c2f2dcab227a4431.1600277634921.1600944916214.1600949777170.25&__hsfp=3469245100&mkt_tok=eyJpIjoiT1RBeU56RTROek16TXpVeSIsInQ.
—. 2020. Magic Quadrant for Robotic Process Automation. [Online] 2020. https://www.gartner.com/doc/reprints?id=1-1ZK435W1&ct=200728&st=sb&__hssc=71912524.10.1600949777170&__hstc=71912524.77802b7b71f84de6c2f2dcab227a4431.1600277634921.1600944916214.1600949777170.25&__hsfp=3469245100&mkt_tok=eyJpIjoiT1RBeU56RTROek16TXpVeSIsInQ.
Ribiero, Jair. 2020. A Simple Approach to Define Human and Artificial Intelligence. [Online] 2020. https://medium.com/towards-artificial-intelligence/a-simple-approach-to-define-human-and-artificial-intelligence-4d91087d16ff.
Rossi, Francesca. 2019. BUILDING TRUST IN ARTIFICIAL INTELLIGENCE. *Journal of International Affairs.* [Online] 2019. https://www.jstor.org/stable/26588348?seq=1.
Russell-Rose, Tony and Tate, Tyler. 2013. Pareto distribution. [Online] 2013. https://www.sciencedirect.com/topics/computer-science/pareto-distribution.
saphanajourney.com. 2020. SAP Analytics Cloud. [Online] 2020. https://saphanajourney.com/sap-analytics-cloud/business-intelligence-overview/.
—. 2020. SAP Analytics Cloud. [Online] 2020. https://saphanajourney.com/sap-analytics-cloud/.
Schober, Patrick MD, PhD, MMedStat, Boer, Christa PhD, MSc and Schwarte, Lothar A. MD, PhD, MBA. 2018. Correlation Coefficients: Appropriate Use and Interpretation. [Online] 2018. https://journals.lww.com/anesthesia-analgesia/fulltext/2018/05000/correlation_coefficients__appropriate_use_and.50.aspx.
SE, SAP. 2020. 7 reasons to automate processe with SAP Intelligent Robotic Process Automation. [Online] 2020. https://www.sap.com/cz/documents/2020/05/f8f46348-987d-0010-87a3-c30de2ffd8ff.html.
—. 2020. Increasing Business Agility by innovating with Intelligent Process Automation. [Online] 2020. https://www.sap.com/cz/documents/2020/07/fc449904-a37d-0010-87a3-c30de2ffd8ff.html.
—. SAP History. [Online] https://www.sap.com/corporate/en/company/history/1972-1980.html.
—. 2021. SAP Intelligent RPA Cloud Studio User Guide. [Online] 2021. https://help.sap.com/doc/464781c43f264b8fb956c6e1594cd723/Cloud/en-US/29e8302075ea4c75a5952d44625ce508.pdf.
—. The Intelligent Enterprise. [Online] https://www.sap.com/products/intelligent-enterprise.html?btp=4f510a3d-ab55-4970-896e-1f1bab48810c.

Seasongood, Shawn. 2016. NOT JUST FOR THE ASSEMBLY LINE: A Case for Robotics in Accounting and Finance. [Online] 2016. http://ksuweb.kennesaw.edu/~snorth/Robots/Articles/article4.pdf.
Sharma, Kush. 2020. Make your finance processes 'Intelligent' with SAP S/4HANA. [Online] July 2020. https://blogs.sap.com/2020/07/06/make-your-finance-processes-intelligent-with-sap-s-4hana/.
Sheen, Harry. 2020. What does Artificial Intelligence and Machine Learning mean for SAP BI? [Online] 22 October 2020. https://www.capgemini.com/gb-en/2020/10/what-does-artificial-intelligence-and-machine-learning-mean-for-sap-bi/.
Shi, Zhongzhi. 2011. Advanced Artificial Intelligence. *ProQuest Ebook Central.* [Online] 2011. [Cited: 13 April 2020.] https://search.proquest.com/legacydocview/EBC/840558?accountid=26997.
Sibalija, Tatjana, Jovanović, Stefan and Đurić, Jelena S. 2019. ROBOTIC PROCESS AUTOMATION: OVERVIEW AND OPPORTUNITIES. [Online] May 2019. https://www.researchgate.net/publication/332970286_ROBOTIC_PROCESS_AUTOMATION_OVERVIEW_AND_OPPORTUNITIES.
Sklar, Elizabeth. 2010. [Online] 2010. http://www.sci.brooklyn.cuny.edu/~sklar/teaching/s10/cis20.2/notes/lecIV.1-notes.pdf.
Slaby, James R. 2012. Robotic Automation Emerges as a Threat to Traditional Low-Cost Outsourcing. *Cheap, easy-to-develop software robots will.* [Online] 2012. https://neoops.com/wp-content/uploads/2014/02/Robotic-Automation-A-Threat-To-Low-Cost-Outsourcing_HfS.pdf.
Spanicciati, Mario. 2019. https://www.blackline.com/blog/rpa/what-robotic-process-automation-really-means-for-accountants/. [Online] 22 June 2019. WHAT ROBOTIC PROCESS AUTOMATION REALLY MEANS FOR ACCOUNTANTS.
Staff, Data Semantics. 2020. Ui Path V/S Automation Anywhere V/S Blue Prism – Which One Is Right Platform for Your Business? [Online] 2020. https://datasemantics.co/ui-path-v-s-automation-anywhere-v-s-blue-prism/.
Statistics, Bureau of Labor. 2021. U.S. Department of Labor. *Occupational Outlook Handbook, Accountants and Auditors.* [Online] 2021. https://www.bls.gov/ooh/business-and-financial/accountants-and-auditors.htm.
Sterling. 2020. What is SAP? Understanding, Use and Importance of SAP in the Company. [Online] April 2020. https://www.sterling-team.com/news/en/what-is-sap-understanding-use-and-importance-of-sap-in-the-company/.
Sulleyman, Aatif. 2017. *AI IS HIGHLY LIKELY TO DESTROY HUMANS, ELON MUSK WARNS.* [Online] Independent-UK's largest quality digtal news brand, 27 November 2017. [Cited: 16 April 2020.] https://www.independent.co.uk/life-style/gadgets-and-tech/news/elon-musk-artificial-intelligence-openai-neuralink-ai-warning-a8074821.html#comments.
Sureka, Akash. 2020. 18 Unparalleled UiPath Features for Successful RPA in Business. [Online] 2020. https://www.clariontech.com/platform-blog/18-unparalleled-uipath-features-for-successful-rpa-in-business.
Suri, Vipin K., Elia, Marianne and Hillegersberg, Jos van. 2017. Software Bots - The Next Frontier for Shared Services and Functional Excellence. *In: Oshri I., Kotlarsky J., Willcocks L. (eds) Global Sourcing of Digital Services: Micro and Macro Perspectives. Global Sourcing 2017. Lecture Notes in Business Information Processing, vol 306. Springer, Cham.* [Online] 2017. https://link.springer.com/chapter/10.1007/978-3-319-70305-3_5.

Suska, Michael and Weuster, Arne. 2019. Shared Services- Digitalise your services. [Online] April 2019. https://www.pwc.de/de/prozessoptimierung/pwc-studie-shared-services.pdf.
—. 2016. Shared Services: Multiplying success. [Online] July 2016. https://www.pwc.de/de/prozessoptimierung/assets/shared-services-multiplying-success.pdf.
Syed, Rehan, et al. 2020. Robotic Process Automation: Contemporary themes and challenges. *Computers in Industry, volume 115.* [Online] February 2020. https://www.sciencedirect.com/science/article/abs/pii/S0166361519304609?casa_token=N6-ZQ8BcXdcAAAAA:CmN6snL0_1XPL0U8qW5k1idNYAtcNvgogXmX3DzTvqBr07KPkER6uKDdoj3VpvE0_a8dtLLi3FY#bib0135.
Taber, Keith S. 2018. The Use of Cronbach's Alpha When Developing and Reporting Research Instruments in Science Education. [Online] 2018. https://link.springer.com/article/10.1007/s11165-016-9602-2.
Taherdoost, Hamed. 2016. Sampling Methods in Research Methodology; How to Choose a Sampling Technique for Research. [Online] 2016. https://www.researchgate.net/publication/319998246_Sampling_Methods_in_Research_Methodology_How_to_Choose_a_Sampling_Technique_for_Research.
Tripathi, Alok Mani. 2018. Learning Robotic Process Automation: Create Software robots and automate business processes with the leading RPA tool- UIPath. [Online] 2018. https://books.google.cz/books?hl=en&lr=&id=SLZTDwAAQBAJ&oi=fnd&pg=PP1&dq=uipath+feature&ots=py1CdWjvJI&sig=5tbvsKG8Mm3c2iWXOA8VfG_QHOI&redir_esc=y#v=onepage&q=uipath%20feature&f=false.
UIPath. Attended, Unattended and Hybrid. [Online] https://www.uipath.com/hubfs/Whitepapers/eGuide_to_the_six_automation_scenarios_UK.pdf?mkt_tok=eyJpIjoiT1dRek5qWTJOMlkxTmpNeSIsInQiOiJqTm5laWtUVUZFRkpyVXlxbWdFc2.
—. UI Studio. *The automation canvas for everyone.* [Online] https://www.uipath.com/hubfs/resources/images/products/UiPath-Studio-Family_One_pager.pdf.
VANNIER, Guillaume. 2020. An Overview of Components for SAP Intelligent Robotic Process Automation. [Online] 24 March 2020. https://blogs.sap.com/2020/03/24/an-overview-of-components-for-sap-intelligent-robotic-process-automation/.
Venkatehs, Viswanath, Y.L.Thong, James and Xu, Xin. 2016. Unified Theory of Acceptance and Use of Technology: A Synthesis and the Road Ahead. [Online] 2016. https://aisel.aisnet.org/jais/vol17/iss5/1/.
Venkatesh, Viswanath. 2021. Adoption and use of AI tools: a research agenda grounded in UTAUT. [Online] 2021. https://link.springer.com/article/10.1007/s10479-020-03918-9.
Viehhauser, Johannes. 2020. Is Robotic Process Automation Becoming Intelligent? Early Evidence of Influences of Artificial Intelligence on Robotic Process Automation. [Online] September 2020. https://link.springer.com/chapter/10.1007%2F978-3-030-58779-6_7.
—. 2020. Is Robotic Process Automation Becoming Intelligent? Early Evidence of Influences of Artificial Intelligence on Robotic Process Automation. In: Asatiani A. et al. (eds) Business Process Management: Blockchain and Robotic Process Automation Forum. BPM 2020. *Lecture Notes in Business Information Processing, vol 393. Springer, Cham.* [Online] 2020. https://link.springer.com/chapter/10.1007%2F978-3-030-58779-6_7.

Viswanath Venkatesh, Michael G. Morris, Gordon B. Davis and Fred D. Davis. 2003. User Acceptance of Information Technology: Toward a Unified View. *Vol. 27, No. 3 (Sep., 2003), pp. 425-478.* [Online] 2003. https://www.jstor.org/stable/30036540?seq=1.
Wallon, Corentin. 2019. Artificial intelligence applications in corporate finance. [Online] 2019. https://matheo.uliege.be/bitstream/2268.2/7558/4/Master%20Thesis%20-%20Artificial%20Intelligence%20applications%20in%20corporate%20finance%20-%20%20WALLON%20Corentin.pdf.
Watson, Tracy. 2019. ARTIFICIAL INTELLIGENCE VS. HUMAN INTELLIGENCE – WHICH ONE YOU'D PREFER TO HIRE. [Online] Skywell.software, 2019. https://skywell.software/blog/artificial-intelligence-vs-human-intelligence/.
Wellmann, Christian, et al. 2020. A Framework to Evaluate the Viability of Robotic Process Automation for Business Process Activities. . *In: Asatiani A. et al. (eds) Business Process Management: Blockchain and Robotic Process Automation Forum. BPM 2020. Lecture Notes in Business Information Processing, vol 393. Springer, Cham.* [Online] 2020. https://link.springer.com/chapter/10.1007%2F978-3-030-58779-6_14#aboutcontent.
Weston, Miller, Feng. 2017. *ParlAI: A new software platform for dialog research.* [https://engineering.fb.com/ml-applications/parlai-a-new-software-platform-for-dialog-research/] s.l. : Facebook Engineering, 2017.
Wilks, Yorick. 2019. Artificial intelligence : Modern magic or dangerous future?. *ProQuest Ebook Central* . [Online] 2019. [Cited: 13 April 2020.] https://search.proquest.com/docview/2225927579/52B117261512411EPQ/33?accountid=26997.
Yessengaliyeva, Saltanat and Kazambayeva, Aigul. 2018. ORGANIZATIONAL AND ECONOMIC ASPECTS OF AGRICULTURAL. *Economic and Engineering Studies.* [Online] 2018. https://ibn.idsi.md/sites/default/files/imag_file/47-52_2.pdf.
ZAHARIA-RADULESCU, Adrian-Mihai, et al. 2017. Rpa And The Future Of Workforce. *Proceedings of the INTERNATIONAL MANAGEMENT CONFERENCE, Faculty of Management, Academy of Economic Studies, Bucharest, Romania, vol. 11(1), pages 384-392, November.* [Online] 2017. https://ideas.repec.org/a/rom/mancon/v11y2017i1p384-392.html.
Zhang, Bryan and Blake, Matthew. 2020. Transforming Paradigms: A Global AI in Financial Services Survey. [Online] January 2020. http://www3.weforum.org/docs/WEF_AI_in_Financial_Services_Survey.pdf.