BUSINESS
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ARTIFICIAL INTELLIGENCE IMPACT IN MANAGEMENT ACCOUNTING

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Abstract

Artificial intelligence (AI) is a trending technology which has the potential to revolutionize many industries and generate a significant impact on society. Management accounting (MA) is experiencing its first steps into AI implementation. To understand how the development and implementation of AI systems impact MA and its professionals, the authors developed a research model based on both quantitative (inferential statistics) and qualitative (descriptive and content statistics) statistical analysis. Results indicate that one in four companies is implement AI technologies to perform their MA function, triggering a technological change, and the most used AI technologies are text analysis and machine learning. AI-based MA solutions have advantages such as improvement of efficiency, effectiveness, and MA professionals' focus on more value-added tasks, but also challenges regarding operation, training, security, communication, and supply. Furthermore, findings suggest that using AI-based MA solutions improves businesses' overall decision making and improves business competitiveness.

Keywords: artificial intelligence, management accounting, decision-making, inferential statistics, content analysis, machine learning, text analysis

JEL Classification System:

- M15 *IT Management;*
- M41 *Accounting*

Resumo

A inteligência artificial (IA) é uma tecnologia de tendência que tem o potencial de revolucionar muitas indústrias e gerar um impacto significativo na sociedade. A contabilidade de gestão (CG) está a dar os seus primeiros passos na implementação da IA. Para compreender de que forma o desenvolvimento e a implementação de sistemas de IA estão a impactar a CG e os seus profissionais, os autores desenvolveram um modelo de investigação baseado não só na análise estatística quantitativa (estatística inferencial) como também na análise qualitativa (estatística descritiva e de conteúdo). Os resultados indicam que uma em cada quatro empresas está a implementar tecnologias de IA para desempenhar a sua função de CG, que estamos a assistir a uma mudança tecnológica, e que as tecnologias de IA mais utilizadas são a análise de texto e o *machine learning*. As soluções de CG baseadas na IA têm vantagens tais como a melhoria da eficiência, da eficácia, e o foco dos profissionais de CG em tarefas de maior valor acrescentado, mas também desafios relativos à operação, formação, segurança, comunicação e fornecimento. Além disso, os resultados sugerem que a utilização de soluções de CG baseadas na IA melhora a tomada de decisão global das empresas e melhora a sua competitividade.

Palavras-Chave: inteligência artificial, contabilidade de gestão, estatística inferencial, análise de conteúdo*, machine learning*, análise de texto

Classificação JEL:

- M15 *IT Management;*
- M41 *Accounting*

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Chapter 1 – Introduction

1.1 Context and Relevancy

Artificial intelligence (AI) is a trending technology which has the potential to revolutionize many industries and generate a significant impact on society (Haenlein & Kaplan, 2018). Currently, many digital tools we are currently using have some form of AI incorporated. For instance, first generation AI applications enabled Facebook to recognize faces in images and tag users, allowed Siri (iOS) to understand human voice and act accordingly, and also enabled Tesla to develop self-driving cars (Haenlein & Kaplan, 2018). Besides, plenty AI generations with more sophisticated technology are yet to come.

In Portugal, companies are actively exploring and pursuing possibilities with AI. However, almost half of Portuguese companies which are interested in implementing AI have not yet begun to actively pilot any AI initiatives. In fact, companies in Portugal are considered late adopters of AI comparing to other European Markets (Ernest & Young LLP, 2018). AI usage in Portugal is concentrated in a few business functions such as IT, Technology, & Digital; Customer Service; and R&D & Product development. Nonetheless, a few companies are implementing AI on group functions such as Admin or Finance (Ernest & Young LPP, 2018).

On the other hand, management accounting is one field that will be greatly impacted by this technology (Nielsen, 2020). Accountants apply their technical knowledge about accounting and finance to help businesses and stakeholders make better decisions. However, to support their decision-making and advice, accountants need high quality financial and non-financial information and its subsequent analysis (Appelbaum *et al*., 2017). To produce new (predictive) insights to support decision-making is the purpose of AI technologies, such as machine learning (Luo *et al.*, 2018). So, by using AI, management accountants can improve their focus on more valuable tasks such as decision-making, problem solving, advising, strategy development, relationship building and leadership (Nielsen, 2020).

Although a few authors have addressed artificial intelligence and management accounting technological trends, there are still not many studies that focus on the relationship between these concepts. Therefore, a deeper study is necessary to understand how artificial intelligence impacts management accounting, either in its raw application, either for MA professionals (competencies, skills or consequences). The significance of artificial intelligence and the importance of management accounting for businesses are nowadays undeniable, so the research theme "Artificial intelligence impact in management accounting" is not only relevant but necessary.

1.2 General Objective

Addressing AI and management accounting, this thesis aims to understand how these concepts are currently related, with the main objective of understanding how the development and implementation of artificial intelligence systems impact management accounting and its professionals.

1.3 Specific Objectives and Research Questions

This research work is divided into two specific objectives: explore implementation, development, and changes in managerial accounting regarding the adoption of intelligent systems; and analyse artificial intelligence impact on managerial accountants' organization, performance and decision making. Each specific objective has two coupled research questions (Table 1), which totals four research questions:

RQ 1: What innovative AI management accounting systems have been implemented in companies so far?
RQ 2: What advantages and challenges does implementing AI on management accounting bring to companies?
RQ 3: How does AI impact management accounting labour functions?
RQ 4: How does AI impact management accountant's decision making?

Table 1 – Specific objectives, research questions and analysis techniques.

Specific Objectives	Research questions	Literature review
Explore implementation, development, and changes in Management Accounting regarding the adoption of intelligent systems.	(Q1) What innovative AI management accounting systems have been implemented in companies so far?	ICAEW, 2017; Rikhardsson & Yigitbasioglu, 2018; CPA, 2019; Corazza & Zanin, 2020; Nielsen, 2020.
	(Q2) What advantages and challenges does implementing AI on management accounting bring to companies?	Yeoh & Koronios, 2010; Appelbaum *et al*., 2017; ICAEW, 2017; Lee, 2017; Luo *et al*., 2018; PwC, 2018; Kaplan & Haenlein, 2019; Ransbotham *et al*., 2019; Reim *et al*., 2020; Nielsen, 2020; Shi, 2020.
Analyse artificial intelligence impact on Management Accountants organization, performance and decision making.	(Q3) How does AI impact management accounting labour functions?	ACCA & IMA, 2015; ICAEW, 2017; Mckinsey & Company, 2017; Richins *et al*., 2017; Rikhardsson & Yigitbasioglu, 2018; Stancheva-Todorova (2018), CPA (2019), Nielsen, 2020; Riem *et al*., 2020; Shi, 2020.
	(Q4) How does AI impact management accountant's decision making?	Appelbaum *et a*l.,2017; ICAEW, 2017; Mckinsey & Company, 2017; Richins *et al*., 2017; Luo *et al.* 2018; Rikhardsson & Yigitbasioglu, 2018; Stancheva-Todorova, 2018; CPA, 2019; Mckinsey & Company, 2019; Nielsen, 2020.

1.4 Structure

To achieve the dissertation's specific objectives and answer all four research questions, the dissertation structure is composed by five chapters. In chapter 1, the object of study is introduced by providing context and relevancy, defining general and specific objectives, and presenting four research questions to which the study intends to answer.

In chapter 2, we conduct the necessary literature review (divided into three subchapters) to understand artificial intelligence impact in management accounting. First and second subchapter review the concept and the evolution of artificial intelligence and management accounting, respectively. The third and last subchapter overviews the main authors and papers on linking artificial intelligence and management accounting.

Consequently, in chapter 3, based on the relevant literature review, the theoretical approach that supports each research question and levers the empirical piece of this study is defined. Then, in chapter 4, the selected methodology is presented by specifying this study's research model and by characterizing the sample.

In chapter 5, results, based on the theoretical approach from chapter 3, are displayed and discussed according to each research question. After discussion, in chapter 6 the dissertation's main conclusions are drawn and final considerations, contributions for both topics, research delimitations and suggestions for future research are displayed.

Chapter 2 – Literature Review

2.1 Concept and evolution of Artificial Intelligence

Artificial intelligence (AI) was first conceptualized in 1950 by Alan Turing. Turing described, in his seminal article "Computing Machinery and Intelligence", how to create intelligent machines and how to test their intelligence (Turing, 1950). "If a human is interacting with another human and a machine, and one's unable to distinguish the machine from the human, then the machine is said to be intelligent." Turing test was so impactful that it's still today considered a benchmark on how to identify an intelligent artificial system (Haenlein & Kaplan, 2018).

AI was formally defined as a research field in 1956. Marvin Minsky and John McCarthy hosted the Dartmouth Summer Research Project on Artificial Intelligence (DSRPAI) in New Hampshire to create a new research area aimed at building machines to simulate human intelligence (Haenlein & Kaplan, 2018). This convention united many researchers from different fields of expertise, such as Nathaniel Rochester (computer scientist who later designed the IBM 701) or Allen Newell (computer scientist who unveiled one of the first AI programs, the Logic Theorist), who would later be considered the founding fathers of AI (McCarthy *et al*., 1955).

Considering all subsequent studies, defining AI is a true challenge, either because AI field has experienced a rapid evolution, or because defining intelligence itself isn't easy at all. In 1955, DSRPAI defined AI as "making a machine behave in ways that would be called intelligent if a human were so behaving" (McCarthy *et al*., 1955). Likewise, in 1968, Minsky considered AI as "the science of making machines do things that would require intelligence if done by men" (Minsky, 1968). Recently, Haenlein & Kaplan (2018) stated it as "a system's ability to interpret external data correctly, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation".

Based on four human competencies/skills (artistic creativity, cognitive, emotional, and social intelligence) and according to Haenlein & Kaplan (2018), there are three types of AI systems: analytical, human-inspired, and humanized. Analytical systems generate a cognitive representation of the world and use learning based on experience to inform

future decisions. Human-Inspired AI systems consider cognitive and emotional elements in their decision making, e.g., social humanoid robot, *Sophia*. Finally, humanized systems would be self-aware and self-conscious in their interactions with others. However, these are not available yet and are a project for the future.

Expert systems (collections of rules programmed by humans in form of if-then statements) are not part of AI since they lack the ability to learn autonomously from external data. In fact, expert systems represent a different approach altogether since they assume that human intelligence can be formalized through rules and hence reconstructed in a top-down approach (also called symbolic or knowledge-based approach) (Haenlein & Kaplan, 2018).

Internet of things (IoT) and big data are AI related concepts. According to Krotov (2017), IoT is a complex system built within three environments: technological (hardware, software, networking, integrated platforms, among others); physical (human objects; non-human objects; and physical surroundings); and socio-economical (consumers; legislative bodies; industry associations; among others). It allows the acquaintance of (external) data and, therefore, IoT can be considered an input for big data (Lee, 2017).

Big data, in the other hand, can be defined based on three main dimensions: volume (amount of data collected and/or generated); velocity (speed at which data is generated or processed); and variety (number of data types like text, photo, audio, video, clickstream, and sensor) (Lee, 2017). However, big data evolution has shown that there is a clear interaction between the former but also with other dimensions. To help managers fully understand the relationships between the dimensions of big data, Lee (2017) presented an integrated view of the topic (Figure 1).

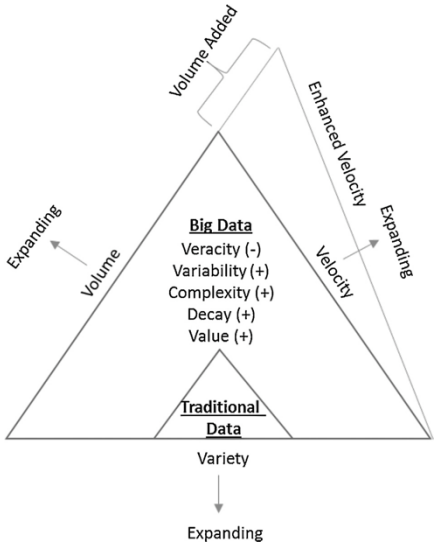


Figure 1 – Integrated view of big data.

Source: Lee, 2017

Inside the triangle are the five dimensions of big data that are affected by the growth of the three triangular dimensions: veracity (unreliability and uncertainty latent in data sources); variability (variation in data flow rates); complexity (number of data sources); decay (the declining value of data over time); and value (data analytics). The growth of the three-edged dimensions is negatively related to veracity, but positively related to complexity, variability, decay, and value. This view also shows that structured data is a subset of big data with a smaller scope (Lee, 2017).

Big data represents a new way of doing business, one where strategy is frequently informed by large volumes of various data sources (CPA, 2019). Big data analytics has many benefits such as: cost savings; better decision making; higher product and service quality; and personalized content based on what consumers are looking and on their interests. Lee (2017) also noted that managers realize that big data has potential impacts on firms, but they still struggle to exploit this technology.

Businesses not only rely on data within their organizations, but also combine it with data sets from non-traditional information sources to drive new, unique, and timely business and financial insights. For instance, satellite images of parking lots outside retail stores or auto dealerships are used to gauge customer volume and inventory turnover; product

reviews are used to forecast sales or even potential recalls; and job postings are used to determine whether a company is expanding into a new area (CPA, 2019).

AI uses external data acquired through IoT or other big data sources as an input for identifying underlying patterns and rules, for example, machine learning (ML) methods, which basically describes methods that help computers learn without being explicitly programmed (Haenlein & Kaplan, 2018). AI has different technologies with different capabilities. Technologies such as: smart robotics; speech recognition; virtual agents; natural language processing; text analysis; biometrics; ML; neural networks / deep learning; and computer vision (Ernest & Young LLP, 2018).

Smart robotics are the combination of artificial intelligence and robots to perform advanced tasks compared to traditional non-intelligent robots (Ernest & Young LLP, 2018). According to Raf & Seamans (2019), the adoption of these technologies will likely alter the bundle of skills and tasks that many occupations are comprised of and affect the composition of the labour force. Considering so, they will reshape organizations and force firms to restructure themselves to account for these changes (Raf & Seamans, 2019).

Speech recognition enables computers to interpret spoken language and to transform it into written text or to treat it as commands for a computer (Ernest & Young LLP, 2018). Speech recognition is based on deep learning algorithms and has been a topic of much research lately (Nassif *et al*., 2019). This AI technology has many applications, such as: dictating to computers instead of typing; voice-controlled spacecraft systems; helping handicapped people; smart homes (vocally command functions of the home, e.g., controlling the lights); and many others (Nassif *et al.*, 2019).

Virtual agents are computer-generated personas that can be used to interact with people in both B2B and B2C contexts (Ernest & Young LLP, 2018). Zhou *et al.* (2019) presented a virtual agent which is capable to interview a candidate through a text-based conversation and automatically infer the user's traits (e.g. big 5 personality traits and strengths). Zhou *et al*. (2019) concluded that an AI interviewer can make a recruiting process more efficient, objective, and inclusive. Additionally, this work enlightens the value of creating hyper-personalized agents based on candidates' characteristics automatically inferred during a conversation (Zhou *et al*., 2019).

Natural Language Processing (NLP) is computer interpretation, understanding, and generation of written natural human language (Ernest & Young LLP, 2018). The role of AI as a tool for enhancing clinical care and research is becoming important in a broad range of practices. As a large amount of valuable information is locked in clinical narratives, NLP techniques have been leveraged to extract information for clinical research and they have proven to be a very useful set of tools (Juhn & Liu, 2019).

Text Analysis is texts' computational analysis and enables the reading by other AI or computer systems (Ernest & Young LLP, 2018). It has been particularly helpful in analysing new sources of big data that were previously underutilized for research, large textual archives for instance. With a collection of video interviews with 61 organizational leaders from emerging markets, Choudhury *et al.* (2019) used textual analysis to code CEOs communication styles. They concluded that CEOs' communication styles help predict a firm's ability to grow, its adaptability, and its reallocation of assets. Another of the study's relevant conclusion was that text analysis (with image recognition) can be used to code communication styles more intuitively.

Biometrics are analysis of human physical and emotional characteristics for identification and access control. According to Iyer *et al.* (2020), AI integrated with biometrics can increase the security and consistency significantly. For instance, Singapore retail businesses Octobox, OMO Store and Pick & Go have recently announced many deployments based on biometrics, such as RFID to track the purchased items, AI to track movement inside the store, and palm scanners that allow the buyer to enter the kiosk.

Computer's ability to learn from input data, either supervised or non-supervised, is known as machine learning (Ernest & Young LLP, 2018). ML is currently one of the most promising and studied AI technologies. It has been employed in several applications such as: credit scoring; web search; ad placement; pricing prediction; transportation; healthcare; fraud detection; and drug design (Domingos, 2012). The learning process is achieved interactively from training data (also known as analysed data) and new input data. This interactive aspect allows machines to identify hidden insights or repeated patterns and use these findings to adapt when exposed to new data (Figure 2).

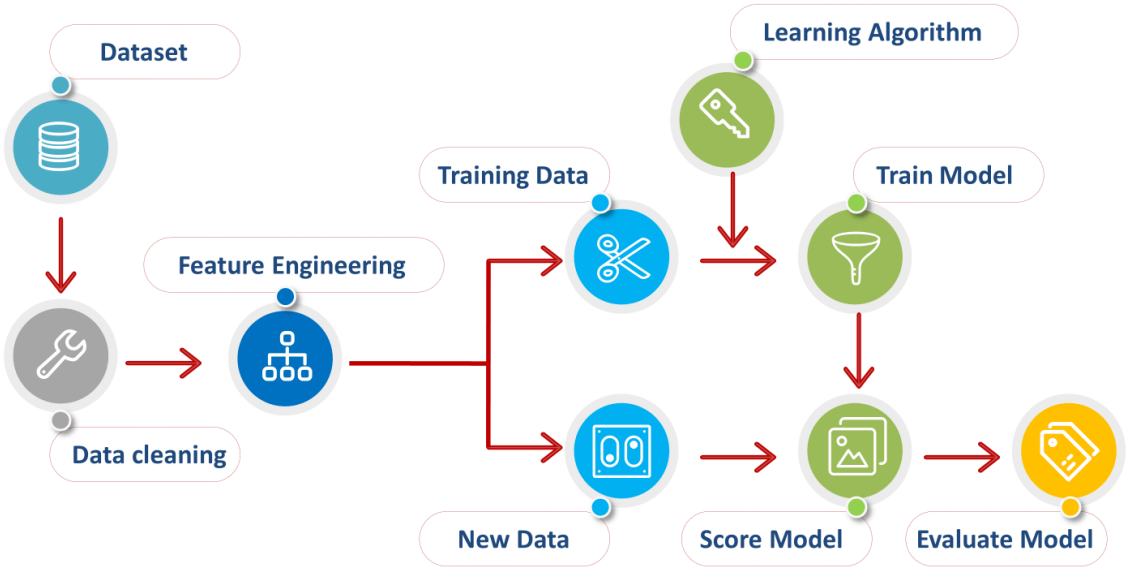


Figure 2 – Machine Learning process diagram

Source: Chakure, 2019

Machine learning's five main techniques are supervised, unsupervised, semi-supervised, reinforcement and deep learning (Figure 3). Supervised learning includes training datasets at which data is presented in pairs, an input (labelled) and its corresponding output (desired) (Dey, 2016). The algorithm uses a training data set and gets feedback from humans to learn the relationship of given inputs to a given output (e.g., how the inputs time of year and interest rates predict housing prices). The goal is to learn a general rule for mapping inputs to the output. Training data supervises by telling algorithm what the response should be for the given values of the predictor variables (Nielsen, 2020).

Unsupervised learning attempts to find common points between the inputs in the dataset (Dey, 2016). The algorithm explores input data without being given an explicit response variable (unlabelled data). For instance, explore demographic data on consumers to identify patterns. In this case, the decision maker aims to find patterns and to classify the consumers based on unlabelled demographic data. These kinds of algorithms can produce highly accurate and precise results. Unsupervised learning is commonly used as data pre-treatment either for supervised or semi-supervised learning algorithms (Nielsen, 2020).

Semi-supervised learning combines the two previously described ML types as the algorithm is trained by a dataset that contains both labelled and unlabelled input points

(Dey, 2016). It becomes useful because labelling enormous amounts of data for supervised learning is disproportionately extensive, expensive and can impose human biases on the model. Combining both data can produce high valuable information that otherwise wouldn't be collected. Developing a model to detect fraud in a large bank is based on some examples of fraud, but not all because one doesn't have access or is not aware of all information, this is one example of semi-supervised learning (Nielsen, 2020).

Reinforcement learning algorithm is not given examples of optimal outputs but must instead find them through a process of numerous trial and errors (interaction with an environment). The goal of this system is to define the best sequence of actions that solve a problem and maximize a long-term reward (Nielsen, 2020). By maximizing a cumulative reward metric, it makes the algorithm understand whether it's going in the right direction or not (Dey, 2016).

Deep learning algorithm is composed by multiple processing layers based on neural networks to learn representations of data with multiple levels of abstraction (Miotto *et al*., 2017; Dey, 2016). Such deep representations can then be used to leverage clinician activities in different domains and applications, such as: disease risk prediction; personalized prescriptions; treatment recommendations; clinical trial recruitment; as well as research and data analysis (Miotto *et al*., 2017).

Wang *et al*. (2016) recently won the Parkinson's Progression Marker's Initiative data challenge on subtyping Parkinson's disease using a temporal deep learning approach. Authors used the LSTM RNN model and identified three interesting subtypes for Parkinson's disease, wherein each subtype demonstrates common disease progression trends. The authors believe that this work shows the great potential of deep learning models in real-world health care problems and how it could lead to more reliable and robust automatic systems soon.

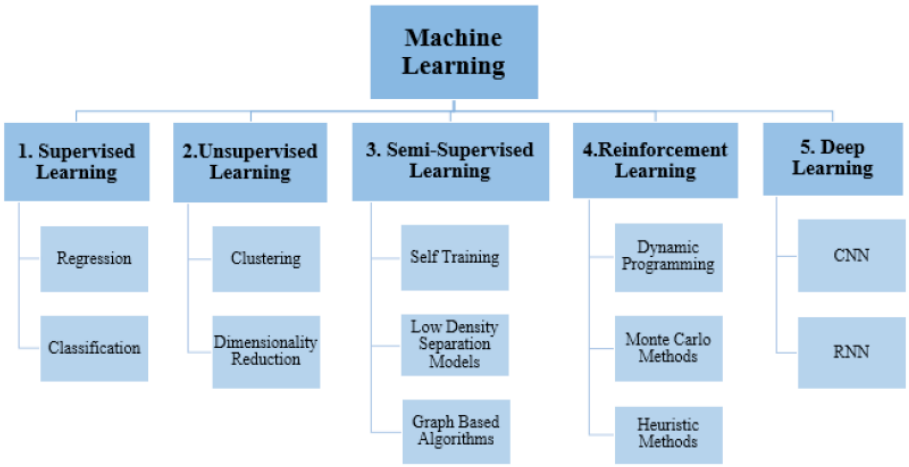


Figure 3 – Machine learning techniques and respective algorithms.

Source: Nassif *et al.,* 2019

Computer Vision gives computers the ability to analyse images similar to how humans analyse (Ernest & Young LLP, 2018). These systems are widely employed in different segments of agricultural production and industrial food production (Patricio & Rieder, 2018). They can be used in grading systems for fruits and vegetables in a non-destructive way and provide a simple, objective, and accurate analysis of the samples. In Portugal, Jerónimo Martins has opened their first "Lab Store" in Carcavelos and is now using computer vision to offer a 24-hour service based on tracking and automatic payment of items (Caetano, 2019).

The underlying assumption of AI is that computers can learn and subsequently perform tasks which were previously considered to require human intelligence. Business Intelligence (BI) is commonly referred as AI (Foley & Guillemette, 2010; Wangoo, 2018). However, BI encompasses technologies for the collection, analysis, and representation of relevant business data (e.g., Business Intelligence & Analytics). These enhance the ability of the decision makers to predict the business future, but, opposing to AI, do not encompass advanced technologies for the process of data analysis (learning component) (Corazza & Zanin, 2020).

Considering its models and algorithms, AI systems have three main features: large data volumes; complex and changing patterns; and consistency (ICAEW, 2017). Such

capabilities are particularly important for organisations aiming to exploit the increasing amount of big data that is available to them. In fact, AI technological progress has led to increased interest among a wide range of businesses. According to the study of Ransbotham *et al*. (2019), 90% of the respondents revealed that AI offers opportunities for companies, such as to improve efficiency and effectiveness, and to increment the quality of the information that is available for decision making.

Nielsen (2020) demonstrates how ML algorithms can be used in decision making (supervised learning) to compare four different performance models (KPIs). The author conducted an experiment comparing three ML algorithms (multiclass decision forest; multiclass logistic regression; and multiclass neural networks) to find out which of the three algorithms gives the best prediction for future policies. Results suggest that the multiclass neural network algorithm is the best performing one when comparing training with test.

However, when the predicted model is processed, the decision maker can try out several scenarios (different KPIs values) and have other best performing algorithm as a result. This type of comparison reveals how KPIs are behaving within the four different types of performance models and the three algorithms, and consequently also gives some information about predictability for the four types of KPIs. Therefore, there's hardly one simple right model within performance management. Instead, modelling should be viewed as an exercise in the approximation between the explainable information and the empirical data (Nielsen 2020).

2.2 Concept and evolution of Management Accounting

In the 19th century, railroad managers had implemented large, complex costing systems that allowed them to compute the costs of carrying different types of freight, such as coal and steel, along multiple routes. This information supported efficiency improvements and pricing decisions. The railroads were the first modern industry to develop and use large quantities of financial statistics to assess and monitor organizational performance (Atkinson *et al*., 2011).

Later in the century, Andrew Carnegie focused on his information systems to reduce costs and close facilities that he felt were irretrievably inefficient. Carnegie exploited his cost advantage by lowering his prices, which then reduced his competition significantly due to their inability to compete price wise. Therefore, Carnegie's costing systems gave him a sustainable competitive advantage in the marketplace and promoted a significant growth of his company (Nasaw, 2016).

In 1920s, General Motors, among other large companies, expanded the focus of management accounting (MA) by considering cost accounting, management planning and management control. General Motors started to operate in different business lines, so executives needed specific information (e.g., return-on-investment by business unit) for control and coordination. By doing so, managers developed ways to measure the profitability and the performance of their units (Johnson, 1978).

In the 1970s, there was a clear intention by western organizations to develop new MA tools, because they were under intense pressure from Japanese manufacturers. These tools included systems that reported on quality, service, and customer and employee performance rather than simple financial summaries of organizational unit performance (Waweru, 2010). MA history shows that innovations were driven by implementation of companies' new strategies. Their implementation demanded further and distinctive information, particularly because companies have become more complex, technologies have changed, and new competitors have appeared (Atkinson *et al*., 2011).

According to the Institute of Management Accountants (2008), MA "involves partnering in management decision making, devising planning and performance management systems, and providing expertise in financial reporting and control to assist management in the formulation and implementation of an organization's strategy", which is aligned with the evolution displayed previously and clearly exhibits MA importance on leading a company to growth and success.

In order to develop a solid and focused framework, Rikhardsson & Yigitbasioglu (2018) conceptualized MA considering four main elements: tasks (planning, control, performance measurement, transaction processing, reporting and decision support); techniques (activity-based costing, balanced scorecard frameworks, volume-based

allocation of costs, strategy maps, zero-based budgeting, and forecasting); organization (management accountants roles in organizations and how MA functions are organized across industries and cultures); and behavioural implications (impact on organization behaviour and management's MA issues perception).

The impact of various information technologies has been studied based on these four main elements. For instance, many authors have focused on how the adoption of enterprise resource planning (ERP) systems (or integrated information systems) affect management accounting tasks and techniques. These systems increase the efficiency of collecting and reporting accounting data (Cooper & Kaplan, 1998; Davenport, 1998; Appelbaum *et al*., 2017; Ociepa-Kubicka, 2017). However, some have concluded that they often have weak effects on MA practices rather than producing any significant modifications (Rikhardsson & Yigitbasioglu, 2018).

Advanced ERP systems integrate Business Intelligence & Analytics (BI&A) technology. Literature identifies BI&A as systematic processes, methodologies, technologies, analytical tools and techniques that use computer-supported systems to collect and analyse information for effective business activities and better decision-making (Božič & Dimovki, 2019). BI&A provides data-centric decision support to management accountants in, for example, planning, performance measurement and cost management techniques. While analytics driven management accounting techniques seem to improve the performance of some tasks, they increase decision makers' cognitive load and bias (Troyansky *et al*., 2015; Volitichn & Ruppert, 2012).

Consensus in BI&A was given by the huge potential for performance management purposes, and it is rooted in MA literature because the combination of these computer-technologies with the management control systems increase the ability to elaborate more relevant information for decision-makers (Rikhardsson & Yigitbasioglu, 2018). However, most papers are theoretical and do not address key tasks in management accounting. In fact, Rikhardsson & Yigitbasioglu (2018) conclude that current understanding of BI&A in management accounting is very limited and may compromise this technology impact on decision making in organizations.

The recent technological advancement has once more shifted the attention to an important form of computer-technology, the AI, an advanced form of business analytics (adds learning element) (Corazza & Zanin, 2020). The possibility of combining different external environmental situations and future development trends allows MA to obtain better predictable and reliable future conditions (ICAEW, 2017). AI technologies facilitate data collection, analysis, and information delivery, and they're designed to support decision-making. Considering that MA is a decision-supporting activity, there is an evident link between AI and MA (Nielsen, 2020).

2.3 Artificial Intelligence & Management Accounting

PwC (2018) conducted a survey to 3200 CEOs in more than 90 countries and estimated that global GDP may increase by up to 14% (US$15.7 trillion) by 2030 due to the rapid development of AI. The report also anticipates that the next wave of digital revolution will be unleashed with the help of data sets generated from the IoT. According to ICAS (2016) and Luo *et al*. (2018), AI widespread adoption in business and accounting is still in early stages. In order to build a positive vision of the future, there's a need to develop a deep understanding of how AI can solve accounting problems, practical challenges and the skills accountants need to work alongside intelligent systems (ICAS, 2016).

International and Portuguese markets have already a few AI-based solutions for MA, such as *SAP S/4HANA* (ERP intelligent system), *Vic.ai*, *AI assistant by 24sevenOffice*, *DOKKA,* among others. Companies like Accenture, AIG, Corticeira Amorim, HIT Group, Lactogal and Mota-Engil are now using *SAP S/4HANA* and displaying satisfactory results (SAP, 2020). PwC, NOMAD Financial, Nurx and Countsy are using *Vic.ai* (Vic.ai, 2020), while Shopify, MailChimp, WordPress and Magento, for instance, are operating with *AI assistant by 24SevenOffice* (24SevenOffice, 2020). *DOKKA*, on the other hand, is being used by Ernest & Young, BDO, OfficePal, and Value Financial Services (Dokka, 2020).

Nonetheless, having machines doing all the tedious and repetitive tasks could sound alarming for many accountants. Stephanie Weil, CEO of Accounteam, alerts that most tedious tasks are time consuming but very lucrative (clients pay to focus on their core

business and not to lose time doing tedious tasks), machines can easily eliminate accounting errors (usually hard to find), reduce liabilities, and focus accountants' role on advisory. Improved access to information has also led to the decentralization of MA function and many MA tasks are progressively performed in other organization functions (Rikhardsson & Yigitbasioglu, 2018).

In fact, due to exponential digitalization of accounting processes, management accountants' roles have become more business-oriented and strategic (Stancheva-Todorova, 2018; Nielsen, 2020; CPA, 2019; Shi, 2020). Time saving is an important benefit of AI and gives accounting professionals a chance to spend more time on research and to deliver more relevant and valuable judgments instead (ICAEW, 2017). However, implementing AI also unveils a few challenges. Riem *et al*. (2020) identify transparency; lacking trust for AI among employees; analogue processes; AI experts' shortage; data quality/amount; cyber security and stakeholders communication – as challenges to any AI application among organizations/departments.

Small-scale AI testing and business alignment with today's fast-paced environment enables employees to perceive and understand how their position will be affected by the implementation. Also, a profound understanding of the technology and how it will increase current operations will likely foster positivity towards the transformation (Yeoh & Koronios 2010; Appelbaum *et a*l., 2017; Riem *et al*., 2020). Therefore, high transparency will lower the barriers for implementation and improve trust for AI among employees.

Data acquisition, infrastructure and amount are pivotal when implementing AI (Lee, 2017; Luo *et al*., 2018; Riem *et al*., 2020). Considering so, assessment of opportunities to digitize analogue processes is challenging but necessary, and it enables comprehensive data collection. AI experts are also important to provide companies and/or departments with a solid understanding of the technology. As the rise of AI is expected to require a broader upgrade of employees' skills, AI training will be core (Luo *et al*., 2018; Haenlein & Kaplan, 2019; Shi, 2020). However, AI experts are few and expensive, which challenges companies' ability to fully capitalize on this technology (Riem *et al*., 2020).

Data quality and integrity are directly correlated with AI technology outcome, which means that qualitative data sets are a precondition that must be fulfilled to achieve success (Appelbaum *et al*., 2017; Riem *et al*., 2020). Riem *et al*. (2020) also advert for challenges concerning stakeholders comunication and cyber security. Companies should consider educating properly stakeholders on AI technology (what it is; how it used and coupled risks) and nurture two-sided comunication channels to enable feedback loops. By storying financial information in electronic form, companies become also vulnerable to cyber-attacks and disclosure of trade secrets (Shi, 2020).

According to ACCA & IMA (2015), there is a growing demand for professionals who can articulate and support the value of data. Management accountants have a very good opportunity to take on such responsibilities because much of their work is data related. As consultants and advisers to businesses, management accountants must maintain awareness of a broad range of technologies and trends. In fact, demand for new data-related skills for management accounting is already high and likely to increase even further (Richins *et al*., 2017). Shi (2020) stresses that AI may put professionals under the pressure of skill transformation.

Nielsen (2020) points out some of the most important learning demands for MA professionals. For instance: statistics and math (e.g., linear, non-linear methods, probability, etc.); simple parametric/non-parametric algorithms and their assumptions; resampling methods (e.g., bootstrapping, and cross-validation techniques); Python/R (go-to language for machine learning); causal and predictive analysis; and SQL database (organize data thru filters and conditions). Beside all these demands, MA professionals can collaborate with data scientists by suggesting content to explore and then interpret the results from a firm's strategic point of view (Stancheva-Todorova, 2018; CPA, 2019).

Nielsen (2020) considers important that decision makers must have a defined business problem before conjugating data and machine learning (AI [ML]) technology. Looking into MA, many topics/business problems are centred around cost reduction (cutting or maintaining costs; increasing the effectiveness of employees; increasing the efficiency of critical processes; etc.); risk reduction (staying in compliance with government regulations; staying within a project budget; among others); and profit improvement

(entering new markets via an improved value proposition; increasing margins; increasing the effectiveness of the sales force; use pricing analytics; etc.).

Nielsen (2020) exemplifies how AI (cluster analysis – unsupervised ML algorithm) can be used on profit improvement by focusing and improving customer profitability. The author uses a small hypothetical data set with observations of 200 KPI over a period of four years, totalling 800 observations. These can be divided, according to the Balance Score Card (BSC) model, into four perspectives: KPIs for learning & growth (organizational capacity); for financials; for customers; and for internal processes. As in any algorithm use, several assumptions/options have to be made and so Nielsen (2020) stresses for the importance of the decision maker awareness of those beforehand.

In this example, one key assumption is that there isn't a response variable just yet (to supervise the algorithm) and thus it is relevant to use self-organizing maps (SOMs) or cluster evaluation to look for the best number of groups for a given clustering algorithm. The author compares results for both three ("hierarchical clustering") and four (BSC model) clusters using SOM. Nielsen (2020) concluded, based on cubic clustering criterion metric, that having four clusters have a better data representation than having just three. Customer profitability can be more accurately focused with four clusters as KPI's specification degree is higher.

According to Mckinsey & Company (2017), activities such as data processing or collecting have higher susceptibility for automation rather than interfacing with stakeholders, developing/managing people or applying expertise to decision making. Nonetheless, automation still has a considerable impact in latter activities. Recently, McKinsey & Company (2019) also conducted a research worldwide and found signs of increasing frustration levels, broken decision-making processes, slow-paced deliberations, and a poor quality of decision-making outcomes. In fact, the estimated opportunity costs were about 530 000 days of managers' time[1] that were potentially misspent each year.

[1] "Assuming that at an average Fortune 500 company of 56,400 employees, 20 percent are managers who work 220 days per year: these managers spend an average of 37 percent of their time making decisions, and 58 percent of this time is used ineffectively." (McKinsey & Company, 2019)

Modern management accountants combine both internal data (e.g., to measure firm performance) and external data to provide decision related information. Professionals deliver descriptive reports to answer questions about prior events and make predictions for consequences, uncertainty, and risk in decisions (Appelbaum *et al*., 2017). Considering its predictive feature, artificial intelligence is likely to influence management accountants overall work, as AI models are designed to suggest appropriate decision-making (Luo *et al*., 2018).

AI models allow test of a few scenarios based on several and different assumptions/options (Nielsen, 2020). The decision-making process starts before running the algorithm itself, so management accountants play a major role through all process. Besides assumptions selection, to support any subsequent decision making, it is also important to have the right data for the right prediction and for the right learning technique (Nielsen, 2020).

According to Nielsen (2020), efficiency and accuracy are becoming the drivers of a successful interaction between AI and ML. Yet, reaching the "right" decision each time is still a challenge. Many authors claim that the existent AI literature lacks empirical analysis, information, and documentation to analyse more deeply AI's impact on management accounting, either for its raw application or for professionals (competencies, skills, or consequences) (CPA, 2019; Nielsen 2020; ICAEW, 2017; Rikhardsson & Yigitbasioglu, 2018).

Chapter 3 – Theoretical approach

Along with the investigation taken for the purpose of the literature review, different authors' point-of-view and our own perception of MA context were contrasted, in both theoretical and practical terms. As a result, emerged a set of key questions, which will be driving the following discussion.

Businesses rely on data from within their organizations and from non-traditional information sources to drive new, unique, and timely business and financial insights (CPA, 2019). Many companies have adopted enterprise resource planning (ERP) systems to perform their MA tasks and techniques. These tend to increase the efficiency of collecting and reporting accounting data. However, often have weak effects on MA practices (Rikhardsson & Yigitbasioglu, 2018).

Advanced ERP systems (e.g., BI&A) integrate systematic processes, methodologies, technologies, analytical tools and techniques that use computer-supported systems to collect and analyse information for effective business activities and better decision-making. While BI&A seems to improve the performance of some tasks, it increases decision makers' cognitive load and bias (Rikhardsson & Yigitbasioglu, 2018). The recent technological development has led to an advanced form of business analytics based on AI and big data, which ads a learning element to the existent features (Corazza & Zanin, 2020). Big data, a precondition for AI, frequently informs companies on large volumes of various data sources (CPA, 2019).

AI technologies facilitate data collection, analysis and they're designed to support decision-making (ICAEW, 2017; Nielsen, 2020). The possibility of combining different external environmental situations and future development trends allows MA to obtain better predictable and reliable future conditions (ICAEW, 2017).

Companies are now embracing management accounting's new technology advancement towards artificial intelligence. Following this perception, the first research question arises in order to understand how companies are incorporating AI on management accounting, but also how AI systems influence the way companies operate. **What innovative AI management accounting systems have been implemented in companies so far?**

As any technological application in a business setting, there is always advantages (usually, core to the motivation and the ambition of application), but also challenges, either for managers, administration, or the business itself. Artificial intelligence implementation on any organization or department, management accounting included, has both features as well.

Managers find many advantages on implementing AI on their business, such as improved efficiency, effectiveness, and information quality for decision making (Ransbotham *et al*., 2019). Moreover, due to the rapid development of this technology, global GDP is expected to increase by 2030 (PwC, 2018) indicating a growth opportunity for most businesses. Besides, AI technologies facilitate data collection, data analysis, information delivery (Nielsen, 2020), and also allow time saving, which gives accounting professionals a chance to focus on research and on delivering relevant and valuable judgements to business management (ICAEW, 2017).

Nonetheless, AI implementation also presents challenges. ICAEW (2017) identifies three challenging requirements: large data volumes, complex and changing patterns and consistency. Additionally, transparency, lacking trust for AI among employees, analogue processes, AI experts shortage, cyber security and stakeholders communication are also considered to be challenges to overcome by any AI implementation in organizations or departments (Yeoh & Koronios 2010; Appelbaum *et al.*, 2017; Lee, 2017; Luo *et al*., 2018; Riem *et al*., 2020). Likewise, this technology requires a broader upgrade of employees' skills and so AI training is said to be essential (Luo *et al*., 2018; Kaplan & Haenlein, 2019; Shi, 2020). As mentioned previously, skill transformation may put professionals under pressure and become a challenge as well (Shi, 2020).

So, the second research question emerges as an attempt to understand how businesses facing AI implementation challenges have organized their management accounting, but also what advantages have they found. **What advantages and challenges does implementing AI on management accounting bring to companies?**

AI technology is commonly perceived as machines' ability to automate all tedious and repetitive tasks, which naturally causes a lack of trust for AI among employees (Riem *et al.,* 2020). Accountants perform, in fact, a set of tedious tasks that are time consuming

(Nielsen, 2020). Through automation, machines can easily eliminate accounting errors and reduce liabilities, which improves accounting tasks overall performance (Mckinsey & Company, 2017; Nielsen, 2020). Besides, it enables accounting professionals to focus on advisory and consulting tasks (Nielsen, 2020).

As consultants and advisers to businesses, management accountants must maintain awareness of a broad range of concepts, technologies, and trends, such as statistics, math, simple algorithms, Python/R, SQL databases, among others (Nielsen, 2020). MA professionals can collaborate with data scientists by suggesting content to explore and then interpret the results from a firm's strategic standpoint (Stancheva-Todorova, 2018; CPA, 2019).

According to ACCA & IMA (2015), market demand for professionals who can articulate and support the value of data is growing. A recent study from Richins *et al.* (2017) reveals that demand for new data-related skills for MA is already high and it is likely to increase even further. In fact, better access to information has also led to a decentralization of the MA function and many MA tasks are progressively performed in other business functions, such as, strategy (Rikhardsson & Yigitbasioglu, 2018; ICAEW, 2017; Shi, 2020).

Therefore, the third research question arises to understand which MA labour functions have been already replaced and which can be further developed. Moreover, understanding how companies have replaced/developed or how intend to replace/develop MA functions is an object as well. **How does AI impact management accounting labour functions?**

Activities like data processing or data collecting have higher susceptibility for automation rather than interfacing with stakeholders, managing people or applying expertise to decision making (Mckinsey & Company, 2017). Recently, McKinsey & Company (2019) conducted a research worldwide focused on better decisions by senior management and found inoperative decision-making processes, a poor quality of decision-making results, signs of increasing employee's frustration levels, and slow-paced deliberations.

Modern management accountants combine both internal data and external data to provide decision related information (Rikhardsson & Yigitbasioglu, 2018) and new data-related

skills are becoming a requirement (Richins *et al*., 2017) Management accountants' role has also become more strategic and business-oriented (ICAEW, 2017; Stancheva-Todorova, 2018; CPA, 2019; Nielsen, 2020; Shi, 2020). MA professionals deliver descriptive reports to answer questions about prior events and make predictions for consequences, uncertainty, and risk in decisions (Appelbaum *et al*., 2017). Considering its predictive and supporting decision making features (Luo *et al.,* 2018), AI models may influence management accountants overall work and judgements.

According to Nielsen (2020), decision makers must have a defined business problem before conjugating data and machine learning (AI) technology. The decision-making process starts before running the algorithm itself, it starts as soon as assumptions are selected and applied (Nielsen, 2020). Besides assumptions selection, to support any subsequent decision making, it is also important to have the right data for the right prediction and for the right learning technique (Nielsen, 2020).

Thus, the fourth and last research question appears to understand to what extent are management accountants using AI tools for deliberation, and also what consequences (employees, department and business) have arisen from using this technology in decision-making. **How does AI impact management accountant's decision-making?**

Chapter 4 – Methodology

4.1 – Research model

Research model is pivotal in the process of collecting data for analysis. It represents the plan to which researchers are going to rely to properly answer all the research questions raised while ensuring information's cohesion and coherence. Dissertation's research model is based on both quantitative and qualitative statistical analysis to allow a complete and rigorous comprehension of the topic without compromising its reliability, and it is composed by five stages (figure 4).

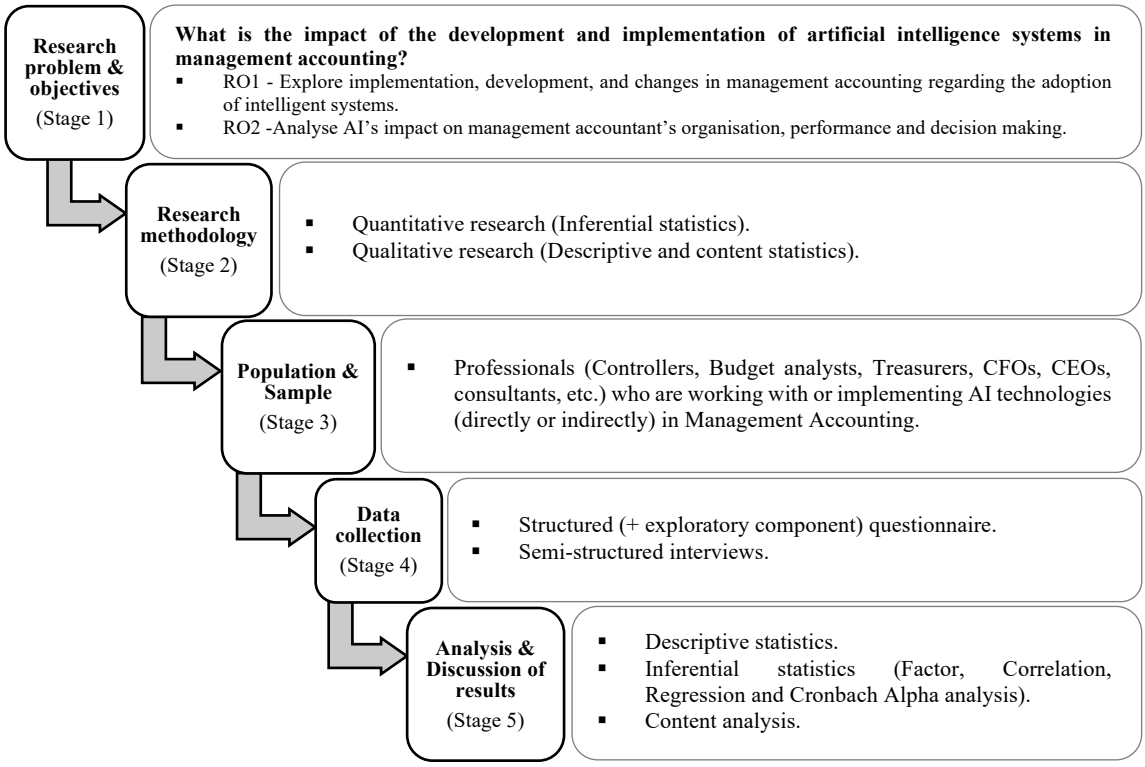


Figure 4 – Research model

Source: The author, 2021

Each research question (RQ) was raised based on the literature review and the theoretical approach built in chapters 1 and 2. To answer each RQ several statistical analysis techniques were applied considering its objective and its nature. Table 2 displays connections between research objectives (column 1), research questions (column 2), questionnaire questions & interviews (column 3), analysis techniques (column 4) and literature review (column 5).

Table 2 – Specific objectives, research questions, questionnaire questions and analysis techniques.

Specific Objectives	Research questions	Questionnaire questions	Analysis techniques	Literature review
Explore implementation, development, and changes in Management Accounting regarding the adoption of intelligent systems.	(Q1) What innovative AI management accounting systems have been implemented in companies so far?	7 to 11	Descriptive analysis.	ICAEW, 2017; Rikhardsson & Yigitbasioglu, 2018; CPA, 2019; Corazza & Zanin, 2020; Nielsen, 2020.
	(Q2) What advantages and challenges does implementing AI on management accounting bring to companies?	12 to 14	Factor; Correlation; Regression and Cronbach Alpha Analysis.	Yeoh & Koronios, 2010; Appelbaum *et al*., 2017; ICAEW, 2017; Lee, 2017; Luo *et al*., 2018; PwC, 2018; Kaplan & Haenlein, 2019; Ransbotham *et al.*, 2019; Reim *et al*., 2020; Nielsen, 2020; Shi, 2020.
Analyse artificial intelligence impact on Management Accountants organization, performance and decision making.	(Q3) How does AI impact management accounting labour functions?	15 & 16 (+ Interviews)	Descriptive analysis & Content analysis.	ACCA & IMA, 2015; ICAEW, 2017; Mckinsey & Company, 2017; Richins *et al*., 2017; Rikhardsson & Yigitbasioglu, 2018; Stancheva-Todorova (2018), CPA (2019), Nielsen, 2020; Riem *et al*., 2020; Shi, 2020.
	(Q4) How does AI impact management accountant's decision making?	17 to 19	Descriptive analysis & Factor; Correlation; Regression and Cronbach Alpha Analysis.	Appelbaum *et al*.,2017; ICAEW, 2017; Mckinsey & Company, 2017; Richins *et al*., 2017; Luo *et al*. 2018; Rikhardsson & Yigitbasioglu, 2018; Stancheva-Todorova, 2018; CPA, 2019; Mckinsey & Company, 2019; Nielsen, 2020.

4.2 – Data collection method

To gather the necessary data to answer all RQs, this study applied a structured questionnaire (mostly quantitative) and a set of semi-structured interviews (mostly qualitative). According to Wilkinson & Birmingham (2013), questionnaire format is one of the most suitable methods for standardized questions (being interpreted in the same way by all respondents) and for explanatory studies that seek relationships between variables, in particular cause-effect relationships, such as this one (Gill & Johnson, 2002; Robson, 2002). Given the existence of time and resources constraints we used a non-probabilistic sample, and the questionnaire was distributed online to professionals via email and LinkedIn. The questionnaire was built and answered on Google forms.

Likert scales are the "most commonly used psychometric scales for examining self-reported perceptions and attitudes" (Ho, 2017), generally preferred by respondents (5-point Likert-scale) (Colman *et al*., 1997), and used in several field related studies with reliable conclusions (Guilding *et al*., 2000; Mia & Clark, 1999). Therefore, this study's questionnaire was built with 5-point Likert-scale adapted to satisfaction, agreement, usage, and improvement. Besides Likert-scale, the questionnaire has also sample characterization questions (gender, age, professional experience, country, sector, and company role) and one open question regarding RQ3 (*How do you describe your company's/client's process of replacing and/or further developing management accounting functions based on artificial intelligence technologies?)*

Regarding semi-structured interviews, a non-probabilistic sample was also used. Fifteen professionals (Management accountants, Treasurers, Directors, CEOs, consultants, etc.) working with or implementing AI technologies (directly or indirectly) in MA were interviewed based on a five questions comprehensive script to help answer RQ3 (*How does AI impact management accounting labour functions?*).

4.3 – Pre-test procedure

Following Cooper and Schindler (2013) and Saunders *et al*. (2009) recommendations, before making the online questionnaire available for professionals, it was conducted a pre-test to uncover format or content errors, validate whether respondents understand

survey's questions, whether there is a need to rephrase ambiguous questions, and validate questions' reliability. The pre test was conducted with 6 professionals who found the overall questionnaire well structured, clear, and capable of giving insightful conclusions about the topic. Their feedback resulted in the following adaptations:

- Clarification of questionnaire's introduction to help respondents understand the context of the study, either for those who are implementing AI technologies in MA or for those who aren't (this study also aims to understand why they are not and what's their perception regarding these technologies).
- Addition of "Other – Please explain if you can." as an option to the question "*Why hasn't your company implemented AI technologies in Management Accounting*?" to allow this study to get more insights regarding its object.
- Addition of a question regarding professional's satisfaction towards AI technologies implementation (*How satisfied are you with your company AI technologies implementation on management accounting?*).

Regarding the interview script validation, both supervisors based on their previous experience in developing academic studies and interview scripts in strategy, management and marketing validated this study's script. The final version of both questionnaire and the full interview script may be consulted in Annex 1 (Annex 1 – Questionnaire, the author, 2021) and Annex 2 (Annex 2 – Full interview script, the author, 2021), respectively.

4.4 – Sample design

Our questionnaire sample is constituted by 117 participants. In terms of gender, 41 are female participants, 75 are male participants and 1 prefer not to say (figure 5). Regarding age, most participants have between 41 and 55 years old (figure 6). 56% of professionals are management accountants (Controller, Budget analyst, Treasurer, etc.), 15% are consultants, 13% CFOs, 8% CEOs, 7% directors and 1% sales.

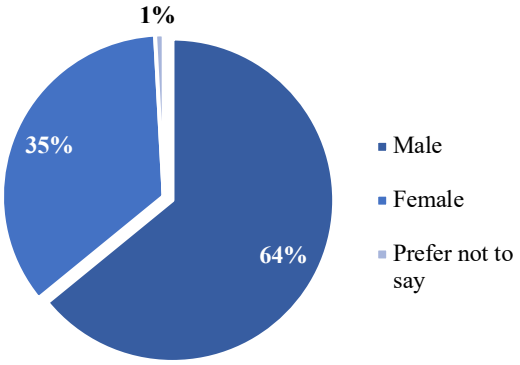


Figure 5 – Sample gender

Source: The author, 2021

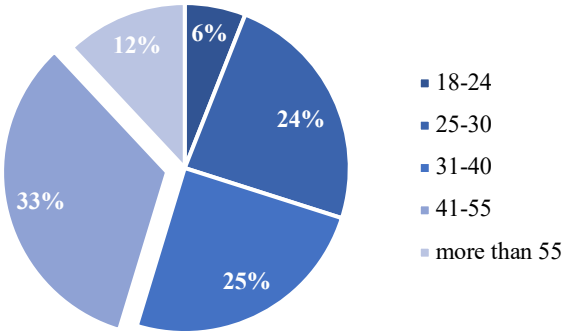


Figure 6 – Sample age

Source: The author, 2021

Regarding professional experience of participants, the great majority holds between 11 and 25 years of experience (49 participants), followed by 2 to 10 years (38 participants), more than 25 years (22 participants) and less than 2 years (8 participants). Most MA professionals are currently working in Portugal (39%) and in the United Kingdom (31%) (figure 7).

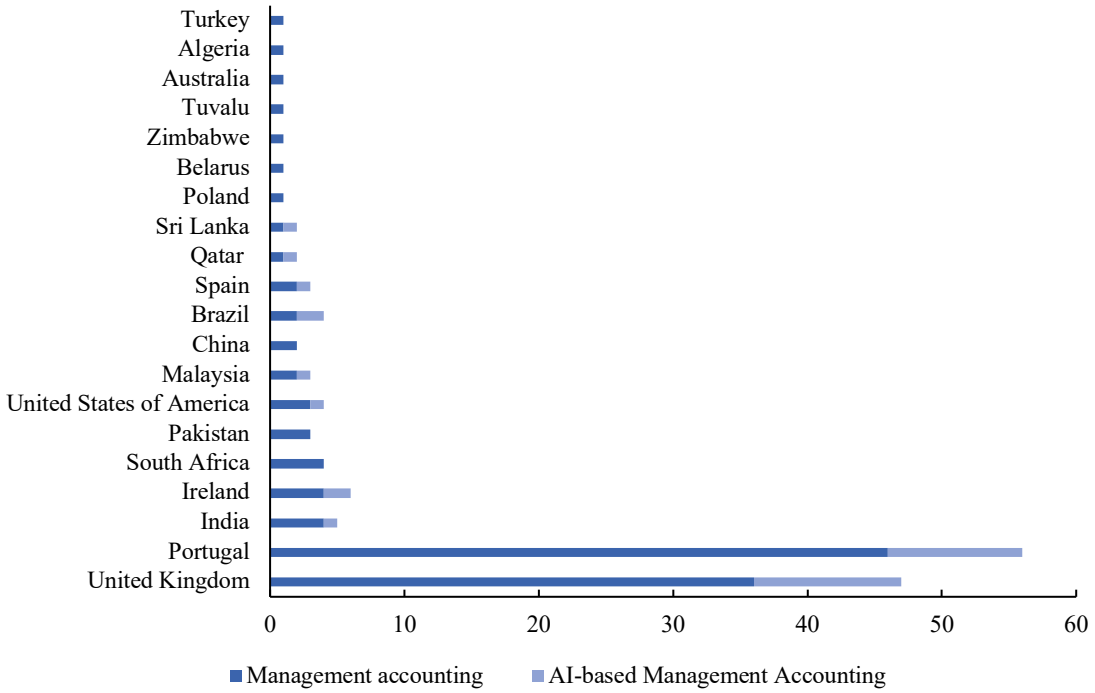


Figure 7 – Sample country

Source: The author, 2021

Also, 31 out of 100 participants are using AI-based Management Accounting and they are also mainly based in the United Kingdom (35%) and in Portugal (32%), reminiscent professionals are based in Ireland, Brazil, Spain, USA, India, Qatar, and Sri Lanka. Europe accounts for 77%, Asia for 13% and America for 10% of the AI-based Management Accounting professionals identified in this study. Regarding sector of activity, almost every sector is represented in this study. Most professionals are working in the Services (35%) and the Finance (20%) sectors. However, based on this sample, Services (Professional Services, Hospitality, Public Services, Membership Organization) is the sector which uses more AI-based management accounting (40%), followed by Finance and Technology, Media/Entertainment & Telecom sectors (both with 17%).

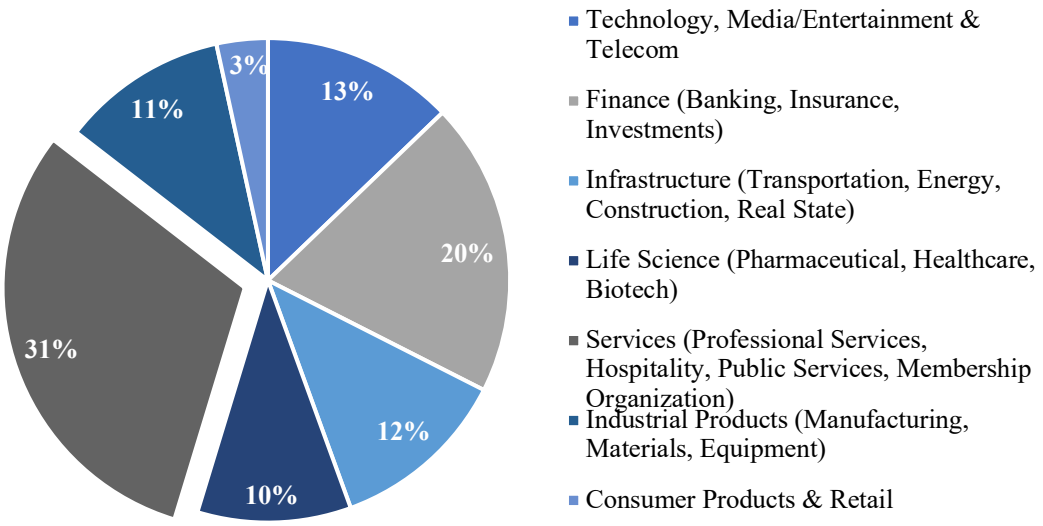


Figure 8 – AI-based Management Accounting by sector.

Source: The author, 2021

Regarding interview sample, 13.3% are women and 86.3% men, and most participants are between 41 and 55 years old (60.0%). Regarding professional experience, 60% are consultants, 13.3% are management accountants and the remaining 27.6% are CEO, director, sales and treasurer. Regarding professional experience, 73.3% has more than 11 years. Most respondents work in Portugal (33.3%) followed by UK (20.0%), Brazil (13.3%), Bulgaria, USA, Qatar, Venezuela, and Algeria (all with 6.7%). Majority of respondents work in the Finance (40.0%), the Services (26.7%) and the Technology, Media/Entertainment & Telecom (26.7%) sectors.

Chapter 5 – Analysis and Discussion of Results

5.1 – **What innovative AI management accounting systems have been implemented in companies so far?**

According to study's respondents, IT/Technology/Digital (17.9%) and Admin/Finance (22.6%) are the departments where most companies are deploying AI technologies (figure 9) to improve their performance, product/service's offer and growth. Most companies are in the first stages of AI implementation and about 44.4% have implemented AI for no more than 5 years now (figure 10).

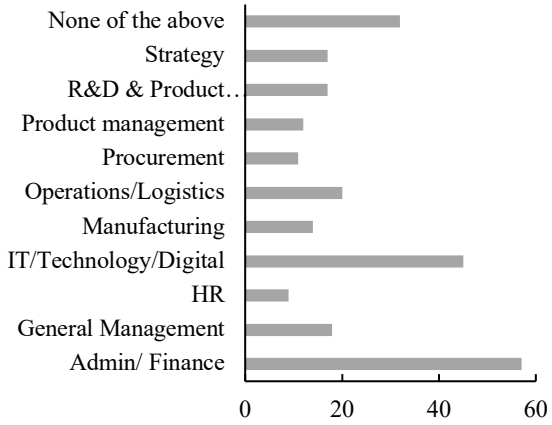


Figure 9 – AI usage by departments.

Source: The author, 2021

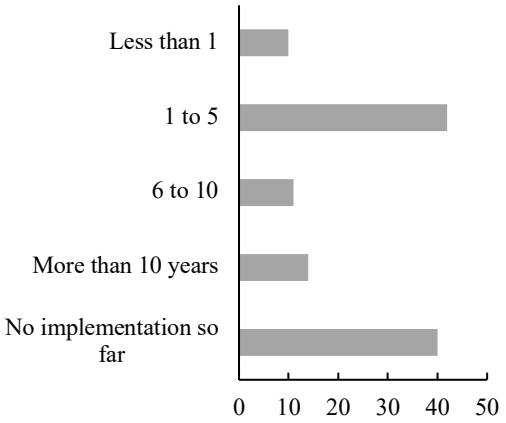


Figure 10 – AI implementation period.

Source: The author, 2021

Regarding AI implementation in MA, about one in four (26%) companies implement these technologies to perform their management accounting function (table 3). According to Rikhardsson & Yigitbasioglu (2018), many companies have adopted enterprise resource planning (ERP) systems to perform their MA tasks and techniques, to increase the efficiency of collecting and reporting accounting data. CPA (2019) also reports that companies are looking for new data sources to drive new, unique, and timely business and financial insights. This study's findings suggest that companies are now implementing systems that display AI technologies and are in fact triggering a technological change.

Table 3 – AI implementation in MA.

	n	**%**
AI not implemented in MA	86	74
AI implemented in MA	31	26

The most used AI technologies according to these findings are Text analysis and Machine Learning, while the less used are Smart robotics and Speech recognition (table 4). According to Corazza & Zanin, 2020, the recent technological development has led to an advanced form of business analytics (BA) based on AI with the addition of a learning element to the existing BA features. Results support this statement as 26% of MA professionals in this study work with AI in MA, and machine learning ("learning element") is one of most applied technologies.

Table 4 – Most used AI technologies in MA.

	μ	σ	M
Smart robotics	1.968	1.197	1.000
Speech recognition	2.000	1.342	1.000
Virtual agents	2.032	1.080	2.000
NLP (Natural language processing)	2.032	1.140	2.000
Text analysis	**3.194**	**1.167**	**3.000**
Biometrics	2.258	1.290	2.000
ML (Machine learning)	**2.871**	**1.204**	**3.000**
Deep learning/Neural networks	2.000	1.000	2.000
Computer vision	2.258	1.182	2.000

Regarding AI usage, this study has revealed that all MA typical tasks have been positively or neutral impacted by this technology as most averages and median are equal or higher than 3 (table 5). Nonetheless, the task which has been impacted the most is transaction processing. Techniques wise, forecasting, strategy maps, and volume-based allocation of costs have higher usage of AI at this point (table 5). Instead, zero-based budgeting and balanced scorecard frameworks techniques are the least influenced by AI technologies at the moment.

Rikhardsson & Yigitbasioglu (2018) noted that ERP systems have weak effects on MA practices. On the other hand, our study shows that AI based systems are producing strong

effects on MA practices, mainly on tasks such as transaction processing and control where AI is being implemented the most. ICAEW (2017) and Nielsen (2020) concluded that AI technologies facilitate data collection, analysis and they're designed to support decision-making. Our research supports these findings as AI systems are well implemented in control, transaction processing, reporting and decision support tasks. Besides, ICAEW noted that AI systems allow MA to obtain predictable and reliable future conditions, which again is supported by our study as techniques such as volume-based allocation of costs and forecasting are being developed with AI technologies.

Table 5 – AI usage in MA tasks and techniques.

	μ	σ	M
Tasks			
Planning	3.000	1.211	3.000
Control	3.258	1.237	3.000
Performance measurement	3.097	1.136	3.000
Transaction processing	**3.710**	**1.071**	**4.000**
Reporting	3.065	1.124	3.000
Decision support	2.968	1.303	3.000
Techniques			
Activity-based costing	2.516	1.288	3.000
Balanced scorecard frameworks	2.290	1.243	2.000
Volume-based allocation of costs	**2.613**	**1.230**	**3.000**
Strategy maps	**2.452**	**1.261**	**3.000**
Zero-based budgeting	2.290	1.296	2.000
Forecasting	**2.839**	**1.068**	**3.000**

Concerning project implementation, most finance departments have chosen to either implement proof-of-concept (pilot) projects or phased projects (figure 11) as the implementation is smoother and resource usage more optimized compared to direct changeover and parallel projects, respectively.

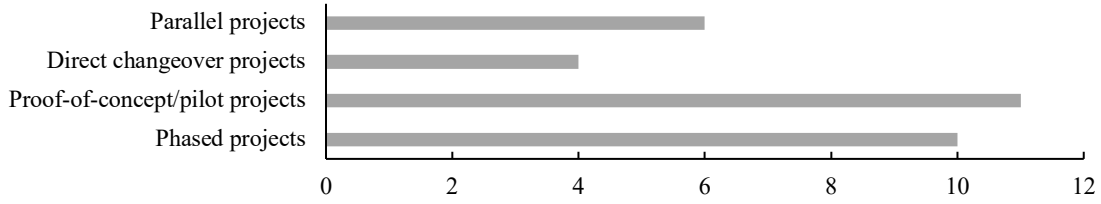


Figure 11 – Type of project implementation regarding AI in MA.

Source: The author, 2021

About companies or finance departments which haven't yet implemented AI in the MA function, several barriers were surveyed. This study revealed (figure 12) that the six most challenging barriers for business decision makers/management accountants are lack of business structure to exploit AI technologies (19%), cost (19%), complexity (17.5%), knowledge (*I don't know*) (15.3%), lack of suitableness for their business operations (13.1%), and business leaders' lack of interest (10.2%). Some of these barriers seem to be linked and can be summarized up to 3 many aspects: technology understanding, implementation, and cost.

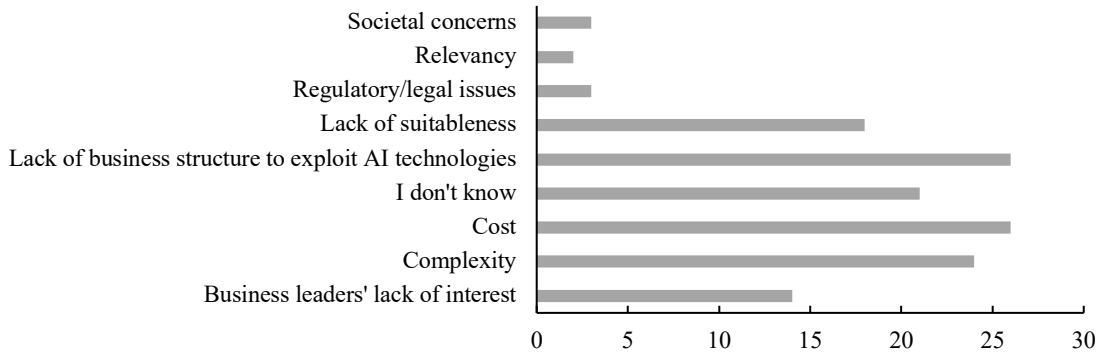


Figure 12 – Barriers to AI implementation in MA.

Source: The author, 2021

5.2 – **What advantages and challenges does implementing AI on management accounting bring to companies?**

Several advantages and challenges regarding AI implementation in MA were objects of study. Three sets of variables were considered: S (Successful AI implementation in MA) – 1 dependent variable; AD (Advantages of implementing AI in MA) – 9 independent variables; and CH (Challenges of implementing AI in MA) – 11 independent variables. All variables and respective identification are presented below in table 6. To analyse the second research question several inferential statistics techniques were used: reliability, distribution, correlation, regression and factorial analysis. After assessing answers' authenticity, 27 observations per variable were used for statistical analysis.

Table 6 – Identification and description of advantages and challenges regarding AI implementation in MA.

ID	Description
AD1	Improved efficiency.
AD2	Improved effectiveness.
AD3	Improved information quality for decision making.
AD4	Growth opportunity.
AD5	Data collection facilitation.
AD6	Data analysis facilitation.
AD7	Improved information delivery.
AD8	Time saving.
AD9	Help deliver relevant and valuable judgements.
CH1	Large data volumes.
CH2	Complex and changing patterns.
CH3	Data consistency.
CH4	Process transparency.
CH5	Lacking trust for AI among employees.
CH6	Analogue processes.
CH7	AI experts' shortage.
CH8	Cyber security.
CH9	Communication with Stakeholders.
CH10	Employee's AI training.
CH11	Skill transformation pressure.
S	Successful AI implementation in MA.

5.2.1 – Reliability analysis

The effective and common technique used to assess the reliability of internal consistency is the Cronbach's Alpha coefficient (Henson, 2001). This coefficient is a direct function of the number of items and their intercorrelated magnitude. It represents the lower limit of the test variance attributable to common factors among the items within each variable (Cronbach, 1951). To perform this technique, only the variables (items) categorized similarly in the survey (Likert scale questions) were included in the internal consistency analysis. Therefore, all questions associated with Advantages and Challenges were included. It is well accepted that for exploratory studies such as the present one, Cronbach's Alpha equal or higher than 0.5 is considered acceptable (Cronbach, 1951). Reliability analysis presented a coefficient of 0.863 based on standardized items (table 7), thus presenting a very high level of internal consistency.

Table 7 – Cronbach's Alpha.

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
0.866	0.863	20

5.2.2 – Correlation analysis

Correlation analysis was performed to analyse whether there are redundant variables and what is the strength of relationships between the Successful AI implementation in MA, Advantages and Challenges variables (Table 8). Correlation coefficient values vary between -1 (negative and perfect correlation) and 1 (positive and perfect correlation) (Pinto and Curto, 2010). No variables presented a degree of correlation above 0.79, so all independent variables were kept for analysis. According to Dancey & Reidy (2006), relations between variables with Pearson's correlation coefficient (r) <0.4 represent weak correlations, r ≥0.4 and <0.7 represent moderate correlations and r ≥0.7 represent strong correlations. Results display strong correlations between the dependent variable S (*Successful AI implementation in MA*) and AD6 (*Data analysis facilitation*, r: 0.776), and AD9 (*Help deliver relevant and valuable judgements*, r: 0.729). Variable S also has moderate correlations with AD1 (Improved efficiency, r: 0.528), AD2 (*Improved effectiveness*, r: 0.690), AD3 (*Improved information quality for decision making*, r: 0.583) AD4 (*Growth opportunity*, r: 0.675), AD5 (*Data collection facilitation*, r: 0.509), AD7 (Improved information delivery, r: 0.638), AD9 (*Help deliver relevant and valuable judgements*, r: 0.480), CH8 (*Cyber security*, r: 0.461), CH9 (*Large data volumes*, r: 0.416), and CH10 (*Employee's AI training*, r: 0.424). Regarding independent variables, AD1 and AD2 have the strongest correlation (r: 0.734), while CH2 (*Complex and changing patterns*) and CH8 (*Cyber security*) have a moderate correlation (r: 0.572).

Table 8 – Pearson correlations.

	S	AD1	AD2	AD3	AD4	AD5	AD6	AD7	AD8	AD9	CH1	CH2	CH3	CH4	CH5	CH6	CH7	CH8	CH9	CH10	CH11
S	-																				
AD1	**.528****	-																			
AD2	**.690****	**.734****	-																		
AD3	**.583****	.465*	**.719****	-																	
AD4	**.675****	**.600****	**.653****	**.650****	-																
AD5	**.509****	0.306	.497**	**.532****	.458*	-															
AD6	**.776****	0.298	.412*	.452*	**.523****	**.600****	-														
AD7	**.638****	0.000	0.189	.432*	.450*	.459*	**.683****	-													
AD8	.480*	0.217	0.170	0.314	0.347	0.222	.431*	**.577****	-												
AD9	**.729****	0.228	**.501****	.434*	.469*	.433*	**.565****	**.556****	0.081	-											
CH1	0.345	0.281	0.320	0.160	0.190	.427*	.483*	0.060	-0.233	0.301	-										
CH2	0.339	0.177	0.308	0.105	0.112	0.379	0.342	0.099	-0.200	**.565****	**.569****	-									
CH3	0.024	0.201	0.193	-0.058	-0.019	.452*	-0.020	-0.301	-0.218	-0.016	**.552****	0.345	-								
CH4	0.131	-0.124	0.140	-0.040	0.110	0.231	0.196	0.046	-0.121	0.243	0.269	.462*	0.181	-							
CH5	0.335	0.116	0.248	0.105	.478*	0.154	0.337	0.168	0.017	0.316	0.313	0.133	0.182	.456*	-						
CH6	-.392*	-0.196	-0.368	-0.304	-0.352	-0.267	-.421*	-0.196	-0.083	-0.295	-.392*	-0.231	-0.245	-.412*	-0.096	-					
CH7	0.356	0.374	0.320	0.094	0.130	0.361	0.322	0.108	-0.031	.396*	0.342	.600**	0.193	0.179	0.166	0.254	-				
CH8	.461*	.404*	.495**	0.274	.423*	**.527****	.399*	0.320	0.013	**.526****	**.527****	**.572****	.478*	0.363	.409*	-0.379	.403*	-			
CH9	.416*	0.053	0.199	0.089	0.217	0.279	0.276	0.275	-0.061	**.580****	0.248	**.520****	0.209	0.346	.417*	-0.146	.423*	.396*	-		
CH10	.424*	0.327	0.280	0.204	.405*	0.362	0.371	0.192	0.189	0.260	.461*	0.330	0.347	0.031	0.209	-0.228	0.110	**.526****	0.183	-	
CH11	0.378	0.000	0.154	0.250	.436*	0.277	0.379	0.290	0.140	.426*	.426*	0.342	0.152	0.351	**.501****	-0.270	0.228	0.333	0.339	.482*	-

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

N=27

5.2.3 – Distribution analysis

Many interferential statistics techniques have several assumptions to meet before presenting strong and reliable results and, consequently, conclusions. For instance, to perform multifactor regression analysis, variables have to display a normal distribution. This type of distribution prevents data from producing spurious results (Saunders *et al*., 2009).

To assess normality of the dependent variable S and independent variables ADi and CHi, and based on the sample size (<100), the Shapiro-Wilk test was performed. All variables presented a significance level lower than 0.05 which indicates that none has a normal distribution. However, as these variables have more than 20 observations, we can proceed to further analysis without greatly compromising results' reliability (Altman, 1991).

5.2.4 – Regression analysis

As an exploratory study, this study aims to identify the advantages and challenges that have the greatest impact on the success of implementing AI in MA. A multiple linear regression analysis is advisable when a relationship between the multiple independent variables (Advantages and Challenges) and the dependent variable (Success of AI implementation) is determined, and when the relative predictive importance of the independent variables is defined (Williams & Monge, 2001). According to McClave & Benson (1988), the multiple linear regression model, assuming that there are k independent variables, can be written as follows:

$$y = \beta_0 + \beta_1\chi_1 + ... + \beta_k\chi_k + \varepsilon$$

where y is the dependent variable, x1, x2, ..., xk are the independent variables, β_i is the regression coefficient and ε is the random error component. Coefficient β_i determines the contribution of the independent variable x1, as the other variables x are held constant and $\beta 0$ is the intercept with y. In the case of this study, it translates into the following equation for Advantages:

$$y = \beta_0 + \beta_1 AD1 + \ldots + \beta_9 AD_9$$

where y is the dependent variable Successful AI implementation in MA, β_i is the partial regression coefficient for i Advantages (AD).

For Challenges, it translates into the following equation:

$$y = \beta_0 + \beta_1 CH_1 + \ldots + \beta_{11} CH_{11}$$

where y is the dependent variable Successful AI implementation in MA, β_i is the partial regression coefficient for i Challenges (CH).

It is expected a positive (direction) relationship between Advantages and the AI implementation success, i.e., the more frequent the occurrence of AD, higher the S. Similarly, it is expected that there is a positive (direction) relationship between Challenges and the AI implementation success, i.e., the higher the occurrence of CH, higher the S.

Besides normality, multiple regression has other assumptions, namely absence of multicollinearity, absence of outliers and a linear relationship between dependent and independent variables. Regarding multicollinearity, tolerance must be lower than 1 and VIF lower than 10, to assume that there's no multicollinearity between variables (Miles, 2014). Absence of outliers can be assessed by calculating Cook's distance, if the model has a value lower than 1, absence of outliers is assured (Stevens, 1984), which is the case for both models (table 10). Concerning linear relationship between dependent and independent variables, remaining ADs and CHs variables presented a fairly linear relationship with S as requested.

Once all assumptions were met, multiple regressions were carried out. For optimization purposes, each model was subject to a step-by-step screening procedure to present as few variables as possible with an acceptable level of significance ($p \leq 0,05$) and, at the same time, predict the success of AI implementation in MA. This procedure ensured that every variable left in the model has a unique and great impact on the success of implementing AI technologies in MA (variables which explain best the outcome of the dependent variable).

After optimization, the F-test p-value was analysed to confirm whether models 1 (Advantages) and 2 (Challenges) were significant or not (table 9). As both have a p-value lower than 0.05, it can be concluded both models are statistically significant.

Table 9 – F-test.

Model		Sum of squares	df	Mean Square	F	Sig.
1	Regression	10.445	4	2.611	35.269	.000[b]
	Residual	1.629	22	0.074		
	Total	12.074	26			
2	Regression	6.273	4	1.568	5.948	.002[c]
	Residual	5.801	22	0.264		
	Total	12.074	26			

a. Dependent variable: S. Successful AI implementation in MA

b. Predictors: (Constant), AD2 (Improved effectiveness), AD6 (Data analysis facilitation), AD8 (Time saving), and AD9 (Help deliver relevant and valuable judgements)

c. Predictors: (Constant), CH4 (Process transparency), CH5 (Lacking trust for AI among employees), CH6 (Analogue processes), and CH7 (AI experts' shortage)

Model 1 has an R Square of 0.865 which reveals that it explains about 87% of the total variance in the dependent variable S (table 10). However, as sample size is small (27 observations), a more cautious approach is advisable, namely consider the Adjusted R Square. Consequently, the model explains 84.1% of total variance in the dependent variable S, which indicates that advantages such as *Improved effectiveness* (AD2), *Data analysis facilitation* (AD6), *Time saving* (AD8), and *Help deliver relevant and valuable judgements* (AD9) are great predictors of the success of an AI implementation in MA.

On the other hand, the model 2 has an R Square of 0.520 and an Adjusted R Square of 0.432 (table 10) which indicates that 43.2% of the total variance in the dependent variable is explained by the model. Therefore, challenges *Process transparency* (CH4), *Lacking trust for AI among employees* (CH5), *Analogue processes* (CH6) and *AI experts' shortage* (CH7) are good predictors of the success of an AI implementation in MA.

Table 10 – Summary of the model.

Model	R	R Square	Adjusted R Square	Estimate Standard Error	Cook's Distance
1	0.930[a]	0.865	0.841	0.272	0.393
2	0.721[b]	0.520	0.432	0.513	0.717

a. Predictors: (Constant), AD2 (Improved effectiveness), AD6 (Data analysis facilitation), AD8 (Time saving), and AD9 (Help deliver relevant and valuable judgements)

b. Predictors: (Constant), CH4 (Process transparency), CH5 (Lacking trust for AI among employees), CH6 (Analogue processes), and CH7 (AI experts' shortage)

Dependent variable: S. Successful AI implementation in MA

The results also show that AD variables present in the model have a standardized coefficient β ranging from 0.253 (AD8) to 0.355 (AD9) respectively and a p value lower than 0.05 for all (table 11). The variable *Help deliver relevant and valuable judgements* (AD9) has the greatest contribution (35.5%) to explain the outcome of dependent variable (S), for a significance level lower than 0.05. As for the Challenges model, β ranges from -0.660 (CH6) to 0.535 (CH7), indicating that variable *Analogue processes* (CH6) has the greatest contribution (66.0%) to explain S's outcome.

Table 11 – Regression coefficients, level of significance and collinearity.

	b	SE b	β	t	Sig.	Tolerance	VIF
Model 1 - Advantages							
(Constant)	-0.197	0.424		-0.435	0.646		
AD2 – Improved effectiveness	0.319	0.088	0.333	3.612	0.002	0.720	1.389
AD6 – Data analysis facilitation	0.255	0.084	0.328	3.034	0.006	0.523	1.911
AD8 – Time saving	0.229	0.081	0.253	2.842	0.009	0.772	1.296
AD9 – Help deliver relevant and valuable judgements	0.242	0.072	0.355	3.403	0.003	0.563	1.777
Model 2 - Challenges							
(Constant)	5.320	0.775		6.864	0.000		
CH4 – Process transparency	-0.297	0.139	-0.404	-2.133	0.044	0.609	1.642
CH5 – Lacking trust for AI among employees	0.221	0.101	0.367	2.191	0.039	0.779	1.284
CH6 – Analogue processes	-0.599	0.159	-0.660	-3.773	0.001	0.714	1.400
CH7 – AI experts' shortage	0.379	0.114	0.535	3.311	0.003	0.835	1.197

a. Dependent variable: S. Successful AI implementation in MA

In sum, table 12 displays the key statistics for each model built based on the multiple regression analysis.

Table 12 – Models' key statistics.

	b	SE b	β
Model 1 – Advantages[a]			
(Constant)	-0.197	0.424	
AD2 – Improved effectiveness	0.319	0.088	0.333*
AD6 – Data analysis facilitation	0.255	0.084	0.328*
AD8 – Time saving	0.229	0.081	0.253*
AD9 – Help deliver relevant and valuable judgements	0.242	0.072	0.355*
Model 2 – Challenges[b]			
(Constant)	5.320	0.775	
CH4 – Process transparency	-0.297	0.139	-0.404**
CH5 – Lacking trust for AI among employees	0.221	0.101	0.367**
CH6 – Analogue processes	-0.599	0.159	-0.660*
CH7 – AI experts' shortage	0.379	0.114	0.535*

a. Adjusted R^2: 0.841 b. Adjusted R^2: 0.432
*p<0.01 **p<0.05

Considering the multiple regression results, from nine advantages identified regarding AI implementation in MA, only four were in fact confirmed by the model and considered statistically relevant to explain the dependent variable *Successful AI implementation in MA* (S) behaviour. These were identified by Ransbotham *et al*. (2019) (AD2), Nielsen (2020) (AD6), and ICAEW (2017) (AD8 and AD9).

Regarding AD variables which weren't included in the model, one should note that AD1 and AD3 (identified by Ransbotham *et al.*, 2019) presented strong correlations with AD2, r: 0.734 and r: 0.719 respectively, but didn't take part of the model. This happened because neither AD1 or AD3 gave a unique and statistically relevant contribution to explain S. Nonetheless, future studies are advised to take these advantages in consideration for further modelling.

From the initial fourteen challenges identified in the literature review, only four challenges were found to be statistically relevant to explain the dependent variable *Successful AI implementation in MA* (S) behaviour. *Process transparency* (CH4), *Lacking trust among employees* (CH5), *Analogue processes* (CH6) and *AI experts' shortage* (CH7) were identified by Riem *et al.* (2020) (CH4-7), Yeoh & Koronios (2010) (CH4), and Appelbaum *et al.* (2017) (CH4). Similarly, to Advantages, some Challenges variables presented moderate correlations with model's variables, namely CH2 with CH4 (r: 0.462) and CH7 (r: 0.600) but didn't produce a statistically relevant contribution to explain S's behaviour. Nevertheless, it advised to consider these in future studies also.

Concerning models' explanations regarding variance in the dependent variable, Challenges' model presented the lowest value (43.2%) and needs further testing to be improved. One possible explanation for this percentage may be the sample size (27 observations), as a more robust sample would certainly allow more consistent results and, consequently, models.

5.2.5 – Factorial analysis

To comprehensively analyse the underlying relationships between measured variables, exploratory factorial analysis was performed. This analysis allows the grouping of a set of variables that are highly correlated between each other and little correlated with others and group them into factors (Williams & Monge, 2001). It also aims to identify the most

representative variables of each factor (Kirch *et al.*, 2017). The factorial analysis was conducted in two dimensions (Advantages and Challenges) and was divided into model validation, extraction of factors, factor rotation and internal consistency of results.

5.2.5.1 Model validation

To validate the model and assert if the sample size is suitable for this analysis, the Kaiser-Meyer-Olkin (KMO) test was used. KMO test compares simple correlations with partial correlations observed between the variables (Dodge, 2008). Kaiser (1974) recommends only accepting values ≥0,5 in the KMO test since values below this limit should lead to more sampling or choosing new variables.

The KMO test results for Advantages and Challenges are 0.768 and 0.613 (table 13), respectively. Both confirm that factor analysis is appropriate for this data sample. Bartlett's sphericity test measures whether factor analysis is appropriate for the problem and whether there is a strong enough correlation for factor analysis to be applied (Bartlett, 1951). As p values for both variables are lower than 0.05, it confirms that factor analysis is adequate and that there are significant correlations between some variables.

Table 13 – KMO and Bartlett's Test of Sphericity indicators.

		Advantages	Challenges
Kaiser-Meyer-Olkin Measure of Sampling Adequacy		0.768	0.613
Bartlett's Test of Sphericity	Approx. Chi-Square	126.039	113.636
	df	36	55
	Sig.	0.000	0.000

5.2.5.2 Extraction of factors

Each variable was also submitted to an adequacy analysis using the Measure of Sampling Adequacy (MSA) test through an anti-image matrix, as well as communalities' analysis, which evaluates the proportion of variation of each variable explained by the factors extracted from the model. Anti-image matrix reveals reduced levels of adequacy of variables if the value of the test is lower than 0.5 (Yong & Pearce, 2013). Results showed that CH5 (0.438) and CH6 (0.399) display low levels of adequacy and so these were removed from the model.

Regarding communalities, extraction values should be equal or higher than 0,5 for each variable to significantly represent some factor of the model. Values lower than 0.5 indicate that there may be a weak relationship with the extracted factors. For optimization purposes, AD8 (0.421), AD9 (0.483), CH4 (0.438) and CH11 (0.374) were removed from the model as all have weak factor representability.

The remaining Challenges variables and all Advantages' have extraction values higher than 0.50 and so they significantly represent some factor of the model (table 14). To validate the optimized model, a new KMO and Bartlett's test of sphericity was performed (table 15) which results were noticeably augmented, especially in the case of the independent variables Challenges (from 0.613 to 0.804).

Table 14 – Communalities.

	Initial	Extraction
Advantages		
AD2 - Improved effectiveness	1.000	0.860
AD7 - Improved information delivery	1.000	0.844
AD1 - Improved efficiency	1.000	0.816
AD6 - Data analysis facilitation	1.000	0.765
AD4 - Growth opportunity	1.000	0.717
AD3 - Improved information quality for decision making	1.000	0.691
AD5 - Data collection facilitation	1.000	0.599
Challenges		
CH2 - Complex and changing patterns	1.000	0.762
CH7 - AI experts' shortage	1.000	0.710
CH8 - Cyber security	1.000	0.677
CH1 - Large data volumes	1.000	0.674
CH10 - Employee's AI training	1.000	0.613
CH9 - Communication with Stakeholders	1.000	0.601
CH3 - Data consistency	1.000	0.582

Extraction Method: Principal Component Analysis.

Table 15 – KMO and Bartlett's Test of Sphericity indicators after optimization.

		Advantages	Challenges
Kaiser-Meyer-Olkin Measure of Sampling Adequacy		0.782	0.804
Bartlett's Test of Sphericity	Approx. Chi-Square	96.460	58.827
	df	21	21
	Sig.	0.000	0.000

Next, it was extracted the number of factors for Advantages and Challenges (table 16). The extraction method used was the main component factor analysis with orthogonal

Varimax rotation of factors. As the average of communalities was larger than 0.7, the Kaiser criterion was followed (Kaiser, 1974) and all factors with Eigenvalues higher than 1 were retained. This led to 2 factors for Advantages and 2 factors for Challenges. These factors explain, respectively, 75.60% and 65.99% of the total model variance for Advantages and Challenges, which represent very satisfactory values according to Yong & Pearce, 2013).

Table 16 – Total variance explained.

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
Advantages									
1	3.935	56.216	56.216	3.935	56.216	56.216	2.82	40.289	40.289
2	1.357	19.379	**75.595**	1.357	19.379	75.595	2.471	35.305	75.595
3	0.546	7.795	83.389						
4	0.493	7.041	90.43						
5	0.299	4.277	94.707						
6	0.202	2.882	97.589						
7	0.169	2.411	100						
Challenges									
1	3.438	49.109	49.109	3.438	49.109	49.109	2.428	34.693	34.693
2	1.182	16.881	**65.991**	1.182	16.881	65.991	2.191	31.298	65.991
3	0.696	9.941	75.932						
4	0.601	8.584	84.516						
5	0.443	6.329	90.845						
6	0.361	5.152	95.997						
7	0.28	4.003	100						

Extraction Method: Main Component Analysis

5.2.5.3 Factor rotation

The interpretation of the factors was made through the matrix of rotated components (table 17), obtained after the Varimax rotation. For each factor and in each line, there were selected loadings equal or higher than 0,6 that represent the variables that contribute more for the formation of each respective factor. Based on these assumptions, no variable registered loadings below 0.6.

Table 17 – Matrix of rotated components.

	Component	
	1	2
Advantages[a]		

AD1 - Improved efficiency	0.903	
AD2 - Improved effectiveness	0.902	
AD4 - Growth opportunity	0.711	
AD3 - Improved information quality for decision making	0.683	
AD7 - Improved information delivery		0.918
AD6 - Data analysis facilitation		0.835
AD5 - Data collection facilitation		0.670
Challenges[a]		
CH10 - Employee's AI training	0.783	
CH1 - Large data volumes	0.760	
CH3 - Data consistency	0.755	
CH8 - Cyber security	0.690	
CH7 - AI experts' shortage		0.838
CH2 - Complex and changing patterns		0.768
CH9 - Communication with Stakeholders		0.767

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.
a. Rotation converged in 3 iterations.

5.2.5.4 Internal consistency of results

To ensure that extracted factors were consistent, Cronbach's Alpha analysis was performed for each factor (table 18). Concerning Advantages, both factor 1 (0.865) and factor 2 (0.803) have a high level of internal consistency. Regarding Challenges, also both extracted factors (0.787 for factor 1 and 0.761 for factor 2) have a high degree of internal consistency. In sum, exploratory factor analysis has produced very consistent statistical results.

Table 18 – Cronbach's Alpha of the extracted factors for Advantages and Challenges.

	Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
Advantages			
Factor 1	0.865	0.875	4
Factor 2	0.803	0.806	3
Challenges			
Factor 1	0.787	0.788	4
Factor 2	0.761	0.761	3

Based on the association produced by factorial analysis, a set of designations are suggested next. Regarding Advantages, "*Performance and results*" and "*Information*" are proposed for factor 1 (AD1, AD2, AD3 and AD4) and factor 2 (AD5, AD6 and AD7),

respectively. Concerning Challenges, "*Operation, training and security*" and "*Communication and supply*" are suggestions for factor 1 (CH1, CH3, CH8 and CH10) and factor 2 (CH2, CH7 and CH9), respectively. That said, results support that implementing AI in MA has advantages such as information/data, performance, and results, and are in accordance with findings from Ransbotham *et al.* (2019) (AD1, AD2 and AD3); PwC (2018) (AD4); and Nielsen (2020) (AD5, AD6 and AD7). But also challenges regarding operation, training, security, communication, and supply, which are aligned with results from Lee (2017) and Luo (2018) (CH1, CH2 and CH3); Riem *et al.*, (2020) (CH7, CH8 and CH9); and Kaplan & Haenlein (2019) and Shi (2020) (CH10).

5.3 – **How does AI impact management accounting labour functions?**

When asked about AI impact on MA labour functions, most respondents agreed that all tested functions (decision support, reporting, transaction processing, performance measurement, control, and planning) are to some extent being replaced by AI technologies (figure 13). *Transaction processing, control*, and *performance management* are indicated as the most replaced functions as "Agree" and "Totally agree" totalise 84%, 71% and 71%, respectively. In the order hand, the least replaced MA function is *planning* with a total agreement of 51%. One should also note that although *performance management* is highly agreed as one of the most replaced functions (about 71%), it also has the higher total disagree percentage (19%), which indicates some conflict regarding this function, or at least suggests different AI implementations in this function.

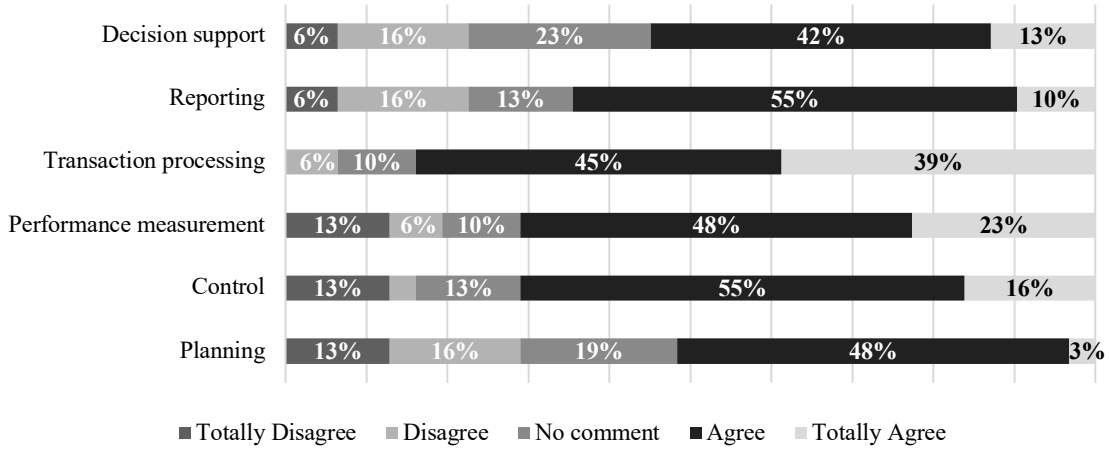


Figure 13 – Management accounting functions replaced by artificial intelligence technologies.

Source: The author, 2021

Regarding MA labour functions being further developed by AI technologies, respondents indicate that all functions are indeed further developed as "Agree" and "Totally agree" ranges from about 77% to about 87%. *Decision support* and *planning* were the only two functions which were not considered to be further developed by a few respondents, however, it represents about 3% (against 77%). Comparing figures 13 and 14, respondents tend to agree more that AI technologies further improve MA labour functions rather than replace these, as agreement ("Agree" + "Totally agree") in every function is higher in figure 14 than in figure 13., except for *transaction processing* (less 4%). To further understand respondents' answers and circumstances, a set of interviews were performed. Its content analysis is displayed and discussed next.

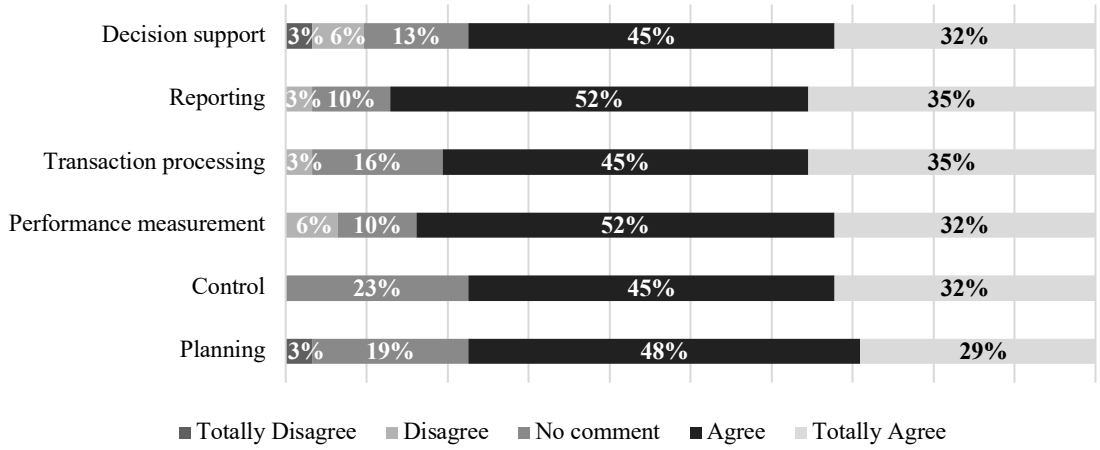


Figure 14 – Management accounting functions further developed by artificial intelligence technologies.

Source: The author, 2021

5.3.1 – Content analysis

To analyze the data reproduced by the interviews, a qualitative analysis technique was performed, specifically content analysis. It aims to relate the semantic (significant) structures with the sociological (meaning) structures to articulate interviewees statements with the factors that determine their characteristics (psychosocial variables, processes, cultural context, and message reproduction) (Duriau, Reger, & Pfarrer, 2007). Based on voice reproductions, the categorization and the codification of the in-depth interviews was performed (figure 15). In accordance with the three chronological poles of Bardin (1977), the process, the systematization, and the expression of message content promoted by content analysis was organized in phases. Primarily, ideas' organization and

systematization, then exploration of all material, and lastly results' analysis and interpretation.

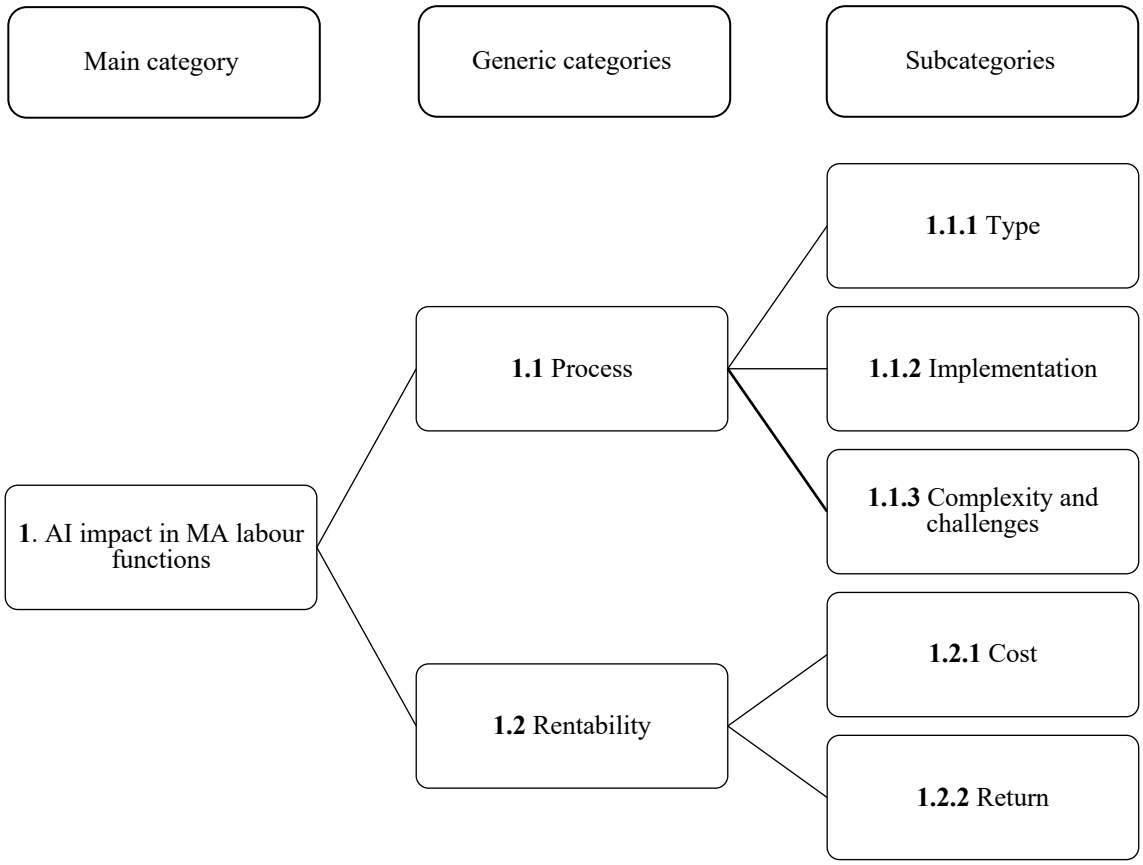


Figure 15 – Categorization and coding of the interview corpus for qualitative analysis.
Source: The author, 2021

Regarding type of process, most respondents agree AI technologies are simultaneously producing replacement and development of AI labour functions (table 19). While transaction processing is being replaced (human to intelligent technology), functions such as planning, control or decision support are being further developed (enhance human performance). This finding is in accordance with questionnaire' findings, Riem *et al.* (2020) and Nielsen (2020), as transaction processing (a tedious and repetitive task) is automated by AI technologies, and MA professionals are improving their task performance in control and decision support (advisory and consulting tasks). Nonetheless, other respondents also report changes in both ends of the spectrum, either all MA functions being replaced (6 respondents), or all MA functions being further

developed (3 respondents), which suggests different applications of AI technologies in MA, and consequently different implementation processes and impacts.

Table 19 – Type of Process.

Key ideas	Main category	Subcategory	Frequency	Respondents
Transaction processing is replaced.	1.1	1.1.1	7	1, 4, 5, 7, 8, 12. 15
Planning, control; performance measurement; reporting; and decision	1.1	1.1.1	7	1, 4, 5, 7, 8, 12. 15
All MA functions are replaced.	1.1	1.1.1	6	2, 6, 8, 10, 11, 13
All MA functions are further developed.	1.1	1.1.1	3	3, 9, 14

Regarding implementation and according to our interviewees, most changing processes happen through phased projects (86.7%) rather than pilot projects (13.3%) (table 20). This result is not totally in accordance with findings from our questionnaire, as phased projects, and proof-of-concept (pilot) projects were indicated by 32.3% and 35.5% of respondents, respectively. However, these two types of implementations are in fact the preferential ones to realise AI-based MA solutions in companies, groups, and industries.

Majority of implementation projects (53.3%) take place having in consideration the automation potential and needs of the implementing company or group (table 20), which suggests that AI solutions to MA are fine tuned to each company, group, and industry. However, 46,7% of interviewees affirmed that their AI-based MA solution was a standard one also following a standard implementation, despite the ability of these solutions to be trained based on a company's/group's specific financial and operation data. Implementation period often takes six months to one year and half, and according to 60% of respondents it is dependent on company size, subsidiaries, company culture, industry, complexity and number of processes, desired level of automation, previous system compatibility and mastery of the users.

Table 20 – Implementation.

Key ideas	Main category	Subcategory	Frequency	Respondents
Pilot project	1.1	1.1.2	2	8, 7
Phased project	1.1	1.1.2	13	1 to 6, 9 to 15

Analogue processes > Concept apprehension > Model incorporation > Data entry point > Automated model training > Employee training > System report for decision making	1.1	1.1.2	7	1, 2, 3, 4, 12, 14, 15
Mapping and integration between systems > Identification of automation potential and level of automation regarding processes > Determination of tools (e.g., prediction) to use in processes > Employee training > Deployment and testing > Go live and stabilization	1.1	1.1.2	8	5 to 11, 13
No specific system adaptation specific to company/group	1.1	1.1.2	6	2, 3, 4, 12, 14, 15
System adaptation to specific company/group	1.1	1.1.2	8	5 to 11, 13
Implementation period dependent of size of company, subsidiaries, company culture, industry, complexity and number of processes, desired level of automation, previous system compatibility and mastery of the users)	1.1	1.1.2	9	5 to 13
Implementation period of 6 months to 1.5 years	1.1	1.1.2	12	1, 2, 3, 5 to 9, 11 to 14
Implementation period of more than 1.5 years	1.1	1.1.2	2	4, 10

Regarding process's complexity and its challenges (table 21), two out of three times this sort of projects is considered to have low to moderate complexity (66,7%), and most typical challenges identified by interviewees are: *Resistance to change & Risk aversion*; *Employee's and decision makers' trust on AI systems*; *Process design or reengineering*; *Lack of technical knowledge (one sided and/or two sided)*; and *Data amount and quality*. These findings support Riem *et al.* (2020) and RQ2's regression model (CH5*, Lacking trust for AI among employees;* and CH4*, Process transparency*) as trust on AI systems is a usual challenge. Employees and decision makers feel threatened by these technologies because their perception is that they are going to lose their jobs as AI based systems are implemented and developed.

Job losing perception also may explain why facing resistance to change and risk aversion is so common in the sense that lacking trust affects confidence and engagement regarding these technologies. A few interviewees also mentioned that, as in any algorithm, there is always risk/ uncertainty in the models and the vast majority of people don't pay enough

attention to it. In the future, this tail risk may affect companies and consequently their decisions if they don't keep close monitorization and act upon it.

Results are also in accordance with Richins *et al.* (2017) and ACCA & IMA (2015), as there's a lack of technical knowledge that is necessary to adopt and take full advantage of AI solutions and so a demand for new data-related skills in this field is high and urgent for further progression. RQ2's regression model is also corroborated by these results as *Analogue processes* (CH6) and *AI expert's shortage* (CH7) are also identified by respondents as Digitalization level (low) and Shortage of AI experts are mentioned.

Table 21 – Complexity and challenges.

Key ideas	Main category	Subcategory	Frequency	Respondents
Low complexity process	1.1	1.1.3	6	6, 7, 8, 9, 11, 12
Moderate complexity process	1.1	1.1.3	4	1, 2, 11, 13
High complexity process	1.1	1.1.3	5	4, 5, 6, 10, 14
Resistance to change / Risk aversion	1.1	1.1.3	5	1, 4, 7, 9, 13
Employee's and decision makers' trust on AI systems	1.1	1.1.3	3	2, 3, 6
Process design / reengineering	1.1	1.1.3	3	5, 10, 11
Lack of technical knowledge (one sided and/or two sided)	1.1	1.1.3	3	1, 6, 8
Data amount and quality	1.1	1.1.3	3	3, 4, 7
Data migration / compatibility	1.1	1.1.3	2	7, 12
Long implementation period	1.1	1.1.3	2	4, 9
Shortage of AI experts	1.1	1.1.3	2	7, 8
Employee's training	1.1	1.1.3	1	4
Digitalization level	1.1	1.1.3	1	2

Cost wise, 80.0% of respondents agreed that AI based MA solutions are fair priced considering its expected return, but 33.3% also point out that these solutions are expensive for small and medium companies (table 22). Also, 20.0% of respondents alert that maintenance costs such as updates or licenses are high and must be taken into consideration.

RQ1's results indicated that cost was one of the main barriers to AI-based MA solutions usage by MA professionals and companies, and this is partially supported by these findings. This barrier seems to be exceptionally high for small and medium companies, rather than for large companies. It suggests that there may be an opportunity to explore AI technologies for MA for these low tier companies by leveraging the amount of small and medium sized companies by AI solution's cost.

Table 22 – Cost.

Key ideas	Main category	Subcategory	Frequency	Respondents
Fair priced based on expected return	1.2	1.2.1	12	1, 2, 3, 5 to 10, 12, 13,
Expensive for small and medium companies	1.2	1.2.1	5	9, 10, 11, 14, 15
Maintenance costs (updates and licenses) are high	1.2	1.2.1	3	9, 10, 12

Several returns regarding implementing AI based MA solutions were mentioned by respondents, namely: *Efficiency improvement* (80.0%), *Effectiveness improvement* (60.0%), *Refocus employee tasks to more value-added ones* (40.0%), *Cost reduction* (personnel, error, etc.) (33,3%), *Time saving* (20.0%), and *Competitive advantage* (20.0%) (table 23). These findings concerning return are then in accordance with findings from Mckinsey & Company (2017) and Nielsen (2020) regarding improvement of efficiency and effectiveness; and ICAEW (2017), Rikhardsson & Yigitbasioglu (2018), Stancheva-Todorova (2018), CPA (2019), Nielsen (2020), and Shi (2020) concerning MA professionals' focus on advisory, consulting and strategy related tasks.

One should note that although 40% of interviewees revealed a MA professionals' shift of focus from performing repetitive and monotonous tasks, to more value-added tasks (e.g., decision making or advisory), some interviewees also indicated a cost reduction regarding personnel. One potential explanation is the market's current offer, as some of the available solutions substitute in fact the professional performing a set of replaceable tasks and that leads to losing jobs (top management decisions). Nevertheless, respondents also mentioned that these technologies represent an opportunity for companies and employees to free employees from tedious and repetitive tasks and to develop fulfilling and challenging jobs, rather than a threat ready to take jobs from humans.

Table 23 – Return.

Key ideas	Main category	Subcategory	Frequency	Respondents
Efficiency improvement	1.2	1.2.2	12	1 to 6, 9 to 12, 14, 15
Effectiveness improvement	1.2	1.2.2	9	1 to 6, 10, 11, 14
Refocus employee tasks to more value-added ones	1.2	1.2.2	6	3, 4, 5, 7, 10, 13
Cost reduction (personnel, error, etc.)	1.2	1.2.2	5	1, 4, 8, 12, 13, 15
Time saving	1.2	1.2.2	3	5, 7, 14
Competitive advantage	1.2	1.2.2	3	7, 9, 11
Data is more prepared and available faster for decision making and stakeholders.	1.2	1.2.2	1	1
Extended market reach	1.2	1.2.2	1	2
Reliability	1.2	1.2.2	1	5
Improve control and tracking	1.2	1.2.2	1	10

5.4 – **How does AI impact management accountant's decision making?**

From all respondents using AI technologies to perform MA functions, 68% also use this setting for decision making. Results (figure 16) show that the decision-making process with embedded AI in MA has either been enhanced or highly enhanced in every single step, as 62% to 81% of respondents answered accordingly. The process steps which are believed to have the highest improvement ("Highly improved") are "Select [suggest] the alternative that appears to best achieve the desired goals or objectives." (19%) and "Obtain the necessary data to evaluate the various alternatives." (19%), being the latter the most improved overall ("Improved" + "Highly improved", 81%). A few respondents (6%) indicated that "Implement the chosen alternative." and "At an appropriate time, evaluate the results of the decisions against standards or other desired results." are performed poorer compared to previous MA systems.

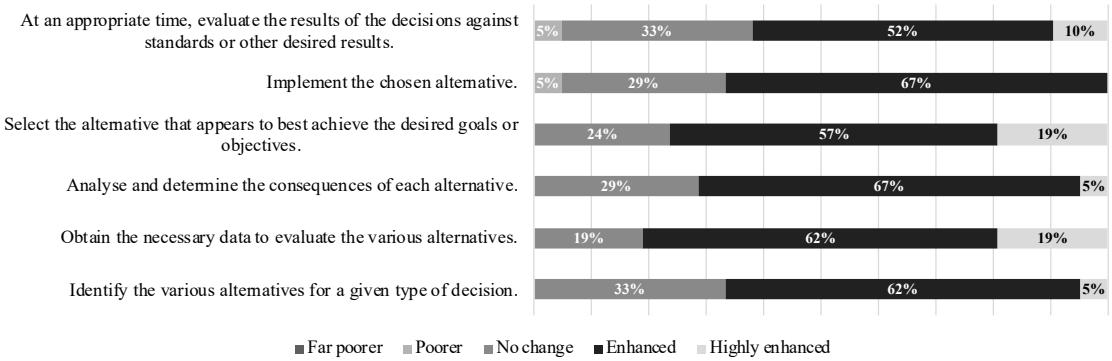


Figure 16 – Decision-making process with AI-based MA.

Source: The author, 2021

Regarding decision quality (figure 17), most respondents (62.5% to 81.2%) believe that overall decisions made by organizations are either “enhanced” or “highly enhanced”. According to these findings, MA decisions have been enhanced with AI technologies usage (agreement ranging from 71.4% to 85.7%), and “MA strategic decisions” such as maintaining minimum cash level without excessive risk or maintaining safety stock are believed to be the most benefiters from this AI usage. However, a very small number of correspondents (4.8%) also believe that “Business long-run decisions (1 year or more)” and “Business short-run decisions (less than 1 year)” are performed poorer.

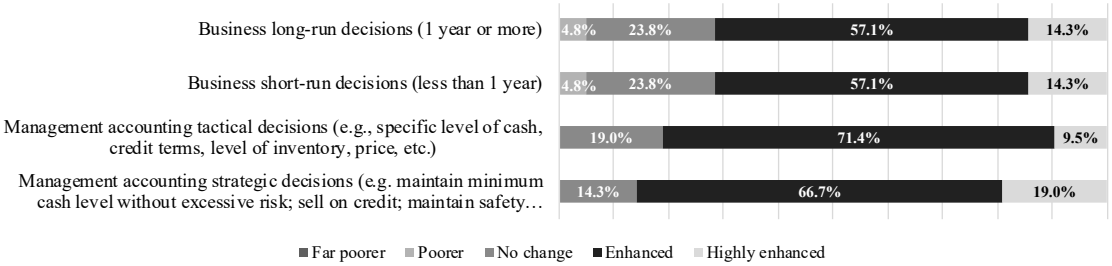


Figure 17 – Decision quality after using AI-based MA.

Source: The author, 2021

To further understand the impact of AI in management accountant’s decision making, several potential consequences were drawn based on the literature review and author’s understanding (table 24) and tested regarding inferential statistics analysis (reliability, distribution, correlation, regression, and factorial analysis). After assessing answers’ authenticity, 21 observations per variable were used for statistical analysis.

Table 24 - Identification and description of consequences regarding the use of AI-based MA for decision-making.

ID	Description
C1	Management accountants' development of new data-related skills.
C2	Lower management accountants' frustration levels.
C3	Management accountants have become more strategic and business oriented.
C4	Management accountants collaborate with data scientists.
C5	Automated data collection.
C6	Automated data processing.
C7	Greater reduction of management accounting errors and liabilities.
C8	Better pace of deliberation.
C9	Better decision-making results.
C10	Better prediction of consequences, uncertainty, and risk in decisions.
C11	Greater focus on matching type of data, prediction, and artificial intelligence technology.
C12	Better overall performance of management accounting tasks.
C13	Better overall business decision making.
C14	Higher business competitiveness.
DM	Successful use of embedded AI in MA for decision making.

5.4.1 – Reliability analysis

As mentioned before, Cronbach's Alpha coefficient is a common and effective technique used to assess the reliability of internal consistency (Henson, 2001). Similarly, to RQ2, to perform this technique, only the variables (items) categorized similarly in the survey (Likert scale questions) were included in the internal consistency analysis. Thus, all questions associated with potential consequences were included. Reliability analysis presented a coefficient of 0.948 (table 25), thus presenting a very high level of internal consistency.

Table 25 – Cronbach's Alpha.

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
0.948	0.955	14

5.4.2 – Correlation analysis

The correlation analysis between variables aimed to analyse the strength of the relationship between the Successful use of AI in MA for decision making (DM) – 1 dependent variable, and Consequences (C) – 14 independent variables (table 26). Based

on Dancey & Reidy (2006) suggested scale, DM and C variables, as anticipated, have a positive correlation (higher the identification of a certain consequence, higher the success in using AI based MA for decision making).

Results display significant moderate correlations between the dependent variable DM (*Successful use of embedded AI in MA for decision making.*) and C1 (*Management accountants' development of new data-related skills*, r: 0.490), C4 (*Management accountants collaborate with data scientists*, r: 0.435), C5 (*Automated data collection*, r: 0.614), C6 (*Automated data processing*, r: 0.565), C9 (*Better decision-making results*, r: 0.523), C10 (*Better prediction of consequences, uncertainty, and risk in decisions*, r: 0.453), C13 (*Better overall business decision making*, r: 0.664), and C14 (*Higher business competitiveness*, r: 0.480). Regarding independent variables, C10 and C12 have the strongest correlation (r: 0.966), and some variables indicate multicollinearity's presence as r is higher 0.790.

The correlation analysis suggests that *Successful use of embedded AI in MA for decision making* is higher when consequences such as: *Automated data collection*; *Automated data processing*; and *Better overall business decision making* are identified, which supports suggestions from Mckinsey & Company (2017) (C5, C6, and C13).

Table 26 – Pearson's Correlation.

	DM	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14
DM	-														
C1	**.490***	-													
C2	0.279	.483*	-												
C3	0.428	**.732****	.485*	-											
C4	**.435***	**.629****	0.212	**.580****	-										
C5	**.614****	**.711****	0.339	**.538***	**.576****	-									
C6	**.565****	**.700****	0.321	**.581****	**.568****	**.966****	-								
C7	0.222	**.717****	0.386	**.641****	0.192	**.522***	**.583****	-							
C8	0.397	**.710****	.489*	**.795****	**.639****	**.669****	**.718****	**.620****	-						
C9	**.523***	**.717****	0.372	**.735****	**.570****	**.582****	**.590****	.469*	**.822****	-					
C10	**.453***	**.796****	0.413	**.816****	**.633****	**.646****	**.655****	**.600****	**.822****	**.900****	-				
C11	0.397	**.710****	0.183	**.596****	**.639****	**.574****	**.638****	**.558****	**.643****	**.658****	**.639****	-			
C12	0.373	.465*	0.115	**.642****	**.590****	**.598****	**.632****	**.504***	**.521***	0.428	**.609****	**.626****	-		
C13	**.664****	**.696****	0.363	**.756****	**.695****	**.693****	**.711****	.495*	**.836****	**.870****	**.848****	**.743****	**.561****	-	
C14	**.480***	**.507***	0.326	**.679****	**.730****	**.733****	**.731****	0.300	**.750****	**.589****	**.654****	**.500***	**.626****	**.789****	-

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

N=21

5.4.3 – Distribution analysis

To assess normality of the independent variables C1-C14 and the dependent variable DM, and considering the sample size (<100), the Shapiro-Wilk test was performed. All variables presented a significance level lower than 0.05 which indicates that none has a normal distribution. However, as these variables have more than 20 observations, we can proceed to further analysis without compromising results' reliability (Altman, 1991).

5.4.4 – Regression analysis

As an exploratory study, this research also aims to identify the consequences that have the greatest impact on the success of using AI-based MA for decision making. As a result, it is appropriate to conduct a multiple linear regression analysis, where the relationship between independent variables (Consequences) and the dependent variable (Successful use of embedded AI in MA for decision making) is determined. According to McClave & Benson (1988), the multiple regression model can be written as follows:

$$y = \beta 0 + \beta 1 \chi 1 + \varepsilon$$

where y is the dependent variable, x1 is the independent variable, β1 is the regression coefficient and Ɛ is the random error component. The value of the coefficient β1 determines the contribution of the independent variable x1 and β0 is the intercept with y. In the case of this study, the above translates into the following equation for Consequences:

$$y = \beta 0 + \beta 1 C1 + \ldots + \beta 14 C14$$

where y is the dependent variable Successful use of embedded AI in MA for decision making, βi is the partial regression coefficient for i Consequences (C).

It is expected that there is a relationship with positive direction between C and DM., i.e. the more frequent the occurrence of a certain consequence, the higher the AI successful use in decision making. As mentioned previously, multiple regression has several assumptions, namely normality (depending on the sample size), absence of multicollinearity, absence of outliers and a linear relationship between dependent and independent variables. All assumptions are met as tolerance is lower than 1 (table 29),

VIF is lower than 10 (table 29), Cook's distance is also lower than 1 (table 28) and C variables (independent) presented a fairly linear relationship with DM (dependent) as demanded.

After assumptions check, multiple regression was performed. Like Advantages and Challenges models, this model was subject to a step-by-step screening procedure to present as few variables as possible with an acceptable level of significance ($p \leq 0,05$) and, at the same time, predict the successful use of AI-based MA for decision making. Following optimization, the F-test p-value was analysed to confirm whether the model was significant or not (table 27). As it has a p-value lower than 0.05 (0.002), it can be settled that this model is indeed statistically significant.

Table 27 – F-test.

Model		Sum of squares	df	Mean Square	F	Sig.
1	Regression	5.601	7	.800	6.355	0.002[b]
	Residual	1.637	13	0.126		
	Total	7,238	20			

a. Dependent variable: DM. Successful use of embedded AI in MA for decision making

b. Predictors: (Constant), C1 (Management accountants' development of new data-related skills), C7 (Greater reduction of management accounting errors and liabilities), C10 (Better prediction of consequences, uncertainty, and risk in decisions), C11 (Greater focus on matching type of data, prediction, and artificial intelligence technology), C12 (Better overall performance of management accounting tasks), C13 (Better overall business decision making), and C14 (Higher business competitiveness)

The model has an R Square of 0.774 which indicates that 77.4% of the total variance in the dependent variable is explained by the model (table 28). However, as sample size is small (21 observations) and following the same procedure as in RQ2, a more cautious approach was taken, and the Adjusted R Square was considered instead. As so, the model explains 65.2% of total variance in the dependent variable DM, which indicates that *Management accountants' development of new data-related skills* (C1), *Greater reduction of management accounting errors and liabilities* (C7), *Better prediction of consequences, uncertainty, and risk in decisions* (C10), *Greater focus on matching type of data, prediction, and artificial intelligence technology* (C11), *Better overall performance of management accounting tasks* (C12), *Better overall business decision making* (C13), and *Higher business competitiveness* (C14) are very good predictors of the success of using AI in MA for decision making.

Table 28 – Summary of the model.

Model	R	R Square	Adjusted R Square	Estimate Standard Error	Cook's Distance
1	0.880[a]	0.774	0.652	0.355	0.243

a. Predictors: (Constant), C1 (Management accountants' development of new data-related skills), C7 (Greater reduction of management accounting errors and liabilities), C10 (Better prediction of consequences, uncertainty, and risk in decisions), C11 (Greater focus on matching type of data, prediction, and artificial intelligence technology), C12 (Better overall performance of management accounting tasks), C13 (Better overall business decision making), and C14 (Higher business competitiveness)
Dependent variable: DM. Successful use of embedded AI in MA for decision making

The results also show that all model's variables are statistically significant, except C7 which has p value slightly above 0.05 (0.056) (table 29). Thus, indicating that C1, C10-14 variables significantly explain the outcome variable (dependent variable DM), for a significance level of p lower than 0.05. However, C13 has the greatest contribution (absolute value) to explain the outcome of dependent variable (DM).

Table 29 – Regression coefficients and level of significance.

	b	SE b	β	t	Sig.	Tolerance	VIF
(Constant)	-0.066	0.790		-0.083			
C1 – Management accountants' development of new data-related skills	1.065	0.308	1.043	3.453	0.004	0.190	5.249
C7 – Greater reduction of management accounting errors and liabilities	-0.274	0.130	-0.438	-2.098	0.056	0.399	2.507
C10 – Better prediction of consequences, uncertainty, and risk in decisions	-1.132	0.322	-1.232	-3.516	0.004	0.142	7.061
C11 – Greater focus on matching type of data, prediction, and artificial intelligence technology	-0.676	0.203	-0.940	-3.329	0.005	0.218	4.586
C12 – Better overall performance of management accounting tasks	0.790	0.255	0.753	3.096	0.009	0.294	3.400
C13 – Better overall business decision making	1.917	0.388	2.051	4.945	0.000	0.101	9.891
C14 – Higher business competitiveness	-0.613	0.232	-0.731	-2.644	0.020	0.228	4.395

a. Dependent variable: DM. Successful use of embedded AI in MA for decision making

Table 30 displays the key statistics for the model built based on the multiple regression analysis.

Table 30 – Models' key statistics.

	b	SE b	β
Model – Consequences[a]			
(Constant)	-0.388	0.657	
C1 – Management accountants' development of new data-related skills	1.065	0.308	1.043*
C7 – Greater reduction of management accounting errors and liabilities	-0.274	0.130	-0.438
C10 – Better prediction of consequences, uncertainty, and risk in decisions	-1.132	0.322	-1.232*
C11 – Greater focus on matching type of data, prediction, and artificial intelligence technology	-0.676	0.203	-0.940*

C12 – Better overall performance of management accounting tasks	0.790	0.255	0.753*
C13 – Better overall business decision making	1.917	0.388	2.051*
C14 – Higher business competitiveness	-0.613	0.232	-0.731**

a. Adjusted R^2: 0.652 *p<0.01 **p<0.05

Considering the multiple regression results, from fourteen potential consequences explaining the dependent variable Successful use of AI-based MA for decision making (DM) behaviour, six were in fact confirmed by the model and considered statistically relevant, C1 and C10-14. This model then supports findings from Richins *et al.* (2017) (C1), Appelbaum *et al.* (2017) (C10), Nielsen (2020) (C11), Luo *et al.* (2018) (C12), and Mckinsey & Company (2019) (C13). RQ3's results are also in accordance with this model as efficiency and effectiveness improvement (C10 and C12), time saving (C12) and competitive advantage (C1, C13 and C14) were mentioned by several respondents.

However, consequences such *Management accountants collaborate with data scientists (C4*, r:0.435*)* mentioned by Nielsen (2020), *Automated data collection* (C5, r: 0.508), *Automated data processing* (C6, r: 0.581) appointed by Mckinsey & Company (2017), or *Better decision-making results* (C9, r: 0.523) cited by Mckinsey & Company (2019), which are moderately correlated with the dependent variable DM, were not included in this model. Its absence is due to their inability to give a unique and statistically relevant contribution to explain DM and so, these consequences, although correlated with the dependent variable, are not statistically confirmed, or supported. Nonetheless, due to the low number of observations it is advisable to further research to consider all identified consequences under a large sample size-based model.

5.4.5 – Factorial analysis

Exploratory Factorial Analysis was performed to analyse the underlying relationships between the measured variables and identify the most representative variables of each factor (Kirch *et al.,* 2017). The factorial analysis was conducted in one dimension (Consequences) and was divided into four distinct steps: (1) model validation, (2) factor extraction, (3) factor rotation, (4) interpretation of results.

5.4.5.1 Model validation

Kaiser-Meyer-Olkin (KMO) test was used to validate the model and the sample size. KMO Test's result for all identified consequences was 0.751 (table 31) which represents

a very good value ((Yong & Pearce, 2013) and confirms that factor analysis is appropriate for the sample data (≥ 0.5). Bartlett's sphericity test (table 31) has a p-value (0.000) lower than the significance level (0.05) which indicates the analysis adequacy and the existence of significant correlations between some variables. (Bartlett, 1951).

Table 31 – KMO and Bartlett's Test of Sphericity indicators.

		Consequences
Kaiser-Meyer-Olkin Measure of Sampling Adequacy		0.751
Bartlett's Test of Sphericity	Approx. Chi-Square	286.934
	df	91
	Sig.	0.000

5.4.5.2 Extraction of factors

Before extracting factors, each variable was submitted to the MSA test through an anti-image matrix and to the analysis of the communality table. The anti-image matrix revealed all variables have a test value higher than 0.5 and consequently all variables have adequacy. Regarding the matrix of communalities (table 32), all variables significantly represent some factor of the model as their extraction value is higher than 0.5 and therefore all were kept for further modelling (Yong & Pearce, 2013)

Table 32 – Communalities.

	Initial	Extraction
Consequences		
C13 - Better overall business decision making.	1.000	0.835
C10 - Better prediction of consequences, uncertainty, and risk in decisions.	1.000	0.832
C8 - Better pace of deliberation.	1.000	0.828
C1 - Management accountants' development of new data-related skills.	1.000	0.791
C3 - Management accountants have become more strategic and business oriented.	1.000	0.768
C14 - Higher business competitiveness.	1.000	0.753
C6 - Automated data processing.	1.000	0.738
C9 - Better decision-making results.	1.000	0.727
C4 - Management accountants collaborate with data scientists.	1.000	0.721
C5 - Automated data collection.	1.000	0.704
C7 - Greater reduction of management accounting errors and liabilities.	1.000	0.640
C11 - Greater focus on matching type of data, prediction, and artificial intelligence technology.	1.000	0.636
C2 - Lower management accountants' frustration levels.	1.000	0.628
C12 - Better overall performance of management accounting tasks.	1.000	0.626

Extraction Method: Principal Component Analysis.

Afterwards, the number of factors was extracted for Consequences based on the main component factor analysis with orthogonal Varimax rotation of factors (table 33). Previous assumptions used for RQ2 were kept, as the average of communalities is larger than 0.7 and factors with Eigenvalues higher than 1 were kept, resulting in 2 factors that explain 73.053% of the total model variance for Consequences. According to Yong & Pearce (2013), this result is considered very acceptable and reliable.

Table 33 – Total variance explained.

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
Consequences									
1	9.027	64.481	64.481	9.027	64.481	64.481	6.21	44.36	44.36
2	1.2	8.572	**73.053**	1.2	8.572	73.053	4.017	28.693	73.053
3	0.918	6.558	79.611						
4	0.811	5.791	85.402						
5	0.589	4.207	89.609						
6	0.485	3.466	93.075						
7	0.303	2.162	95.238						
8	0.254	1.813	97.051						
9	0.159	1.132	98.183						
10	0.117	0.833	99.016						
11	0.06	0.432	99.448						
12	0.041	0.29	99.738						
13	0.023	0.163	99.901						
14	0.014	0.099	100						

Extraction Method: Main Component Analysis

5.4.5.3 Factor rotation

Like RQ2 analysis, factors' interpretation was made through the matrix of rotated components obtained after Varimax rotation (table 34). For each factor and in each line, loadings were selected equal or higher than 0,6 (higher contribution). No variable registered loadings below 0.6.

Table 34 – Matrix of rotated components.

	Component	
	1	2
Consequences[a]		
C4 - Management accountants collaborate with data scientists.	0.840	
C14 - Higher business competitiveness.	0.839	
C12 - Better overall performance of management accounting tasks.	0.778	

C13 - Better overall business decision making.	0.774	
C6 - Automated data processing.	0.770	
C5 - Automated data collection.	0.757	
C11 - Greater focus on matching type of data, prediction, and artificial intelligence technology.	0.712	
C10 - Better prediction of consequences, uncertainty, and risk in decisions.	0.657	
C8 - Better pace of deliberation.	0.651	
C9 - Better decision-making results.	0.603	
C2 - Lower management accountants' frustration levels.		0.792
C7 - Greater reduction of management accounting errors and liabilities.		0.750
C1 - Management accountants' development of new data-related skills.		0.707
C3 – Management accountants have become more strategic and business oriented.		0.659

Extraction Method: Principal Component Analysis.

Rotation Method: Varimax with Kaiser Normalization.

a. Rotation converged in 3 iterations.

5.4.5.4 Internal consistency of results

To ensure that extracted factors were consistent, Cronbach's Alpha analysis was performed for each factor (table 35riv). Both factor 1 (0.952) and factor 2 (0.803) have a high level of internal consistency, which indicates that this exploratory factor analysis has produced very consistent statistical and reliable results.

Table 35 – Cronbach's Alpha of the extracted factors for Consequences.

	Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
Consequences			
Factor 1	0.952	0.953	10
Factor 2	0.803	0.843	4

Based on the association produced by the analysis, designations for each factor are suggested. "Higher efficiency, new skills and user friendly" and "Higher effectiveness, collaboration and competitiveness" are proposed for factor 1 (C4, C5, C6, C8, C9, C10, C11, C12, C13 and C14) and factor 2 (C1, C2, C3, and C7), respectively. That said, results support that successfully using AI-based MA for decision making leads to effective and efficient results (higher performance), new skills, collaboration, competitiveness, and it is user friendly.

Therefore, factors' designation and the exploratory factor analysis model is in accordance with findings from Richins *et al.* (2017) (C1); Rikhardsson & Yigitbasioglu (2018) (C1);

Mckinsey & Company (2019) (C2, C8 and C9); ICAEW (2017) (C3); Stancheva-Todorova (2018) (C3 and C4); CPA (2019) (C3 and C4); Nielsen (2020) (C3, C7, C11 and C12); Mckinsey & Company (2017) (C5, C6, C7 and C12); Luo *et al* (2018) (C9); Appelbaum *et al*. (2017) (C10); and Mckinsey & Company (2017) (C13). This exploratory factor analysis model also supports C14 (*Higher business competitiveness*) introduced by the author as valid consequences of using AI technologies in MA for decision making.

Chapter 6 – Conclusion

6.1 – Final considerations

Based on the results, several conclusions can be drawn. First, we are witnessing a technological change as currently one in four companies implement AI technologies to perform their management accounting function. The most used AI technologies are Text analysis and Machine Learning, and AI systems are well implemented in control, transaction processing, reporting and decision support tasks. MA techniques such as: forecasting, strategy maps, or volume-based allocation of costs have the higher usage of AI at this point.

Second, implementing AI in MA brings advantages but also challenges for companies. Regarding advantages, implementing AI offers improved effectiveness, data analysis facilitation, time saving, and help deliver relevant and valuable judgements. Advantages can be divided into two factors, "Performance and results" and "Information". Regarding challenges, implementing these technologies faces process transparency issues, lacking trust for AI among employees, analogue processes, and also AI experts' shortage. Challenges can be also represented by two factors: "Operation, training and security"; and "Communication and supply".

Third, AI is impacting MA labour functions as there's replacement and further development of labour functions ongoing. While transaction processing is being replaced, functions such as control and decision support are being further developed. Phased projects and proof-of-concept (pilot) projects are the two preferential types of implementations to realise AI-based MA solutions and its period often takes six months to one and half years. Regarding complexity and challenges, two out of three projects are considered to have low to moderate complexity and most typical challenges are: resistance to change & risk aversion; employee's and decision makers' trust on AI systems; and lack of technical knowledge. AI-based MA solutions are considered fair priced based on its expected return (improvement of efficiency and effectiveness; and professionals' focus on advisory and strategy related tasks).

Fourth, AI technologies are also used for decision making. The decision-making process has improved in every single step with embedded AI in MA, where selecting the alternative that appears to best achieve the desired goals/ objectives and obtaining the necessary data to evaluate the various alternatives have the highest improvement. Regarding consequences, using AI technologies for decision making offers: management accountants' development of new data-related skills; greater reduction of MA errors and liabilities; better prediction of consequences, uncertainty, and risk in decisions; greater focus on matching type of data, prediction, and AI technology; better overall performance of MA tasks; better overall business decision making; and higher business competitiveness. Consequences can also be factored in "Higher efficiency, new skills and user friendly" and "Higher effectiveness, collaboration and competitiveness".

Fifth, we can also conclude that both objectives drawn for this study are accomplished as we did explore implementation, development, and changes in MA regarding the adoption of intelligent systems and we analysed AI impact on Management Accountants organization, performance and decision making, and AI technologies have already a considerable impact in MA, but have a great potential to have even more if companies, consultants, suppliers and professionals develop more trust for this technology (keeping close monitorization), share more knowledge and make it accessible for more companies.

6.2 – Contribution to state of the art

Several authors affirm that the existent AI literature lacks empirical analysis and information to investigate AI's impact on MA, either for its direct application or for professionals (competencies, skills, or consequences) (CPA, 2019; Nielsen 2020; ICAEW, 2017; Rikhardsson & Yigitbasioglu, 2018). That said, this study presents itself as one of the first ever empirical evidence studies regarding MA professionals' perceptions on advantages, challenges, impact on labour functions and decision makings consequences after using AI-based solutions in their practice, but also evidence on what are the barriers preventing more MA professionals, companies, and industries from using and developing AI technologies. Through this work, we start unfolding this new technological era for the MA field and give some scientific insights despite the natural limitations of studies which are first wave.

6.3 – Limitations of the study

Being one of the first ever empirical studies on the impact of AI in MA, some limitations are inevitably to be considered. First, sample gathering (structured questionnaire) was based on a non-probabilistic sample given the existence of time and resources constraints, and online distribution was done via email and LinkedIn, which also restrained sample reach and representation. Second, considering that AI technologies are still new in MA and there were some misunderstandings between concepts (MA and Financial Accounting) by some respondents (invalid answers), our sample size is a limitation. This affects specially all inferential statistics techniques and resulting conclusions. Any generalization or inference based on this study must be done carefully. Third, this study has also an exploratory component (semi-structured interviews) which uses a non-probabilistic sample and limits any type of conclusion regarding population (inference).

6.4 – Suggestions for future research

Based on our work, we suggest for future research modelling advantages, challenges and consequences of decision making of AI-based MA solutions with a wider and more robust sample size capable of representing different countries, continents, and industries. During the development of this study several professionals reached out saying that their company was not yet using AI technologies to perform their MA, but they will soon as part of a natural transition from their existing solution. In this sense, we suggest creating and developing a case study for specific firms undergoing this transformation to understand the different stages of the process, compare performance after and before this transformation and measure the actual impact of such systems regarding firms, groups but also industries. We also suggest conducting a study focused on developers responsible for creating AI-based MA solutions to allow decision makers, employees, and top managers to better understand these technologies and fill in one of the gaps identified in this study (lack of technical knowledge).

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Appendix

Annex 1 - Questionnaire

1. What's your gender? (masculine/feminine/prefer not to say)

2. What's your age? (18-24; 25-30; 31-40; 41-55; >55)

3. Professional experience (yrs.)? (<2/2-10/11-25/>25)

4. Country you're currently working on? _____

5. Sector? (Life Science (Pharmaceutical, Healthcare, Biotech)/ Industrial Products (Manufacturing, Materials, Equipment)/ Finance (Banking, Insurance, Investments)/ Services (Professional Services, Hospitality, Public Services, Membership Organization)/ Consumer Products & Retail/ Technology, Media/Entertainment & Telecom/ Infrastructure (Transportation, Energy, Construction, Real State))

6. What's your role? (CFO/controller/budget analyst/treasurer/consultant/other:____)

7. In which departments/business functions is the company using AI technologies? (Strategy / General Management / HR / Admin/Finance / R&D & Product Development / Product Management / Procurement / Manufacturing / Operations/Logistics / IT/Technology/Digital / None of the above)

7.1. For how long have AI technologies been implemented in the company you work for years)? (less than 1/ 1 to 5/ 6 to 10/ more than 10 / no implementation so far)

8. In the company you work/consult for, are artificial intelligence technologies (e.g., machine learning, deep learning, voice recognition, etc.) being applied in management accounting? (Yes/No)

9. (If "No"). Why hasn't your company implemented any AI technologies in management accounting? (Business leaders' lack of interest / Complexity / Cost / Lack of suitableness

/ Structural lack to exploit AI technologies / Regulatory issues / Societal concerns / I don't know)

Thank note & end of survey.

10. Based on the company you work/consult for, rate the following statements according to the usage scale bellow.
[none/ low /moderate /high /extremely high]

10.1) Artificial Intelligence technologies usage on management accounting:

a) smart robotics; b) speech recognition; c) virtual agents; d) natural language processing; e) text analysis; f) biometrics; g) machine learning; h) neural networks and deep learning; i) computer vision.

10.2) Artificial intelligence technologies usage in management accounting tasks and techniques:

a) planning; b) control; c) performance measurement; d) transaction processing; e) reporting; f) decision support; g) activity-based costing; h) balanced scorecard frameworks; i) volume-based allocation of costs; j) strategy maps; k) zero-based budgeting; l) forecasting

11) How has your company/client been implementing artificial intelligence systems on their management accounting? (proof-of-concept pilot projects/ direct change over projects / phased projects/ parallel projects/ Other:_____)

12) Based on the company you work/consult for, rate the following statements according to the agreement scale bellow.
[totally disagree / disagree / no comment / agree /totally agree]

12.1) Advantages on implementing successfully artificial intelligence technologies in management accounting:

a) improved efficiency; b) improved effectiveness; c) improved information quality for decision making; d) growth opportunity; e) data collection facilitation; f) data analysis facilitation; g) improved information delivery; h) time saving; i) help deliver relevant and valuable judgements

12.2) Challenges on implementing artificial intelligence technologies in management accounting successfully:
a) large data volumes; b) complex and changing patterns; c) data consistency; d) process transparency; e) lacking trust for AI among employees; f) analogue processes; g) AI experts' shortage; h) cyber security; i) stakeholders communication; j) AI employee's training; k) Skill transformation pressure; l) Others:____

13) Based on the agreement scale bellow, rate your company's/client's AI technologies successful implementation in management accounting.
[totally disagree / disagree / no comment / agree / totally agree]

14) How satisfied are you with your company AI technologies implementation on management accounting?
[totally dissatisfied/ dissatisfied / neutral/ satisfied /totally satisfied]

15) Based on the company you work/consult for, rate the following statements according to the agreement scale bellow.
[totally disagree/ disagree / no comment / agree /totally agree]

15.1) Management accounting functions replaced by artificial intelligence technologies:
a) planning; b) control; c) performance measurement; d) transaction processing; e) reporting; f) decision support.

15.2) Management accounting functions with potential to be further developed by artificial intelligence technologies:
a) planning; b) control; c) performance measurement; d) transaction processing; e) reporting; f) decision support.

16) How do you describe your company's/client's process of replacing and/or further developing management accounting functions based on artificial intelligence technologies? _____

17) Based on the usage scale bellow, rate your company's/client's use of AI technologies for decision making.
[none/ low /moderate /high /extremely high]

18) Based on the improvement scale bellow, rate the following after artificial intelligence technologies usage on management accounting.
[far poorer/ poorer / no change / enhanced / highly enhanced]

18.1) Decision making process statements of the company you work/consult for:
a) Identify the various alternatives for a given type of decision.
b) Obtain the necessary data to evaluate the various alternatives.
c) Analyse and determine the consequences of each alternative.
d) Select the alternative that appears to best achieve the desired goals or objectives.
e) Implement the chosen alternative.
f) At an appropriate time, evaluate the results of the decisions against standards or other desired results.

18.2) Decisions of the company you work/consult for:
a) Management Accounting Strategic (e.g., maintain minimum cash level without excessive risk; sell on credit; maintain safety stock; etc.)
b) Management Accounting Tactical (e.g., specific level of cash, credit terms, level of inventory, price, etc.)
c) Busines short run (less than 1 year)
d) Business long-run (more than 1 year)

19) Based on the agreement scale bellow, rate the following consequences after artificial intelligence technologies usage on management accounting for decision making.
[totally disagree / disagree / no comment / agree / totally agree]

a) Management accountants' development of new data-related skills.

b) Lower management accountants' frustration levels.

c) Management accountants have become more strategic and business oriented.

d) Management accountants collaborate with data scientists.

e) Automated data collection.

f) Automated data processing.

g) Greater reduction of management accounting errors and liabilities.

h) Better pace of deliberation.

i) Better decision making results.

j) Better prediction of consequences, uncertainty and risk in decisions.

k) Greater focus on matching type of data, prediction and artificial intelligence technology.

l) Better overall performance of management accounting tasks.

m) Better overall business decision making.

n) Higher business competitiveness.

Thank you very much for your time and help!

Annex 2 — Interview script

Main/base question: How do you describe your company's/client's process of replacing and/or further developing management accounting functions based on artificial intelligence technologies?

1. Regarding management accounting functions, did your company replace, further developed, or did both based on AI technologies implementation?

2. Please describe in most detail as possible the process.

3. Rate the complexity of the changing process from 1 to 5, being 1 - Very low and 5 Very high. Why?

4. Do you consider it expensive? Overpriced? What's the expected return? Implementation period?

5. Any improvement so far? If not, for how long after implementation do you expect it?