

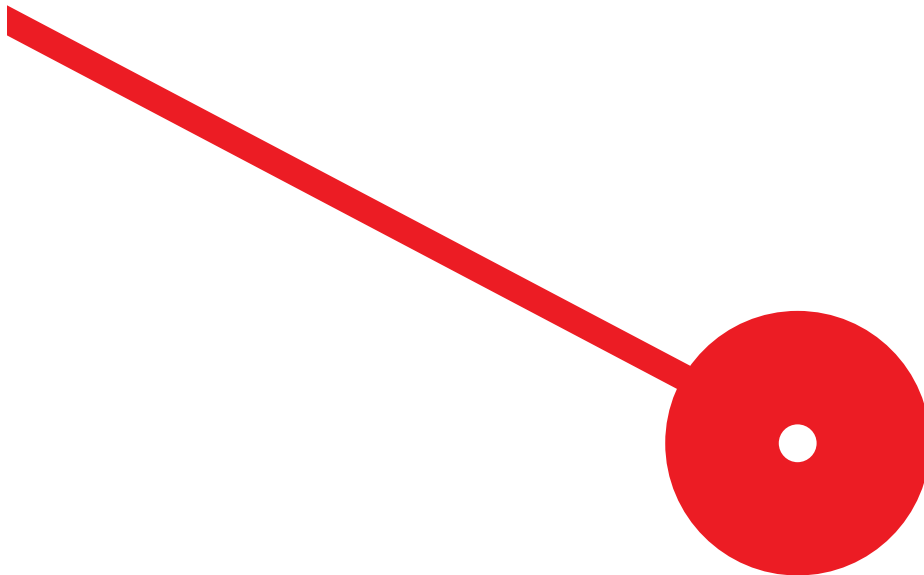


How Accounting Automation Tools influence Business Performance

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Dissertação de Mestrado apresentada ao Instituto Superior de Contabilidade e Administração do Porto para a obtenção do grau de Mestre em Contabilidade e Finanças, sob orientação da Professora Doutora Amélia Cristina Ferreira da Silva e da Professora Doutora Maria José Angélico Gonçalves



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Resumo:

A marcha do avanço tecnológico trouxe consigo uma era de transformação. À medida que as empresas navegam na complexa interação entre inovação digital e gestão financeira, a adoção de ferramentas de automação surgiu como um aspecto crítico da estratégia. Este estudo tem como objetivo investigar a influência dessas ferramentas no desempenho empresarial, examinando o impacto através de uma perspectiva quantitativa.

Objetivo: Explorar a relação dinâmica entre tecnologia e contabilidade no âmbito dos negócios e finanças. Esta pesquisa procura avaliar o grau de adoção de ferramentas de automação nas organizações e o impacto percebido da automação em vários aspectos do desempenho empresarial.

Metodologia: Através de um questionário, ferramentas estruturadas de recolha de dados e análise estatística, esta pesquisa reúne eficazmente informações de diversos inquiridos, desde contabilistas certificados a funcionários do departamento financeiro. Um modelo conceptual orienta a investigação, sustentando as questões de pesquisa e hipóteses.

Resultados: A pesquisa confirma o forte impacto positivo da intenção de utilizar ferramentas de automação na sua utilização em várias áreas. Enfatiza-se a importância da percepção de facilidade de uso e utilidade percebida na promoção da intenção de usar estas ferramentas. A responsabilidade social surge como um impulsionador notável da adoção, melhorando a qualidade da informação contabilística e dos sistemas de informação.

Significado: Este estudo é relevante para organizações que procuram aproveitar o potencial da automação enquanto enfrentam os potenciais riscos. Ao desvendar a complexa relação entre ferramentas de automação e desempenho empresarial, este estudo fornece percepções valiosas para orientar decisões estratégicas, alocar recursos e integrar tecnologia no domínio da contabilidade.

Em conclusão, este estudo oferece uma análise detalhada de como as ferramentas de automação moldam o desempenho empresarial, promovendo uma compreensão da evolução do cenário contabilístico numa era marcada pela inovação tecnológica.

Palavras chave: Automação Contabilística; Desempenho Empresarial; Transformação Digital; Qualidade da Informação Contabilística

Abstract:

The relentless march of technological advancement has ushered in an era of profound transformation in accounting practices. As businesses navigate the complex interplay of digital innovation and financial management, the adoption of Accounting Automation Tools has emerged as a critical facet of their strategies. This study investigates the multifaceted influence of these tools on business performance, scrutinizing the impact from a quantitative perspective.

Objective: Exploring the dynamic relationship between technology and accounting in the domain of business and finance, this research assesses the extent of Accounting Automation Tools' adoption within organizations and their perceived impact on business performance.

Methodology: Employing a questionnaire survey, structured data collection tools, and statistical analysis, this research efficiently gathers insights from diverse respondents, ranging from certified accountants to financial department employees. A conceptual model guides the investigation, underpinning research questions and hypotheses.

Findings: The study affirms the strong positive impact of intention to use Accounting Automation Tools on their utilization across various domains. The significance of perceived ease of use and usefulness in fostering intention to employ these tools is emphasized. Social responsibility emerges as a notable driver for adoption, enhancing the quality of Accounting Information and Information Systems.

Significance: This research is crucial for organizations harnessing automation's potential while addressing potential risks. By unraveling the intricate relationship between Accounting Automation Tools and business performance, this study guides strategic decisions, resource allocation, and technology integration in accounting.

In conclusion, this study offers a nuanced examination of how Accounting Automation Tools shape business performance, fostering an understanding of the evolving landscape of accounting in an era defined by technological innovation.

Key words: Accounting Automation; Business Performance; Digital Transformation; Accounting Information Quality

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List of Abbreviations

AI – Artificial Intelligence

AIS – Accounting Information System

AVE - Average Variance Extracted

BC – Blockchain

BD – Big Data

CR – Composite Reliability

CSR – Corporate Social Responsibility

ERP – Enterprise Resource Planning

FTE – Full-time employee

GBS – Global Business Services

HTMT – Heterotrait-Monotrait Ratio

ICT – Information and Communication Technology

IPA – Intelligent Process Automation

IQ – Information Quality

MIT – Massachusetts Institute of Technology

NFI – Normed Fit Index

OECD – Organization for Economic Co-operation and Development

RPA – Robotic Process Automation

SRMR – Standardized Root Mean Residual

TAM – Technology Acceptance Model

TEA – Triple-Entry Accounting

TLI – Tucker-Lewis Index

CHAPTER I - INTRODUCTION

Accounting Automation Tools have become increasingly popular in recent years, and understanding their impact on business performance is crucial. In the era of digital transformation, the world of accounting is undergoing a profound evolution. Traditional manual processes are giving way to advanced technologies, fundamentally reshaping the landscape of financial management. Central to this transformation are Accounting Automation Tools, a diverse array of software and systems designed to streamline accounting operations, enhance data accuracy, and empower businesses to make informed financial decisions (Abad-Segura & González-Zamar, 2020; Gonçalves, 2022; Joseph et al., 2023; Mahraz et al., 2019; Mihiu et al., 2023). As organizations across industries embrace the potential of Accounting Automation Tools, a pivotal question arises: How do Accounting Automation Tools influence business performance? It is this question that forms the nucleus of our inquiry, guiding our exploration into the dynamic relationship between automation and the bottom line of enterprises.

The significance of this study lies in the intersection of technology and business, where a convergence of forces is reshaping financial practices. The adoption of Accounting Automation Tools represents more than just a shift in how financial data is processed, it signifies a strategic pivot toward efficiency, agility, and enhanced decision-making (Abad-Segura & González-Zamar, 2020). Consequently, understanding the impact of these tools on business performance becomes paramount for companies and decision-makers alike.

While Accounting Automation Tools promise significant benefits, they also introduce complexities and challenges. The reliance on technology necessitates a fresh examination of business processes, workforce capabilities, and cybersecurity concerns. By delving into these complexities and opportunities, this study seeks to provide a holistic perspective on the transformative potential of accounting automation (Davenport & Dyché, 2013; Mahraz et al., 2019; Wongsim & Gao, 2011). In light of these considerations, this study aims not only to investigate the extent to which businesses are adopting Accounting Automation Tools and the factors influencing this adoption (Abad-Segura & González-Zamar, 2020; Slavinskaitė, 2022) but also to analyze the perceived impact of automation on various aspects of business performance, including efficiency, accuracy, decision-making, and competitiveness (Mahraz et al., 2019; Mihiu et al., 2023; Wongsim & Gao, 2011). We also look to assess the challenges and limitations associated with the implementation of Accounting Automation Tools and explore strategies for

mitigating these challenges (Ferreira et al., 2021). Ultimately, we look to contribute valuable insights that can guide organizations in their journey toward harnessing the potential of automation while addressing potential risks.

This study is organized into several chapters, each dedicated to a specific aspect of the research. Chapter 1, the current introduction, lays the groundwork by elucidating the research topic, significance, and objectives. In Chapter 2, we embark on a thorough examination of the existing literature. We delve into the theoretical foundations and empirical insights that underpin our research. By synthesizing knowledge from various sources, we construct a solid conceptual framework upon which our study is built. Chapter 3 introduces our conceptual model, a structured framework that outlines the relationships between key variables. This model forms the theoretical underpinning for our research questions and hypotheses, guiding our investigation into the intricate dynamics of automation tools and their impact on accounting and business performance. In Chapter 4, we detail our research methodology, elucidating the methods, tools, and approaches employed in this study. Our focus on questionnaire surveys, data collection processes, and the development of the survey instrument is articulated. We also discuss the significance of the chosen methodology and its suitability for our research objectives. Chapter 5 presents the empirical findings of our study. We report on the data collected through our questionnaire surveys and analyze the results in the context of our research questions and hypotheses. This chapter illuminates the practical implications of our research by translating data into insights. The final chapter, Chapter 6, provides a comprehensive analysis of our findings and offers conclusions based on our research objectives. We draw insights, make connections, and present a holistic view of the impact of Accounting Automation Tools on business performance and stakeholder perceptions. Our findings contribute to the evolving discourse on accounting technology and its implications for organizations and their stakeholders.

CHAPTER II – LITERATURE REVIEW

In the world of accounting, a digital revolution is quietly reshaping the way financial processes are conceptualized, executed, and managed. The relentless march of technology has started a transformation, not just within financial institutions, but across industries at large. This chapter embarks on a journey through the realm of Accounting Automation Tools, uncovering the driving forces, key advancements, and critical insights that are shaping this dynamic landscape. As organizations strive for greater efficiency, accuracy, and adaptability, the intersection of accounting and automation emerges as a cornerstone of modern business strategies. Delving into the latest research and industry trends, this chapter navigates the intricate contours of automation, setting the stage for a deeper exploration of its integration within the broader context of digital transformation.

2.1 Digital Transformation

Digital transformation is a hot topic in the business world. It is irreversible, inevitable and progresses extremely fast (Mahraz et al., 2019). Companies that want to stay competitive in this digital age must adapt and make significant changes to the way they exist, operate, and interact with their customers, not only reshaping and reorganizing their processes and operations but also redefining the role of humans in the value creation process (Mihu et al., 2023).

Despite being quite an old term, which first appeared in 2000 and was linked to digitization, digital transformation is still a relatively new concept, frequently used by scholars and organizations alike. However, depending on the context in which it is used, the concept changes form as the literature is still lacking an in-depth definition of the concept (Mahraz et al., 2019). The authors were able to identify three distinct elements that can be used to categorize the different definitions of digital transformation:

- **Technological** – when the concept of digital transformation is based on the use of digital technologies.
- **Organizational** – when the concept of digital transformation is based on the organizational processes or the creation of new business models.
- **Social** – when the concept of digital transformation is based on a phenomenon that is influencing all aspects of human life.

According to Huong and Duc (2023), the term has been mistakenly used in the past, which led to varying definitions. Several researchers believe that the term was coined in 2011 by Capgemini, a consulting firm working with the Massachusetts Institute of Technology

(MIT), referring to the ability to radically improve the performance or reach of a business by using technology. Likewise, both Westerman et al. (2014) and Bekkhus (2016) defined digital transformation as the process of enhancing business performance and expanding reach through the application of technology. Fors and Stolterman (2004) presented us with the first strict definition for the concept, describing it as the changes that digital technology brings about in all aspects of human life.

Disruptive technologies are progressively assuming a more prominent role across various sectors of modern business. The process of digital transformation is recognized as a fundamental driver that is reshaping how companies innovate, create value, and attain a competitive advantage (Jędrzejka, 2019). According to Abad-Segura and González-Zamar (2020) the use of digital technologies has significantly increased both the productivity and performance of companies by incorporating technological advances into specific company systems, enabling them not only to handle large amounts of data but also to turn this data into valuable decision-making information. By embracing digital technologies such as Big Data, companies looking to gain a competitive advantage enable a major success factor for operations management (Gölzer & Fritzsche, 2017). Mihiu et al. (2023) also states that companies must have a digital competency to stay strategically competitive in today's market. However, this is a rather long journey since companies must also be willing to embrace new technologies and continually adapt to digital changes to build success in the long run. This is particularly relevant as emerging technologies such as AI and Big Data are pushing for profound changes which are expected to impact all areas within a company (Mahraz et al., 2019). As such, Slavinskaitė (2022) believes that companies looking to be successful in this digital age need to understand their inefficiencies, know the result they are seeking and find motivation and willingness to change. The ever-increasing challenges that companies face make them look for ways to innovate and become more efficient. Emerging technologies are presenting opportunities to streamline and automate several processes that will allow for better decision-making which will then lead to improved efficiency and effectiveness (Mihiu et al., 2023). One of the challenges that has led to significant changes regarding digital transformation was the COVID-19 pandemic. According to the OECD (2021) over 60% of businesses have increased their use of digital technologies due to COVID-19. Mihiu et al. (2023) has found that the digital business landscape has undergone several significant changes because of the pandemic. Primarily, there has been a rapid acceleration toward digital business

models which encompasses a surge in e-commerce, digital transactions, and virtual services, as businesses have had to adjust to cater to the requirements of remote customers. Subsequently, remote work and digital collaboration tools have gained greater prominence, driven by the need for companies to sustain their operations with employees working from home. Lastly, the pandemic has propelled an upswing in the adoption of digital technologies aimed at enhancing operational efficiency and bolstering supply chain resilience.

2.2 Accounting Information Quality

In the realm of modern business, accounting has evolved far beyond its traditional role. With the pervasive influence of automation and emerging technologies, the landscape of accounting is undergoing a profound transformation. This chapter delves into the impact of these technologies on accounting information quality and how it, in turn, shapes business performance. We explore how automation and emerging technologies enhance data quality and reshape the dynamics of organizational success in the digital age.

Accounting plays an indispensable role within the broader information system framework. It serves as the primary source of managerial information, facilitating sound decision-making to attain organizational objectives (Geddes, 2020). In modern organizations, accounting information systems (AIS) are instrumental in furnishing crucial financial data for informed decision-making (Deepak & Jain, 2017). As such, information quality (IQ) has surfaced as a pressing concern in contemporary organizations. The management of IQ holds pivotal significance in the realm of AIS adoption. The level of IQ bears substantial implications for all accounting processes and profoundly influences decision-making in business (Wongsim & Gao, 2011). As data warehouses proliferate and stakeholders gain direct access to information from diverse sources, the importance of high-quality information has become increasingly apparent (Lee et al., 2002). In fact, a well-designed AIS can confer a competitive advantage upon an organization, exerting a positive impact on firms' performance (Oweis, 2022). Conversely, the failure to implement such a system can have detrimental effects on organizational success (Al-Hiyari et al., 2013). Furthermore, under conditions of advanced manufacturing technology, strategic alignment between management accounting information systems and organizational objectives contributes significantly to enhanced production performance (Choe, 2017).

An effective accounting control system assumes paramount importance in bolstering firms' competitiveness, performance, and long-term success. Such a system upholds adherence to accounting standards and can foster sustainable value, advantages, and contributions in a complex business landscape. This system not only enhances a firm's capabilities but also serves as a strategic mechanism for delivering qualified accounting information, creating incremental business value, and promoting sustained organizational success. This aspect stands as a cornerstone of a firm's enduring prosperity, facilitating efficient capital allocation in the market and offering investors a higher degree of protection (Phomlaphatrachakom, 2020). The prevalence of routine tasks in daily operations often results in unavoidable errors, leading to both time wastage and financial losses for companies. The automation of business processes and delegation of routine functions can significantly enhance operational efficiency and yield cost savings (Slavinskaitė, 2022).

2.3 Accounting Automation Tools and Emerging Technologies

In the contemporary business landscape, the field of accounting is undergoing a profound transformation, driven by advanced technologies and innovative automation tools. This transformation encompasses Robotic Process Automation (RPA), AI, Big Data analytics, and Blockchain integration, collectively reshaping accounting practices. These technologies are no longer optional, but a necessity for organizations seeking to thrive in the digital age (Slavinskaitė, 2022). Automation tools streamline tasks, allowing professionals to focus on value-added activities. Emerging technologies provide real-time analytics, predictive capabilities, and enhanced security. This chapter examines how RPA, AI, Big Data, and Blockchain are redefining accounting in the digital era, by promising efficiency, accuracy, and strategic insight.

The digital transformation sweeping across industries has extended its reach into the world of accounting, ushering in a new era where Information and Communication Technology (ICT) intertwined with emerging technologies take centre stage. This evolution has the potential to reshape the accounting profession, a transition marked by contrasting opinions. While ICT offers swiftness and reduces error rates, it lacks the finesse of critical thinking. At the heart of this transformation lies the pivotal role of digital skills among professionals, as they navigate the terrain of emerging technologies within organizations (Ferreira et al., 2021). In the modern accounting landscape,

technology proficiency is indispensable for comprehending the intricacies of accounting systems and processes. The automation of routine bookkeeping tasks not only enhances working conditions but also injects a sense of purpose into professionals' roles. It paves the way for more engaging work, time and cost savings, and a migration from manual data entry to automated operations. This shift towards cyberspace storage and automated data entry marks a stride towards standardization, data integration, and digital document processing, essential facets of enhanced accounting practices embraced by businesses aiming for competitive edges in both local and global markets (Slavinskaitė, 2022).

Undoubtedly, technology, including emerging technologies, holds profound implications for both accounting students and the profession (Chiu et al., 2019). The landscape of accounting tools has seen remarkable developments, streamlining financial operations' registration and maintenance processes (Abad-Segura & González-Zamar, 2020). Big Data, Cloud Computing, the Internet of Things, and Blockchain represent the technological pillars of digital transformation, exerting significant influence (Mahraz et al., 2019). Among the technologies poised to disrupt the sector are AI, machine learning, cloud computing, and RPA (Jędrzejka, 2019). However, the true challenge lies in adapting operational and decision-making processes to harness the potential of these new technologies and methods (Davenport & Dyché, 2013). The adoption of these technologies yields a myriad of benefits, from error reduction, fraud risk mitigation, and workflow automation to Big Data analysis, cost reduction, and enhanced information reliability. Rather than viewing these technologies as threats, accounting professionals are increasingly recognizing them as opportunities to create value to organizations, embracing new roles within organizations. The prevailing perspective is one of optimism, digital transformation is more of an opportunity than a threat for accounting and accountants (Ferreira et al., 2021).

2.3.1 Robotic Process Automation

In an era defined by rapid technological advancements, businesses and organizations are continually seeking innovative solutions to enhance their operational efficiency, reduce costs, and optimize resource allocation. RPA has emerged as a transformative technology with the potential to revolutionize traditional workflow management and streamline repetitive tasks. RPA leverages the capabilities of software robots, or "bots", to automate rule-based processes, liberating human employees from mundane and time-consuming

activities (Accenture, 2016; Cooper et al., 2019; Deloitte, 2015; Jędrzejka, 2019; Willcocks et al., 2015; Zhang et al., 2023)

According to Deloitte (2015), the concept of RPA can be succinctly defined as the utilization of specialized software, often referred to as a 'robot', with the primary objective of capturing and interpreting pre-existing applications. This technology is designed to facilitate essential functions such as transaction processing, data manipulation, and seamless communication across diverse information technology systems. In the context of their report, Deloitte articulates RPA as a tool that demonstrates its prowess in enhancing operational efficiency through the automation of various tasks that involve interactions with digital systems. A similar perspective is presented by Fernandez and Aman (2018), who see RPA as a business process automation system that uses software tools to interact with existing applications and replace humans. Jędrzejka (2019) simply describes RPA as an alternative to traditional automation. Unlike traditional automation methods, which often require extensive programming and significant ICT involvement, RPA offers a more accessible approach. It allows non-technical users to configure software robots to mimic human interactions with digital systems, applications, and data sources. This democratization of automation has opened avenues for efficiency gains across various industries, ranging from finance and healthcare to manufacturing and customer service (Jędrzejka, 2019; Zhang et al., 2023).

In Deloitte's 2015 survey, RPA implementation emerged as a significant priority for clients, gaining prominence within their organizations. The survey highlighted process automation as a leading technology concern among shared services and Global Business Services (GBS) leaders, predicted to be pivotal in the forthcoming year. Additionally, elevating automation levels ranked as the second most crucial strategic priority. This signals a shift from traditional automation approaches, suggesting that future automation advancements will surpass incremental Enterprise Resource Planning (ERP) enhancements. Augmenting automation retains its second-tier strategic focus for shared services and GBS leaders. The survey also foresees a substantial rise in RPA adoption by 2017, with over half of surveyed shared services leaders planning greater integration. As a result, automation solidifies its position as a prevalent concern echoing through shared services and GBS leaders' strategic agendas. This ongoing momentum reflects automation's long-term strategic importance, poised to be a significant focus for the coming decade (Deloitte, 2015). Accounting firms are already actively implementing

RPA in the services they provide to clients to elevate quality and enhance profits. This includes heightened profitability in fixed-fee projects and amplified competitiveness in variable-fee project bids due to the cost-effectiveness and efficiency of bots. The economic advantages of automated processes, marked by reduced operational costs and swifter task execution compared to human counterparts, underscore this benefit. Notably, concerns linger within the accounting sector regarding the potential emergence of a "race to the bottom" phenomenon in fee structures due to RPA deployment. Recognizing the significance of this issue, accounting firms are diligently investigating its potential impact and implications (Cooper et al., 2019). The evolution of RPA is closely intertwined with the evolution of AI and automation technologies. According to Jędrzejka (2019) employing the unattended approach for RPA implementation, particularly when incorporating AI, Cloud, or Blockchain integration, incurs higher expenses, complexity, and a lengthier timeline compared to the attended version. Nevertheless, even with these considerations, the costs and time investment remain lower in comparison to the conventional approach of full automation. Cooper et al. (2019) found that the use of RPA will continue to grow, as businesses explore new methods to integrate it into their operational strategies. Moreover, RPA's adoption might gain even more momentum as it embraces the integration of AI. The study defined RPA as a stepping-stone to more sophisticated automation, envisioning a future where RPA will progressively enhance their intelligence and adeptness, enabling them to perform intricate tasks demanding human-like judgment. This stands in contrast to the current scenario, where most current RPA tasks are rule-based and entail minimal to no human judgment.

In the face of these shifting dynamics, the anticipated advancement of automation in the public accounting industry to include forms of AI that can make judgment-based decisions raises the concern of how the accounting profession will evolve to avoid becoming obsolete. Since there is significant potential to automate accounting processes through RPA, it is anticipated that robots will take over a substantial share of tasks traditionally handled by accountants. Such a transformation has the potential to render entry-level accounting positions obsolete, while concurrently giving rise to new roles for accountants. In the upcoming landscape, accountants' duties will transcend basic bookkeeping and financial reporting, encompassing more strategic realms such as business advisory and spearheading the RPA-driven transformation (Cooper et al., 2019; Jędrzejka, 2019). According to Cooper et al. (2019), the Big 4 accounting firms are aware

of this possibility and are being proactive in terms of making strategic changes to protect themselves from complete automation. Fernandez and Aman (2018) also found that RPA technology brings noteworthy effects on both individuals and organizations. However, its introduction can inadvertently trigger competition between humans and robots, instilling job security concerns among employees. This underscores the significance of addressing technology acceptance issues effectively. Organizations adopting RPA for human replacement could inadvertently spark competition between the two, necessitating thoughtful management (Fernandez & Aman, 2018; Jędrzejka, 2019; Slavinskaitė 2022). Opinions on RPA's effect on future skill demand vary. While some acknowledge the value of computer coding familiarity, many believe that extensive programming isn't required due to RPA's user-friendly nature and the involvement of programming experts for complex implementations. Accounting professionals are now sought with a mix of education, credentials, and skills, including data analysis and business intelligence. RPA's extensive impact is reshaping job roles across industries, but the general view is that RPA's effect is positive, with technological progress seen as an avenue for seizing opportunities, not a looming threat (Cooper et al., 2019; Ferreira et al., 2021; Fernandez & Aman, 2018; Jędrzejka, 2019; Zhang et al., 2023).

The integration of bots has yielded a significant upswing in quality and operational efficiency. Despite being a relatively new technology, organizations have reported impressive reductions of 70 to 80 percent in processing times, translating to a reduction of over a million human work hours in 2017 alone. What once consumed two man-days of effort can now be completed in a mere 17 seconds (Cooper et al., 2019). The robots remain operational and accessible for case processing round the clock, every day of the week, and since companies are required to comprehend their processes prior to automation, process analysis often unveils areas of weakness that can be rectified, ultimately leading to enhancements in both efficiency and overall effectiveness. There has been a general improvement in quality, primarily attributed to accountants being empowered to concentrate on value-added tasks, while bots proficiently manage the repetitive, rule-based tasks that once occupied them. (Cooper et al., 2019; Deloitte, 2015).

While the technology itself is notable, the primary benefit of RPA lies in freeing human resources to concentrate on tasks involving judgement, decision-making, and interpersonal interactions with employees or customers. According to Jędrzejka (2019) the predominant advantages frequently associated with RPA are:

- Cost reduction.
- Increased process speed.
- Improved process control and performance visibility.
- Higher quality data (accuracy, consistency, compliance).
- Continuous operation (24 hours a day).
- Improved process flexibility for easier scaling.
- The relative ease of implementation.
- Geographical and cultural independence.
- Positive impact on employees.

Robots, especially in onshore locations like the UK, cost only a fraction of a full-time employee (FTE). This transition cuts down overheads and fixed expenses tied to employing an FTE, leading to heightened productivity, lower error rates, and subsequently reduced risks. This shift toward automation approaches a bot accuracy of 99.9 percent, a substantial increase from the usual human performance around 90 percent, which ultimately bolsters customer satisfaction and enhances overall quality (Cooper et al., 2019; Deloitte, 2015; Fernandez & Aman, 2018; Slavinskaitė, 2022). Reducing errors in work processes is a universally desirable goal, contributing to smoother services and organizational performance enhancement. RPA stands out by offering round-the-clock availability and excellent features that bolster organizational effectiveness. Unlike other automation solutions, RPA has democratized automation by making it affordable and scalable. It particularly benefits processes that were previously deemed either impossible or too complex to automate traditionally, due to high deployment costs (Fernandez & Aman, 2018; Jędrzejka, 2019).

2.3.2 Artificial Intelligence

In the ever-evolving landscape of business technology, RPA is not the only acronym that has become synonymous with transformation. While RPA laid the foundation for intelligent automation, it is AI that takes us a step further into the realm of cognitive computing and autonomous decision-making. As we have explored in the previous section, RPA revolutionized how repetitive, rule-based tasks are handled. Now, it is time to meet its more sophisticated sibling, AI. While RPA excels in automating manual processes, AI adds a layer of intelligence, enabling machines to think, learn, and make human-like decisions.

The term “Artificial Intelligence” was coined by John McCarthy, Marvin Minsky, Nathaniel Rochester, and Claude E. Shannon in a proposal, dated August 31, 1955, for the renowned Dartmouth Conference, marking the birth of AI (Hasan, 2021; Luo et al., 2018). Since then, several authors have tried to define AI. Martinez (2019) argued in his definitional analysis of AI that a broadly adaptable definition, one capable of accommodating the advancements in autonomous AI, could be universally applied across diverse fields and applications. Zhang et al. (2020) defined AI characterizing it as the result of successful applications of Big Data and machine learning technology to comprehend both historical data and forecast the future using extensive data sets. Hasan (2021) stated that AI, according to most definitions, refers to the combination of hardware and software that can learn, think, adapt, analyze, make decisions, and perform complex tasks, just like how our human brains do. Likewise, Li and Zheng (2018) stated that at its core, AI is like a computer's attempt at mimicking the way human brains think and gather information. AI acts as a bridge, turning regular information systems into smart ones, which leads to increased automation and optimization. While RPA specializes in automating structured tasks, AI is effective in handling less structured or unstructured tasks. Consequently, the concept of Intelligent Process Automation (IPA) emerges. IPA can be thought of as a pre-configured software framework that seamlessly integrates RPA, AI, and other emerging technologies. Its primary purpose is to streamline processes, activities, and tasks across various software systems, thereby automating repetitive and routine functions with minimal human intervention. IPA's core components encompass RPA and AI, however, it also harmonizes with various complementary technologies, including drones, workflow management systems, cloud services, Blockchain, the Internet of Things, analytics, Big Data, and mobile technologies. This comprehensive integration transforms IPA into an ecosystem of evolving technologies working cohesively to achieve adaptable and intelligent service automation (Zhang, 2019).

While the individual components within IPA exist independently, their synergy and integration collectively enhance the potential of each constituent, thereby advancing the state of automation. By the middle of 2017, non-assurance organizations had initiated the integration of RPA and AI by leveraging RPA to input unstructured data into AI systems, subsequently utilizing AI to convert this unstructured information into structured data compatible with RPA functionalities. IPA presents several avenues for enhancing audit efficiency and effectiveness. Firstly, it has the potential to significantly reduce the time

allocated to repetitive and routine audit tasks. Additionally, it can liberate auditors from mechanical duties, which can then be automated, enabling auditors to allocate more time to areas of high risk that necessitate professional judgement. IPA's capacity to automate structured tasks also contributes to a reduction in human errors, as bots can execute these tasks with greater speed and precision than human auditors. Moreover, IPA offers the advantage of comprehensive assurance of financial statements by scrutinizing the entire dataset of the client, subsequently selecting, and investigating the most suspicious items. Furthermore, it empowers auditors to make more informed judgements through the assistance of cognitive computing. Finally, IPA strengthens predictive analytics by enabling data created and collected by RPA to be channeled to a data analytics or machine learning module within the IPA, facilitating the prediction of future client behavior. However, the predominant unintended consequence associated with the incorporation of AI in auditing is the potential overreliance on automation systems at the expense of human judgement. This overreliance may lead to a de-skilling effect, which, in turn, could impair decision-making and reduce the overall effectiveness of the audit process (Zhang, 2019).

In the realm of accounting, AI remains relatively new, but its adoption is swiftly progressing. Scholars such as Baldwin et al. (2006) and Greenman (2017) have documented AI's presence in accounting for over a quarter-century, tracing its roots back to the 1980s. The integration of AI technology into the accounting sector is an undeniable and transformative trend poised to reshape the industry significantly (Luo et al., 2018). It is important to note that AI is a multifaceted technology, and not all its applications are directly pertinent to accounting (Kroon et al., 2021). In a broader business context, AI serves three main purposes: automating processes, data analysis for insights, and enhancing connections with stakeholders. In accounting and auditing, the adoption of AI is expected to bring various advantages such as improved efficiency, accuracy, productivity, decision-making, and communication. It also offers structured audit processes, better staff training, and shorter decision times. However, this progress is accompanied by challenges including income inequality, job displacement, and workforce skill development (Hasan, 2021). Automation, as highlighted by Greenman (2017), has the potential to relieve accountants of time-consuming tasks, allowing them to focus on consulting and higher-value work. This shift in the accounting landscape, facilitated by AI, enhances efficiency, and alters the traditional division of labor. While

AI's extensive application in accounting reduces the need for many traditional roles (Li & Zheng, 2018), it can't replace human capabilities like reasoning, expressing emotions, professional skepticism, and judgement (Hasan, 2021). In this AI era, accountants delegate complex tasks to software, greatly improving efficiency, reducing errors, enhancing competitiveness, and promoting industry transformation (Li & Zheng, 2018). Numerous firms are actively seeking individuals well-versed in AI technology (Damerji & Salimi, 2021; Kroon et al., 2021) because AI's progress is approaching a pivotal moment where it could reshape the accounting profession worldwide. Consequently, staying informed about AI and its interdisciplinary advancements is imperative, and it is possible to anticipate the emergence of professional hybrids who will lead the field. The development and integration of AI into accounting and auditing represents a double-edged sword, with future outcomes subject to change over time (Hasan, 2021). However, one thing is certain, the accounting and auditing profession is poised for a profound transformation. AI marks the beginning of this renewal, adapting to the evolving business environment and changing management demands. The once-feared threat of labor displacement is now more a myth than a future reality. Instead, the profession is shifting from concerns about automating accounting tasks to embracing AI's capabilities for mutual benefit. As the accounting role converges with management functions due to business complexity and the importance of accounting information for decision-making, the risk of rising unemployment in the accounting profession due to computerization is minimal (Kokina & Davenport, 2017; Stancheva-Todorova, 2018; Sutton et al., 2018).

2.3.3 Big Data

With the proliferation of digital technologies, the sheer volume, velocity, and diversity of data have led to the emergence of a phenomenon known as Big Data. Mahraz et al. (2019) describes Big Data as a large or complex amount of continuously changing data, that no longer can be interpreted with conventional analysis methods and data processing tools. Similarly, McKinsey Global Institute (2011) refers to Big Data as datasets whose size is beyond the ability of typical database software tools to capture, store, manage, and analyze. Both these definitions are subjective and do not define how big a dataset needs to be to be considered Big Data. According to McKinsey Global Institute (2011), the underlying assumption is that, with the progression of technology, the threshold for what constitutes Big Data will also rise over time.

Big Data is part of our day-to-day life. (Zikopoulos et al., 2011). It can be generated by online transactions, emails, videos, audios, images, posts, search queries, health records, social networking interactions, science data, sensors, and mobile phones (Sagiroglu and Sinanc, 2013), and these are just a few examples. However, this data is raw and comes in several different formats, which makes processing it in a traditional relational system impractical or impossible (Zikopoulos et al., 2011). In 2001, Doug Laney introduced the 3 V's concept to describe the key challenges and characteristics of Big Data. The 3 V's are Volume, Variety, and Velocity and comprise the three main data management challenges:

- **Volume** refers to the sheer size of the data generated and collected, which can range from terabytes to petabytes or even exabytes.
- **Variety** implies that data comes in various formats and types. It can be structured (like traditional data, usually easily sorted), semi structured (doesn't fit into traditional data, but contains some level of structure and organization) or unstructured (text, images, videos, without a specific and predefined format).
- **Velocity** refers to the speed at which data is generated, collected, and processed.

According to Zikopoulos et al. (2011), everywhere we look, we see domains with velocity, volume, and variety combined to create Big Data. However, the true power of Big Data lies not just in its size, variety or speed, but in its potential to create highly specific segmentations and to tailor products and services to precisely fulfill those needs (McKinsey Global Institute, 2011). Kubina et al. (2015) showed that by utilizing Big Data, companies can gain a big competitive advantage and get ahead of their rivals. Even though it is less understood, Big Data offers businesses much bigger growth potential than traditional technologies. The authors highlighted the fact that Big Data enables increased transparency and broader, deeper, and more precise insights, therefore enhancing the decision-making process. Furthermore, it provides companies with a clearer and more complete image of their customers and consequently offers more customized products and services. In essence, companies take advantage of Big Data by transforming raw data into actionable insights that drive innovation, improve efficiency, and enhance decision-making processes across various aspects of their operations (Kubina et al., 2015). Likewise, Sagiroglu and Sinanc (2013) emphasized that Big Data analytics allow for a better targeted marketing, direct business insights, client-based segmentation and the faster recognition of sales and market chances. At the same time,

Davenport and Dyché (2013) state that one of the advantages of Big Data is time reduction through the rapid data capture, aggregation, processing, and analytics. Companies can interact with customers in real time, using analytics and data derived from the customer experience.

Furthermore, Davenport and Dyché (2013) stated that Big Data has the potential to lead to significant decreases in costs, considerable enhancements in the time required to perform a task, or the introduction of a new product and service. Hence why, organizations with a focus on cost reduction opted for embracing Big Data tools primarily within the ICT organization, mainly based on technical and economic considerations. According to Davenport and Dyché (2013), Big Data technologies encompass a range of hardware and software architectures, such as clustered parallel servers utilizing Hadoop/MapReduce, in-memory analytics, in-database processing, among other approaches. All these technologies are considerably faster compared to earlier generations of data management and analysis tools. Tasks that used to require hours or days in the past can now be completed in a matter of seconds. In addition to the faster technologies, new analytical methods and machine learning techniques are being utilized to generate insights at a much faster rate (Davenport and Dyché, 2013).

While the proliferation of Big Data promises remarkable insights and transformative potential, it is important to recognize the challenges and disadvantages that come hand in hand with its application. Sagioglu and Sinanc (2013) identified several potential obstacles when it comes to implementing Big Data analytics. These challenges include financial constraints, the difficulties in designing effective analytical systems, the inadequacy of current database software for analytics tasks, and the availability of experienced personnel. McKinsey Global Institute (2011) also agrees that the creation of value from Big Data will be significantly constrained by a shortage of talent, particularly of people with deep expertise in statistics and machine learning. Additionally, the shortage extends to managers and analysts who can proficiently utilize insights from Big Data to effectively manage companies. For Appelbaum et al. (2017), the emergence of Big Data has changed the management accountant's task. A business utilizing Big Data would have invested significant resources to collect, process, prepare, and eventually analyze it and consequently expects deeper insights and knowledge as results. Another critical disadvantage lies in the complexities of data privacy and security. According to McKinsey Global Institute (2011), the growing economic importance of Big Data raises

many legal concerns, particularly because data are fundamentally different from the conventional assets. Contrary to physical assets, data can be perfectly copied, easily combined with other data, and simultaneously used by more than one person. This gives rise to several questions on intellectual property rights, such as “Who owns a piece of data and what rights come attached with a dataset?”, “What defines fair use of data?” or “Who is responsible when an inaccurate piece of data leads to negative consequences?”. To capture the full potential of Big Data, these legal issues need to be clarified (McKinsey Global Institute, 2011).

According to Ibrahim et al. (2021), Big Data can also provide several remarkable development opportunities in the accounting field, as it combines various and inconsistent data sources into one integrated information accounting system. It is an excellent opportunity to improve integrated reporting and to document both financial and non-financial information. Moreover, managers and investors need to have access to financial information in a timely manner, to assess and measure the current and potential risks efficiently and to disclose high-quality risk information. Big data can play a significant role in providing a massive amount of internal and external data to managers in real-time, and therefore allow a better risk assessment and measurement.

2.3.4 Blockchain

In today's dynamic business environment, Blockchain technology has emerged as a disruptive force, poised to revolutionize accounting practices and, consequently, business performance. Blockchain technology currently occupies a prominent position on the Gartner hype cycle. It comes as no surprise that this technology, primarily recognized as the foundation of cryptocurrencies like Bitcoin, possesses the capacity to revolutionize entire sectors of the economy (Mahraz et al., 2019). This chapter explores how Blockchain, with its core attributes of transparency, immutability, and automation, shapes the quality of accounting information and influences business outcomes. Blockchain's decentralized ledger, cryptographic security and smart contract capabilities have ushered in a new era of trust and efficiency in accounting. By creating a tamper-resistant and transparent ledger accessible to authorized participants, Blockchain enhances the integrity of accounting data (Gonçalves, 2022; Joseph et al., 2023). Transactions are securely recorded and become part of an immutable historical record. In the realm of accounting, this transparency and accuracy streamline processes, reduce costs, and minimize errors (Hasan, 2021; Zhang et al., 2020). Smart contracts automate financial agreements, further

increasing efficiency (Mahraz et al., 2019). In summary, Blockchain's integration into AIS represents a paradigm shift, bolstering trust and accuracy in financial data while enhancing operational efficiency. As we navigate this chapter, we will uncover the transformative potential of Blockchain, setting new standards for financial transparency and informed business performance.

Blockchain technology, as implied by its name, is essentially a series of interconnected blocks that securely and transparently store transaction information. These blocks are validated by users within a decentralized network on the internet. Utilizing Blockchain has the potential to establish absolute certainty regarding the origin and ownership of goods and assets. In the realm of accounting, Blockchain serves as a ledger where records undergo distributed validation and remain immutable, impervious to deletion or alteration. Its adoption holds the potential to significantly enhance the security and transparency of accounting operations (Gonçalves, 2022). The Blockchain revolution can be categorized into three distinctive phases: Blockchain 1.0, 2.0, and 3.0. Blockchain 1.0 primarily encompasses cryptocurrencies and digital payment systems. In contrast, Blockchain 2.0 extends its reach to the economic market, including transactions involving stocks, bonds, and smart contracts. Finally, Blockchain 3.0 shifts its focus towards advanced applications, such as digital voting, digital health records, and digital art, building upon the foundations laid by Blockchain 1.0 and 2.0 (Secinaro et al., 2021).

The Blockchain ecosystem relies on cryptographic hashes that symbolize input information. Data encryption, a crucial component of Blockchain technology, serves to safeguard individual privacy. Consequently, cryptographic hashes play a pivotal role in preserving data integrity, ensuring the accuracy and validity of information. These cryptographic foundations provide the framework for Blockchain-based accounting systems. In this context, the traditional double-entry accounting system is augmented by Blockchain, introducing the concept of triple entries, which involves cryptographic and hashing mechanisms. These triple entries record credit and debit data, which are then transcribed within the system, accessible not only to the involved parties but also to external entities utilizing specific bookkeeping systems (Secinaro et al., 2021).

Triple-entry accounting (TEA) denotes a concept where a Business-to-Business transaction is documented in three separate books: 1) the first party's records, 2) the second party's records, and in a shared ledger that remains visible not only to the involved parties but also to the public, governed by defined rules (Joseph et al., 2023). According

to Cai (2021), in 2016, Deloitte published a concise article proposing that the implementation of TEA in conjunction with Blockchain technology could potentially revolutionize the field of accounting. It becomes evident that TEA represents a novel and more efficient approach to addressing the fundamental trust and transparency challenges that currently afflict conventional accounting systems. When adequately implemented, the integration of Blockchain into TEA has the potential to bring about a substantial transformation in the field of accounting (Cai, 2021). However, it's important to note that some experts, like Coyne and McMickle (2017), express skepticism about the feasibility of implementing Blockchain in accounting. They outline three significant challenges that impede the widespread application of Blockchain technology in accounting:

- **Confidentiality Concerns:** Public blockchains, which are inherently transparent, may not align with the need for confidentiality in certain accounting contexts.
- **Retroactive Manipulation:** Firms might possess the ability to retroactively manipulate private blockchains, compromising data integrity.
- **Limited Transaction Verification:** The blockchain's transaction verification capabilities may have limitations that hinder its effectiveness in accounting processes.

The widespread desire to adopt Blockchain technology stems from its multitude of advantages, including decentralization, persistence, anonymity, and auditability. While applicable across various industries, Blockchain technology is especially regarded as a powerful tool within the realm of accounting. It is noteworthy that Blockchain has the potential to enhance productivity and fundamentally reshape traditional accounting and bookkeeping practices. Despite this potential, accounting systems have been slower to adopt digital innovations compared to other industries. This hesitancy can be attributed to stringent legal requirements that mandate the utmost accuracy and integrity of data and information in accounting practices (Joseph et al., 2023). Another major obstacle to the integration of Blockchain in accounting is the knowledge gap that exists between Blockchain developers and accounting experts. On one hand, accounting professionals and academic researchers often lack comprehensive training in Blockchain concepts and infrastructure, resulting in a deficiency of the requisite knowledge and skills for effective engagement. On the other hand, for Blockchain to bring about substantial changes in business processes, including accounting, Blockchain experts require greater support

from the accounting profession and academia in terms of specialized business and accounting knowledge (Cai, 2021).

CHAPTER III – CONCEPTUAL MODEL, RESEARCH QUESTIONS AND HYPOTHESES

In this chapter, we lay the foundation for our research. We begin by presenting our conceptual model, a framework that guides our study. From this model, we derive our research questions and hypotheses. This chapter serves as a roadmap for our exploration of the impact of accounting automation on business performance.

3.1 Research Questions

According to Souza and Souza (2011), the research question is at the heart of research and stands as the initial and pivotal stride in the research process. It should possess significance, specificity, and avoid clear or routine solutions. Consequently, the research question for this study will be:

- How do Accounting Automation Tools influence Business Performance?

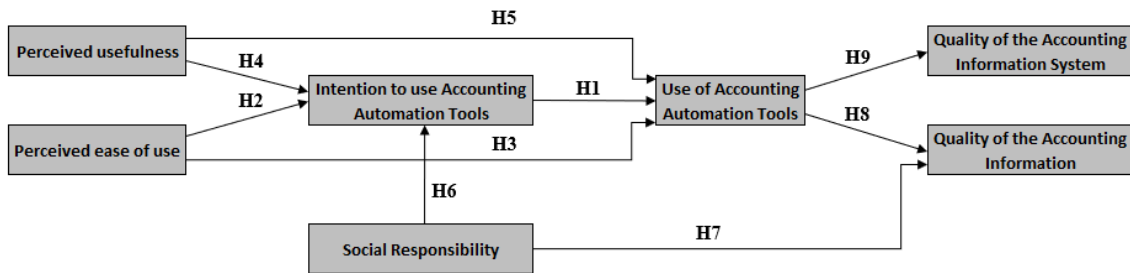
To address the research question, the following specific research questions have been defined:

- Do Accounting Automation Tools influence the quality of accounting information?
- How do ease of use and usefulness impact the adoption of Accounting Automation Tools?
- Does Social Responsibility play a role in the intention to use Accounting Automation Tools?
- What is the relationship between the use of Accounting Automation Tools and accounting information quality?

3.2 Proposed Conceptual Model

Our research is founded upon a comprehensive conceptual model, informed by established theories and empirical evidence. This model comprises several key components, each of which plays a significant role in our exploration of the dynamic relationship between technology and accounting in the domain of business and finance.

Figure 1 - Conceptual Model



Source: Own elaboration

- Perceived usefulness:** At the core of our model is the concept of perceived usefulness, as originally defined by Davis (1989). This variable represents the extent to which individuals in the accounting domain believe that Accounting Automation Tools hold value and benefit their work. Perceived usefulness is a cornerstone of our model, embodying the driving force behind the adoption of technology in accounting.
- Perceived ease of use:** Complementing perceived usefulness, as outlined by Davis (1989), is the variable of perceived ease of use. This addresses the degree of ease and convenience associated with using Accounting Automation Tools. It is intrinsic to our model as it recognizes the pivotal role of user-friendliness in technology acceptance.
- Intention to use Accounting Automation Tools:** The intention to use Accounting Automation Tools, as drawn from the work of Venkatesh et al. (2003), is a significant precursor to actual adoption. This variable reflects individuals' expressed willingness and inclination to employ these tools in their accounting practices. It is central to our model as it signifies the initial step towards technological integration.
- Use of Accounting Automation Tools:** Actual use, as defined by Davis (1989), is a fundamental outcome variable in our model. It represents the tangible

implementation of Accounting Automation Tools in the workplace. It is vital as it encapsulates the real-world application of technology within accounting.

- **Social responsibility:** An integral component introduced in this study, as stated by Patten (2002), encompasses the organization's commitment to ethical, sustainable, and socially responsible practices. It has the potential to influence technology adoption and data quality.
- **Quality of the Accounting Information System:** The quality of the AIS, a construct from the Delone and McLean (1992) Information Systems Success Model, is a critical intermediary variable in our model. It signifies the integrity, efficiency, and reliability of the system that manages accounting data. It is crucial as it mediates the relationship between the use of automation tools and the quality of accounting information.
- **Quality of the Accounting Information:** Quality of accounting information, another construct from the Delone and McLean (1992) Information Systems Success Model, is the ultimate outcome variable in our model. It denotes the reliability and accuracy of financial data generated within the accounting system. It is of paramount importance as it reflects the goal of accounting practices – to produce high-quality financial information.

Within our model, these variables are not isolated entities but are interconnected. Perceived usefulness and perceived ease of use influence the intention to use Accounting Automation Tools (Davis, 1989; Venkatesh et al., 2003). This intention, in turn, drives actual use (Davis, 1989). The use of automation tools impacts the quality of the accounting information (Abdelraheem et al., 2021), which is also influenced by Corporate Social Responsibility (CSR) (Patten, 2002). These relationships represent the intricate web of interactions that our study seeks to unravel.

Table 1: Constructs

Construct	Items	Source
Perceived ease of use	Learning to operate ... would be easy for me	Davis (1989)
	It is easy to perform tasks using ...	
	It would be easy to become skillful using ...	
	I would find it easy to get ... to do what I want it to do	
	My interaction with ... would be clear and understandable	
Actual use	Robotic Process Automation	Davis (1989)
	Artificial Intelligence	

Construct	Items	Source
	Big Data	
	Blockchain	
Intention to use	Assuming that ... would be available on my job, I predict that I would use it on a regular basis	Davis (1989)
	I would prefer using ... to my current way of working	
Perceived usefulness	Using ... in my job would enable me to accomplish tasks more quickly	Davis (1989)
	Using ... would improve my job performance	
	Using ... in my job would increase my productivity	
	Using ... would enhance my effectiveness on the job	
	Using ... would make it easier to do my job	
Quality of the AIS	I would find ... useful in my job	Algrari and Ahmed (2019)
	AIS is flexible in data processing	
	AIS help to achieve goals accurately and quickly	
	Data are processed through AIS consistent with accounting polices	
	The cost of AIS in the company is consistent with the nature and size of the accounting information provided by the system	
	AIS in the company is easily updated data	
	The AIS provides comparable accounting information	
	The AIS provides integrated accounting information that will affect the effectiveness of the company	
	AIS is characterized by the case ease and high quality	
	The inputs of AIS are presented in an easy and clear manner	
Input and output of AIS are maintained in a secure manner		
Quality of the accounting information	The company is distinguished by its accounting information quality	Algrari and Ahmed (2019)
	Accurate accounting information helps companies make better financial decisions	
	Accounting information is prepared to ensure its quality, accuracy, and correctness.	
	The provided accounting information is consistent with user's needs in different financial periods	
	The company's accounting information is flexible in its use in various aspects	
	The company's accounting information is clear and uncomplicated	
	The company's accounting information is easily understood among its various users	
	The company's accounting information is inclusive for all the financial aspects that users need in the decision-making process	
The accounting information is provided in appropriate time		

Construct	Items	Source
	Accounting information are easily saved, are retrieved at any time	
Business performance	The size of the company	Škrinjar et al. (2008)
	The company's operating profit	
	Return (EBIT) on equity	
	Profitability (EBIT) on sales	
	Return on Assets	
	Value added per employee	
	Operational cash flow	
	Quality of relationships with suppliers	
	Net fluctuation of employees	
	Work productivity of employees	
	Trust in leadership	
	Employees mutual trust	
	Work organization of employees	
	Commitment of employees	
	Employees prepared to go the extra mile	
	Satisfaction with work conditions	
	Learning ability and adaptability	
	Risk taking	
	Customer satisfaction	
Customer complaints speed of solving		
The retaining client's capability		
Reputation of a company in customers eyes		
Social responsibility	I work for a socially responsible organization that services the greater community.	Id Bouichou et al. (2022)
	My organization gives time, money, and other resources to socially responsible causes	

Source: Own elaboration

3.3 Hypotheses

In this chapter, we will outline the research hypotheses that have emerged from our examination of the relationships between variables. These hypotheses provide a practical framework for testing our initial assumptions, as suggested by Bell and Waters (2018).

The Technology Acceptance Model (TAM), first introduced by Davis (1985) and subsequently refined in Davis (1989), forms the foundation for understanding users' acceptance of technology. The TAM states that intention to use is a precursor to actual use. Davis (1989) emphasized the pivotal role of intention in predicting technology adoption. Numerous studies, such as those by Taylor and Todd (1995) and Venkatesh et

al. (2003), have corroborated the TAM's central tenet that intention is a strong predictor of technology use. Therefore, it is reasonable to posit that **H1**: the intention to use Accounting Automation Tools positively influences the use of Accounting Automation Tools.

Perceived ease of use, another core component of the TAM, relates to the extent to which individuals believe that using a system will be free of effort. Davis (1985) introduced this concept in his original TAM, highlighting its pivotal role in technology acceptance. Subsequent studies by Venkatesh and Davis (2000) have shown that perceived ease of use significantly affects users' intention to adopt technology. Therefore, it is reasonable to posit that **H2**: perceived ease of use positively influences the intention to use Accounting Automation Tools.

Consistent with the TAM, perceived ease of use should also have a direct influence on the use of Accounting Automation Tools. The work of Davis (1985) and the subsequent research by Venkatesh and Davis (2000) have demonstrated that the perceived ease of use not only impacts users' intention but also has a direct relationship with technology usage. Further research, such as the study conducted by Agarwal and Prasad (1999), has confirmed this relationship in the context of information technology acceptance. As such, it is reasonable to posit that **H3**: perceived ease of use positively influences the use of Accounting Automation Tools.

According to the TAM, perceived usefulness, a key construct in the model, is defined as the degree to which a person believes that using a specific system will enhance their job performance. Davis (1989) underscores the significance of perceived usefulness as a determinant of users' acceptance of technology. This concept has been validated and extended in various contexts, including accounting and financial systems, by researchers such as Gefen and Keil (1998). Therefore, given the established significance of perceived usefulness in technology acceptance, it is reasonable to posit that **H4**: perceived usefulness positively influences the intention to use Accounting Automation Tools.

Building upon the TAM framework, it is reasonable to assert that perceived usefulness not only influences intention but also directly impacts the actual use of technology. This concept is supported by Davis (1989), where he argued that perceived usefulness plays a dual role by affecting both intention and usage. Additionally, studies by Igarria and Iivari (1995) and Straub (2009) in the information systems field have provided empirical

evidence that perceived usefulness is a crucial factor in determining technology adoption and usage. Thus, it is reasonable to posit that **H5**: perceived usefulness positively influences the use of Accounting Automation Tools.

Several studies suggest a positive connection between a company's commitment to social responsibility and its intention to adopt technological innovations. Organizations with a strong CSR focus tend to be more inclined to invest in technologies that align with their ethical and sustainability objectives. Research by Fernández-Gago et al. (2016) suggests that socially responsible organizations are often early adopters of technology, including automation tools. The alignment of CSR with technological advancements stems from the idea that responsible companies aim to enhance their operations, minimize negative impacts, and maximize transparency, all of which are facilitated by technology. Therefore, it is reasonable to assert that **H6**: social responsibility positively influences the intention to use Accounting Automation Tools.

The relationship between CSR and the quality of the accounting information is an area of increasing interest. Scholars have recognized that organizations committed to CSR tend to have higher standards of accountability and transparency. This ethical orientation has a positive spillover effect on the quality of the financial data they produce. For instance, research by Patten (2002) found that firms that engage in social responsibility activities tend to produce higher-quality financial reports. As such, it is reasonable to assert that **H7**: social responsibility positively influences the quality of the accounting information.

Both Askary et al. (2018) and Abdelraheem et al. (2021), underscore the potential of information technology, including Accounting Automation Tools, to enhance the quality of accounting information. Askary et al. (2018) present a model that leverages AI to produce high-quality accounting information, while Abdelraheem et al. (2021) directly links information technology to improved accounting information quality. Thus, it is reasonable to posit that **H8**: the use of Accounting Automation Tools positively influences the quality of the accounting information.

The literature, as highlighted by Wisna (2013) and Meiryani and Susanto (2018), underscores the positive influence of information technology, including Accounting Automation Tools, on the quality of the AIS. These tools can lead to improved data accuracy, faster reporting, and reduced manual effort, collectively enhancing the quality and reliability of the AIS. Therefore, it is reasonable to posit that **H9**: the use of

Accounting Automation Tools positively influences the quality of the accounting information system.

Table 2: Summary of research hypotheses

Hypotheses		Article
H1	The intention to use Accounting Automation Tools positively influences the use of Accounting Automation Tools	Davis (1989), Taylor and Todd (1995) & Venkatesh et al. (2003)
H2	Perceived ease of use positively influences the intention to use Accounting Automation Tools	Davis (1985) & Venkatesh and Davis (2000)
H3	Perceived ease of use positively influences the use of Accounting Automation Tools	Agarwal and Prasad (1999), Davis (1985) & Venkatesh and Davis (2000)
H4	Perceived usefulness positively influences the intention to use Accounting Automation Tools	Davis (1985), Davis (1989) & Gefen and Keil (1998)
H5	Perceived usefulness positively influences the use of Accounting Automation Tools	Davis (1989), Igarria and Iivari (1995) & Straub (2009)
H6	Social Responsibility positively influences the intention to use Accounting Automation Tools	Fernández-Gago et al. (2016)
H7	Social Responsibility positively influences the quality of the Accounting Information	Patten (2002)
H8	The use of Accounting Automation Tools positively influences the quality of the Accounting Information	Abdelraheem et al. (2021) & Askary et al. (2018)
H9	The use of Accounting Automation Tools positively influences the quality of the Accounting Information System	Meiryani and Susanto (2018) & Wisna (2013)

Source: Own elaboration

This chapter provides a comprehensive overview of the research methodology employed in this study, explaining its purpose and significance in the research process. It focuses on the research design and elucidates why this method was considered the most suitable for the research objectives, details the data collection process with a focus on the development and structure of the questionnaire, question types and scales used, pilot testing, sampling, target population, ethical considerations, data analysis process, and the measures used to ensure validity and reliability of the questionnaire.

4.1 Research Design

The chosen research design for this study is a questionnaire survey. A questionnaire survey is a widely used quantitative research approach that allows for the collection of data from a large and diverse sample of respondents efficiently. The design is characterized by structured questions and standardized response options, making it suitable for examining specific relationships and patterns in a systematic manner.

4.2 Data Collection Process

The data collection process was executed through a questionnaire survey, systematically designed to gather invaluable insights regarding the impact of Accounting Automation Tools on company performance, the quality of the AIS, accounting information quality and CSR. The questionnaire consisted of six sections:

- **Respondent profile:** This section captured demographic information about the respondents.
- **The use of automation tools:** Exploring how respondents position themselves in relation to the digital transformation, identify their familiarity with terms related to emerging technologies, and identify the degree of agreement with perceived usefulness, perceived ease of use, intention to use, and actual use.
- **The impact of automation tools on company performance:** Investigating the perceived effects of automation tools on business performance.
- **The accounting information system:** Assessing perceptions of the AIS.
- **Accounting information quality:** Examining opinions about the quality of accounting information.
- **Corporate Social Responsibility:** Investigating the organization's commitment to ethical, sustainable, and socially responsible practices.

The questionnaire incorporated closed-ended questions with multiple-choice options. Several scales were employed, including:

- **Technology Acceptance Model:** A 12-item scale developed by Davis (1989) to measure two subdimensions of technology acceptance. The TAM scale provides a structured and validated measurement instrument (Davis, 1989).
- **5-Point Likert Scale:** Utilized for questions regarding the use of automation tools within the department. It featured a range of responses, including a "not familiar with" option to accommodate varying degrees of familiarity.
- **7-Point Numeric Scale:** Employed for questions assessing the likelihood of certain scenarios, anchored by "extremely likely" to "extremely unlikely".

Prior to full-scale data collection, a pilot test was conducted to evaluate the questionnaire's clarity and understandability. Adjustments were made to questionnaire questions based on the pilot test results, ensuring that the instrument was comprehensible to respondents. Random sampling was employed to select participants, which enhances the generalizability of the findings to the target population. The target population for this study consisted of certified accountants and other employees of financial departments. The participants were approached via multiple channels, including email, the official websites of Ordem dos Contabilistas Certificados and Ordem dos Revisores Oficiais de Contas, accounting professionals' groups on Facebook, LinkedIn, and personal contacts. This multi-pronged approach aimed to ensure comprehensive coverage and accessibility for the target population.

This research was conducted with the utmost regard for ethical principles:

- **Data privacy and confidentiality:** Respondents' responses were collected without any trace of their identities, ensuring that individual responses were not disclosed or linked to specific participants.
- **Informed consent:** All participants were informed of the research's objectives, and their informed consent was sought before proceeding with data collection.

The questionnaire was administered using Google Forms, a web-based platform that facilitated the ease of data collection for both researchers and respondents. Respondents received the questionnaire via a provided link, and responses were recorded online on Google Forms. The questionnaire was available from August 25th to October 18th. The primary challenge during data collection was effectively reaching the target population,

which was overcome by the varied approaches mentioned earlier, including websites, social media, and personal contacts.

4.3 Data Analysis Process

Statistical analysis of empirical model followed a partial least squares structural equation modelling (PLS-SEM) approach according to Hair et al. (2017) recommendations. PLS-SEM was used instead of a covariance-based (CB) technique for model estimation due to data dimension and no need to meet normality assumptions (Silva et al., 2017).

We followed a two-step procedure. First, we computed measurement model's reliability, convergent and discriminant validity.

For assessing reliability, we observed outer loadings, considering the removal of items with loadings between 0.4-0.7 as suggested by Hair et al. (2017). Cronbach's alpha and composite reliability (CR) were calculated to assess construct reliability. We used both measures as suggested by Hair et al. (2017) because the true reliability of measures lower-bounded by Cronbach's alpha and upper-bounded by CR. As thresholds we used Nunnally (1978) > 0.7 cut-off for Cronbach's alpha and CR.

For convergent validity we examined average variance extracted (AVE) considering $AVE > 0.50$ as acceptable (Hair et al., 2017), meaning that each construct explains at least half of its item's variance. For discriminant validity we used Fornell and Larcker's (1981) criterion, which states that each construct shares more variance with its items than with other latent variables' indicators. For that purpose, we compared the squared root of AVE (\sqrt{AVE}) with other inter-construct correlations. Discriminant validity is ensured when \sqrt{AVE} is higher than each construct correlations with others. We also calculated the heterotrait-monotrait ratio of correlations (HTMT) as a criterion to assess discriminant validity, considering that discriminant validity is established between two reflective constructs when HTMT value is below 0.90.

Second, we assessed the structural model. To assess the explanatory power of the model we calculated R squared (R^2) for each endogenous variable (dependent).

Model fit was assessed with Standardized Root Mean Square Residual (SRMR) attempting for a value under 0.10, allowing to reject misspecification (Henseler et al., 2014). Root Mean Squared Residual Covariance Matrix of the Outer Model Residuals (rms Theta), only applied to reflective models, was checked to assess the degree to which

the outer model residuals correlate. A result close to zero indicates good fit, implying that the correlations between the outer model residuals are small. In our study we used Henseler et al. (2014) criterion of 0,12. Normed Fit Index (NFI), defined as 1 minus the Chi^2 value of the proposed model divided by the Chi^2 values of the null model was calculated. Good fit was considered for $\text{NFI} > 0.90$.

Effect size (f^2) was calculated to measure how much an exogenous construct contributes to the R^2 of a given endogenous latent variable. Following Hair et al. (2017) recommendation we considered values of 0.02, 0.15 and 0.35 as cutoffs for small, medium, and large effects, respectively.

To assess predictive relevance of the model, we calculated Stone-Geiser's Q^2 (Q^2) using a blindfolding procedure (Hair et al., 2019). Results higher than 0 suggest that the model has good predictive relevance.

Finally, hypotheses were assessed by conducting a 5000-sample bootstrap analysis. Strength and direction of association was estimated with non-standardized coefficients (β). T-test statistic was calculated by dividing β coefficient by the estimated standard deviation (SD). Rejection of the null hypothesis was considered for p-values lower than 0.05.

This methodology chapter provides a comprehensive overview of the research methodology, from the selection of the questionnaire survey as the research design to the specifics of the data collection process, ensuring the study's adherence to ethical principles and robust execution. It forms the groundwork for subsequent chapters, where the collected data will be analyzed and discussed in detail.

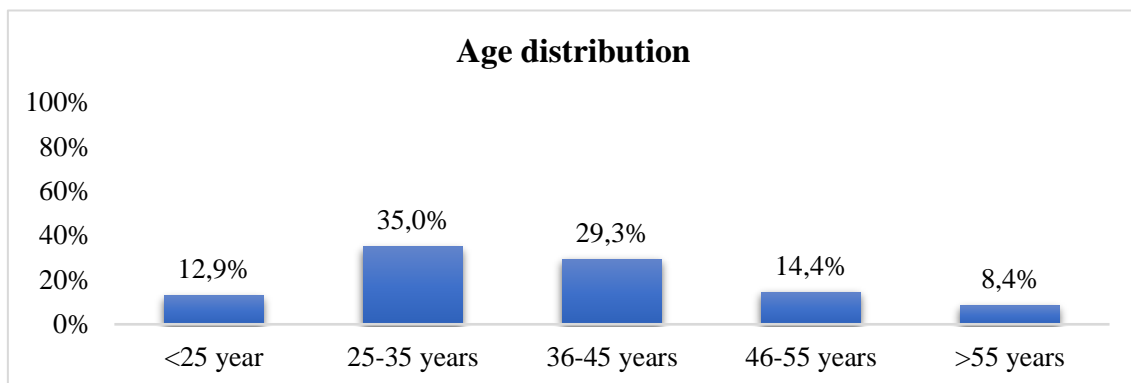
CHAPTER V – RESULTS PRESENTATION AND DISCUSSION

In this pivotal chapter, we delve into the heart of our research findings, revealing the outcomes of our investigation into the impact of Accounting Automation Tools on Business Performance. The purpose of this chapter is to provide a comprehensive and structured presentation of the empirical data obtained through our study. We will present a detailed analysis of the collected data, which encompasses responses from a diverse group of participants, including certified accountants and financial department employees. This section offers a comprehensive overview of the statistical analysis, hypothesis testing, and key findings that emerged from our research.

5.1 Sample Characteristics

A total of 263 participants formed the study's sample. Among them, approximately 77.2% were under the age of 45. Notably, the most frequently occurring age group fell within the range of 25 to 35 years, comprising 35.0% of the participants. You can visualize the age distribution in Figure 2.

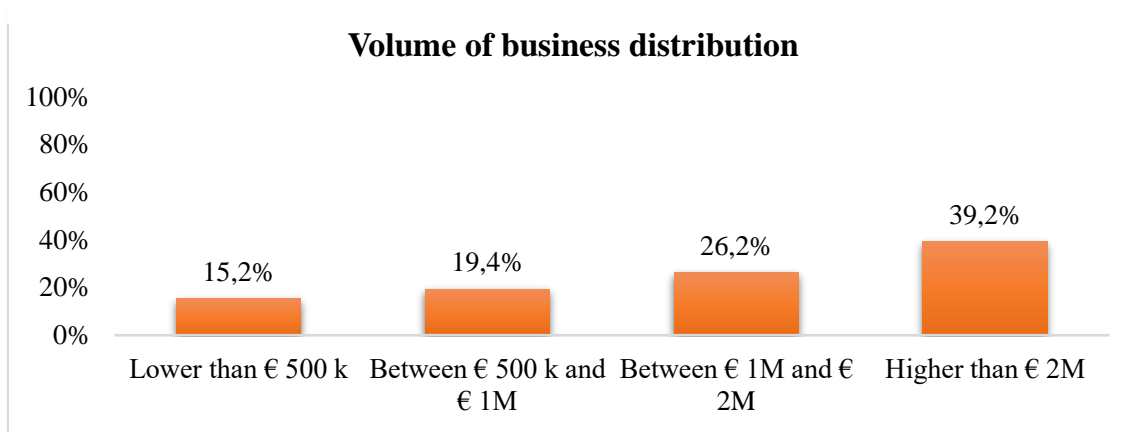
Figure 2 - Age distribution of the sample



Source: Own elaboration

When examining the volume of business, Figure 3 illustrates that a majority of the sample belonged to companies with a minimum volume of €1 million. Specifically, 26.2% of the participants represented businesses with a volume of €1 million to €2 million, while 39.2% were associated with companies with a business volume exceeding €2 million.

Figure 3 - Volume of business distribution



Source: Own elaboration

Table 3 presents a breakdown of the departments in which the majority of our sample's participants were employed. Notably, the accounting/finance department had the highest representation, with 180 individuals, constituting 68.4% of the total. Other departments included marketing (n=28, 10.6%), research (n=25, 9.5%), customer service (n=21, 8.0%), and a category labeled as "other" (n=9, 3.4%).

Table 3: Frequency and percentage of participants in each department

Department	n	%
Accounting/Finance	180	68.4%
Marketing	28	10.6%
Research	25	9.5%
Customer service	21	8.0%
Other	9	3.4%

Source: Own elaboration

As for the roles held by the participants within their respective companies, Table 4 offers insights into the distribution. The largest group, comprising more than half of the sample, occupied roles within the operational branch (n=147, 55.9%). Additionally, 48 individuals (18.3%) served as supervisors, 33 (12.6%) held managerial positions, 13 (4.9%) were directors, 9 (3.5%) acted as administrators, and another 13 (4.9%) were engaged in various other roles.

Table 4: Frequency and percentage of participants role at the company

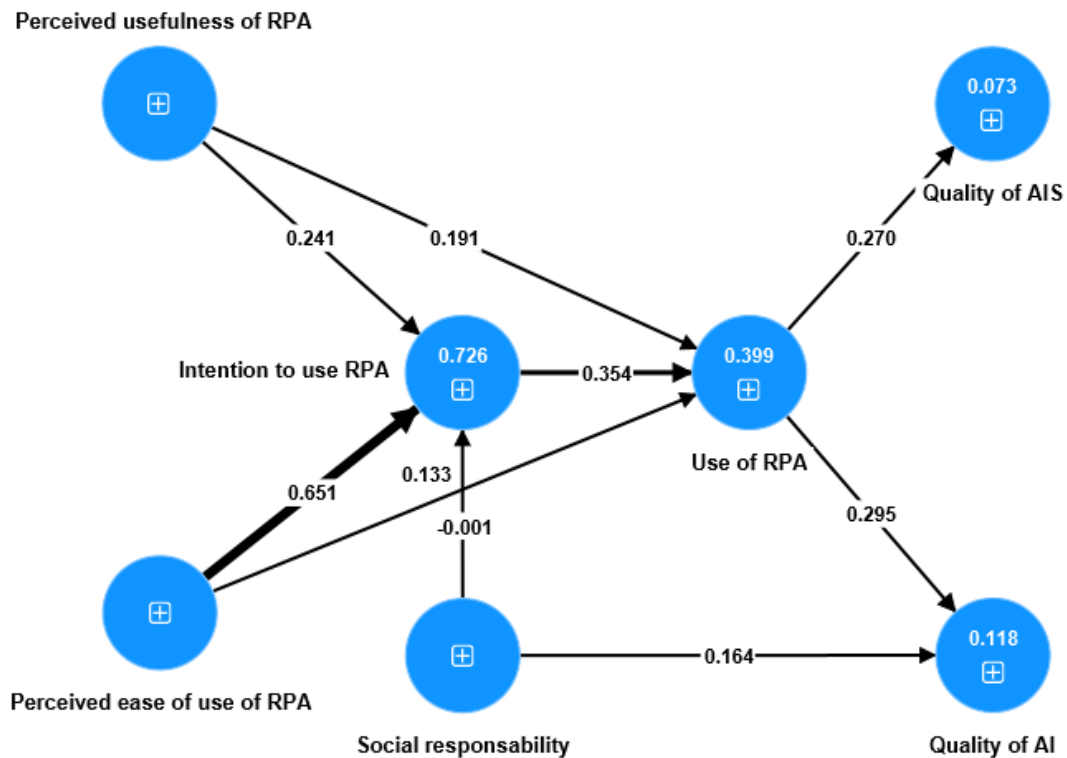
Role	n	%
Operational	147	55.9%
Supervisor	48	18.3%
Manager	33	12.6%
Director	13	4.9%
Administrator	9	3.4%
Other	13	4.9%

Source: Own elaboration

5.2 Research Models

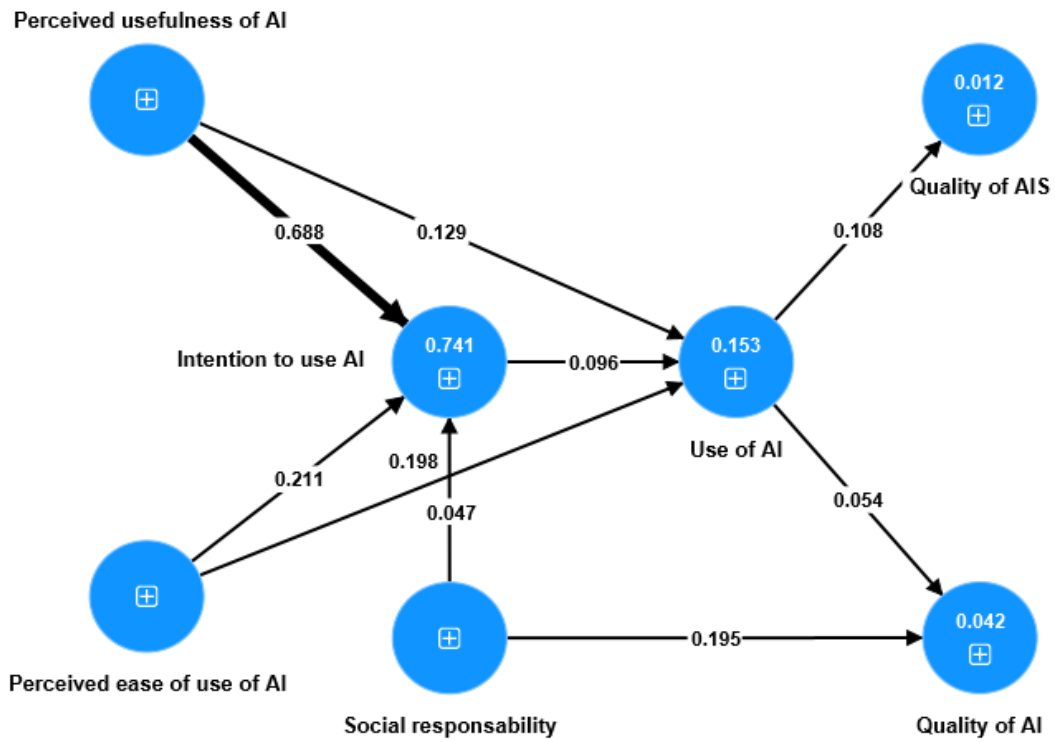
We constructed four distinct research models, each tailored to examine the influence of different types of Accounting Automation Tools: Robotic Process Automation (RPA), Artificial Intelligence (AI), Big Data (BD), and Blockchain (BC). In the following sections, we will present the findings in terms of standardized path coefficients for relationships and R-squared values for constructs, shedding light on the unique impact of each technology on our study variables.

Figure 4 - Research model for RPA



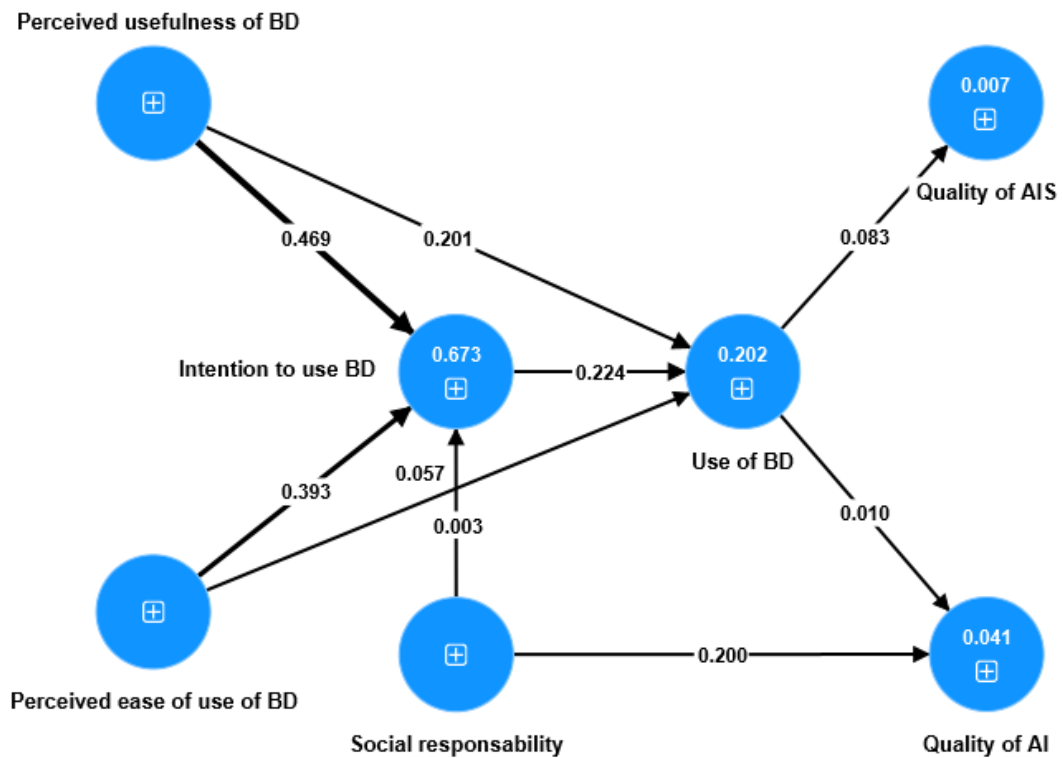
Source: Own elaboration

Figure 5 - Research model for AI



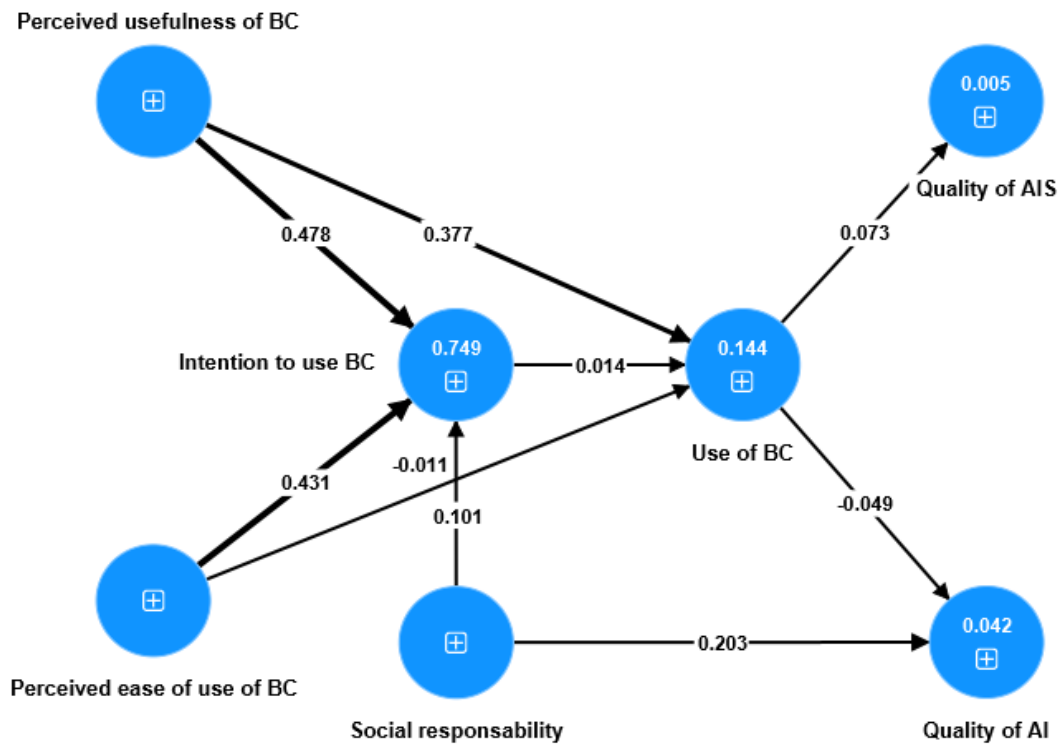
Source: Own elaboration

Figure 6 - Research model for Big Data



Source: Own elaboration

Figure 7 - Research model for Blockchain



Source: Own elaboration

We systematically assessed all the models to ensure their robustness and reliability. This evaluation involved several criteria:

- **Outerloadings:** We scrutinized the outerloadings of the indicators, ensuring they fell within the 0.4-0.7 range. This range was selected to maintain a balance between reliable measurement and model parsimony.
- **Cronbach's Alpha and Composite Reliability (CR):** Both Cronbach's Alpha and CR were examined, with the requirement that they should exceed 0.7 for all constructs. This ensured the internal consistency and reliability of the measurement model.
- **Average Variance Extracted (AVE):** We checked that the AVE for each construct surpassed the threshold of 0.5. This indicates that the construct effectively captures variance from its indicators, confirming good convergent validity.
- **Square Root of AVE and Inter-Construct Correlations:** We compared the square root of AVE for each construct with inter-construct correlations. This helped ascertain that constructs had greater shared variance with their indicators than with other constructs, reinforcing their discriminant validity.

- **Heterotrait-Monotrait Ratio (HTMT):** We examined the HTMT values, ensuring they remained below 0.90. This criterion helped establish the distinctiveness between constructs.

As a result of this comprehensive evaluation, we decided to remove the QAIS construct from all models due to its consistently low outerloadings, falling below the 0.7 threshold.

Table 5 provides a summary of the results related to reliability and convergent validity. For all constructs, both Cronbach’s alpha and CR exceeded 0.7, indicating a high level of internal consistency and reliability. Additionally, the AVE values were all above 0.5, reinforcing the good convergent validity of the measurement model.

Table 5: Reliability and convergent validity assessment for all models

	RPA			AI			BD			BC		
	α	CR	AVE	α	CR	AVE	α	CR	AVE	α	CR	AVE
1 Intention to use AAT	0.956	0.979	0.958	0.934	0.968	0.938	0.948	0.975	0.951	0.959	0.980	0.961
2 Perceived ease of use	0.959	0.968	0.860	0.957	0.967	0.853	0.965	0.973	0.878	0.965	0.973	0.879
3 Perceived usefulness	0.984	0.987	0.925	0.978	0.982	0.901	0.982	0.985	0.919	0.983	0.986	0.921
4 QAI	0.938	0.947	0.620	0.938	0.945	0.612	0.938	0.945	0.609	0.938	0.945	0.609
5 QAIS	0.956	0.962	0.739	0.956	0.961	0.733	0.956	0.946	0.662	0.956	0.958	0.720
6 Social responsibility	0.907	0.955	0.915	0.907	0.955	0.915	0.907	0.955	0.914	0.907	0.955	0.915
7 Use of AAT	-	-	-	-	-	-	-	-	-	-	-	-

RPA, Robotic Process Automation; AI, Artificial Intelligence; BD, Big Data; BC, Blockchain; AAT, Accounting Automation Tools; QAIS, Quality of the accounting information system; QAI, Quality of the accounting information

Source: Own elaboration

Tables 6 to 13 present a comprehensive assessment of discriminant validity for all models, as per the criteria outlined by Fornell and Larcker (1981) and HTMT.

Following Fornell and Larcker's (1981) criterion, we found that the square root of AVE (\sqrt{AVE}) for each construct exceeded the respective construct's correlations with other constructs. This outcome established a clear distinction between the constructs, underscoring their discriminant validity.

Furthermore, when examining the HTMT values, we observed that all associations remained below the 0.90 threshold. This observation signifies that the constructs in these associations are indeed distinct from one another, reaffirming the models' strong discriminant validity.

In sum, the results from these analyses provide robust evidence of the models' discriminant validity.

Table 6: Evaluation of Discriminant Validity Based on Fornell and Larcker's Criterion for RPA Model

Construct	1	2	3	4	5	6	7
1 Intention to use AAT	0.979						
2 Perceived ease of use	0.838	0.927					
3 Perceived usefulness	0.745	0.774	0.962				
4 QAI	0.496	0.442	0.473	0.787			
5 QAIS	0.427	0.415	0.459	0.676	0.860		
6 Social responsibility	0.109	0.128	0.112	0.177	0.032	0.956	
7 Use of AAT	0.608	0.578	0.558	0.302	0.270	0.046	1.000

AAT, Accounting Automation Tools; QAIS, Quality of the accounting information system; QAI, Quality of the accounting information

Source: Own elaboration

Table 7: Evaluation of Discriminant Validity Based on HTMT Criterion for RPA Model

Construct	1	2	3	4	5	6	7
1 Intention to use AAT							
2 Perceived ease of use		0.875					
3 Perceived usefulness		0.768	0.796				
4 QAI		0.516	0.460	0.485			
5 QAIS		0.435	0.423	0.462	0.707		
6 Social responsibility		0.117	0.138	0.119	0.188	0.051	
7 Use of AAT		0.622	0.590	0.562	0.305	0.264	0.048

HTMT, heterotrait-monotrait ratio of correlations; AAT, Accounting Automation Tools; QAIS, Quality of the accounting information system; QAI, Quality of the accounting information

Source: Own elaboration

Table 8: Evaluation of Discriminant Validity Based on Fornell and Larcker's Criterion for AI Model

Construct	1	2	3	4	5	6	7
1 Intention to use AAT	0.969						
2 Perceived ease of use	0.739	0.924					
3 Perceived usefulness	0.847	0.757	0.949				
4 QAI	0.561	0.465	0.583	0.782			
5 QAIS	0.504	0.387	0.555	0.657	0.856		
6 Social responsibility	0.066	0.146	-0.018	0.198	0.037	0.956	
7 Use of AAT	0.352	0.367	0.360	0.065	0.108	0.055	1.000

AAT, Accounting Automation Tools; QAIS, Quality of the accounting information system; QAI, Quality of the accounting information

Source: Own elaboration

Table 9: Evaluation of Discriminant Validity Based on HTMT Criterion for AI Model

Construct	1	2	3	4	5	6	7
1 Intention to use AAT							
2 Perceived ease of use	0.779						
3 Perceived usefulness	0.885	0.780					
4 QAI	0.607	0.489	0.624				
5 QAIS	0.521	0.396	0.555	0.707			
6 Social responsibility	0.074	0.157	0.042	0.188	0.051		
7 Use of AAT	0.364	0.374	0.364	0.067	0.092	0.058	

HTMT, heterotrait-monotrait ratio of correlations; AAT, Accounting Automation Tools; QAIS, Quality of the accounting information system; QAI, Quality of the accounting information

Source: Own elaboration

Table 10: Evaluation of Discriminant Validity Based on Fornell and Larcker's Criterion for BD Model

Construct	1	2	3	4	5	6	7
1 Intention to use AAT	0.975						
2 Perceived ease of use	0.773	0.937					
3 Perceived usefulness	0.787	0.810	0.959				
4 QAI	0.392	0.342	0.439	0.781			
5 QAIS	0.296	0.242	0.335	0.591	0.813		
6 Social responsibility	0.058	0.076	0.054	0.201	0.070	0.956	
7 Use of AAT	0.426	0.392	0.423	0.039	0.083	0.148	1.000

AAT, Accounting Automation Tools; QAIS, Quality of the accounting information system; QAI, Quality of the accounting information

Source: Own elaboration

Table 11: Evaluation of Discriminant Validity Based on HTMT Criterion for BD Model

Construct	1	2	3	4	5	6	7
1 Intention to use AAT							
2 Perceived ease of use	0.807						
3 Perceived usefulness	0.815	0.831					
4 QAI	0.423	0.363	0.473				
5 QAIS	0.305	0.252	0.355	0.707			
6 Social responsibility	0.064	0.082	0.059	0.188	0.051		
7 Use of AAT	0.437	0.398	0.427	0.059	0.040	0.157	

HTMT, heterotrait-monotrait ratio of correlations; AAT, Accounting Automation Tools; QAIS, Quality of the accounting information system; QAI, Quality of the accounting information

Source: Own elaboration

Table 12: Evaluation of Discriminant Validity Based on Fornell and Larcker's Criterion for BC Model

Construct	1	2	3	4	5	6	7
1 Intention to use AAT							
2 Perceived ease of use	0.842						
3 Perceived usefulness	0.842	0.814					
4 QAI	0.440	0.360	0.451				
5 QAIS	0.403	0.341	0.477	0.707			
6 Social responsibility	0.091	0.030	0.040	0.188	0.051		
7 Use of AAT	0.320	0.305	0.383	0.050	0.050	0.075	

AAT, Accounting Automation Tools; QAIS, Quality of the accounting information system; QAI, Quality of the accounting information

Source: Own elaboration

Table 13: Evaluation of Discriminant Validity Based on HTMT Criterion for BC Model

Construct	1	2	3	4	5	6	7
1 Intention to use AAT							
2 Perceived ease of use	0.807						
3 Perceived usefulness	0.815	0.831					
4 QAI	0.423	0.363	0.473				
5 QAIS	0.305	0.252	0.355	0.707			
6 Social responsibility	0.064	0.082	0.059	0.188	0.051		
7 Use of AAT	0.437	0.398	0.427	0.059	0.040	0.157	

HTMT, heterotrait-monotrait ratio of correlations; AAT, Accounting Automation Tools; QAIS, Quality of the accounting information system; QAI, Quality of the accounting information

Source: Own elaboration

Table 14 provides an overview of model fit, as assessed through SRMR and NFI, as well as explained variances represented by R-squared (R²) for each model.

The research model for RPA elucidates 72.6% of the intention to use RPA as an accounting automation tool, 11.8% of the quality of the accounting information, 7.3% of the quality of the accounting information system, and 39.9% of the use of RPA as an accounting automation tool.

For the AI model, it accounts for 74.1% of the intention to use AI as an accounting automation tool, 4.2% of the quality of the accounting information, 1.2% of the quality of the accounting information system, and 15.3% of the use of AI as an accounting automation tool.

The Big Data model explains 67.3% of the intention to use Big Data as an accounting automation tool, 4.1% of the quality of the accounting information, 0.7% of the quality

of the accounting information system, and 20.2% of the use of Big Data as an accounting automation tool.

In the case of the Blockchain model, it clarifies 74.9% of the intention to use Blockchain as an accounting automation tool, 4.2% of the quality of the accounting information, 0.5% of the quality of the accounting information system, and 14.4% of the use of Blockchain as an accounting automation tool.

Regarding model fit, the Tucker-Lewis Index (TLI) yielded acceptable results. Specifically, TLI values were as follows: TLI=0.851 for the RPA model, TLI=0.834 for the AI model, TLI=0.829 for the Big Data model, and TLI=0.845 for the Blockchain model. Although all values were below the 0.90 threshold, they remained above 0.80, with the RPA model achieving a TLI higher than 0.85.

However, the SRMR (Standardized Root Mean Residual) values for all models exceeded the 0.10 threshold. The best fit was observed in the RPA model, where SRMR registered at 0.210.

Table 14: Model fit and explained variances for all models

	RPA		AI		BD		BC	
	R ²	Model fit	R ²	Model fit	R ²	Model fit	R ²	Model fit
Intention to use AAT	0.726		0.741		0.673		0.749	
QAI	0.118	SRMR=0.210	0.042	SRMR=0.296	0.041	SRMR=0.247	0.042	SRMR=0.268
QAIS	0.073	NFI=0.851	0.012	NFI=0.834	0.007	NFI=0.829	0.005	NFI=0.845
Use of AAT	0.399		0.153		0.202		0.144	

RPA, Robotic Process Automation; AI, Artificial Intelligence; BD, Big Data; Blockchain, BC; AAT, Accounting Automation Tools; QAIS, Quality of the accounting information system; QAI, Quality of the accounting information

Source: Own elaboration

Effect size (f^2) was computed to assess the magnitude of the contribution of an exogenous construct to the R² of a specific endogenous latent variable. The effect size information for all research models is presented in Table 15. Notably, high effect sizes were observed in several key associations, including:

- The perceived ease of use of RPA in relation to the intention to use RPA ($f^2=0.618$), which exhibited the second-highest effect size among all relationships.
- The perceived usefulness of AI and its association with the intention to use AI ($f^2=0.750$), representing the highest effect size observed in the study.

- The perceived usefulness of Big Data in connection with the intention to use Big Data ($f^2=0.232$).
- The perceived ease of use of Big Data associated with the intention to use Big Data ($f^2=0.162$).
- The perceived usefulness of Blockchain and its impact on the intention to use Blockchain ($f^2=0.338$).
- The perceived ease of use of Blockchain and its influence on the intention to use Blockchain ($f^2=0.275$).

In contrast, the effect sizes for all other relationships were relatively low.

Table 15: Effect size (f^2) for all models

	RPA	AI	BD	BC
Intention to use AAT → Use of AAT	0.057	0.003	0.021	0.000
Perceived ease of use of AAT → Intention to use AAT	0.618	0.069	0.162	0.275
Perceived ease of use of AAT → Use of AAT	0.007	0.018	0.001	0.000
Perceived usefulness of AAT → Intention to use AAT	0.085	0.750	0.232	0.338
Perceived usefulness of AAT → Use of AAT	0.022	0.005	0.014	0.047
Social responsibility → Intention to use AAT	0.000	0.008	0.000	0.040
Social responsibility → QAI	0.030	0.039	0.041	0.043
Use of AAT → QAI	0.098	0.003	0.000	0.003
Use of AAT → QAIS	0.078	0.012	0.007	0.005

RPA, Robotic Process Automation; AI, Artificial Intelligence; BD, Big Data; BC, Blockchain; AAT, Accounting Automation Tools; QAIS, Quality of the accounting information system; QAI, Quality of the accounting information; Results presented as f^2 , following Hair et al. (2017) recommendation we considered values of 0.02, 0.15 and 0.35 as cutoffs for small, medium, and large effects, respectively

Source: Own elaboration

Table 16 presents the assessment of predictive validity relevance, as determined by Stone-Geiser's Q2. Notably, all the models exhibited substantial predictive relevance. Specifically, the models yielded the following Stone-Geiser's Q2 results:

- Intention to use Robotic Process Automation ($Q^2=0.705$).
- Intention to use Artificial Intelligence ($Q^2=0.734$).
- Intention to use Big Data ($Q^2=0.661$).
- Intention to use Blockchain ($Q^2=0.741$).

Additionally, relevant predictive relevance was identified for the following constructs:

- Use of Robotic Process Automation ($Q^2=0.341$).
- Use of Artificial Intelligence ($Q^2=0.137$).
- Use of Big Data ($Q^2=0.171$).

- Use of Blockchain (Q2=0.131).

Moreover, a notable level of predictive relevance was observed in the prediction of the quality of accounting information (Q2=0.149).

Table 16: Predictive relevance assessment with Stone-Geiser's Q²

	RPA	AI	BD	BC
Intention to use AAT	0.705	0.734	0.661	0.741
QAI	0.149	0.046	0.027	0.006
QAIS	0.121	0.040	0.011	0.024
Use of AAT	0.341	0.137	0.171	0.131

RPA, Robotic Process Automation; AI, Artificial Intelligence; BD, Big Data; Blockchain, BC; AAT, Accounting Automation Tools; QAIS, Quality of the accounting information system; QAI, Quality of the accounting information; Results presented as Stone-Geiser's Q²

Source: Own elaboration

5.3 Hypotheses Testing

We now turn our attention to the results for the set of hypotheses outlined below:

H1: Intention to use Accounting Automation Tools positively influences the use of Accounting Automation Tools.

H2: Perceived ease of use positively influences the intention to use Accounting Automation Tools.

H3: Perceived ease of use positively influences the use of Accounting Automation Tools.

H4: Perceived usefulness positively influences the intention to use Accounting Automation Tools.

H5: Perceived usefulness positively influences the use of Accounting Automation Tools.

H6: Social responsibility positively influences the intention to use Accounting Automation Tools.

H7: Social responsibility positively influences the quality of the Accounting Information.

H8: Use of Accounting Automation Tools positively influences the quality of the Accounting Information.

H9: Use of Accounting Automation Tools positively influences the quality of the Accounting Information System.

Table 17 showcases the estimated coefficients for the structural model and the outcomes of hypothesis testing, which were obtained through bootstrapping. For the RPA model, the validated hypotheses are as follows:

H1: $\beta=0.344$ ($p=0.004$)

H2: $\beta=0.636$ ($p=0.004$)

H4: $\beta=0.257$ ($p=0.045$)

H7: $\beta=0.166$ ($p=0.007$)

H8: $\beta=0.300$ ($p<0.001$)

H9: $\beta=0.276$ ($p<0.001$)

In the AI model, the validated hypotheses include:

H2: $\beta=0.211$ ($p=0.001$)

H3: $\beta=0.200$ ($p=0.022$)

H4: $\beta=0.257$ ($p=0.045$)

H7: $\beta=0.210$ ($p=0.001$)

The Big Data model confirms the following hypotheses:

H2: $\beta=0.391$ ($p<0.001$)

H4: $\beta=0.471$ ($p<0.001$)

H7: $\beta=0.216$ ($p=0.001$)

Lastly, for the Blockchain model, the validated hypotheses encompass:

H2: $\beta=0.433$ ($p<0.001$)

H4: $\beta=0.476$ ($p<0.001$)

H5: $\beta=0.374$ ($p<0.001$)

H6: $\beta=0.100$ ($p=0.003$)

H7: $\beta=0.218$ ($p<0.001$)

Table 17: Estimated coefficients for structural model and hypothesis results obtained with bootstrapping

	RPA			AI			BD			BC			
	β	p	R*	β	p	R*	β	p	R*	β	p	R*	
H1: IU of AAT → Use of AAT	0.344	0.004	✓	0.094	0.386	✗	0.226	0.007	✗	0.016	0.891	✗	
H2: PEU of AAT → IU of AAT	0.636	<0.001	✓	0.211	0.001	✓	0.391	<0.001	✓	0.433	<0.001	✓	
H3: PEU of AAT → Use of AAT	0.132	0.310	✗	0.200	0.022	✓	0.056	0.609	✗	-	0.011	0.921	✗
H4: PU of AAT → IU AAT	0.257	0.045	✓	0.689	<0.001	✓	0.471	<0.001	✓	0.476	<0.001	✓	
H5: PU of AAT → Use of AAT	0.202	0.078	✗	0.128	0.258	✗	0.199	0.035	✗	0.374	<0.001	✓	
H6: SR → IU of AAT	0.000	0.970	✗	0.048	0.191	✗	0.004	0.936	✗	0.100	0.003	✓	
H7: SR → QAI	0.166	0.007	✓	0.210	0.001	✓	0.216	0.001	✓	0.218	<0.001	✓	
H8: Use of AAT → QAI	0.300	<0.001	✓	0.055	0.421	✗	0.010	0.886	✗	-	0.053	0.497	✗
H9: Use of AAT → QAIS	0.276	<0.001	✓	0.122	0.243	✗	0.044	0.533	✗	0.069	0.530	✗	

IU, intention to use; PEU, perceived ease of use; PU, perceived usefulness; SR, social responsibility; RPA, Robotic Process Automation; AI, Artificial Intelligence; BD, Big Data; BC, Blockchain; AAT, Accounting Automation Tools; QAIS, Quality of the accounting information system; QAI, Quality of the accounting information; Results presented as unstandardized coefficients (β), p-value (p) and hypothesis result; R*, Hypothesis result

Source: Own elaboration

In this concluding chapter, we bring our research journey to a close by presenting the main conclusions drawn from our study on the impact of Accounting Automation Tools on Business Performance. This chapter encapsulates the culmination of our efforts, offering a synthesis of the key findings and their significance within the broader context of the accounting and business landscape.

We will not only elucidate the primary takeaways but also emphasize the contributions that this study makes to the field. While celebrating our achievements, we will candidly acknowledge the limitations of our research, providing a balanced view of our work. Moreover, we will set the stage for future investigations by sharing recommendations for prospective studies in this evolving and dynamic area.

6.1 Main Conclusions

The following key conclusions emerge from the study:

6.1.1 Influence on Business Performance

The investigation into this subject was driven by prior research conducted by experts in the field, including Abad-Segura and González-Zamar (2020), who had already identified the transformative potential of emerging technologies in corporate accounting. While the literature had laid the groundwork for understanding the potential influence of Accounting Automation Tools on business performance, it was essential to empirically verify these claims.

A pivotal hypothesis, H1, posited that the intention to use Accounting Automation Tools positively influences the use of Accounting Automation Tools, aligning with earlier works by Davis (1989), Taylor and Todd (1995), and Venkatesh et al. (2003). This research has not only confirmed this hypothesis but has gone further to reveal the significant impact of intention on actual Accounting Automation Tools usage. In the context of RPA, the findings revealed a strong and positive relationship between intention and usage, indicating that companies intending to embrace RPA are, indeed, implementing it, ultimately enhancing their business performance.

The alignment of the findings with the works of Davis (1989), Taylor and Todd (1995), and Venkatesh et al. (2003) signifies the continued relevance and applicability of these seminal works in the digital age. It underscores that an organization's intention to employ

Accounting Automation Tools, such as RPA, directly contributes to its actual adoption, which, in turn, augments business performance.

6.1.2 Role of Perceived Ease of Use and Perceived Usefulness

The role of perceived ease of use was highlighted by Davis (1985) and Venkatesh and Davis (2000) in the context of intention to use Accounting Automation Tools. In the AI model, the validated hypotheses confirm that perceived ease of use (H2) and perceived usefulness (H4) positively influence the intention to use Accounting Automation Tools (Davis, 1985, 1989; Gefen and Keil, 1998).

6.1.3 Impact on Accounting Information Quality

The influence of Accounting Automation Tools on accounting information quality was analyzed. The results show that the use of Accounting Automation Tools positively impacts the quality of accounting information (Abdelraheem et al., 2021; Askary et al., 2018; Wisna, 2013). Furthermore, in the AI model, the validated hypothesis (H7) establishes a positive relationship between social responsibility and the quality of the Accounting Information (Patten, 2002).

6.2 Contribution

This study contributes to the fields of accounting, automation, and digital transformation in several significant ways:

6.2.1 Empirical validation of hypotheses

By empirically validating the proposed hypotheses within the context of different Accounting Automation Tools (RPA, AI, Big Data, and Blockchain), this research provides substantial evidence to support or refute the assumed relationships. These findings expand the theoretical foundations and empirical understanding of Accounting Automation Tools adoption.

6.2.2 Comparative analysis

The study compares the influence of Accounting Automation Tools on business performance, and the relationship between perceived ease of use, perceived usefulness, and social responsibility with the intention to use Accounting Automation Tools across various technology platforms. This comparison elucidates nuances that can guide

organizations in making informed choices based on specific Accounting Automation Tools types.

6.2.3 Insight into Social Responsibility

The study offers insights into the role of social responsibility in technology adoption. It establishes that social responsibility can positively influence the intention to use Accounting Automation Tools and enhance the quality of the accounting information.

6.2.4 Practical implications

The findings provide practical guidance to businesses, helping them to understand the significance of Accounting Automation Tools adoption and the role of ease of use and usefulness in encouraging their utilization. Moreover, it underlines the relevance of corporate social responsibility in technology adoption and accounting quality enhancement.

6.3 Limitations

Despite the valuable insights provided by this study, it is essential to acknowledge certain limitations. Firstly, the study's findings are based on a specific data set and sample. As such, the generalizability of results to a broader population might be constrained. Future research should aim to replicate these findings with a more diverse and extensive dataset. Secondly, this study focused on validating existing hypotheses. Future research could explore novel hypotheses or alternative conceptual frameworks to deepen our understanding of Accounting Automation Tools dynamics. Lastly, this study utilizes the NFI as a measure for model fit assessment. While NFI is a robust indicator of model fit, it is important to recognize that it is an incremental index. Unlike other fit indices, NFI does not penalize models for the number of estimated relations. Consequently, in complex structural models like the ones in this study, there is the possibility of overfitting, wherein a model may be too tailored to the sample data. This calls for caution in interpreting the results as they relate to model fit. Future research should consider exploring alternative model fit indices that account for model complexity and provide a more comprehensive evaluation of the model's goodness of fit.

6.4 Future Studies

Based on the main conclusions and the identified limitations, the following areas are suggested for future research:

6.4.1 Cross-Cultural Studies

Examining the impact of culture and regional differences on Accounting Automation Tools adoption, and whether these factors influence perceived ease of use and social responsibility.

6.4.2 Dynamic Assessment

Investigating how Accounting Automation Tools adoption and accounting information quality evolve over time, considering the dynamic nature of technology and accounting practices.

6.4.3 Unexplored Accounting Automation Tools

Exploring the implications of emerging Accounting Automation Tools not covered in this study, such as natural language processing or machine learning in accounting, to broaden the scope of research in this field.

6.4.4 Case Studies

Conducting in-depth case studies to uncover the practical implications of Accounting Automation Tools adoption within specific organizations, industries, or contexts.

In conclusion, this study advances our understanding of Accounting Automation Tools adoption, its role in accounting, and its impact on business performance. By validating and extending existing theories, this research provides valuable insights for both academics and practitioners and suggests avenues for further exploration into the realm of Accounting Automation Tools.

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Appendix I – Questionnaire

1. Autorizo a utilização dos dados exclusivamente para fins de investigação *

Marcar apenas uma oval.

- Sim
 Não

2. Idade *

Marcar apenas uma oval.

- <25 anos
 25-35 anos
 36-45 anos
 46-55 anos
 >55 anos

3. Em que departamento trabalha? *

Marcar apenas uma oval.

- Contabilidade/Finanças
 Marketing
 Investigação
 Serviço de apoio ao cliente
 Outro:

4. Qual a sua função na empresa? *

Marcar apenas uma oval.

- Administrador
 Diretor
 Manager
 Supervisor
 Operacional
 Outro:

5. Qual o volume de negócios da empresa? *

Marcar apenas uma oval.

- Inferior a 500 mil euros
 Entre 500 mil e 1 milhão de euros
 Entre 1 e 2 milhões de euros
 Superior a 2 milhões de euros

(continues)

Utilização de tecnologias emergentes

6. Em que medida considera que as seguintes tecnologias são utilizadas no seu departamento? *

Marcar apenas uma oval por linha.

	Não estou familiarizado	Nunca	Raramente	Ocasionalmente	Frequentemente	Diariamente
Robotic Process Automation (RPA)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Artificial Intelligence (AI)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Big Data	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Blockchain	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

(continues)

Robotic Process Automation (RPA)

Utilidade percebida

7. Quão provável é cada uma das afirmações apresentadas abaixo? *

Marcar apenas uma oval por linha.

	Extremamente provável	Bastante provável	Provável	Nem provável nem improvável	Improvável	Bastante improvável	Extremamente improvável
A utilização de RPA permitiria concluir as minhas tarefas mais rapidamente	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
A utilização de RPA melhoraria a minha performance no trabalho	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
A utilização de RPA aumentaria a produtividade no trabalho	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
A utilização de RPA aumentaria a eficácia no meu trabalho	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
A utilização de RPA tornaria o meu trabalho mais fácil	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
A utilização de RPA seria útil no meu trabalho	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

(continues)

Facilidade de uso

8. Quão provável é cada uma das afirmações apresentadas abaixo? *

Marcar apenas uma oval por linha.

	Extremamente provável	Bastante provável	Provável	Nem provável nem improvável	Improvável	Bastante improvável	Extremamente improvável
Aprender a utilizar a RPA seria fácil para mim	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Seria fácil executar as minhas tarefas utilizando a RPA	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Seria fácil tornar-me competente (ou mais competente) na utilização de RPA	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Conseguiria facilmente fazer com que a RPA fizesse aquilo que eu preciso	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
A minha interação com a RPA seria clara e perceptível	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

(continues)

Utilização futura

9. Quão provável é cada uma das afirmações apresentadas abaixo? *

Marcar apenas uma oval por linha.

	Extremamente provável	Bastante provável	Provável	Nem provável nem improvável	Improvável	Bastante improvável	Extremamente improvável
Assumindo que a tecnologia está disponível, utilizaria a RPA no meu dia a dia	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Preferia utilizar a RPA do que manter a minha forma atual de trabalhar	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

(continues)

Artificial Intelligence (AI)

Utilidade percebida

8. Quão provável é cada uma das afirmações apresentadas abaixo? *

Marcar apenas uma oval por linha.

	Extremamente provável	Bastante provável	Provável	Nem provável nem improvável	Improvável	Bastante improvável	Extremamente improvável
Aprender a utilizar a permitiria concluir as minhas tarefas mais rapidamente	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
A utilização de AI melhoraria a minha performance no trabalho	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
A utilização de AI aumentaria a minha produtividade no trabalho	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
A utilização de AI aumentaria a minha eficácia no trabalho	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
A utilização de AI tomaria o meu trabalho mais fácil	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
A utilização de AI seria útil no meu trabalho	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

(continues)

Facilidade de uso

11. Quão provável é cada uma das afirmações apresentadas abaixo? *

Marcar apenas uma oval por linha.

	Extremamente provável	Bastante provável	Provável	Nem provável improvável nem	Improvável	Bastante improvável	Extremamente improvável
Aprender a utilizar a AI seria fácil para mim	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Seria fácil executar as minhas tarefas utilizando a AI	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Seria fácil tornar-me utilização competente da AI	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Conseguiria facilmente fazer com que a AI fizesse aquilo que eu preciso	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
A minha interação com a AI seria clara e perceptível	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

(continues)

Utilização futura

12. Quão provável é cada uma das afirmações apresentadas abaixo? *

Marcar apenas uma oval por linha.

	Extremamente provável	Bastante provável	Provável	Nem provável nem improvável	Improvável	Bastante improvável	Extremamente improvável
Assumindo que a tecnologia está disponível, eu utilizaria a AI no meu dia a dia	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Preferia utilizar a AI do que manter a minha forma atual de trabalhar	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

(continues)

Big Data

Utilidade percebida

13. Quão provável é cada uma das afirmações apresentadas abaixo? *

Marcar apenas uma oval por linha.

	Extremamente provável	Bastante provável	Provável	Nem provável nem improvável	Improvável	Bastante improvável	Extremamente improvável
A utilização de Big Data permitiria concluir as minhas tarefas mais rapidamente	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
A utilização de Big Data melhoraria a minha performance no trabalho	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
A utilização de Big Data aumentaria a minha produtividade no trabalho	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
A utilização de Big Data aumentaria a minha eficácia no trabalho	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
A utilização de Big Data tornaria o meu trabalho mais fácil	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
A utilização de Big Data seria útil no meu trabalho	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

(continues)

Facilidade de uso

14. Quão provável é cada uma das afirmações apresentadas abaixo? *

Marcar apenas uma oval por linha.

	Extremamente provável	Bastante provável	Provável	Nem provável nem improvável	Improvável	Bastante improvável	Extremamente improvável
Aprender a utilizar o Big Data seria fácil para mim	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Seria fácil executar as minhas tarefas utilizando o Big Data	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Seria fácil tornar-me competente na utilização de Big Data	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Conseguiria facilmente fazer com que o Big Data fizesse aquilo que eu preciso	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
A minha interação com o Big Data seria clara e perceptível	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

(continues)

Utilização futura

15. Quão provável é cada uma das afirmações apresentadas abaixo? *

Marcar apenas uma oval por linha.

	Extremamente provável	Bastante provável	Provável	Provável nem improvável nem	Improvável	Bastante improvável	Extremamente improvável
Assumindo							
que a tecnologia está disponível no meu dia a dia	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Preferia utilizar o Big Data do que manter a minha forma atual de trabalhar	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

(continues)

Blockchain

Utilidade percebida

14. Quão provável é cada uma das afirmações apresentadas abaixo? *

Marcar apenas uma oval por linha.

	Extremamente provável	Bastante provável	Provável	Nem provável nem improvável	Improvável	Bastante improvável	Extremamente improvável
A utilização de Blockchain permitiria concluir as minhas tarefas mais rapidamente	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
A utilização de Blockchain melhoraria a minha performance no trabalho	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
A utilização de Blockchain aumentaria a minha produtividade no trabalho	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
A utilização de Blockchain aumentaria a minha eficácia no trabalho	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
A utilização de Blockchain meu trabalho tornaria o mais fácil	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
A utilização de Blockchain seria útil no meu trabalho	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

(continues)

Facilidade de uso

14. Quão provável é cada uma das afirmações apresentadas abaixo? *

Marcar apenas uma oval por linha.

	Extremamente provável	Bastante provável	Provável	Nem provável nem improvável	Improvável	Bastante improvável	Extremamente improvável
Aprender a utilizar o Blockchain seria fácil para mim	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Seria fácil executar as minhas tarefas utilizando o Blockchain	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Seria fácil tornar-me competente na utilização de Blockchain	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Conseguiria facilmente fazer com que o Blockchain fizesse aquilo que eu preciso	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
A minha interação com o Blockchain seria clara e perceptível	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

(continues)

Utilização futura

18. Quão provável é cada uma das afirmações apresentadas abaixo? *

Marcar apenas uma oval por linha.

	Extremamente provável	Bastante provável	Provável	Nem provável improvável nem	Improvável	Bastante improvável	Extremamente improvável
Assumindo							
que a tecnologia está disponível para utilizar o Blockchain no meu dia a dia	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Preferia utilizar o Blockchain do que manter a minha forma atual de trabalhar	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

(continues)

Impacto das tecnologias emergentes no desempenho da empresa

19. Em que medida considera que as tecnologias emergentes influenciam os seguintes indicadores de desempenho? *

Marcar apenas uma oval por linha.

	Concordo plenamente	Concordo bastante	Concordo	Nem concordo nem discordo	Discordo	Discordo bastante	Discordo plenamente
Volume de negócios	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Resultado operacional	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Rentabilidade dos capitais próprios	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Rentabilidade das vendas	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Rentabilidade dos ativos	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Valor acrescentado por colaborador	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Fluxo de caixa operacional	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Qualidade da relação com os fornecedores	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Rotatividade e retenção dos colaboradores	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Produtividade dos colaboradores	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Confiança na liderança	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Confiança mútua entre colaboradores	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

(continues)

Organização das tarefas dos colaboradores	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Compromisso dos colaboradores	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Entrega dos colaboradores	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Satisfação dos colaboradores	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Capacidade de aprendizagem e adaptabilidade	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Propensão ao risco	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Satisfação dos clientes	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Rapidez na resposta às reclamações dos clientes	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Capacidade de retenção de clientes	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Reputação da empresa	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

(continues)

empresa
Sistema de Informação Contabilística (SIC)

20. Em que medida concorda com cada uma das afirmações apresentadas abaixo? *

Marcar apenas uma oval por linha.

	Concordo plenamente	Concordo bastante	Concordo	Nem concordo nem discordo	Discordo	Discordo bastante	Discordo plenamente
O SIC é flexível no processamento de dados	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
O SIC permite que os objetivos sejam atingidos com precisão e rapidez	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
O SIC processa os dados de acordo com os normativos contabilísticos	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
O custo do SIC para a empresa é proporcional à quantidade e qualidade dos dados tratados	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
O SIC permite uma fácil atualização da informação contabilística comparável	<input checked="" type="radio"/>	<input checked="" type="radio"/>	<input checked="" type="radio"/>	<input checked="" type="radio"/>	<input checked="" type="radio"/>	<input checked="" type="radio"/>	<input checked="" type="radio"/>
O SIC produz informação contabilística que afeta a eficácia da empresa	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
O SIC é caracterizado pela facilidade de uso e alta qualidade	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
As entradas de dados no SIC							
e clara							
A informação contabilística gerada pelo SIC é mantida de forma segura	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

(continues)

Qualidade da Informação Contabilística

20. Em que medida concorda com cada uma das afirmações apresentadas abaixo? *

Marcar apenas uma oval por linha.

	Concordo plenamente	Concordo bastante	Concordo	Nem concordo nem discordo	Discordo	Discordo bastante	Discordo plenamente
A empresa diferencia-se através da qualidade da sua informação contabilística	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
A precisão da informação contabilística permite tomar melhores decisões financeiras	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
A informação contabilística é preparada assegurando a sua qualidade, precisão e exatidão	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
A informação contabilística é adequada à necessidade dos utilizadores em diferentes períodos financeiros	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
A informação contabilística é flexível na sua utilização	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
A informação contabilística é clara e descomplicada	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
A informação contabilística é facilmente interpretada pelos utilizadores	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

(continues)

A informação contabilística engloba todos os aspetos financeiros utilizados na tomada de decisão

A informação contabilística é disponibilizada atempadamente

A informação contabilística é facilmente arquivada e acedida a qualquer momento

A informação contabilística e financeira apresenta-se com qualidade

(continues)

Responsabilidade Social Corporativa

22. Em que medida concorda com cada uma das afirmações apresentadas abaixo? *

Marcar apenas uma oval por linha.

	Concordo plenamente	Concordo bastante	Concordo	Nem concordo nem discordo	Discordo	Discordo bastante	Discordo plenamente
Trabalho numa empresa socialmente responsável que procura servir a comunidade em que se insere	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Trabalho numa empresa que disponibiliza recursos a causas tempo, dinheiro e socialmente responsáveis	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>