Contemporary Advancements in Financial Technology and Adoption

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ABSTRACT,

Opportunity. Emerging technologies, such as artificial intelligence (AI), the internet of things (IoT), machine learning, and big data, had transformed the way we lived and worked. These technologies had enabled organizations to enhance their efficiency, reduce costs, and possibly gain a competitive advantage. Despite the many benefits of these emerging technologies, many businesses were still struggling to leverage them to achieve their targets. As a result, there was a growing need for research on how these technologies could impact business functions and processes. ***Requirements***. The aim of this research was to highlight the technologies available for financial applications, and their ability to support core financial processes, and financial implementation. ***Prototype***. A qualitative survey was conducted with selected stakeholders to assess the data gathered from the systematic literature review. The main goal of this research was to construct a comprehensive paper that might assist firms in comprehending the types of technologies that were currently available in the field of finance and how they supported these core activities. This resulted in assessing various company states of technology, these key stakeholders could identify the present contemporary technologies, implementation, and impact, leading to judgments on how to optimize their use, by reviewing the status of their businesses and their operations. A literature review was instrumental in identifying the key trends and developments in these technologies, providing a foundation for the research development. The data was then tested through qualitative research. ***Evaluate***. The study helped organizations recognize the benefits/drawbacks of these technologies, recognize the barriers to their implementation, and the strategies for their successful adoption.

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1. INTRODUCTION

To begin with, as the state of technology advances rapidly, such as the doubling of transistor counts in an integrated circuit board represented by Moore's law. This creates an environment that constantly challenges present and future innovations in a short period of time. The doubling of transistors enables ever more powerful processing power from CPUs which allows more intelligent technologies to develop at a similar pace. The need for higher computational power has also driven the invention of more efficient computational codes and triggered the development of new hardware (Raischel et al., 2014). Repeatedly mentioned in (Scardovi, 2017), 'to remain competitive and achieve longevity in the market, financial operations have to keep up with digital transformation. By adoption of innovation, and embracing digital changes, to improve the efficiency and the performance within the organization'. Likewise, everyday businesses face similar challenges. A company which fails to adapt to changing environments with new technology have a risk to fall behind familiar competitors who have not failed to do so. As technology advances, new technologies appear over the horizon to be possibly implemented into various applications. It is the task of a business stakeholder to always conduct for example Exploration, Planning, Action, and Integration for change management (R.J.Bullock, 1985) to stay ahead of competitors in the market.

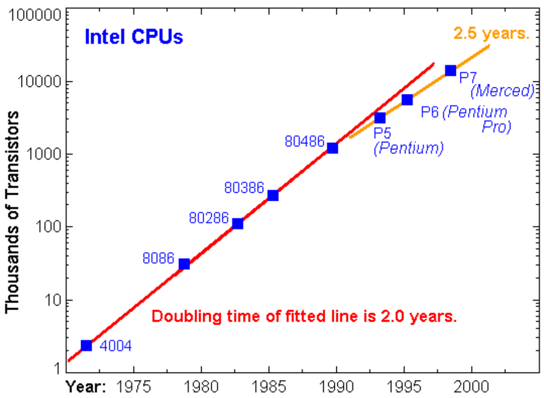

Figure 1. Moore's Law by (Föll, 2019)

The sudden explosion of new technologies could be considered as the 4th industrial revolution where some career paths would cease to exist when evaluating the long run and evidently substituted by contemporary technology due to it being cheaper, efficient, and effective. These new technologies talked about today and mentioned in the abstract are artificial intelligence (AI), the internet of things (IoT), big data, and last but not least, machine learning. Technology can be defined as part of artificial intelligence (AI) when it obtains the ability to demonstrate engagement, creativity, sentience, self-awareness, or consciousness in its abilities (Eluwole & Akande, 2022). It possesses technologies like robotics, machine learning, speech recognition, machine vision, expert systems and natural language procession which can be implemented into various business operations (Dennehy et al., 2023). Whereas advanced computing capability has paved the way for big data analytics. social media, mobile, analytics, cloud, and even application program interface technologies have allowed different data streams to provide value in a highly efficient manner (Mosteanu, 2020).

Contemporary advancements in this study emphasize the use of AI which consists of big data, machine learning, robotics, process automation, and deep learning in finance applications and operations. The history of contemporary technology in finance began with optimization algorithms, credit risk, deep learning, and decision support systems & BI in 1984 – 2009 to uses in customer relationships, deep learning, stock market, banks investments & financial markets, big data, and risk management in 2019 – 2020 (Heinz & Becksndale, 2022). The use cases have increased significantly throughout the financial industry during this period. The benefits AI provides to financial operations are for example data accumulation, structuring, and operating large amounts of financial information in a convenient and understandable manner (Oneshko et al., 2022). Machine learning technology is already widely used in high-frequency trading bots in the FX market by Morgan Stanley to also in clearing house operation efficiency improvements at Deutsche Boerse Group London (Cao & Zhai, 2022).

The development of Fintech 1.0, Fintech 2.0, to Fintech 3.0 is shown by (Heinz & Becksndale, 2022) in Figure 2 with the 'Area of Focus' of this research paper. Fintech hype has grown massively during the past last few years as a significant portion of publications (>85%) were published in the last decade. The topics range from financial text mining to financial sentiment analysis in the areas of big data, artificial intelligence, and machine learning (Nguyen et al., 2023).

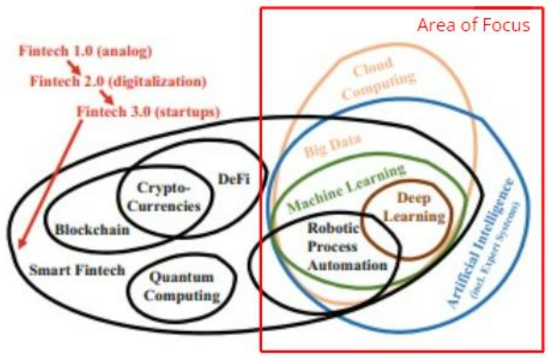

Figure 2. An overview of fintech and AI technologies by (Heinz & Becksndale, 2022)

Given the critical importance of change transition and management in every company with financial operations, it is vital to focus on the application of contemporary technologies in financial business processes. As pointed out by (Eisenhardt & Martin, 2000), companies should understand that dynamic capabilities are not limited to the response to changes in the external market environment, but should also include the ability of enterprises to actively innovate to change the market, that is, dynamic capabilities refer to an organizational and strategic practice by which firms realize new resource allocations as markets collide, fragment, evolve, and die (Ji, 2022).

The pace of technology growth, as exemplified by Moore's Law (depicted in Figure 1), has increased exponentially. Advances in AI, machine learning, robotics, and other technologies have accelerated the rate of change tenfold (Kuiken, 2022). Yet, companies often lag in adopting these emerging technologies (Wright et al., 2004), and are unlikely to keep pace and compete in the new digital reality (Kraus et al., 2022). As the saying goes 'If it isn't broken, don't fix it', this is where businesses start to fall behind, become irrelevant, and miss opportunities (Alton, 2016). Therefore, the purpose and importance of this study are to provide business managers with a comprehensive understanding of the current technological domain and answer the main research question mentioned in Section 1.2 (i). On top of that, it emphasizes the need to bridge the gap between technology and core financial processes for businesses. It will aid businesses to be informed, understand the potential of technology, and evaluate the strengths and weaknesses of these technologies in the current status quo of technology in the financial domain with example(s). Through this study, companies can understand, utilize, and realize where they stand from a technological standpoint. Interest and value are created in academia by reviewing and plotting the current state of technology, as shown in Figure 6, exponential growth has only occurred recently. Nevertheless, a minimal amount of literature has been conducted with a similar research direction to this research as reflected in Figure 7.

1.1 Research Objective

The research objective of this paper is to provide an overview of current contemporary technologies in the finance domain to selected core processes, additionally, to briefly evaluate the state of technology of the companies who are a part of this study. This also includes developing a tool to evaluate what AI applications a company is using and spread awareness of what they could use in the future to improve on their core financial processes.

Contemporary technologies selected are shown in the area of focus in Figure 2. These technologies will then be researched and evaluated to what financial core processes they can be integrated into.

1.2 Research Questions

To fulfil the research objective mentioned above, we have to ask the following research questions:

(i) What kind of emerging digital informational technologies related to financial technology are available to be utilized currently for core financial processes?

(ii) What is the current level of technology among companies, and to what extent are they demonstrating eagerness to adopt AI in their operations? This also includes clarity of information provided.

1.3 Research Relevance

To begin with, in 2021, 881 Scopus documents were found based on the topic surrounding artificial intelligence in banking, financial services, and insurance, while only 651 publications in 2019 and 90 publications in 2014 (Heinz & Becksndale, 2022). This shows a significant increase and interest in research on the topic as the years progress.

Furthermore, funding for innovation in the field has grown comparably. In the general domain of machine learning applications, 31.7 billion U.S. dollars have been cumulatively invested, and machine learning platforms securing another 15.3 billion U.S. dollars of cumulative funding till June 2019 (Nguyen et al., 2023).

This research is relevant because it will provide practical and theoretical evidence on the main research questions and will help companies understand the current developments of contemporary technologies in the field of finance or if they are lacking behind with these implementations.

1.4 Acronyms

Acronyms would be a part of this research to increase the readability and compactness of the literature. Here are the acronyms used in this research paper:

ML	Machine Learning
RPA	Robotic Process Automation
CC	Cloud Computing
AI	Artificial Intelligence
BI	Business Intelligence
DL	Deep Learning
CA	Cognitive Automation
IPA	Intelligent Process Automation
BD	Big Data
NN	Neural Networks
ERP	Enterprise Resource Planning
AWS	Amazon Web Services
FX	Foreign Currency Exchange
SLR	Systematic Literature Review

2. LITERATURE REVIEW

In this section, it is important to create a critical analysis to address the current state of knowledge in the field, and to explain important concepts related to core financial processes and financial technology. A theoretical background is given to fintech, opportunities with fintech applications, and challenges with these applications.

2.1 Core Financial Processes

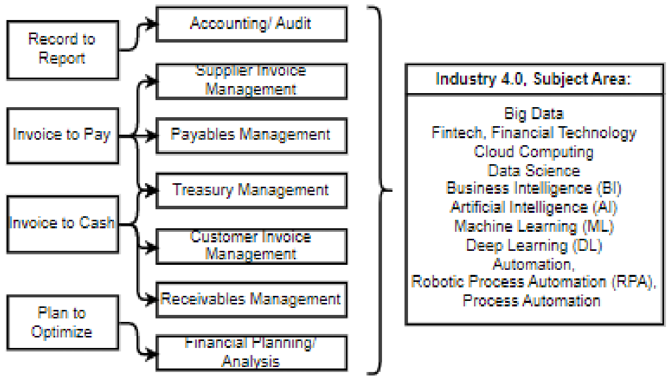

Figure 3. Process of Finance (Sarferaz, 2022) + (Heinz & Becksndale, 2022)

The core financial processes support every value chain and keep track of the financial health of the company. Which results to finance playing a vital role in everyday company operations. As shown in the diagram previously, the four main core processes are Record to Report, Invoice to Pay, Invoice to Cash, and Plan to Optimize, nonetheless, these core processes have various subprocesses. Firstly, Record to Report, the subprocesses focus on accounting and financial closer (create a financial record, perform financial accounting, perform financial closing, perform financial reporting). Secondly, in Invoice to Pay, there is supplier invoice management, payables management (manage financial settlement, process accounts payable, manage payables financing, process payments), and treasury management (manage payments and banks communications, manage cash and working capital, secure financial risk, analyze and implement procedures). Thirdly, Invoice to Cash consists of customer invoice management (perform pre-invoicing of billing content, manage invoices), receivables management (manage settlements and customer credit risk, process accounts receivables, process disputes, manage receivable financing and process collections), and also part of treasury management. Last but not least, Plan to Optimize is mainly about financial planning and analysis (planning, budgeting, forecasting, management account, financial analysis) (Sarferaz, 2022; Delta CPE LLC, 2014). There are various systematic subprocesses incorporated into these core processes.

2.2 Digital Technologies

Financial technology (Fintech) has grown today into a topic that represents terms such as innovation, disruption, revolution, big data analytics, and blockchain in the domain of finance (Nguyen et al., 2023).

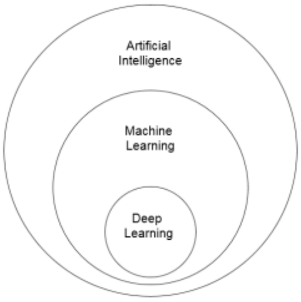

Figure 4. AI, ML, DL (Gupta & Tham, 2019)

Nevertheless, the popularity of fintech technology has only grown. One example is the utilization of AI and ML solutions as a major selling point for digital finance services in an established company called Plaid. Their main advantages over traditional credit scoring and underwriting processes are that they are cost-efficient and time-efficient and, at the same time, less restrictive and more transparent (Nguyen et al., 2023). 31% of companies surveyed registered a <10% decrease in the cost of strategy and corporate finance operation from AI adoption similarly, 41% registered an increase in revenue by ≤5% in 2021 shown in Appendix 3 (Maslej et al., 2023).

In the financial context, the field of big data refers to the analysis of vast amounts of data with the goal of making better-informed investment decisions, improving corporate operations, and enhancing decision-making on the buy and supply sides of the transactions (Walker et al., 2022).

When talking about cloud computing, it refers to software and computing services that run on a remote computer and are available over the internet using a web browser or applications on a computing device. An example is Microsoft Azure or OneDrive, Amazon AWS or Cloud Drive, Google Drive, and many more (Gupta & Tham, 2019). This enables large amounts of data to be always available digitally to be utilized through, for example, big data and machine learning to create vital insight.

When reviewing about automation in this study, it is often referring to the process of robotic process automation (RPA). RPA is considered an innovative approach to unlocking automation potential from a managerial standpoint, while from a technical perspective, its implementation involves software products and has implications for artificial intelligence (AI) and machine learning (ML) in the field. (Czarnecki & Fettke, 2021).

The introduction of machine learning enabled computers to learn real-world knowledge by identifying patterns from the data, and self-correction from this learning process to enable decision-making (Gupta & Tham, 2019). However, machine learning algorithms also suffered from a trade-off as their performance was dependent on how data was presented to them. Deep learning algorithms solved this problem by extracting information by themselves. Deep learning is a particular type of machine learning that makes computer learning more powerful, flexible, and abstract (Gupta & Tham, 2019) as displayed in Figure 4.

The area of computer science that concentrates on enhancing computer intelligence to replicate intelligent human behaviour is known as artificial intelligence (AI). AI serves as a platform to enable computers to acquire human-like thinking abilities, including learning, reasoning, and self-correction (Gupta & Tham, 2019).

Applying various financial technologies like ML, CC, DL, RPA and AI solutions previously stated into core financial processes, would provide meaningful value from the cost/revenue perspective. As these applications remain an important focal point when it comes to digital payments, forecasting, engagement, and data security (Nguyen et al., 2023). Such an example of this is Shaw Industries Group. Shaw Industries Group adopted an AI-powered analytics tool for continuous transaction monitoring. This tool helped identify duplicate vendors, improving their accounts payable and procurement processes. The shift from manual to automated processes led to significant savings, recovering the system's cost within just four months (Cangemi & Taylor, 2018).

One dark side holds in all of this, such as, 'AI degrades human ability', 'AI decreases jobs availability', 'AI lacks accountability' and 'AI reinforces bias' and often connected with overleveraging AI and big data analytics with social dominance, organization inertia and organizational information processing theories (Nguyen et al., 2023). One of the most prominent challenges is enabling new systems to work with current legacy systems based on a survey done by (Capgemini, 2018). Other challenges emphasized are also the gap between technological know-how and the current state of technology. One client of Capgemini mentioned, "If intelligent automation changes the nature of finance work, finance workers will need to be equipped with the necessary skills to adapt accordingly.". In the long run, on top of the minds of multiple executives are whether these applications generate tangible returns on investment and how this will impact on the bottom line. From the perspective of cost saving due to these contemporary applications, but also value creation.

3. METHODOLOGY

3.1 Research Design

The research aims to create a tool for companies to utilize and understand their state of technology and provide awareness of the various technologies available today in the domain of finance and its core processes. The research methodology chosen for this study is a qualitative approach instead of a quantitative approach. Since the tool would be designed for company evaluation, the quantitative result would be insignificant, therefore, a focus on qualitative answers is the focus of this research.

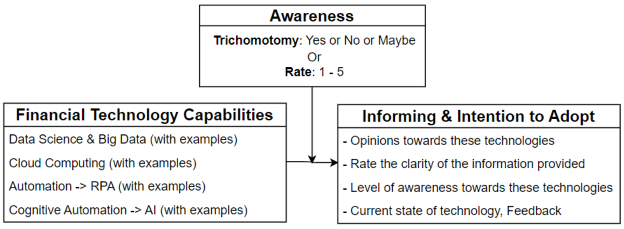

Figure 5. Conceptual Framework based on (Quaddus & Hofmeyer, 2007)

The research is divided into two separate parts. The primary research that is being undertaken consists of existing data extracted from the systematic literature review and that is based on already existing research papers currently available. The information gathered from the literature review will be analyzed and elaborated under results to aid the research. The secondary part of the research consists of an online questionnaire that is being used to assess the clarity of information provided, opinions, adoption, current state of technology to collect feedback based on the technologies through the literature review (shown in Figure 5).

The ‘Financial Technology Capabilities’ are extracted from the theoretical framework where they are analyzed, defined, and supported by example(s) and applications. This approach provides the opportunity for a more precise description of the specific technological capability. It also aids research participants in better identifying the information presented to them. These elements serve as an informational segment in the secondary part of the research, drawing from the primary research grounded in the literature review and defined at the theoretical framework level.

Questions and examples in the online questionnaire should provide a sufficient overview of the state of technology the company currently utilizes in their finance operations and provides the ability to be acquainted with current contemporary technologies in the financial domain.

Ultimately, the primary section of the research allows the description and analysis of ‘Informing & Intention to Adopt’. The level of clarity of the information provided and adoption are both dependent variables of this research. The level of ‘Awareness’ of these technologies is an independent variable. This is important as it aids the primary part of the research in realizing the gap between technology and core processes as discussed earlier.

The research design is broken down into the following steps to build on Figure 3.

1. Understanding the *opportunities* new financial contemporary technologies provide.
2. To evaluate the inputs and *requirements* needed for the technology to function in their financial settings in a company.
3. Start *prototyping* on an online questionnaire to receive the results to find out on factors shown in Figure 5.
4. *Evaluate* the result created by the tool, help companies realize the strength/weakness, communicate the technologies available, and general strategies for implementation.

Furthermore, the goal of this review is to also gather what kinds of contemporary technology are available that utilize ML, AI, big data, and data science technologies in finance, as well as the benefits and challenges of these technologies. A literature review would need to be conducted through already existing literature available. For qualitative research, a qualitative research methodology is required to systematically gather data from existing literature and analyze it for a concrete end result.

Based on (Webster & Watson, 2002), there are only two types of qualitative literature review methods. The first method is to extract and construct a body of knowledge on the topic through a thorough literature review and a conceptual model, and the second method is based on tackling an emerging issue that would benefit from exposure to potential theoretical foundations. The first method is applicable in this research context which is a systematic literature review, as we are not conducting research on a societal phenomenon based on the research direction. Since the literature review needs to identify what is known in the current literature available in this domain, it is important to execute a literature review in a systematic manner = systematic literature review (SLR). The results from the SLR will be used as a foundation to answer the research questions combined with the survey conducted.

Scopus is a major academic database with various subject areas. The criteria selection plays an important role in gathering relevant data. The first stage of the data-gathering process is to focus on relevant literature. A complex search term was defined to create search results on Scopus. This search input is created to focus on the subjects related to the topic being researched: ‘TITLE-ABS-KEY (accounting, OR "Risk Management" , OR forecasting, OR "Financial Management" , OR "Management Accounting" , OR "Audit" , OR "Payables Management" , OR "Invoice Management" , OR "Planning" , OR "Reporting" , OR "Management" , OR "Risk" , OR "Payment" , OR "Budgeting" , OR "Investment" , OR "Invoicing" , OR "Analysis" , OR "Treasury" , AND finance, AND "…" , AND NOT "Banking") AND (LIMIT-TO (SUBJAREA , "DECI") OR LIMIT-TO (SUBJAREA , "BUSI") OR LIMIT-TO (SUBJAREA , "ECON") OR LIMIT-TO (SUBJAREA , "SOCI") OR LIMIT-TO (SUBJAREA , "ARTS") OR LIMIT-TO (SUBJAREA , "PSYC")) AND (LIMIT-TO (PUBYEAR , 2023) OR LIMIT-TO (PUBYEAR , 2022) OR LIMIT-TO (PUBYEAR , 2021) OR LIMIT-TO (PUBYEAR , 2020) OR LIMIT-TO (PUBYEAR , 2019) OR LIMIT-TO (PUBYEAR , 2018)) AND (LIMIT-TO (LANGUAGE , "English")). English would be the only written language included in the search. Limited to certain subject areas to prevent diving too in-depth into technicalities as that is not the direction of the research, similarly, excluding subject areas of banking, trading, financial institutions, blockchain, and the stock market due to the focus on only core organizational financial processes utilizing data, AI, or/and cloud computing. This input found a total of 20,696 articles without the inclusion of fintech technologies.

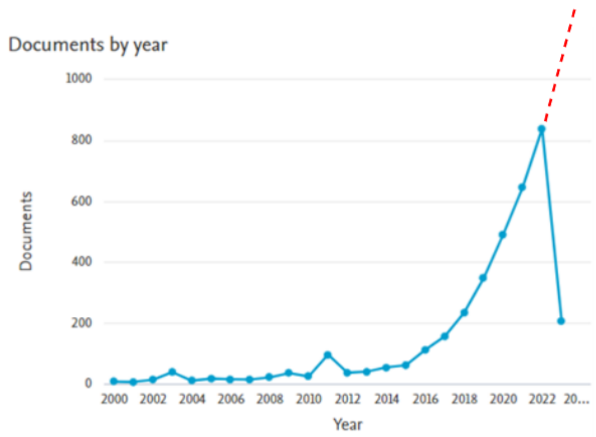

Figure 6. Scopus Search Results

The outcome of the search input above resulted in a current total of 2734 document results when analyzing separately fintech articles in the field of finance. The decline for 2023 is apparent as the year has yet to fully conclude, almost 200 documents have been published this year to date.

Due to the nature of this study to display contemporary technologies, it is important to focus on data from 2018 to date. As shown in Appendix. 5 by (Heinz & Becksndale, 2022), major new technological changes have only appeared during this period, such as banking, risk management, stock market, and deep learning. Also, focusing on the core financial processes selected. This meant inclusion and exclusion criteria can be added to further filter the result. Inclusion criteria are

'Publications since 2018', 'Core financial processes 2.1 puts a focus on processes and subprocesses which can be used to additionally filter Scopus search results. Exclusion criteria have been already applied. However, additional inclusion criteria can be applied based on the various technologies available mentioned by (Heinz & Becksndale, 2022). This means approaching the search by applying all the financial core processes as input shown previously, consequently, adding each fintech technology keyword to the end of the input separately. This means under 'AND "…"', this would be the input of the various technologies such as 'Artificial Intelligence', 'Big Data', and 'Cloud Computing'.

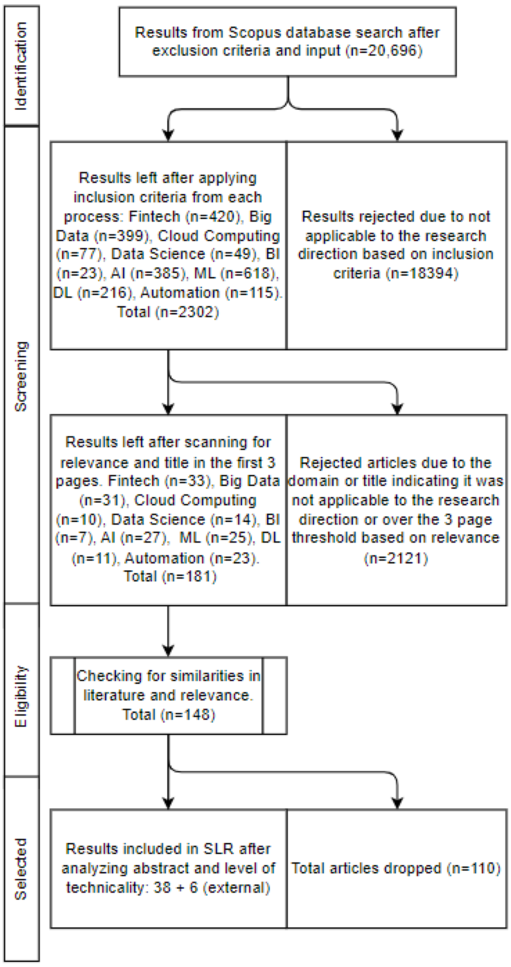

Figure 7. Flow Chart of Search

A total of 6 external research articles have been chosen as an addition to the systematic literature review due to their high amount of relevance to the topic and research direction. These external articles were the result of citations from the current scope of the literature review and were executed for further readings into the topic.

3.2 Data Sample

The target for the data sample would be 5-6 company representatives who are knowledgeable about their financial operations. The interviewees should be controllers, managers, accountants, directors or related to the field of finance. The size of the organization represented is not relevant as financial operations are highly systematic despite the company size.

4. SYSTEMATIC LITERATURE REVIEW

This section of the results focuses on an overview of the current domain and technologies related to the research direction of interest. Each topic below doesn't act as a single unrelated topic but as an addition to highlighting the various levels, areas and factors that make what contemporary technology what is today in the financial domain in company core processes. Each topic is a piece of a larger picture to answer the research question, starting with the foundation with data science and finishing with advanced AI.

As explained under Section 3.1 Research Design, to support the findings of the literature review, example(s) will be presented that utilize contemporary technologies for core financial activities. In the same manner, to support answering the research question, technological applications currently available for internal integration will be presented. These solutions will enable adoption and a foundation for the technologies mentioned in the research previously. As a result, the structure begins with a summarization into the main technology followed by sub-technologies and concluded with utilization in core processes, strengths & weaknesses, and finally, application & example(s). At the end, the results are concluded with Section 5. Analysis to highlight the main points of the literature review.

4.1 Data Science

Data science is an interdisciplinary field that uses the concepts of statistics, mathematics, computer science, and domain expertise to extract meaningful insights from data that can generate some business value (Gupta & Tham, 2019). Data science plays a vital role in automating anything in the financial domain. Companies need to first digitalize and decipher unstructured data gathered and convert to structured data for any level of automation to happen, which is also a requirement for AI (Gotthardt et al., 2019). On top of this, accounting and finance data is a subset of enterprise data, which includes a wide range of data sets for analysis and even forecasting (Cockcroft & Russell, 2018).

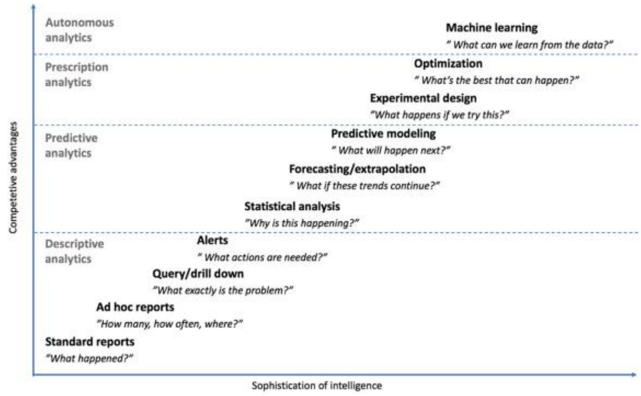

Figure 8. Concepts of exploratory data analysis (Nielsen, 2021)

A company's level of sophistication in these technologies can be viewed between descriptive analytics to autonomous analytics. Nevertheless, companies are on different levels of sophistication and should strive to move up towards autonomous analytics and not remain at the level of descriptive analytics (Nielsen, 2021). Since autonomous analytics uses AI or ML to create and improve models and learn from data with less human involvement.

When it comes to types of data there are structured, semi-structured and unstructured data. Structured data is data that can be stored in relational databases (such as SQL tables) with rows and columns, common examples are ERP systems. When it comes to semi-structured data, data is not stored in relational databases but has some organizational properties for analysis. Some examples of these types of data are emails, tweets, and webpage data. Lastly, unstructured data is all other data that does not possess organizational structure, this can be for example audio and images.

On the contrary, AI, machine learning, and deep learning do not comprise a branch of data science. Rather, data science uses them to solve problems. Big data also is not a branch of data science. Data science can be used to solve problems using various types and sizes of datasets (Gupta & Tham, 2019).

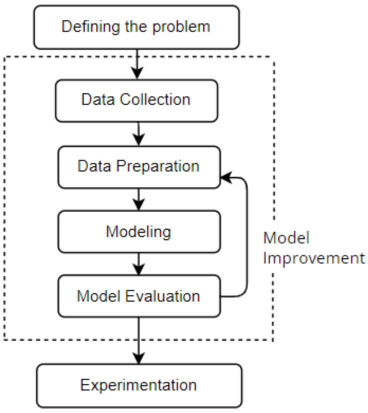

Figure 9. Data Science Project Lifecycle (Gupta & Tham, 2019)

To enable big data in financial operations, it needs to begin with data science. As shown in Figure 9 by (Gupta & Tham, 2019), defining the problem is the first step, such as, "How to measure the impact of a machine learning model in the real world?". The second step is to evaluate whether the source of data is primary or secondary with structured, semi-structured, or unstructured data. After gathering data from various sources, the next step is to process and transform this data into a usable form for analysis while performing data quality checks. The next step is to build the right model to answer the problem. Model evaluation for error analysis (irreducible errors, bias, and variance) After evaluating the errors, the next step is to improve the performance of the model further to create a final model. Experiments should be designed in such campaigns in order to test out different hypotheses and quantify the actual impact of the models and know whether it meets the desired expectations. A more in-depth into the steps can be seen in Appendix 6.

4.1.1 Big Data

Big data means *large* data, whereas *large* depends on the context and computational processing power (Gupta & Tham, 2019). With the progression of information technologies, a diverse array of data has become accessible, positioning data as one of the most precious resources in managing automated systems (Hasan;Popp;& Olah, 2020). As the economy dives deeper into the digital economy, data volumes increase exponentially. This data is leveraged over cloud-based storage. CFOs are tasked with getting value from this stored data (Karlgaard, 2011). Only by utilizing these services, can businesses have the capability to acquire, clean, store, and share data throughout the company with resources to develop, test, and implement big data (Gupta & Tham, 2019). With big data combined with processing power, sophisticated algorithms and advanced statistical methods bring new opportunities. As a result, big data analytics can especially provide a competitive advantage in the accounting and finance industry in decision-making, customer insights, and fraud detection/prevention (Cockcroft & Russell, 2018).

For data to be considered big data, 4 features are required. The features are volume (large data scale), variety (different data formats), velocity (real-time data streaming), and veracity (data uncertainty). These factors have various challenges in the domain of management, analytics, finance, and different applications (Sun et al., 2019; Hasan et al., 2020; Gupta & Tham, 2019).

The main technologies in the field of big data are 1) NoSQL database (any non-relational database) which aids in denoting the number of approaches in implementing database storages, 2) MapReduce technology is a distributed computing model used for parallel computation in server setups, 3) Hadoop technology is a set of utilities, libraries, and frameworks for the development and execution of distributed programs running on clusters of hundreds and thousands of nodes, 4) R – a programming language for statistical data processing and graphics, 5) Business intelligence (BI) technology — designation of computer methods and tools for data visualization and insights (Bataev, 2018).

At the end of the day, data quality should not be disregarded in the big data domain where accuracy, completeness, and timeliness are of significant importance (Cockcroft & Russell, 2018).

4.1.2 Core Processes for Big Data

As shown in Appendix 5, big data is mentioned in record-to-report, invoice-to-cash, invoice-to-pay, and plan-to-optimize processes from Figure 3.

Opportunities exist within core financial processes with big data, particularly in the realm of treasury management, with a key focus on fraud prevention and detection. As illustrated in Figure 3 on Treasury Management, (Ferguson & Seow, 2011) reports an example of utilizing behavioral analytics. Where big historical data were used to predict how behavioral antecedents might lead to fraud. Likewise, (Chivers et al., 2010) reported a similar approach to detecting insider attacks within an organization.

However, big data is often the foundation for the other technologies part of this study. This means it caters indirectly to the value provided by RPA and AI in other core financial processes shown in Figure 3. Technological contributions to these core processes will be explained further in the next few sections. RPA itself doesn't need big data to function as it is a rule-based system, nevertheless, RPA can generate big amounts of data. On the other hand, to achieve enhanced IPA models, big data is needed for training.

4.1.3 Strengths

Data by itself bring little value, however, paired with other technologies, big data can create an impact on core processes. Likewise, in the context of a financial professional, their ability to analyze, predict and control economic activity data is limited. Therefore, it is necessary to establish financial data management system in the big data and cloud computing environment (Chang & Wang, 2022).

The relationship between big data and cloud computing is strong and complex, but cloud computing provides major solutions for big data while accelerating the benefits of digital data management. Big data can be utilized, repurposed, transferred, and altered swiftly and inexpensively, yielding positive outcomes for senior management (Ionescu & Andronie, 2021).

4.1.4 Weaknesses

A common problem is that companies lack computing power available internally, this could be factors like processing power, memory, production environment, and storage to effectively study large data sets data science can provide. This places data science operations with an electronic barrier. Without these factors, companies would be held back from entering Industry 4.0 (Gupta & Tham, 2019). Nevertheless, this problem can be solved and explained under 4.1.3 Cloud Computing.

Other common problems which must not be disregarded are different kinds of biases throughout the data science process when integrating contemporary technologies such as RPA and ML model development (Jauhiainen & Lehner, 2022). The volume of data a company handles often aligns with its size, as larger operations inherently generate more data. Consequently, smaller companies may struggle to leverage big data effectively, potentially hindering their ability to meet the demands of contemporary financial technology (Hasan;Popp;& Olah, 2020). Additionally, a problem with large data sets is that financial personnel need to be efficient and accurate in data analysis for impactful actions (Chang & Wang, 2022).

1. Data Collection (historical data, internal & external, big data) →	Historical Bias, Information Availability Bias
2. Data Preparation (cleaning, parsing, organizing) →	Representation Bias, Aggregation Bias, Information Availability Bias
3. Model Development (ML, AI, DL) →	Measurement Bias, Aggregation Bias, Information Availability Bias
4. Model Evaluation (performance analysis on testing data) →	Measurement Bias, Aggregation Bias, Evaluation Bias, Information Availability Bias
5. Model Post-processing (testing on validation data) →	Evaluation Bias, Information Availability Bias
6. Model Deployment	Deployment Bias, Information Availability Bias

Table 1. Types of bias and where they can occur (Jauhiainen & Lehner, 2022)

4.1.5 Applications & Example for Big Data

Common commercial applications for big data can be found in Appendix 6. Big Data Technology Stack. These applications form a backbone for any data science project. Apache Hadoop provides a collection of open-source software libraries that can efficiently store and process big datasets (Gupta & Tham, 2019). Another big data application is Google BigQuery, designed for handling big data through Google Cloud services.

An example of big data is a case study into Huawei technologies and the utilization of big data solutions in their financial operations (Yang, 2020). Huawei utilized big data as a foundation for its financial reimbursement system. Before the new system, the reimbursement had to go through 3 separate employees to be processed. They needed to analyze large amounts of unstructured data along with structured data to make accurate financial decisions. With the new system, cost, simplification, and efficiency have been achieved by utilizing big data technologies to process the data and facilitate decision-making which reduced the workload of employees in the simplified reimbursement process.

4.2 Cloud Computing

The cloud gave a new meaning to data science by removing the electronic barrier mentioned in Section 4.1.4. The barrier held back today is the big data revolution that drives machine learning with unlimited scalability without the need of hiring staff or investing in new equipment (Gupta & Tham, 2019). The application and integration of cloud computing together with big data can eliminate information silos through information technology support such as master data services, data mining, and RPA. This aids the process of speeding up the flow of enterprise information, analysing environmental changes in real time, adjusting enterprise strategic planning, and optimising business and financial processes to increase enterprise value (Ji, 2022).

Hardware requirements are vital for any implementation of contemporary advancements into core processes. This is one reason why automation, ML, or even AI are not prominently applied. In addition, data volumes and complexity of tasks. While computational power continuously increases as shown in Figure 1, parallelization has had an even bigger impact on performance increases. This is made possible by only leveraging cloud architecture and computing (Esswein et al., 2020).

Cloud services provide various types of services: 1. Software as a Service (SaaS), 2. Platform as a Service (PaaS), and 3. Infrastructure as a Service (IaaS) (Huang, 2022). When it comes to SaaS cloud providers use web browsers as points of access. This also means they are responsible for the deployment, management, and maintenance of the applications. Some examples of this are Dropbox and Salesforce through a subscription model. While PaaS provides platforms that can be utilized for the development and deployment of applications, such as Google App Engine. While IaaS focuses on a basic infrastructure foundation for companies to scale computing resources on-demand, examples are Exoscale and Softlayer (Gupta & Tham, 2019).

There are also other options than public/external cloud services, such as private and hybrid. The private cloud is often mentioned in the literature as the organization's internal cloud operations. This is often the chosen method for data protection, and not sharing computing resources with other organizations in a public cloud. However, hybrid options are also popular due to non-sensitive data to public cloud domains, while freeing internal resources from the private cloud. Public cloud services still provide unmatched state-of-the-art performance and cost throughout its entire customer base. While many public cloud providers provide operational cloud centers globally with sophisticated security measures often better than private cloud operations (Gupta & Tham, 2019; Ionescu & Andronie, 2021).

4.2.1 Core Processes for Cloud Computing

Similarly, to big data, cloud computing contributes indirectly to the next few contemporary technologies for the core financial processes mentioned in Figure 3. Such as providing computational power, data source, and on-demand natural language processing AI models through cloud services to be utilized in invoice recognition and data extraction into automated tasks like RPA (Gotthardt et al., 2019).

4.2.2 Strengths

As mentioned by (Gupta & Tham, 2019; Huang, 2022) and previously, ease of increasing computing capacity, rapid two-way scalability, the latest technology available, reduced time to market with the help of advance computing resources, disaster recovery, no maintenance required for public cloud, and sophisticated security measures are often implemented.

4.2.3 Weaknesses

There are some drawbacks with cloud computing in general, this includes: connectivity to the internet is needed to utilize cloud capabilities, high volumes of traffic for cloud providers might lead to slower loading times, software incompatibility might become a problem, cybersecurity is an active threat, and cloud provider dependency which makes shifting providers difficult (Gupta & Tham, 2019).

4.2.4 Applications & Example

Main external cloud providers are for example Microsoft Azure, Google Cloud, Cloudera, and AWS. These cloud providers enable the following: 1) Cloudera (ML, Big Data, Cloud Computing): Instant ML workspace implementation. Democratized access to governed data. Open tools available. Model monitoring, catalogue, lineage. Computing power through the cloud, 2) Microsoft Azure (Cloud Computing, Big Data, NLP, ML, AI): Rapid integration of on-demand cloud services with pay when use model, other similar services are AWS and Google Cloud.

An example is provided by Deloitte. Customer X wanted real-time data for impactful insights. Speed and accuracy were of great importance. Through cloud computing, they were able to utilize continuous accounting, real-time reporting, and most importantly, helped the organization with robotic enhancements such as RPA. This meant leveraging data from various online organizational databases through cloud services (Daas et al., 2018).

4.3 Automation

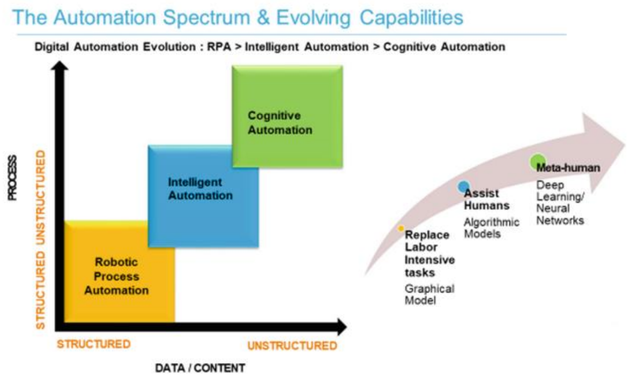

Figure 10. Evolution of Automation & Capabilities by (Suri et al., 2019)

Under the context of automation, the level of automation ranges from the rising popularity of robotic process automation (RPA) to intelligent automation, and finally cognitive automation. RPA focuses on both human or system-triggered activities with rules and high-volume processes in areas ranging from front, middle and back office. RPA utilizes structured data with multiple systems at the enterprise level of a corporation. One level higher of automation from RPA is intelligent automation or also called intelligent process automation (IPA). This automation process is supported by basic analytics and decision support from financial employees with optical character recognition, intelligent document processing, and processing structured and unstructured data. IPA examples are simple web chatbot applications or simple AI integration into RPA processes. Automation complexity increases significantly when cognitive automation is implemented, it focuses on higher complexity processes and decisions than the previous automation processes mentioned. Cognitive automation is supported by predictive/ prescriptive analytics. Algorithmic automation is often spoken in the setting of machine learning and basic reasoning with unstructured to big data. Possible Internet of things integration with examples such as natural language processing to advance chatbots. Also, it utilizes cognitive technology of emulating human capability including empathy with full end-to-end autonomy, hypothesizing, and reasoning. AI is often supported by technologies such as deep learning and deep neural networks. It can recognize speeches and also generate. AI is represented as fully capable virtual agents with omnichannel integration in augmented and virtual reality environments (Polak et al., 2019).

Rule-based RPA is the simplest form of machine intelligence, which refers to a system that applies human-made rules to store, sort and manipulate data. To work, rule-based systems need a set of facts or sources of data and a set of rules (“IF x THEN y” instructions) to choose an action (Mixson, 2021).

Around 30% to 50% of all RPA initiatives fail today because of misapplication, yet RPA is one of the only technologies capable of reducing the costs of existing manual operations by 25% to 40% or more without changing existing systems. The number one issue is not considering RPA as business-led, as opposed to IT-led (Ravn et al., 2016).

Therefore, initiating new technologies into current processes requires new skills and competencies, not only for RPA but for other contemporary advancements in the field of finance. Traditional accountants need to build on corresponding skills and competencies for the successful integration of RPA into managerial and financial accounting processes (Kokina & Blanchette, 2019). Not every accountant needs to be a technical expert in these technologies but a solid foundation. For example, management accounting roles divide into categories of Guardian, Service Expert, Pathfinder, and Business Partner at BASF. BASF utilizes wide RPA technology, which then accountants are then assigned to designated roles supporting RPA in their core financial processes. Where new accounting positions like Pathfinder focus on sourcing new trends and technologies into accounting processes with responsibilities such as monitoring and controlling an automated end-to-end process. To bridge the gap between business and technology.

Ultimately, RPA can create value in multiple ways. It can be implemented into core processes as a support function (minor routine tasks), substitution (RPA system takes over complete tasks that were previously performed by employees), or complete innovation (The RPA system enables completely new workflows, that can be, for example, part of new business models) (Auth et al., 2019).

A key foundation for preventing weaknesses is shown in 4.3.3. is continuous risk management assessment of automation by (Jauhiainen & Lehner, 2022) is 1. Identify, 2. Assess, 3. Control, 4. Monitor & Report, and 5. Repeat.

The applied methodology for RPA implementation can be seen in Appendix 7.

4.3.1 Core Processes for Automation

Once big data and cloud computation has been enabled, then only RPA can be utilized for added value in Figure 3 core processes.

As the level of automation fluctuates, it all comes down to adding pieces to the puzzle for higher automation processes, each stage requires a separate stage of factors. Based on (Polak et al., 2019; Czarnecki & Fettke, 2021), high automation potential in financial core processes are financial operations (operational reconciliation, procurement), accounting close and consolidation (financial reconciliation, pre-close execution, consolidations, intra-company/transfer pricing), external financing reporting (financial statements preparation, regulatory reporting production), business performance management (management reporting), Planning & Forecasting (budget and forecast preparation), risk and compliance management (risk reporting, compliance and controls reporting), treasury & investments (bank account reconciliation), speciality services (internal audits execution), and financial administration (master data maintenance). Medium automation potential covers a larger range of financial processes such as control monitoring, FX exposure management, fixed assets accounting to KPI monitoring. Low automation potential is often defining KPIs, risk scoring evaluation, and investment modelling. These processes were selected by (Polak et al., 2019) based on automation process criteria (processes with high-cycle times, processes with low error rates, digitized data, standardized/structured data, fluctuations in demand/backlogs, processes with high FTEs).

In line with the information mentioned previously and in Figure 3, high automation potential is record-to-report, plan-to-optimize financials, manage treasury, invoice-to-cash, and invoice-to-pay core processes. Similar execution can be implemented into these core processes shown in Figure 3 based on the example by (Gotthardt et al., 2019). Also, as shown in Appendix 5, RPA is the most common contemporary technology to be implemented into various core financial processes.

4.3.2 Strengths

In relation to RPA, some strengths include people performance (increase productivity, retention, resources focus on high-value activities), effectiveness (codifying human knowledge into digital labour), quality (better mean time to respond, minimization of error), compliance (automation drives adherence to standards), proactive risk management (human error, forward-looking, staff attrition), and scalability (superhuman capabilities, multi-level integration) (Capgemini Consulting, 2016).

Based on a survey by (Ionescu & Andronie, 2021), 61% of individuals registered that 'Automation helps improve the customer experience', 59% that 'Automation leads to higher productivity', and 50% 'Automation will enhance knowledge sharing within their organization'.

RPA can be used in financial processes which require repetitive tasks carried out 50-60 times a day; working with process list and file storage; period reporting, data entry and data analysis; mass email generation, archiving and extracting; conversion of data format and graphics; ERP and other back office transactions (Capgemini Consulting, 2016). However, RPA is sometimes misconceived as technology soon to be replaced by AI, but that is not the case. Both technologies do not replace one another but are often used separately or together to the value of financial operations (Gotthardt et al., 2019). Since AI capabilities combined with RPA provide true cognitive capabilities such as comprehension and judgement of difficult events with a deep human-like perspective (Bhattacharyya et al., 2023).

4.3.3 Weaknesses

Some weaknesses in RPA are data protection and cyber security by 34% of companies already using RPA, too many processes by 25% of companies using RPA, and too expensive to integrate the various technologies by 16% already using RPA based on a report by (Capgemini Consulting, 2016) with a participation amount of 150+ company executives ranging from Europe to North America, and 43% with over 1 billion € in revenue.

Risks shown in Table 2 need to be considered below integration of RPA solutions into organizational internal systems. Data leakage, breaches of privacy, and threats are cyber risks tied to the implementation and usage of RPA technology. Therefore, hacking into these financial systems is more effective and harder to prevent. Four different factors that are tied to these risks are abuse of privileged access, disclosure of sensitive data, security vulnerabilities, and denial of service attacks. Factors like these are then exploited to access sensitive data processed by RPA systems. Other risks also involved based on Table 2 are key stakeholders not grasping the concept. As the level of knowledge in RPA fluctuates among staff, consequently, the risk of misuse would grow and faults not due to system failure but from upper management (Gotthardt et al., 2019).

Additional and similar challenges highlighted by (Shidaganti et al., 2023) are the following: 1) *fragmented process*. Adopting intelligent automated systems sounds easier said than done when companies have hundreds of diverse processes. 2) *Lack of IT readiness*. Since substantial IT resources are needed for intelligent automation due to the needed computational power, while standard RPA systems do not. 3) *Employee resistance to change*. Often thinking only of the technological element is a mistake, the human element is equally important. Evaluation of changes to roles, procedures, activities, and styles of working must not be disregarded. As human adaption is important, without this, the innovation would be shortsighted and high chance of failure. 4) *Lack of Clear Vision*. Correct integration of vision and strategy is vital for execution. According to Deloitte, 26% of organizations are testing automation out of which only 38% of those who are adopting and expanding have an enterprise-wide intelligent automation strategy (Automation Anywhere, 2021). 5. *Quality of Da*ta as mentioned previously. 6) *Trust and Transparency*. Staff who fail to understand the intricacies of such technologies would lack confidence in adoption. Transparency aims to disclose information about the AI process, raw data utilized, algorithms chosen, and modelling to reduce misunderstanding in the integration.

Business Risks		Automation Risks	
Change Manageme nt	How is HR tackling the impacts of RPA? How are changes to be communicated?	Identity and access management, secured business processes	Center of Excellence
Executive	Who has the ownership of RPA initiatives? Who will manage the framework and promote efficiencies?	License compliance, automation strategy and governance	Proof of Concept
Functional	Who designs control systems? Is there scalability limitation in RPA and core systems?	Adaptation schemes of existing systems with new features. Legacy systems for simultaneous and unified operations across technical testing and rollout	Backward Compatibil ity
Technical	How will the data quality and accuracy be ensured? How are the tests, validations, maintenances?	Incident management and business continuity. Regulatory compliance.	Implement ation
Operationa l	What controls exists to monitor performance? How will the business comply with regulatory requirements?	Data leakage and privacy, cyber threats	Business Case

Table 2. Identified targeted risk categories for implementing a program with RPA (Gotthardt et al., 2019)

4.3.4 Applications & Example

The most common applications are UiPath (RPA, AI, ML), BluePrism (RPA, AI, ML), Automation Anywhere (RPA, AI, ML), NICE (RPA, AI, ML), and Kryon (RPA, AI, ML). These commercial applications are very similar but fluctuate slightly in product offerings. However, UiPath received the most points based on the criteria (Herm et al., 2021). Most of these RPA solution providers have in-house automation enhancement processes with AI to be integrated into RPA and discussed further under Section 4.4.6.

An example of how RPA contributes to core financial processes presented in Figure 3 is the invoice-to-cash process. As mentioned previously, the invoice-to-cash process consists of customer invoice management (performing pre-invoicing of billing content and managing invoices). This is traditionally a highly manual process prone to human errors, slow, repetitive, multiple systems, and high volume. This is an environment RPA thrives in. The RPA software retrieves new orders from the customer system, downloads the purchase orders, and inputs them into the legacy system. A human supervisor then validates these orders for accuracy and adherence to customer contract terms. Once validated, the RPA robot uploads the orders to an internal ERP system, such as SAP or Oracle, where discounts based on customer agreements are automatically applied. The process is ongoing, with the RPA software continuously checking for new orders (Gotthardt et al., 2019).

4.4 Artificial Intelligence

Artificial Intelligence is also a part of automation, nonetheless, in this section technologies related to intelligent process automation and cognitive automation are more emphasized.

To begin with, (Gartner, 2020) mentioned AI techniques solve a wide array of business problems and generate significant returns on investment (ranging from 20% to over 800%).

There are forms of AI, and also subfields of AI. Forms of AI are reactive machines, limited memory, theory of mind, cognitive (self-aware), artificial general intelligence, artificial narrow intelligence, and artificial super intelligence. Each form of AI requires a different set of inputs. Diving into the subfields of AI, there are machine learning, machine & computer vision, natural language processing, and robotics. AI auxiliaries include, for example, data science, mathematics, statistics, and operations research (Eluwole & Akande, 2022). Furthermore, AI can be divided into 3 categories: weak, general, and strong (Sawwalakhe et al., 2023).

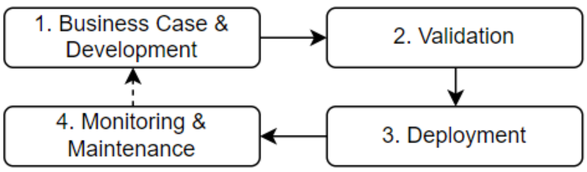

Table 3. AI system life cycle (Jauhiainen & Lehner, 2022)

To successfully implement AI-based systems for example into accounting systems, there is a need for an AI strategy (Jauhiainen & Lehner, 2022). It begins with 1) *Purpose* (what are the intended areas of use? How will AI be used? What are the areas where AI will not be used?), 2) *Risk Management* (Can AI risk management be embedded into current risk management models, what are the regulatory requirements?), 3) *Validation* (Set the policies for model validation and its frequency), 4) *Monitoring* (Set the policies for system monitoring), and lastly 5) *Change Management* (Define accountable business owner in functions and who will ensure that systems are updated). Nevertheless, one thing needs to be kept in mind there is not one fit model for all in AI strategy but a general framework that highlights the most important aspects.

A more technical AI strategy for integrating AI systems for smart finance is from (Li & Xiao, 2022). Emphasis is firstly put on building a database layer. This means building a database layer that handles both structured and unstructured data. While establishing an intelligent technology engine layer that upgrades financial work. Consequently, setting up a comprehensive application layer covering various aspects of finance and automating the "smart finance" workflow while controlling negative impacts. The implementation paths include firstly creating a "cloud-based model" for data standardization to improve real-time financial data, aiding corporate decision-making. Which building an open financial system that links internal and external financial information, establishing a virtual sharing platform for in-depth interaction can begin.

All-in-all, to implement AI into financial core processes, a strategy is needed that outlines AI's purpose, risk management, validation, monitoring, and change management. This includes creating a data handling system, an intelligent technology engine, and a comprehensive application layer, along with a cloud-based model for data standardization and an open financial system for information linkage.

4.4.1 Machine Learning

Machine learning is a subset of artificial intelligence. The success of ML at intelligence tasks is largely due to its ability to discover complex structures that were not known in advance (Nielsen, 2021). ML is another part of the overall AI domain. ML systems get trained by absorbing the learnings from data and decisions and can make simple decisions and classifications (Gotthardt, et al., 2019). Consequently, ML enables cognitive-based automation to learn based on a series of examples (historical data) to recognize patterns and learn based on logical operations. Where the input for ML would aid to perform a task more effectively in the next task (Esswein et al., 2020).

In the light of (Esswein et al., 2020), when implementing machine learning to core processes businesses need to evaluate the entire process thoroughly. Firstly, key stakeholders should truly understand the business need and become acquainted with the process and automation. Since considering replacing human labor with machines might be controversial, thus the solution to replacing the current system has to prove a significant improvement. Secondly, an extensive amount of data needs to be reinforced with quality data for the best results. Keep in mind the quality of training data, since missing or corrupted data creates a risk of replicating past mistakes. This puts emphasis on data cleaning Thirdly, applying a combination of expert judgement and ML for feature selection and assigning weights speeds up the training process for integration. This highlights the need for ML experts to configure, consult and integrate. In addition, computing power plays a crucial role as mentioned previously. Processing large amounts of data with ML requires resources that a cloud-based system can only provide when compared to local hardware. Last but not least, businesses should keep a fallback solution for employees to override entries and enable machine learning to learn from expert input. For example, the ability of accountants to override situations that require human assessment for high-frequency invoice processing.

Diving into technicalities, machine learning is based on advanced algorithms. These algorithms are classified as rule system, reinforcement learning, regularization, regression, neural network, instance-based, ensemble, dimensionality reduction, deep learning, decision tree, clustering, Bayesian, and association rule learning. Machine learning functions with two kinds of models, supervised and unsupervised. A supervised model involves building a model to predict a target using various features, where the foundation is historical data. These kinds of models include classifications and regressions. Classification is a problem in which the target variable is qualitative (two or more categories), such as fraud or not fraud. While regression is a problem in which the target variable is a quantitative value. Commonly used in forecasting and price prediction. In unsupervised models, the machine learns from the input data without any target. This basically means that the algorithm tries to draw conclusions from useful associations and patterns in the raw data. Clustering is included in unsupervised learning models to divide the data into homogenous groups, such as purchase behavior (Gupta & Tham, 2019).

A subset of machine learning is Deep Learning. The deep learning network classifiers typically have many more layers and use a large number of features and several outputs or classes than basic ML applications. The goal of learning is to find the weight on every edge and the bias for every neuron that minimizes the out-of-sample error (Dixon et al., 2020). This basically means the more layers the network has, the more complex tasks it can understand and execute. It compares its predictions to the correct answers and adjusts the settings based on the mistakes it made. Deep learning continuously executes until it frequently improves at recognizing the objective set for the machine.

4.4.2 Natural Language Processing

Another subset of artificial intelligence is Natural Language processing. Natural language processing (NLP) is a branch of artificial intelligence that is concerned to make computers understand text and spoken words in the same way human beings can. It can interpret texts from various sources, analyzing and classifying them to extract meaningful data and take decisions (IBM, 2023). The most common application and rose to popularity of NLP is ChatGPT by OpenAI. OpenAI's GPT-3 itself has various applicative potential into core financial processes highlighted by (Ranta et al., 2022).

4.4.3 Core Processes for Artificial Intelligence

As shown in Appendix 5, AI has been implemented into core processes such as managing treasury (fraud and risk management, advisory for financial insights), invoice-to-cash (invoice management), plan to optimize financials (budgeting & forecasting), and invoice-to-pay processes (payables processing & management) based on figure 3.

Derived from the literature, AI has been often implemented as an addition to digitally automated core processes. Such as invoice form recognizer to extract data for RPA financial processes from cloud service providers. One provider of such service is Microsoft Azure Form Recognizer utilizing AI. AI is needed to reach higher forms of automation, for example, rule-based RPA to Intelligent processing automation to cognitive automation shown in Figure 10.

4.4.4 Strengths

As depicted in Figure 10, the progression of automation advances from intelligent automation to cognitive automation. This represents the integration of an Artificial Intelligence (AI) component into existing Robotic Process Automation (RPA) processes, thereby enhancing their capabilities. Intelligent Process Automation (IPA) emulates human tasks and improves over time, leveraging advancements in machine learning, deep learning, and cognitive technology. This enhances rule-based automation with decision-making capabilities. The strengths of IPA include significantly improved efficiency, enhanced worker performance, reduced operational risks, and faster response times, leading to an improved customer experience (Suri et al., 2019). Some conclusions drawn by (Suri et al., 2019) are 1. *An expert, AI-enabled system is as good, if not better, than what a human can deliver, but costs way less*. 2. *Scaling an expert system comes at near zero additional cost whereas adding another single human doubles the cost*. 3. *The expert, AI-enabled system can be improved over time, and it can be tracked objectively whereas for humans it will be difficult because an employee can exit the organization anytime and a new employee comes with a different expertise level*.

4.4.5 Weaknesses

While AI holds a significant upside but there are risks involved. For successful adoption, risks must be managed. Risks related to AI adoption and mentioned previously are: 1) *Algorithmic bias*, 2) *Overestimating the capabilities of AI*, 3) *Programmatic errors*, 4) *Risk of cyber-attacks*, 4) *Legal risk and liabilities*, and last but not least 5) *Reputational risks* (Boillet, 2018).

However, at the landscape level of AI in finance it changes, there are challenges in localization, integration, transparency, ethics, governance, and expertise along with mitigation of these risks by (Eluwole & Akande, 2022) as shown below.

Threat/Risk/Challenge	Potential Mitigation
• Accuracy • Consistency • Transparent/trust • Ethics • Legal • Governance • Shortage of Expertise • Localization • ML design and Build (MLDB)	-Incorporate AI explainability in MLDB -Incorporate AI ethics in MLDB -Stakeholder collaboration -Ethical-socio-legal awareness -Safeguard mechanisms for data privacy -Robust governance frameworks -Human centric approach in MLDB -Progressive regulatory control -Continuous oversight and monitoring -MLOps (ML Operations) combined with DevOps (Development and Operations) for consistency and serviceability -White-boxing as opposed to black-boxing MLDB to minimize opacity -Risk identification, categorization and containment -Extensive stress testing in MLD

Figure 11. AI in Finance - Threats and Remedies (Eluwole & Akande, 2022)

4.4.6 Application & Examples

When it comes to AI applications, there are a large variety of AI-based applications. One of the most popular solutions currently available is leveraging ChatGPT API into cloud services. The ChatGPT API can be utilized to analyze large Excel files for impactful insights (Ranta et al., 2022). Other applications are UiPath's in-house AI application for document processing to add value to simple RPA rule-based systems (UiPath). Bluebird leverages AI to handle fraud detection in an automated process (SS&C blueprism). As shown previously, AI is integrated into already existing rule-based RPA systems to achieve higher levels of financial automation in core processes.

There are large amounts of examples of utilizing AI in financial processes. Deloitte utilizes AI for document review, inventory counts, confirmations, predictive risk analytics, disclosure research and preparation of client request lists (Abedin et al., 2021). Another example is PayPal using ML tools to separate transactions such as money laundering from legitimate transactions (Gotthardt et al., 2019). A global software firm used an AI-based analytics solution to audit its travel and expense (T&E) spending. This automated system detected high-risk transactions and duplicate expenses, leading to improved policy compliance and reduced fraud (Cangemi & Taylor, 2018). Lastly, Canon utilises AI for financial document processing. (UiPath).

5. ANALYSIS

It must not be mistaken that big data, machine learning, AI and cloud computing are fuelling the finance industry towards digitalization (Hasan et al., 2020). Where it can be concluded that when it comes to contemporary technologies in financial core processes, it is about the level of automation. Various level of automation has a different set of challenges to overcome to reap the benefits, but often, the strengths exceed the weaknesses if the transition is handled accordingly. The most common contemporary technologies mentioned are RPA, IPA, CA with big data and cloud computing as building blocks for successful integration into organizational operations. These technologies can be seen working together. These technologies are deployed according to the insights from the comprehensive literature review. They primarily focus on labour-intensive and repetitive core processes that have a clear progression from point A to B. Several factors are considered during integration, including the diversity of data types (structured and unstructured), the availability of high-quality data, clear and standardized process flows, management support, focus on security and compliance standards, level of the technical infrastructure, technological expertise of staff, and a clear strategy for solid execution. It has become apparent that these technologies are utilized mostly in the realms of financial and managerial accounting. On the other hand, the adoption rate in pure financial processes, such as Risk Management and Investment Advisory, remains relatively low. However, it is worth noting that their utilization in these areas is growing exponentially and the use cases are increasing as seen in Figure 6.

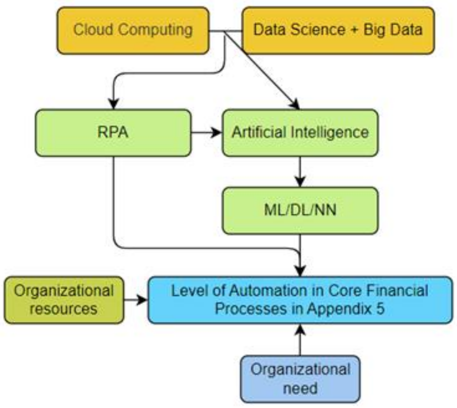

Figure 12. Digital Automation Ecosystem

The applications of these technologies are mentioned in various core processes such as Reporting & Analysis, Budgeting & Forecasting, Project Accounting, Expense Processing & Management, Receivables Processing & Management, Payables Processing & Management, Tax Accounting & Management, and Invoice & Verification.

At the end of the day, it comes down to various levels of automation, organizational need & resources available, the amount of data, and the nature of the core financial process to utilize these contemporary technologies successfully.

6. EMPIRICAL STUDY RESULTS

The questionnaire is broken down into four main sections: Demographics, Current technological landscape, applications of contemporary technologies in Finance, and Adoption of contemporary technologies in Finance. At the end of the survey, an opportunity to provide feedback is also available. The exact structure of the questionnaire can be seen in Appendix 8. The results can be examined in Appendix 9.

Primarily, in the demographics section, this research paper has achieved to gather input from industry professionals in the roles of CEO (1), CFO (3), Digitalization & Innovation Manager (1) and Financial Controller (1), where 4/6 are from a company with 250+ employees (large business), and 2/6 are from 50 – 249 employees (medium business). The industries they are in are electronics, machinery, agriculture, education, development & construction, and composites manufacturing.

Subsequently, for the current technological landscape, all respondents registered 'Yes' that their company does utilize contemporary technologies. The technologies are RPA (3), Cloud Computing (3), AI (2), Big Data (1) and Data Science (1). These technologies are implemented into processes such as: 'budgeting and planning', 'Invoice processing, report generation, financial statement preparation', 'Invoice handling; forecasting', 'cloud-based raise & tracking billing operations', 'document management', and 'cloud-based financial control'. The extent of implementation of these technologies is rated on a scale of 1-5: 2 (1), 3 (2) and 4 (3). When it comes to the effectiveness of these applications from a similar scale of 1-5, the results have been: 3 (2), 4 (4). Satisfaction of current technological applications resulted: 2 (2), 3 (2), and 4 (2). Three respondents mentioned challenges with these applications are 'internal resources', 'new technology, which is new to many employees, errors were made often in the beginning. Benefits are showing once staff get used to the new system', and 'limitations surrounding the full adoption of new technologies is the biggest issue currently'.

Moreover, for applications of contemporary technologies in finance, in this section, examples based on the literature are provided. For the Procure-to-Pay example, 5/6 are aware this existed, 3/6 utilize a similar application already, while 3/6 would consider investing and the rest registered 'Maybe'. One respondent registered that the 'Number of transactions and variability of input reduce payback for the investment' and 'size of the organisation' would influence the decision for adoption. For the Order-to-Cash example, 5/6 were aware of its existence, 4/6 already utilize a similar application, 4/6 would consider investing and the rest registered 'Maybe'. For the Record-to-Report example, 6/6 were aware of its existence, 4/6 utilize a similar application, and 6/6 considered investing in it. For Fraud Management Application, 4/6 are aware this existed, 5/6 registered that they don't currently utilize a similar application, while 3/6 would consider investing and the rest registered 'Maybe'. Some comments are 'There are currently some more cost-effective options surrounding automated reporting and detection which can produce the same result with less cost.' and 'would need more information into the matter'. For the last example, an example in Predictive Analytics, 5/6 are aware of its existence but 6/6 do not utilize the technology, while 4/6 would consider investing and the rest registered 'Maybe'. Similarly, 'variability and the number of transactions keep payback low' influences the adoption of this application.

Lastly, the section on the adoption of contemporary technologies in finance where adoption, clarity, and factors in guiding strategic decisions are gathered. A question about the potential for AI to create value in the financial space, the answers were: 3 (2), 4 (2), and 5 (2). Next is the level of clarity or understanding of the material provided and usefulness: Yes (4/6), Not sure (1/6), and one respondent registered that he or she already understood the potential before the survey. The most popular factor of consideration that would guide strategic decision-making of these technologies is Cost (4). Other results were Competitive advantage (2), Scalability (3), and Industry Trends (0).

When it comes to feedback, the respondents rated 4 (2), 3 (3), and 2 (1) on how much more informed they feel about growing possibilities in the financial domain. 2/6 of respondents mentioned that they recognized all the technologies mentioned, while 3/6 answered 'Most of them', and 1/6 'Some of them'. When it comes to clarity of descriptions and examples, the respondents answered: 4 (5) and 5 (1). Some comments about what they appreciate or find most informative were 'good summary of different technologies', 'everything was really good and covered the subject', 'examples of RPA and AI use', and 'all this is very topical in the financial department at the moment'. When it comes to feedback about improvements or topics missing, the comments were ‘some ideas related to AI solutions’ and ‘Further exploration surrounding some of the businesses’ reasons for slow adoption or lack of awareness’, and ‘co-working of different innovations’.

Based on this result, we can conclude that all respondents showed awareness of these technologies and applications in the current technological domain. All companies utilized some form of RPA to AI in their financial operations with varying levels of effectiveness to satisfaction. Most RPA processes have been currently utilized but more advanced applications like fraud management and predictive analytics have shown lower awareness. Despite this, most of the representatives would consider investing. The potential of AI to create value in the financial space is widely recognized, with cost being the main driver of implementation and relatable to Section 4.4.4. Industry trends were not a significant factor for adoption. Respondents found the survey informative; the clarity of descriptions and examples was rated high and showed appreciation for the technological summaries and examples. Feedback for improvements included more insights into AI solutions, reasons for slow adoption or lack of awareness, and how different innovations can work together. In the end, the organizations participating in this research show signs of technological implementation and effectiveness could be improved since not one respondent registered a 5 for the extent of implementation, satisfaction, or effectiveness of these applications. This can also be seen in the ratings for satisfaction in current technological applications, where the results equalled an average.

Regardless, the questionnaire lacks input from small to medium sized companies, a new conclusion can be created if the scope is increased into this factor.

7. CONCLUSION

The intention of this research was to investigate what emerging digital informational technologies related to financial technology are available, as well as, gathering data on the current level of technology, adoption, and clarity of information provided among companies. In order to establish an understanding of the technologies available based on the research direction, a systematic literature review has been conducted and plotted into a matrix. The secondary research was done with quantitative analysis of an online survey with the input of 6 responses from industry professionals and company representatives. The research has demonstrated that new technologies in the financial domain are rapidly advancing, likewise companies have adapted well to basic advancements but room for more advanced applications are still left unfulfilled. As mentioned previously, the results highlight well the input from large companies but lack input from small and medium size companies, which could have been more emphasized in this research. As smaller companies might even lack basic technologies mentioned in this research. The use of a systematic literature review was a successful strategy for forming a comprehensive typology. Furthermore, the review process shed light on many current use cases, technologies, and processes.

8. LIMITATIONS & FUTURE RESEARCH

The study has certain limitations that need to be considered. For instance, the sample size of participants in the research is relatively small, and the geographic demographics within them were limited. It is crucial to note that different companies may yield different results from the participants. As a result, the findings may not be applicable to all companies but only to those with comparable business models to the companies chosen for the research. Additionally, this research also faces other limitations due to the rapid evolution of contemporary financial technology. As new technologies emerge, the current findings may quickly become outdated or irrelevant, underscoring the transient nature of research in this swiftly changing field. This is shown in Appendix 4 and Figure 7, the literature relevant to this research is limited and changing rapidly. Also, due to time and length of research constraints, all fields couldn’t be covered.

Future research could focus on overcoming implementation challenges and highlighting integration of advanced AI solutions based on the feedback in Section 6. Other topics of interest are how organizational size influences technological adoption and learning curves of employees during change and integration.

Improvements this research could be a more extensive literature review as the material in the SLR might not fully provide the capabilities of these technologies, such as including other sites like Google Scholar. Then again, the questionnaire lacks input from small to medium-sized companies. If the scope were expanded to include a more diversified sample that includes these businesses, it could potentially yield a different conclusion.

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10. REFERENCES

Abedin, M., M. Kabir, H., Hajek, P., & Uddin, M. M. (2021). *The Essentials of Machine Learning in Finance and Accounting.* New York: Routledge.

Agarwal, S., Kandoria, V., Kankriya, Y., Kuckian, A., & Wadhe, V. (2022). Innovation in Financial Intelligence Applications using Artificial Intelligence. *2022 5th International Conference on Advances in Science and Technology (ICAST)* (p. 21). IEEE.

Alton, L. (2016, October 21). *Staying Technologically Relevant Has Suddenly Become A Full-Time Responsibility*. Retrieved from Forbes Under 30: https://www.forbes.com/sites/larryalton/2016/10/21/staying-technologically-relevant-has-suddenly-become-a-full-time-responsibility/

Ansari, W., Diya, P., Sahishnu, P., & Sunita , P. (2019). A Review on Robotic Process Automation- The future of Business Organizations. *2nd International Conference on Advances in Science & Technology (ICAST-2019)*, (p. 5). Mumbai.

Auth, G., Czarnecki, C., & Bensberg, F. (2019). Impact of Robotic Process Automation on Enterprise Architectures. *Lecture Notes in Informatics (LNI), Gesellschaft für Informatik, Bonn 2019 59*, (p. 7).

Automation Anywhere. (2021, September 15). *Top 4 Challenges in Implementing Intelligent Automation*. Retrieved from https://www.automationanywhere.com/company/blog/rpa-thought-leadership/top-4-challenges-in-implementing-intelligent-automation

Bataev, A. (2018). *Analysis of the Application of Big Data Technologies in the Financial Sphere.* Saint-Petersburg: IEEE.

Beccalli, E., Elliot, V., & Virili, F. (2020). Artificial Intelligence and Ethics in Portfolio Management. In R. Agrifoglio, R. Lamboglia, D. Mancini, & F. Ricciardi, *Digital Business Transformation* (pp. 19 - 30). Springer.

Bhattacharyya, S., Banerjee, J. S., & De, D. (2023). *Confluence of Artificial Intelligence and Robotic Process Automation.* Singapore: Springer Nature.

Boillet, J. (2018, April 1st). *Why AI is both a risk and a way to manage risk.* Retrieved from EY - Building a better working world: https://www.ey.com/en_gl/assurance/why-ai-is-both-a-risk-and-a-way-to-manage-risk

Cangemi, M., & Taylor, P. (2018). Harnessing Artificial Intelligence to Deliver Real-Time Intelligence and Business Process Improvements. *EDPACS*, 7.

Cao, Y., & Zhai, J. (2022). A survey of AI in finance. *Journal of Chinese Economic and Business Studies*, 125 - 137.

Capgemini. (2018). *Reimagining the future of finance: Opportunities and challenges of intelligent automation for the finance community.* Retrieved from https://www.capgemini.com/insights/research-library/opportunities-and-challenges-of-intelligent-automation-for-the-finance-community/

Capgemini Consulting. (2016). *Robotic Process Automation - Robots conquer business processes in back offices.* Capgemini.

Chang, Y., & Wang, J. (2022). Research on Optimization of Enterprise Financial Management System Based on Big Data Hadoop. *2022 IEEE Conference on Telecommunications, Optics and Computer Science (TOCS)* (p. 6). Luoyang: IEEE.

Chivers, H., Clark, J., Nobles, P., Shaikh, S., & Chen, H. (2010). Knowing who to watch: Identifying attackers whose actions are hidden within false alarms and background noise. *Information System Frontiers*, 18.

Chukwuani, V., & Egiyi, M. (2020). Automation of Accounting Processes: Impact of Artificial Intelligence. *International Journal of Research and Innovation in Social Science (IJRISS) |Volume IV, Issue VIII, August 2020|ISSN 2454-6186*, 6.

Cockcroft, S., & Russell, M. (2018). Big Data Opportunities for Accounting and Finance Practice and Research. *Australian Accounting Review*, 11.

Czarnecki, C., & Fettke, P. (2021). *Robotic Process Automation - Management, Technology, Applications.* De Gruyter.

Daas, Y., Bhushan, R., Goumas, T., Moradei, P., & Goris, M. (2018). *Cloud case studies*. Retrieved from Deloitte: https://www2.deloitte.com/us/en/pages/consulting/articles/real-time-closing-insights-real-time.html?icid=learn_more_content_click

Delta CPE LLC. (2014). *Accounting and Finance for Business Anaysis.*

Dennehy, D., Griva, A., Pouloudi, N., & Mäntymäki, M. (2023). Artificial intelligence for decision-making and the future of work . *International Journal of Information Management.*

Dixon, M., Halperin, I., & Paul, B. (2020). *Machine Learning in Finance - From Theory to Practice.* Chicago, Brooklyn, London: Springer.

Drew, J. (2013, June 1). *Survey spotlights need for data and security strategies*. Retrieved from Journal of Accountancy: https://www.journalofaccountancy.com/issues/2013/jun/20137330.html

Eisenhardt, K. M., & Martin, J. A. (2000). DYNAMIC CAPABILITIES: WHAT ARE THEY? *Strategic Management Journal*, 17.

Eluwole, O., & Akande, S. (2022). *Artificial Intelligence in Finance: Possibilities and Threats.* Retrieved from Scopus: https://ieeexplore.ieee.org/abstract/document/9887488

Esswein, M., Mayer, J., Sedneva, D., Pagels, D., & Albers, J.-P. (2020). Improving Invoice Allocation in Accounting - An Account Recommender Case Study Applying Machine Learning. In R. L. Rocco Agrifoglio, *Digital Business Transformation* (pp. 137 - 154). Switzerland: Springer.

Farooq, A., & Chawla, P. (2021). Review of Data Science and AI in Finance. *2021 International Conference on Computing Sciences (ICCS)* (p. 7). IEEE.

Ferguson, C., & Seow, P. (2011). *Accounting information systems research over the past decade: Past and future trends.* Singapore, Melbourne.

Föll, H. (2019, October). Semiconductor Technology - Script. Kiel, Germany.

Gartner. (2020). *What is artificial intelligence? Seeing through the hype and focusing on business value.*

Gotthardt, M., Koivulaakso, D., Paksoy, O., Saramo, C., Martikainen, M., & Lehner, O. (2019). Current State and Challenges in the Implementation of Smart Robotic. *ACRN Journal of Finance and Risk Perspectives Process Automation in Accounting and Auditing*, 13.

Gupta, A., Dengre, V., Kheruwala, H. A., & Shah, M. (2020). *Comprehensive review of text-mining applications in finance.* Gujarat: Springer Open.

Gupta, P., & Tham, T. (2019). *FINTECH - The New DNA of Financial Services.* Berlin, Boston: Walter de Gruyter.

Hasan, M., Popp, J., & Olah, J. (2020). Current landscape and infuence of big data on finance. *Journal of Big Data*, 17.

Heinz, H., & Becksndale, M. (2022). Three and a half decades of artificial intelligence in banking, financial services, and insurance: A systematic evolutionary review. *Wiley*.

Herm, L.-V., Janiesch, C., Steinbach, T., & Wullner, D. (2021). Managing RPA implementation projects. In C. Czarnecki, & P. Fettke, *Robotic Process Automation* (pp. 51 - 70). Degruyter.

Huang, H. (2022). Data Mining and Analysis of Business Administration Based on Cloud Computing. *2022 2nd International Conference on Networking, Communications and Information Technology (NetCIT)* (p. 4). Guangdong: IEEE.

IBM. (2023, May 16). *IBM Robotic Process Automation*. Retrieved from IBM: https://www.ibm.com/docs/en/rpa/21.0?topic=automation-natural-language-processing

IBM. (2023, May 16). *Robotic Process Automation*. Retrieved from IBM: https://www.ibm.com/docs/en/rpa/21.0?topic=learning-knowledge-base

Ionescu, L., & Andronie, M. (2021). Big Data Management and Cloud Computing: Financial Implications in the Digital World. *SHS Web of Conferences*, (p. 7). Bucharest.

Jauhiainen, T., & Lehner, O. (2022). Good Governance of AI and Big Data Processes in Accounting and Auditing. In O. M. Lehner, *Artificial Intelligence in Accounting* (pp. 121 - 177). London: Routledge.

Ji, Y. (2022). Research on the Integration of Management Accounting tools Based on Cloud Financial Sharing. *2022 International Conference on Computer Network, Electronic and Automation (ICCNEA)*, (p. 5). Shaanxi, China.

Karlgaard, R. (2011, 8 24). *Surfing the Big Data Wave: EMC's Joe Tucci*. Retrieved from Forbes: https://www.forbes.com/forbes/2011/0912/opinions-rich-karlgaard-innovation-rules-emc-joe-tucci.html

Kokina, J., & Blanchette, S. (2019). Early evidence of digital labor in accounting: Innovation with. *International Journal of Accounting Information*, 13.

Kraus, S., Durst, S., Ferreira, J., Veiga, P., Kailer, N., & Weinmann, A. (2022). Digital transformation in business and management research: An overview of the current state quo. *International Journal of Information Management 63 (2022) 102466*, 18.

Kuiken, S. V. (2022, October 21). *Tech at the edge: Trends reshaping the future of IT and business*. Retrieved from McKinsey Technology : https://www.mckinsey.com/capabilities/mckinsey-digital/our-insights/tech-at-the-edge-trends-reshaping-the-future-of-it-and-business

Langmann, C., & Kokina , J. (2021). RPA in accounting. In C. Czarnecki, & P. Fettke, *Robotic Process Automation: Management, Technology, Applications* (pp. 268 - 285). Berlin/Boston: De Gruyter.

Lehner , O., Leitner-Hanetseder, S., Eisl, C., & Knoll, C. (2022). Artificial Intelligence-drive Accounting (AIDA). In O. Lehner, & C. Knoll, *Artificial Intelligence in Accounting* (pp. 7 - 31). London: Routledge.

Li, Y., & Xiao, H. (2022). Financial automatic management system based on artificial intelligence technology. *2022 International Conference on Electronics and Devices, Computational Science (ICEDCS)* (p. 5). Fujian: IEEE.

Longbing, C. (2022, February 3). *AI in Finance: Challenges, Techniques, and Opportunities.* Retrieved from ACM Computing Surveys: https://doi-org.ezproxy2.utwente.nl/10.1145/3502289

Ma, J. (2021). Research on the Application of Financial Intelligence Based on Artificial Intelligence Technology. *2nd International Conference on Artificial Intelligence and Education (ICAIE)* (p. 4). Cebu: IEEE.

Maslej, N., Fattorini, L., Brynjolfsson, E., Etchemendy, J., Ligett, K., Lyons, T., . . . Perrault, R. (2023). *Artificial Intelligence Index Report 2023.* Stanford, CA: Stanford University - Human-Centered Artificial Intelligence.

Metawea, M., Metawa, S., & Metawa, N. (2023). An Overview of Neural Network in Financial Risk Management. In N. Metawa, M. Hassan, & S. Metawa, *Artificial Intelligence and Big Data For Financial Risk Management: Intelligent Applications* (pp. 229 - 249). Routledge.

Microsoft. (n.d.). *Azure Form Recognizer*. Retrieved from Microsoft: https://azure.microsoft.com/en-us/products/form-recognizer/

Minichiello, V., Rosalie, A., & Terrence Neville, H. (2008). *In-depth Interviewing: Principles, Techniques, Analysis.* Frenchs Forest, Australia: Pearson Education Australia.

Mixson, E. (2021, November 8th). *Rules Based Automation Explained*. Retrieved from Intelligent Automation Network: https://www.intelligentautomation.network/intelligent-automation-ia-rpa/articles/rules-based-automation-explained

Mosteanu, N. R. (2020). Digital Systems and New Challenges of Financial Management - FinTech, XBRL, Blockchain and Cryptocurrencies. *Journal of Management Systems*, 9.

Nguyen, D. K., Sermpinis, G., & Stasinakis, C. (2023). Big data, artificial intelligence and machine learning: A transformative symbiosis in favour of financial technology. *WILEY - European Financial Management*, 517 - 548.

Nielsen, S. (2021, October 28). *Management accounting and the concepts of exploratory data analysis and unsupervised machine learning: a literature study and future directions.* Retrieved from Emerald: https://www.emerald.com/insight/1832-5912.htm

Oneshko, S., Osotropolska, Y., Pomazun, O., Hrynchyshyn, Y., & Rak, R. (2022). Development of Digital Innovations in Company Financial Management. *Review of Economics and Finance, 2022, 20, 826-835*, 10.

Polak, P., Nelischer, C., Guo, H., & Robertson, D. C. (2019). "Intelligent" finance and treasury management: what we can expect. *AI & Society (2020)*, 12.

Quaddus, M., & Hofmeyer, G. (2007). An investigation into the factors influencing the adoption fo B2B trading exchanges in small business. *European Journal of Information Systems (16)*, 202 - 215.

R.J.Bullock, D. B. (1985). It's Just a Phase We're Going Through: A Review and Synthesis of OD Phase Analysis. *SAGE journals*, Page 382 - 412.

Raischel, F., Moreira, A., & Lind, P. (2014). From human mobility to renewable energies: Big data analysis to approach worldwide multiscale phenomena. *The European Physical Journal*, 12.

Ranta, M., Ylinen, M., & Järvenpää, M. (2022). *Machine learning in management accounting research: Literature review and pathways for the future.* Vaasa: European Accounting Review.

Ravn, R., Halberg, P., Gustafsson, J., & Groes, J. (2016). *Get ready for robots: Why planning makes the difference between success and disappointment.* EY.

Sarferaz, S. (2022). Compendium on Enterprise Resources Planning - Market, Functional and Conceptual View based on SAP S/4HANA. Walldorf: Springer Nature Switzerland AG.

Sawwalakhe, R., Arora, S., & Singh, T. (2023). Opportunities and Challenges for Artificial Intelligence and Machine Learning Applications in Finance Sector. In M. Irfan, M. Elhoseny, S. Kassim, & N. S. Metawa, *Advanced Machine Learning Algorithms for Complex Financial Applications* (p. 1171). IGI Global.

Scardovi, C. (2017). *Digital Tranformation in Financial Services.* London: Springer International.

Shidaganti, G., Karthik, K., Anvith, & Kantikar, N. (2023). Integration of RPA and AI in Industry 4.0. In S. Bhattacharyya, J. Banerjee, & D. De, *Confluence of Artificial Intelligence and Robotic Process Automation* (pp. 267 - 287). Singapore: Springer Nature.

Singh, G., Garg, V., & Tiwari, P. (2020). Application of Artificial Intelligence. In O. Castillo, J. Dipak, G. Debasis, & A. Arif, *Recent Advances in Intelligent Information Systems and Applied Mathematics* (pp. 342 - 353). Ghaziabad: Singer Nature.

Sun, Y., Shi, Y., & Zhang, Z. (2019). Finance Big Data: Management, Analysis, and Applications. *International Journal of Electronic Commerce*, 9 - 11.

Suri, V., Elia, M., Arora, P., & van Hillegersberg, J. (2019). Automation of Knowledge-Based Shared Services and Centers of Expertise. In J. Kotlarsky, I. Oshri, & L. Willcocks, *Digital Services and Platforms* (pp. 56 - 75). IEEE.

UiPath. (n.d.). *Canon leverages AI for document processing to save 6,000 hours*. Retrieved from Automation Case Studies: https://www.uipath.com/resources/automation-case-studies/canon-leverages-ai-for-document-processing

Walker, T., Schwartz, T., & Davis, F. (2022). *Big Data in Finance - Opportunities and Challenges of Financial Digitalization.* Montreal: Springer Nature.

Weber, P., Carl, K., & Hinz, O. (2023). Applications of Explainable Artifcial Intelligence in Finance—a systematic review of Finance, Information Systems, and Computer Science literature. *Management Review Quarterly*, 41.

Webster, J., & Watson, R. T. (2002). *Analyzing the past to prepare for the future: Writing a literature review.* Kingston, Athens GA: MIS Quarterly Vol. 26 No. 2, pp. xiii-xxiii/June 2002.

Wright, G., van der Heijden, K., Bradfield, R., Burt, G., & Cairns, G. (2004). The Psychology of Why Organizations Can Be Slow to Adapt and Change. *Journal of General Management Vol. 29 No. 4* , 16.

Yang, W. (2020). Analysis on the influence of big data era on enterprise financial accounting -- a case study of HUA WEI technologies co., LTD. *E3S Web of Conferences*, (p. 6). Dalian.

11. APPENDIX

11.1 Appendix 1 – Systematic Literature Review Results

Author(s)	Year	Title	Main Benefits	Main Challenges	Subject Area
H. Herrmann, B. Masawi	2022	Three and a half decades of artificial intelligence in banking, financial services, and insurance: A systematic evolutionary review Applications N/A	+Overview into traditional computer vs Machine Learning and Deep learning +Overview of research statistics in the field +Progress to what became fintech today		AI, ML, DL
L. Cao	2020	AI in Finance: Challenges, Techniques, and Opportunities Applications N/A	+ AIDS: Artificial intelligence and Data science +Extensive review into the domain of AI in Finance, excellent overview into various technologies in the field +AI utilizes various models and methods to reach a certain outcome	- Effectiveness of AI depends on the quality of data, if there are errors, the AI will have errors -Bias data equals bias results -The black box phenomena is when it is difficult to know how AI arrived with a certain result	AI, ML, DL, Finance
P. Polak, C. Nelischer, H. Guo, D. C. Robertson	2019	“Intelligent” finance and treasury management: what we can expect Applications Forecasting, reporting,	+ Great overview of AI, ML, Automation activities + Help staff execute tasks effectively +RPA aids repetitive, low value	-Staff unaware how AI can help -failure to maximize use of AI -RPA conversion of non-digital inputs	AI, Automation, ML, Core Processes, RPA

		audit, budgeting, procurement, reconciliation, KPI monitoring, project accounting, fraud management, FX exposure, Trading	work +AI enhances performance based on data and learning +focus on quick wins, executives need to understand the importance	-Ability to identify unstructured document formats -Adapting to changing rules or business logic -Staff may lose creativity	
S. Nielsen	2021	Management accounting and the concepts of exploratory data analysis and unsupervised machine learning: a literature study and future directions Applications Financial & Management accounting	+ML models are designed to be as accurate as possible +ML can process large volumes and various types of data often without human intervention +Purpose of ML is to detect patterns and to learn how make predictions and recommendations +Data is only as good as the data that go into them to be +Great overview of ML, Data Analysis, AI +Encourage embracing new tools and processes to add value	-Bad data= output becomes useless -ML is complicated and requires preparation, test, and insight for success -Management accountants have risk of being replaced -Wrong data=may disrupt the company completely= opposite result -Be aware of biases	Management Accounting, ML, AI, Data Analysis
S. Bhattacharyya, J. S. Banerjee, D. De	2023	Confluence of Artificial Intelligence and Robotic Process Automation Applications Audit, Accounting	+RPA helps to automate repetitive tasks, billing, data upkeep +detection of fraud and scams +different levels of RPA: cognitive, autonomic, orchestration, scripting, manual +quick and efficient +excellent comparison between conventional automation vs RPA, and Standard IT vs RPA +List of RPA advantages +List of advantages in automation in Finance +Explanation of AI in Audit	-still a technology in its infancy and still needs to be studied	RPA, Audit, Accounting, AI, NLP
M. Z. Abedin, M. K. Hassan, P. Hajek, M. M. Uddin	2021	The Essentials of Machine Learning in Finance and Accounting Applications Audit, Accounting	+technical input into the implementation of machine learning in the finance and accounting domain		ML, AI, Accounting, Finance, RPA, Cloud Computing
Capgemini Consulting (external)	2016	RPA – Robots conquer business process in back offices. Applications Accounts- payable, receivable, fixed asset accounting, travel expense calculation, treasury, invoice verification	+all back-office functions will see an increase in RPA usage +86% of participants said that RPA can significantly reduce costs +Most standardized are also the processes most likely to see a significant increase in RPA usage +RPA frees employees from repetitive to focus instead on value adding initiatives that require creativity and decision-making, with cost savings	-concerns are: data protection, cyber security, too many processes, too expensive, RPA implementation cost > ROI, implementing artifacts is very tedious	RPA, Processes, Statistics

			+Blueprism 28%, NICE 13%, UiPath 10% solutions +73% less time spent on repetitive tasks, 47% fewer errors, 37% reduced workload peaks		
M. Ranta, M. Ylinen, M. Järvenpää (external)	2022	Machine learning in management accounting research: Literature review and pathways for the future Applications Accounting estimates, income statements,	+ML algorithms are best suited from problems in which the set of variables, their interactions, and the mapping onto outcomes are not theoretically obvious +ML offer powerful predictive tools for discovering the functional forms between variables +GPT for interpretation of qualitative data		AI, ML, Managerial Accounting, ChatGPT, Python, R
W. A. Ansari, P. Diya, S. Patil, S. Patil (external)	2019	A Review on Robotic Process Automation- The future of Business Organizations Applications fraud detection, trade finance, reconciliation process	+RPA and AI are both only different level of automation +provides good overview of RPA in general business domain +RPA will disrupt audit, also front/back office to be automated +RPA is easy to configure, with ease of use interfaces +RPA is non-invasive +other software is not effect by the use of RPA +RPA is enterprise safe	-commercial RPA are often very costly -false belief of the need for technical ability for RPA -worry that RPA will replace employees -major changes, if not done properly, might cause more problems than solve them	RPA, Automation, AI, UiPath, Blue Prism
M. Gotthardt, D. Koivulaakso, O. Paksoy, C. Saramo, M. Martikainen, O. Lehner (external)	2019	Current State and Challenges in the Implementation of Smart Robotic Process Automation in Accounting and Auditing Applications Internal Audit, Managerial & Financial Accounting	+only 15% mature in RPA use, 5% in AI use in companies +AI and RPA combined can turn large amount of data to actionable insights +45% of work activities can be automated and this will save 2trillion$ globally annually +simple RPA implementation examples utilizing UiPath with automation into SAP – invoice processing +excellent future outlook for RPA	-lack of understanding of RPA from employees=lack of interest -afraid that automation will negatively impact employees -reluctant to adopt due to data issues -RPA has some limitation such as not able to process informal interactions, only digital form -RPA threats are abuse of privileged access, disclosure of sensitive data, security vulnerabilities and denial of service	SAP, RPA, Audit, Accounting, AI, UiPath
R. Agrifoglio, R. Lambogia, D. Mancini, F. Ricciardi	2020	Digital Business Transformation: Organizing, Managing and Controlling in the Information Age Applications Portfolio management, invoice automation, record-to-report, purchase-to-pay	+machine ethics is vital to ensure functionality in an ethically responsible manner +truly understand the business need -> more data can only get you so far -> give the machine a good starting position -> computing power is crucial -> include manual intervention +Great automated invoice processing model – page 147 +in-depth foundation for invoice processing automation using ML	-algorithms are ethically challenging because of the scale of analysis and complexity of decision making	AI, Machine Ethics, Accounting, ML, SAP

			+their automated prototype can handle more than 500000 invoices per year		
J. Ma	2021	Research on the Application of Financial Intelligence Based on Artificial Intelligence Technology Applications Intelligent processing (receipts), risk monitoring	+free human resources from tedious tasks, create more value and achieve efficiency +example of AI usage in a financial environment		AI, Financial Technology
C. Larkin, C. C. Otten, J. Arvai	2022	Paging Dr. JARVIS! Will people accept advice from artificial intelligence for consequential risk management decisions? Applications Risk management	+businesses are leveraging AI for advice when making judgements in low stakes forecasting tasks +future work on algorithm aversion or appreciation should consider not only factors influencing trust but also factors influencing the extent to which human expertise is trusted in the task domain	-Participants from finance in the research still show a strong preference for advice from human experts over AI -cost of developing in-house AI solutions -shortage of experts in the AI domain -localization & mitigation challenges	AI, Risk Management
S. Agarwal, V. Kandoria, Y. Kankriya, A. Kuckian, V. Wadhe	2022	Innovations in Financial Intelligence Applications using Artificial Intelligence Applications Invoice verification, risk management,	+improve work efficiency of financial professionals +good overview of workflow of financial transaction bot		AI, Financial Robots
K. Veeraiah, S. Raju, Y. Vangaveti, V. Kumar, S. S. Ali	2022	Role of Artificial Intelligence in Financial Management Applications Fraud detection, virtual assistant, chatbot	+can generate large savings in financial management	-machine learning design	AI, Financial Management
J. Kokina	2020	Accountant as Digital Innovator: Roles and Competencies in the Age of Automation Applications N/A	+excellent input into roles in modern accounting systems: trainer role, identifier role, explainer role, sustainer role, analyzer role. +Each role plays a vital part in integrating AI accounting into company landscape	-job losses are bound to happen due to substitution with AI accounting systems	Accounting
C. Czarnecki, P. Fettke	2021	Robotic Process Automation: Management, Technology, Automation Applications Audit, Management accounting (summary, consolidation, reporting, maintenance of master data, reporting system and data process), Financial accounting (order-to-cash, procure-to-pay, record-to-report)	+Good structure of the concept and architecture of RPA – page 14. Excellent overview of RPA solutions available. +RPA utilization in Excel +Great overview of RPA cost of ownership – page 56 +Process selection for RPA matrix – page 100 +IPA = RPA + AI/ML +RPA suits best for processes with mature, rule-based, high volume, digital and repetitive. +Financial accounting processes for RPA – Page 252	-Shift in RPA for Accounting require new skills and competencies than traditional accountants	RPA, UiPath, Excel, Accounting, Audit,

Y. Chang, J. Wang	2022	Research on Optimization of Enterprise Financial Management System Based on Big Data Hadoop Applications	+ The use of big data, specifically with the Canopy+K-means algorithm and Hadoop, can lead to more accurate clustering result		Big Data, Hadoop, NoSQL,
M. Hasan, J. Popp, J. Olah	2020	Current landscape and influence of big data on finance Applications Risk/fraud management, forecasting, analysis, predictive analytics	+data is seen as one of the most valuable commodities when it comes to managing automation systems +benefits of big data in multiple processes	-managing large data sets is expensive and difficult -small companies can't excess big data to be utilized	Big Data, Automation, Financial Management, Risk Management, Applications
Y. Ji	2022	Research on the Integration of Management Accounting tools Based on Cloud Financial Sharing Applications Predictive analytics, Accounting	+Advance information technology can improve speed and processing efficiency of standardized information = more time for value adding activities +Increase optimization possibilities for big data, RPA, data mining, and analytics. +With cloud financial sharing, enterprises have improved the integration of management accounting tool +Identifying, integrating, and utilizing information in the information age is the key to sustainable development +Use technologies such as big data and cloud computing to continuously improve application level and integration level of management accounting tools to create more corporate value		Accounting, Cloud Computing, Big Data, Financial Sharing, RPA, Value Creation
A. Farooq, P. Chawla	2021	Review of Data Science and AI in Finance Applications Modelling, forecasting, investment optimization, risk management, corporate finance, governance			AI, Big Data, FinTech, Management, Data Science
S. Cockcroft, M. Russell	2018	Big data opportunities for Accounting and Finance practice and research Applications Fraud prevention, customer insight	+Great insight into application of big data in accounting and finance		Data Science, Big Data, Cloud Computing
M. F. Dixon, I. Halperin, P. Bilokon	2020	Machine Learning in Finance – From Theory to Practice Applications Robo-advisors, fraud detection,	+in-depth technical information about ML for finance +technical and mathematical implementation		ML,

P. Gupta, T. M. Tham	2019	FINTECH – The New DNA of Financial Services Applications Behavioural pricing, underwriting, claims assessment, robo advisory, fraud detection	+comprehensive insight into cloud computing, AI, ML, DL, RPA: Are AI and ML the same thing? Page 205 +Big data technology stack for implementation: page 96		ML, DL, AI, Cloud Computing, Data Science
K. Veeraiah, S. Raju, Y. Vangaveti, V. Kumar, S. Ali	2022	Role of Artificial Intelligence in Financial Management Applications AML, fraud detection, robo advisory, front office, centre office	+reduce requirement for monotonous work +reducing human errors +expense savings		AI, ML
J. Kokina, S. Blanchette	2019	Early evidence of digital labor in accounting: Innovation with Robotic Process Automation Applications procure-to-pay, report-to-record, order-to-cash, reporting, back office processes, reporting, contract management, reconciliations tasks, invoice management, tax payment	+extensive interview with executives about RPA implementation +order-to-cash best suited for RPA based on company A +tasks suitable for RPA are labor-intensive, high volume, rule based, in digital form, use multiple systems. Structured data are strong candidates for RPA. +As RPA implementation expands, organizations move to a less-centralized or federated model of governance	- RPA implementation is the complexity associated with documenting a process at a granular level of detail. The need to understand the process in detail before enabling automation, while emphasizing the importance of process standardization.	RPA, Accounting
G. Auth, C. Czarnecki, F. Bensberg	2019	Impact of Robotic Process Automation on Enterprise Architectures Applications N/A	Impact of RPA on EA: (1) routine tasks in which data is copied or combined from different application systems; (2) structured tasks with rule-based decisions, in which data from different application systems is used and evaluated on the basis of a set of rules; (3) unstructured tasks and decisions that require experience knowledge in addition to existing data and rules +excellent insight into the different levels of RPA into either supporting, substituting, or innovating a process.		RPA, EA, ERP systems, Automation
Mosteanu, N. R & Faccia	2020	Digital Systems and New Challenges of Financial Management – FinTech, XBRL, Blockchain and Cryptocurrencies Applications N/A	+Minimize human error + Advanced computing capability has paved the way for big data analytics. + Artificial Intelligence solutions have the potential to transform such diverse and critical areas as education, research, healthcare, finance, accounting, auditing, transport and energy.		AI, Financial Technology
N. Metawa, K. Hassan, S. Metawa	2023	Artificial Intelligence and Big Data for Financial Risk Management – Intelligent	+technical information behind machine learning techniques in finance		AI, Big Data, Risk Management

		Applications Applications Forecasting, risk modelling	+explains neural networks in finance		
M. Irfan, M. Elhoseny, S. Kassim, N. S. Metawa	2023	Advanced Machine Learning Algorithms for Complex Financial Applications Applications N/A	+highly technical input into ML for financial applications		AI, ML, Applications
O. T. Eluwole, S. Akande	2022	Artificial Intelligence in Finance: Possibilities and Threats Applications Fraud detection, predictive analytics, Risk analytics,	+great insight into ML domain and financial capabilities +utilizing ML, big data, IoT, businesses can achieve predictive, prescriptive, descriptive, or diagnostics analytics	-transparency and regulatory control -ethical responsibilities are needed -mitigation measures are need throughout model development	RPA, ML, Big Data,
O. Lehner, S. Leitner-Hanetseder, C. Eisl, C. Knoll	2022	Artificial Intelligence-driven Accounting (AIDA) Applications Accounting systems	+great overview into different levels of AIDA: Digitally assisted accounting, semi-autonomous accounting, full autonomous accounting		AI, Accounting
T. Jauhiainen, O. M. Lehner	2022	Good Governance of AI and Big Data Processes in Accounting and Auditing	+excellent insight into AI strategy and governance		AI
A. V. Bataev	2018	Analysis of the Application of Big Data Technologies in the Financial Sphere	+insight into software for big data	-high cost for big data implementation -data confidentiality and protection -lack of skilled personnel -insufficient volume of data	Big Data, Financial Services
Z. Li, H. Liang, N. Wang, Y. Xue, S. Ge	2021	Efficiency or Innovation? The Long-Run Payoff of Cloud Computing Applications N/A	+cloud computing is highly suitable for firms striving for efficiency +Generally, CC integration starts first effecting negatively financial performance, it eventually leads to improved operational performances, enhanced enterprise agility, and increased financial performance.	-adopting CC with innovation involves more complex and risky transformations that can lead to a significant financial performance decline -payoff takes multiple years for CC to take effect	Cloud Computing
H. Huang	2022	Data Mining and Analysis of Business Administration Based on Cloud Computing Applications N/A	+cloud computing can execute data mining through parallel processing, which improve the real-time and effectiveness of data mining +Data mining through the cloud is more convenient and faster	-security of cloud computing and data mining is still a topic to be questioned	Cloud Computing, Data Mining
L. Ionescu, M. Andronie	2021	Big Data Management and Cloud Computing: Financial Implications in the Digital World Applications Finance, Accounting, Audit	+Big data is an important trend in financial services, but also in accounting and insurance sectors, not only because of volume but also complexity and speed. +key areas where automation was implemented in 2019: 25% finance/accounting/auditing,		Cloud Computing, Automation, Big Data

			23% marketing, 18% sales, and etc. +Cloud computing and big data go hand-in-hand +improved efficiency, communication, and resource management, while big data management can structurally facilitate both internal and customer intractions		
C. Zhang	2021	The Application of Financial Analysis Based on the Perspective of Big Data Applications N/A	+The development of big data technology is closely related to the development of cloud computing technology +the demand for accounting talents has changed, data driven individuals are sought after		Big Data, Cloud Computing, Accounting, Education
J. Gu, S. Du	2020	Research on the Relevance of Big Data Accounting and Financial Information Applications N/A	+insights into improving decision-making process through big data and cloud +big data accounting vs traditional accounting +Big data technology makes unstructured, unsystematic and fragmented data the mainstream of data types		Big Data, Accounting, Financial Decision-making, Cloud Computing
M. Metawea, S. Metawa, N. Metawa	2023	An Overview of Neural Network in Financial Risk Management Applications Forecasting, risk management, credit analysis, underwriting analysis, business cycle recognition	+Artificial neural networks basically resemble biological neural networks +ANN have the ability to learn and model non-linear and complex relationships +types of learning in NN, supervised, unsupervised, and reinforcement learning.		Risk Management, Deep Learning, Neural Networks
V. N. Chukwuani, M. M. Egiyi (external)	2020	Automation of Accounting Processes: Impact of Artificial Intelligence Applications Accounting, Audit and Advisory	+Financial personnel need to adapt with professional, management, computer, analytical, and decision making skills. +AI cannot be avoided by firms +Automation with both RPA and AI will bring about significant changes to the accounting industry. Repetitive and mundane tasks usually done by junior staff will be replaced by robots and human expertise will be needed at a higher level for decisions that require judgment		Accounting, Audit, AI, RPA, Automation
V. K. Suri, M. D. Elia, P. Arora, J. van Hillegersberg (external)	2019	Automation of Knowledge-Based Shared Services and Centers of Expertise Applications N/A	+there is RPA, IPA = IA, CA, AI in the automation industry +RPA are for processes that are routine, methodical, repetitive, rule based. Able to only follow instructions. Implementation is in weeks. +IPA are for processes that are non-routine, require thoughtful		RPA, IPA, IA

			consideration. It is able to come to conclusions. Implementations is in months. +with CA, an advance machine that utilizes NLP, big data, real time analytics, and AI in one package. +Vast amount of information into levels of automation		
Y. Li, H. Xiao	2022	Financial automatic management system based on artificial intelligence technology Applications Invoice management system, financial forecasting, financial statistics, asset management, advisory	+input into AI strategy for building smart finance models +significantly improves the speed of information dissemination in modern society and the efficiency of industrial and commercial operations +The study pointed out that artificial intelligence will replace more than 300 occupations in the future, and more than 80% of the jobs can be completed by artificial intelligence. +reduce labour cost while Artificial intelligence enables the financial department to devote more energy and wisdom to participate in the operation of the enterprise, and artificial intelligence can more comprehensively grasp and analyze the operation status of the enterprise and provide more accurate and effective financial decision support for the enterprise	-Enterprises lacks awareness of available financial software -Vulnerabilities of financial software need to be acknowledged	AI, Cloud Computing, Automation
P. Weber, K.V. Carl, O. Hinz	2022	Applications of Explainable Artificial Intelligence in Finance—a systematic review of Finance, Information Systems, and Computer Science literature Applications Portfolio optimization, risk management, fraud management, financial transaction classification	+extensive systematic literature review into multiple domains +benefiting from Big Data, cheap computing power and storage, and improved algorithms, AI faces unseen opportunities nowadays	-emphasizes regulation is needed so that AI risks are minimized and it is safe, transparent and trusted. -practical implementation lags due to the so-called black-box nature of most AI based systems, thus missing to unlock the full potential of AI implementation. The black-box nature refers to a lack of explainability and interpretability of AI-based systems, primarily arising from the opacity of many of today’s AI-based systems	AI, ML, Financial Applications

11.2 Appendix 2 - Diagram

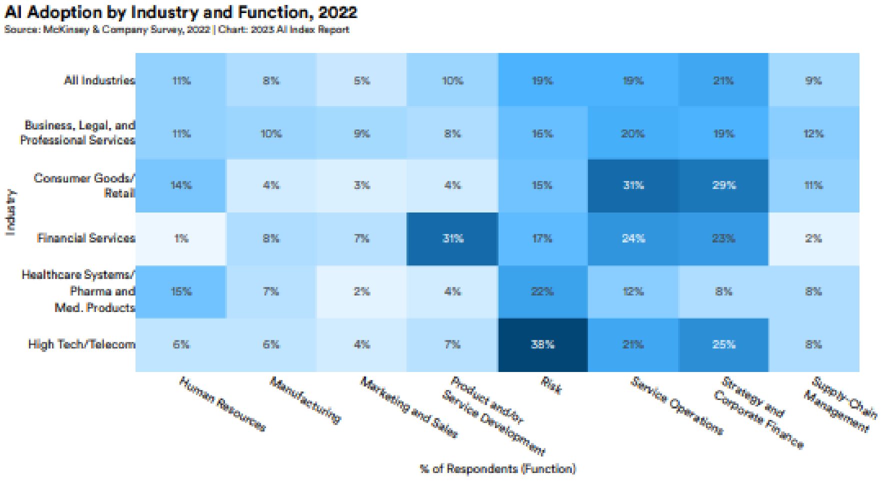


Figure 13. AI adoption by industry and AI function (Maslej et al., 2023).

11.3 Appendix 3 - Diagram

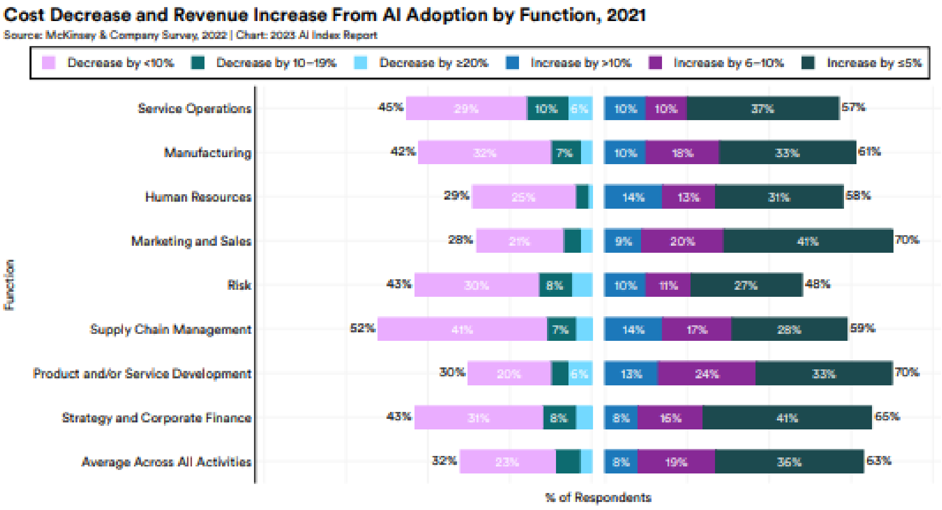


Figure 14. Cost Decrease and Revenue Increase from AI Adoption (Maslej et al., 2023).

11.4 Appendix 4 – Diagram

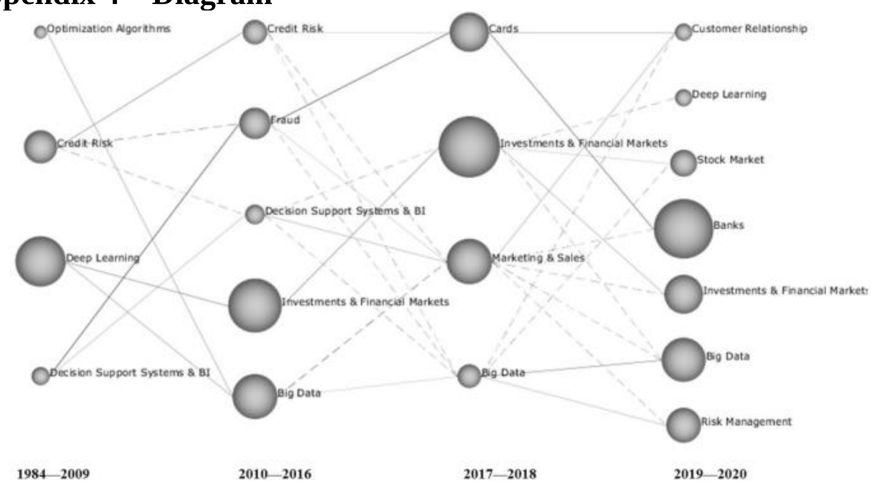


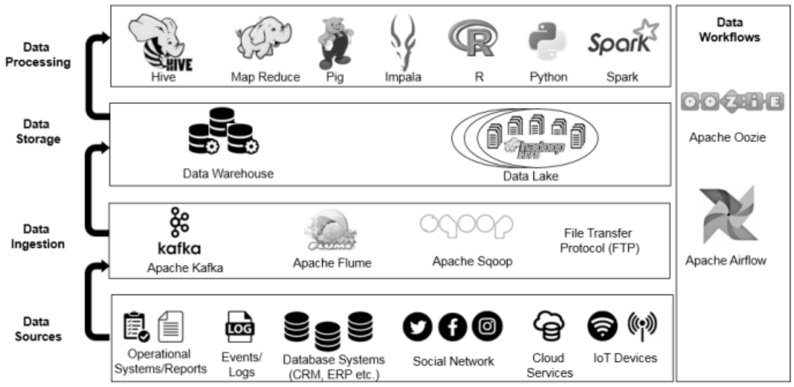
Figure 15. Evolutionary map of themes for artificial intelligence in banking, financial services, and insurance—Sphere size denotes the count of publications (Heinz & Becksndale, 2022)

11.5 Appendix 5 – Applications mentioned based on SLR.

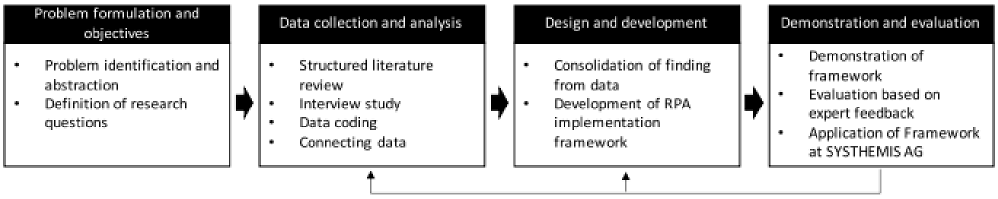
Authors	Reporting & Analysis	Reconciliation	Budgeting & Forecasting	Self/internal Auditing	Data Maintenance, Governance, Management	Compliance Monitoring & Management	FX Exposure Management	KPI Measurement & Monitoring	Cost Accounting Management	Project Accounting	Expense Processing & Management	Receivables Processing & Management	Payables Processing & Management	Tax Accounting & Regulation	Financial Procurement	Invoicing & Verification	Robo-Advisory & Insights	Behavioral Analysis	Risk Management & Monitoring	Fraud Management & Detection	Cost & Pricing Analysis	Portfolio/ Asset Management	Predictive Analytics	Financial Optimization Measures, Modeling	Payment Management, Payroll Management	Fixed Asset Accounting
(Polak;Nelischer; Guo;& Robertson, 2019)	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X					
(Nielsen, 2021)	X		X							X		X	X	X												
(Bhattacharyya;Banerjee;& De, 2023)	X			X						X		X	X													
(Abedin;M. Kabir;Hajek;& Uddin, 2021)				X		X				X	X	X	X	X												
(Capgemini Consulting, 2016)	X	X				X		X	X	X	X	X	X	X		X					X					
(Ranta;Ylinen;& Järvenpää, 2022)	X		X					X																		
(Ansari;Diya;Sahishnu;& Sunita , 2019)	X	X	X	X		X		X		X	X	X	X	X							X					
(Gotthardt et al., 2019)	X			X					X	X	X	X	X	X		X										
(Beccalli;Elliot;& Virili, 2020)																						X				
(Esswein;Mayer; Sedneva;Pagels; & Albers, 2020)													X			X										
(Ma, 2021)																X			X							
(Ji, 2022)	X			X		X				X	X	X	X	X		X							X			
(Cockcroft & Russell, 2018)																				X						
(Lehner ;Leitner-Hanetseder;Eisl; & Knoll, 2022)	X		X							X	X	X	X	X			X		X				X	X		
(Farooq & Chawla, 2021)	X		X		X			X											X	X	X		X			
(Eluwole & Akande, 2022)																			X	X			X	X		
(Agarwal;Kandoria;Kankriya;Kuckian;& Wadhe, 2022)																X			X							
(Cangemi & Taylor, 2018)				X							X		X							X						
(Langmann & Kokina , 2021)	X			X	X	X	X			X	X	X	X	X	X	X	X			X		X	X		X	
(Hasan;Popp;& Olah, 2020)	X		X																X	X			X			
(Chukwuani & Egiyi, 2020)	X	X			X						X	X	X	X		X	X							X	X	X
(Metawea;Metawa;& Metawa, 2023)	X		X																X			X				
(Kokina & Blanchette, 2019)	X				X							X	X	X		X										
(Suri;Elia;Arora; & van Hillegersberg, 2019)			X			X			X		X			X						X		X		X		
(Li & Xiao, 2022)	X		X	X											X	X	X					X				
(Weber;Carl;& Hinz, 2023)																			X	X		X				
	16	4	10	9	5	7	2	5	4	10	11	12	14	12	3	11	5	1	9	9	3	6	6	4	2	1

Low RPA	Medium RPA	High RPA	Neutral RPA	AI (ML/DL/NN)	~~AI + RPA~~	Big Data

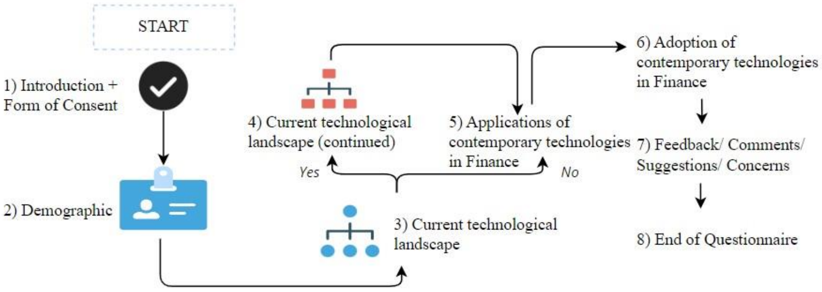
11.6 Appendix 6 – Big Data Technology Stack by (Gupta & Tham, 2019)



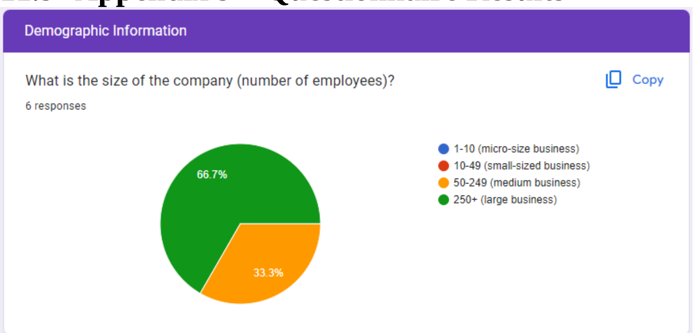
11.7 Appendix 7 – RPA Selection Applied Methodology by (Herm et al., 2021)



11.8 Appendix 8 – Questionnaire Structure



11.9 Appendix 9 – Questionnaire Results



What is your role within the company?

6 responses

CEO

CFO

Chief Financial Officer

Cfo

Finance controller

Manager digitalization and innovation

What is the field of business/industry conducted by the company?

6 responses

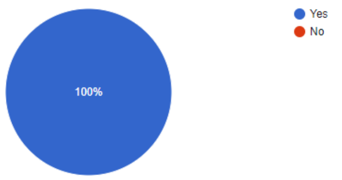
- Electronics industry
- Machinery
- Agriculture - specifically growing, packing and sales of potatoes and onions
- Composites manufacturing
- financial support, mainly debtors
- Development and construction

Current technological landscape

Do you utilize any of the contemporary technologies listed in the description for the company's financial domain?

Copy

6 responses

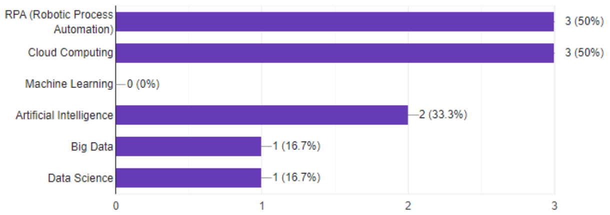


Current technological landscape (continued)

Which of the following technologies are implemented in your organization?

Copy

6 responses



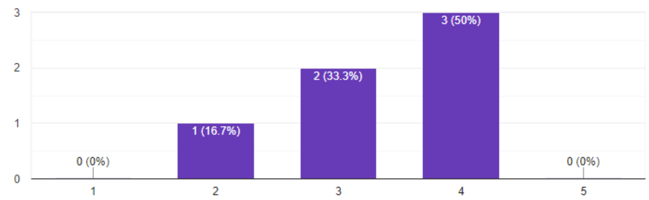
Specify in which core financial process are these technologies are currently implemented into? Example: 'Procure-to-pay with RPA technology', 'Predictive Analytics with ML'

6 responses

- Whole ERP (financial control) is in cloud
- Invoice handling; forecasting
- Invoice processing, report generation, financial statement preparation
- Budgeting and planning
- At the financial department of UT we use a program called UNIT4. It is a cloud-based accounting and financial management solution. it helps with making it easier for our team to raise and track billing documents. Use workflows to get bills approved and ready to send more promptly. Help our business and finance people work together more efficiently and improve invoice accuracy to reduce customer disputes and receive payments faster.
  Post bills straight back into our accounts for accurate reporting and better-informed action.
- AI within tendermanagement, AI for developing projectdocuments, Big Data within co-working systems/software 'Interoperable'.

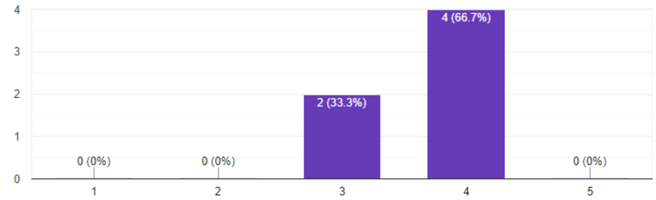
Rate the extent of implementation for each technology on a scale (e.g., 1-5) to evaluate the depth of adoption

6 responses



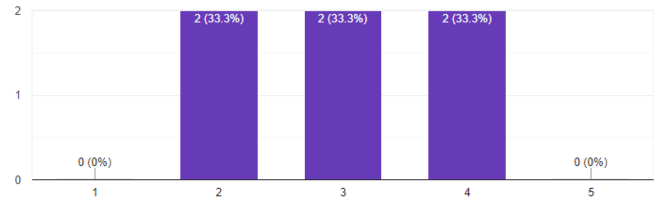
How would you rate the effectiveness of these applications in use in terms of achieving your business goals?

6 responses



How satisfied are you with the current applications used in your organization?

6 responses



Are there any challenges or limitations experienced with the current technology implementation?

5 responses

Not much

internal resources

Limitations surrounding the full adoption of new technologies is the biggest issue right now

We just implemented this system, so it's new for a lot of employees which makes it hard and mistakes were made often. But now everyone is working with the system for quite some time and the benefits are really coming out now.

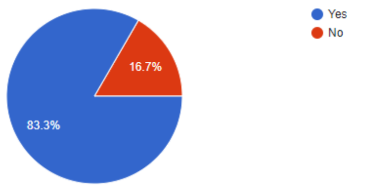
Mainly human use

Applications of contemporary technologies in Finance

1) Procure-to-Pay Application: Invoice Management

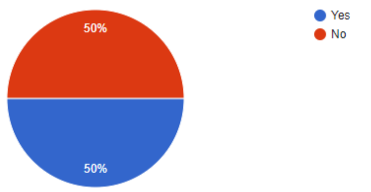
1.1) Is this something you were aware existed?

6 responses



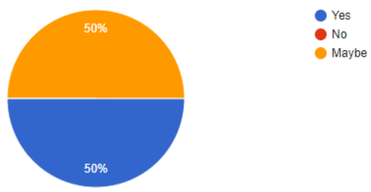
1.2) Do you use a similar application like this already?

6 responses



1.3) Would you consider investing in a similar technology for your organization?

6 responses



1.4) If the answer is 'No' for 1.3, what factors would influence your decision to adopt and utilize this technology within your organization?

2 responses

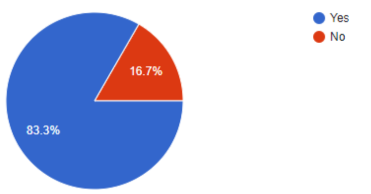
Number of transactions and variability of input reduce payback for the investment

It depends on the size of the organization.

2) Order-to-Cash Application

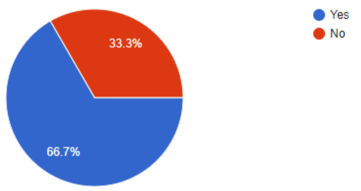
2.1) Is this something you were aware existed?

6 responses



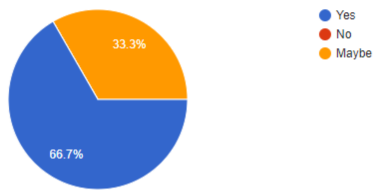
2.2) Do you use a similar application like this already?

6 responses



2.3) Would you consider investing in a similar technology for your organization?

6 responses



2.4) If the answer is 'No' for 2.3, what factors would influence your decision to adopt and utilize this technology within your organization?

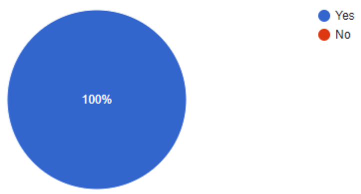
0 responses

No responses yet for this question.

3) Record-to-Report Application

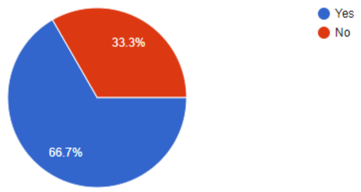
3.1) Is this something you were aware existed?

6 responses



3.2) Do you use a similar application like this already?

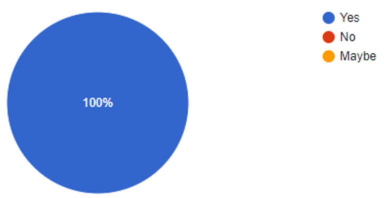
6 responses



3.3) Would you consider investing in a similar technology for your organization?

Copy

6 responses



3.4) If the answer is 'No' for 3.3, what factors would influence your decision to adopt and utilize this technology within your organization?

0 responses

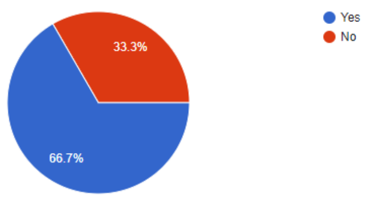
No responses yet for this question.

4) Fraud Management Application

4.1) Is this something you were aware existed?

Copy

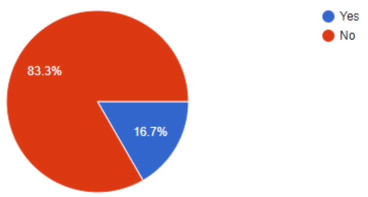
6 responses



4.2) Do you use a similar application like this already?

Copy

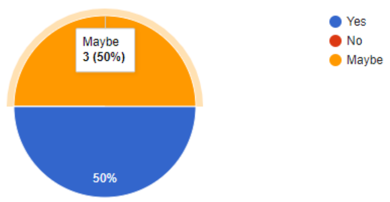
6 responses



4.3) Would you consider investing in a similar technology for your organization?

Copy

6 responses



4.4) If the answer is 'No' for 4.3, what factors would influence your decision to adopt and utilize this technology within your organization?

2 responses

There are currently some more cost effective options surrounding automated reporting and detection which can produce the same result with less cost.

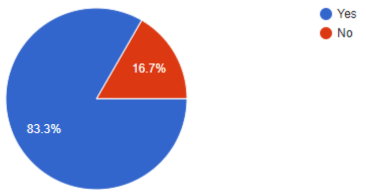
Would need more information

5) Predictive Analytics Application

5.1) Is this something you were aware existed?

Copy

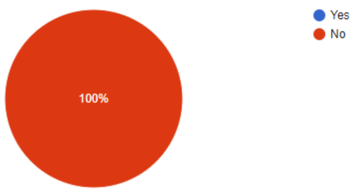
6 responses



5.2) Do you use a similar application like this already?

Copy

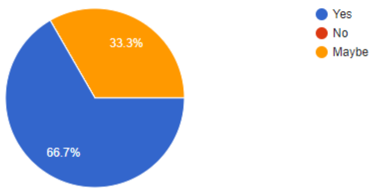
6 responses



5.3) Would you consider investing in a similar technology for your organization?

Copy

6 responses



5.4) If the answer is 'No' for 5.3, what factors would influence your decision to adopt and utilize this technology within your organization?

1 response

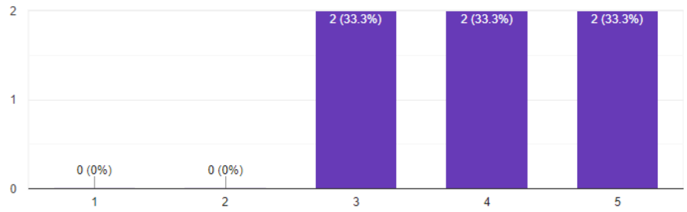
Same as previous , variability and number of transactions keep's payback low

Adoption of contemporary technologies in Finance

Is there potential for AI to create value in the financial space?

Copy

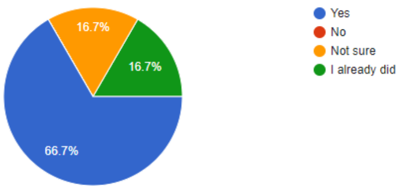
6 responses



Do you now understand how these applications can be useful in your business?

Copy

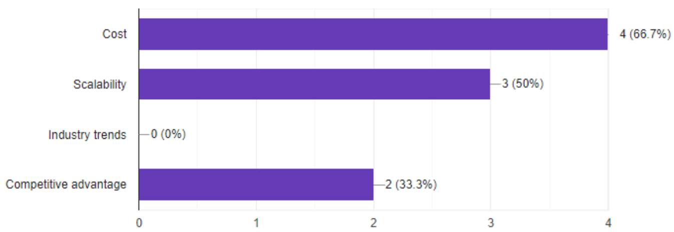
6 responses



What considerations would guide your strategic decision to incorporate these technologies into your current business operations?

Copy

6 responses

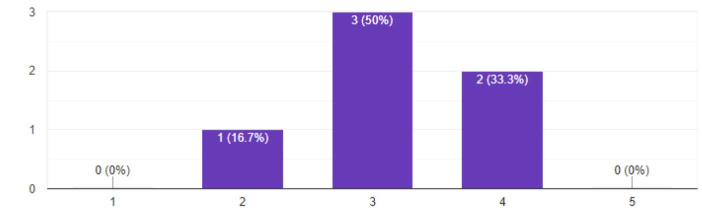


Feedback/ Comments/ Suggestions/ Concerns

On a scale of 1 to 5, how much more informed do you feel about the growing possibilities in the financial domain from a corporate perspective after completing this questionnaire?

Copy

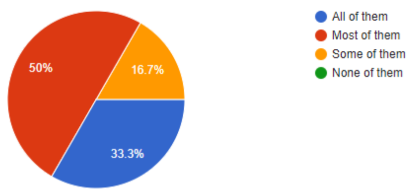
6 responses



Did you recognize these technologies?

Copy

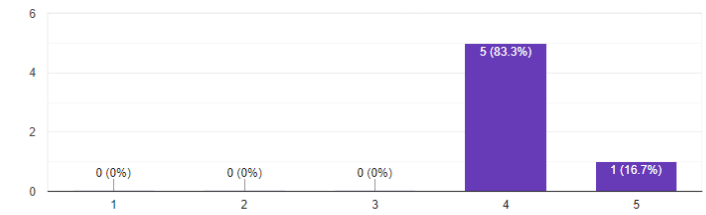
6 responses



Are the descriptions and examples in this research understandable?

Copy

6 responses



What aspects of this questionnaire did you appreciate or find most informative?

4 responses

- good summary of different technologies
- This is all very topical in finance departments at the moment.
- everything was really good and covered the subject
- The examples of RPA and AI use

What additional information or topics do you think should have been covered in this questionnaire? or improved upon?

4 responses

- some ideas related to AI solutions
- Further exploration surrounding some of businesses reasons for slow adoption or lack of awareness
- No improvements
- The co-working of the different innovations