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The impact of Intelligent Systems on Management Control of 21st century Organizations

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Resumo

Os sistemas inteligentes permitem cada vez mais oferecer perspetivas tecnológicas capazes de executar funções que se aproximam à capacidade racional do ser humano. O aumento da automação, produtividade e a sua própria arquitetura é cada vez mais um tema estudado. O constante desenvolvimento dos métodos de controlo de gestão, bem como das novas soluções tecnológicas, fizeram com que as organizações alterassem as suas perspetivas e se adaptassem. Os sistemas inteligentes aparecem nas áreas de controlo de gestão por forma a dar resposta à necessidade de informação pertinente e atualizada para o processo de tomada de decisão.

Este estudo teve como objetivo perceber as implicações de dois tipos de sistemas inteligentes no controlo de gestão das organizações do sec. XXI, nomeadamente os seus benefícios, desafios e o interesse em implementá-los por parte de controllers de diferentes idades e organizações. Os sistemas inteligentes estudados foram a inteligência artificial e o Machine Learning. Através de um questionário online, concluímos que ambos têm efetivamente características que impactam e sustentam positivamente o interesse na sua implementação, não obstante dos desafios e limitações que ainda enfrentam.

Com base nas respostas do questionário, concluímos que apesar de existirem ainda alguns desafios latentes na implementação destes sistemas inteligentes, as organizações preferem implementá-los, uma vez que os seus benefícios são reconhecidos como mais-valias. Concluímos ainda, através do questionário que existem algumas organizações que ainda não tem recursos suficientes e otimizados para implementação e sucesso destes sistemas, pelo que os mesmos devem que ser implementados consoante as necessidades das organizações.

Palavras-chave: Sistemas Inteligentes, Inteligência Artificial, Machine Learning, Controlo De Gestão, Processo De Tomada De Decisão.

Classificação JEL:

M10 Administração de Empresas: Geral

M15 Administração de Empresas: IT Gestão

O32 Gestão de Inovação Tecnológica e P&D

Abstract

Intelligent systems are increasingly allowing technological perspectives capable of performing functions that approach rational capabilities of the human understanding. The increase in automation, productivity and its own architecture is progressively a studied topic. The constant development of management control methods, as well as new technological solutions, have made organizations change their perspectives and adapt. Intelligent systems appear in management control areas to respond to the need for relevant and updated information for the decision-making process.

This study aimed to understand the implications of two types of intelligent systems in the management control of 21st century organizations, namely its benefits, challenges, and the interest in implementing them by controllers of different ages and organizations. The intelligent systems studied were artificial intelligence and Machine Learning. Through an online survey, we concluded that both effectively have characteristics that positively impact and sustain interest in their implementation, despite the challenges and limitations they still face.

Based on the answers to the survey, we concluded that although there are still some latent challenges in the implementation of these intelligent systems, organizations prefer to implement them, since their benefits are recognized as an added value. We also concluded, through the survey, that there are some organizations that still do not have enough and optimized resources for the implementation and success of these systems, so they must be implemented according to the needs of organizations.

Keywords: Intelligent Systems, Artificial Intelligence, Machine Learning, Management Control, Decision-Making Process.

JEL Classification:

M10 Business Administration: General

M15 Business Administration: IT Management

O32 Management of Technological Innovation and R&D

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List of Abbreviations

ADMS - Automated Decision-Making Systems

AI – Artificial Intelligence

AVE - Average Variance Extracted

CR - Composite Reliability

HTMT - Heterotrait-Monotrait Ratio

IS – Intelligent Systems

IT - Information Technology

LV - Latent Variable

ML – Machine Learning

PLS-SEM - Partial Least Squares Based Structural Equation Modeling

PwC – PricewatherhouseCoopers

QoC - Quality of Context

RQ – Research Question

SEM - Structural Equations Model

VIF - Variance Inflation Factor

CHAPTER 1 - INTRODUCTION

1.1 FRAMEWORK AND RESEARCH PROBLEM

This dissertation aims to analyze the impact of intelligent systems in management control of 21st century organizations. The investigation problem arises not only from new working concept but also from my own professional experience as a controller in a multinational organization.

Management control appears as a means of achieving organizational goals, as it is responsible for delivering actual and relevant information to decision making processes. Controlling is responsible for comparing actual and predicted situations and its planned performance, but the amount of information that we have access to, and its relevance differs a lot. So, to deliver relevant information to management teams, controlling needs to sum up with consistent, applicable, pertinent, and suitable information. Controlling is responsible for delivering relevant information so that management can implement strategies and, thus, make decisions.

1.2 OBJECTIVES AND RESEARCH QUESTIONS

This dissertation's objective is to analyze the role of intelligent systems on decision making processes, namely for Artificial Intelligence and Machine Learning systems, using two distinct research questions (RQ). The research questions, which will be further explained are listed below:

(RQ1) - How do Artificial Intelligence systems improve decision making processes of organizations?

(RQ2) How do Machine Learning systems improve decision making processes of organizations?

The purpose of the present research is to contribute with new and relevant knowledge to the scientific community, by using different conceptual models and valid hypothesis that could be result oriented. The objective will be to relate the impact of intelligent systems, specifically artificial intelligence, and Machine Learning with decision-making processes on management control of 21^{st} century organizations with recent studies on intelligent systems in the organizational context.

1.3 DISSERTATION STRUCTURE

This dissertation is divided into six chapters. The first chapter is the introduction (1) and presents the research problem, the objective, research questions and the dissertation structure. The second chapter (2) is the literature review and is split into three theoretical sections, first Intelligent systems (2.1), second Management Control (2.2) and third Decision Making Processes (2.3). The first theoretical section – Intelligent systems (2.1) is divided into the three systems studied - "Big Data" (2.1.1), Artificial Intelligence (2.1.2) and, Machine Learning (2.1.3).

On the first sub section “Big Data” (2.1.1), we defined “Big Data” (2.1.1.1) and then correlate “Big Data” do Artificial Intelligence (2.1.1.2). On the second sub section Artificial Intelligence (2.1.2), we proposed to define Artificial Intelligence concept (2.1.2.1) with the support of scientific articles and relevant documents, as well as connect Artificial Intelligence to Management Control, particularly its applicability (2.1.2.2), on a third phase we applied Artificial Intelligence to Decision Making Process within an organization (2.1.2.3); fourth we correlated Artificial Intelligence to Business Analytics in Decision Making Process (2.1.2.4).

On the third sub section Machine Learning (2.1.3), we defined the concept of Machine Learning (2.1.3.1), found a relation between Machine Learning and Management Control (2.1.3.2) and applied Machine Learning to the Decision-Making Processes (2.1.3.3).

The second theoretical section Management Control (2.2), we purposed to define its concept also with support to relevant literature and understand what has been explored on this topic so far. On the third theoretical section Decision Making Processes (2.3), we purposed to provide an intellectual context with related research and identify where we are in the story currently, by identifying past research.

After the literature review chapter, on chapter 3, we presented the theoretical approach, by identifying the objective, research questions and hypotheses to this investigation, based on the previews chapter (3.1).

On chapter 4, the methodology, where we presented the research models (4.1), and then the conceptual models (4.2) the conceptual model of the first research question (4.2.1) and then the same conceptual model for the second research question (4.2.2). Both resulted in questions for our survey. On the same chapter, we presented a sample description of our survey (4.3).

On chapter 5, we presented a statistical analysis of the two research questions, a quantitative result and subsequently a result discussion. On the same chapter, we presented the number of articles cited in this study published by year (5.3).

The last chapter 6 presents the conclusions, where we presented the final considerations (6.1), limitations of our investigation (6.2) as well as some suggestions for future investigations (6.3).

CHAPTER 2 - LITERATURE REVIEW

2.1 INTELLIGENT SYSTEMS

Intelligent systems (IS) have been a topic of discussion for the past few years as the trust on these systems have increased their level of acceptance. According to Siau & Wang (2018) both initial and trust formation are crucial for the increasing development of intelligent systems. Trust can have several dimensions as it differs from its context. Regarding human-robot interaction, it refers to the willingness of people to follow instructions and accept the information provided by the systems. Hoffman *et al*. (2013) refers five factors for trust in automation that can be listed as accuracy, efficacy, serviceableness, robustness and finally the percentage of false alarms. Hengstler *et al*. (2016) proposes a range of tree aspects of trust in Artificial Intelligent systems as accomplishment (meaning security, protection, and safety); action (usability and compatibility) and finally its intention and aim.

According to Meister (2017), investment in Artificial Intelligent has increased 746% in five years from 2011 to 2015. Later and according to the Stanford University's Artificial Intelligence Index Report of 2021 (D. Zhang *et al*., 2021), COVID-19 contributed to an acceleration of people's attendance to AI conferences. Also, on the past four academic years the number of courses that taught Artificial Intelligence at graduate level has increased 41,7%. While Machine Learning leads at the functional short courses, in the European Union. According to the same report Machine Learning and Artificial Intelligence lead with 22,8% all computer science PhD graduates in 2019, in the United States. The number of those two specialties is higher than the next five all together (Theory and Algorithms; Robotics/Vision; Databases/Information Retrieval; Security/ Information Assurance and Graphics/Visualization).

2.1.1. "BIG DATA"

2.1.1.1 "BIG DATA" DEFINITION

"Big Data" was first named by IBM and other relevant leading technology organizations in 2012 and until now many more definitions have risen (Gandomi & Haider, 2015). According to one of its first definitions, (Chen *et al*., 2012), (Kwon *et al*., 2014) "Big Data" had 3 V's, named – *volume*, *variety*, and *velocity*. *Volume* was described as a variable of time and size of data because of advances of industries and technologies of data management. *Variety* was point out as diversity in dataset for example, videos, texts, and images. Finally, *velocity* was referred as the speed which companies receive, store, and manage data. Gartner, Inc. defined it as "Big data is high-volume, high-velocity and/or high-variety information assets that demand cost-effective, innovative forms of information processing that enable enhanced insight, decision making, and process automation." ("Gartner IT Glossary, n.d.). *Volume* and *variety* accredit value creation to an organization, as *variety* collaborates with *volume* to produce benefits capable of affecting firm's performance. The higher the value of *veracity*, the greater the benefit to companies' performance, as it is possible to obtain value through *volume* and *variety* of data, capable of increasing the performance of organizations (Cappa *et al*., 2021).

"Big Data" definitions have been updated in recent years, highlighting its multiple concepts going from the classic 3v's to the 6v's. Gandomi & Haider (2015) introduced *value, veracity,* and *variability*. *Value* refers to the effect of data quality concerning decision making process, *veracity* refers to the complexity of data's *velocity*, while *variability* refers to the complexity of innumerous sources where data is generated and its constantly need to remodel. Given the rapid proliferation and popularity of devices and smartphones, companies will soon have to start dealing with thousands of databases that require real-time analytics. Since traditional systems are not able to manage this amount of data that is processed instantly, "Big Data" technologies emerge (Gandomi & Haider, 2015).

Organizations believe that the new technological advances, that mainly help organizations to store and analyze data on another dimensions, will significantly modify the methods of actual business running (X. Wang *et al*., 2015). The table 2.1 below shows the definitions of "Big Data" V's according to some authors, over time.

Table 2.1 - Definition of "Big Data" V's according to literature

Volume	*Velocity*	*Variety*	*Value*	*Veracity*	*Variability*
(Chen *et al*., 2012; Kwon & Sim, 2013; Mcafee & Brynjolfsson, 2012)	(Chen *et al*., 2012; Kwon & Sim, 2013; Mcafee & Brynjolfsson, 2012)	(Chen *et al*., 2012; Kwon & Sim, 2013; Mcafee & Brynjolfsson, 2012)	(Gandomi & Haider, 2015)	(Gandomi & Haider, 2015)	(Gandomi & Haider, 2015)
A variable of time and size of data because of advances of industries and technologies of data management	Speed at which information is generated and in turn analyzed.	Diversity in dataset for example, videos, texts, and images	The value of raw data is lower than the value obtained by analyzing massive quantity of data coming from many channels	Possibility of using tools that reduces uncertainty addressed for management	Refers to the flow of data and the constant need of gather data from different sources

AUTHOR'S ELABORATION

"Big Data" is defined as having the potential to transform business process and hence generate business value. In addition, "Big Data" is also defined as having the capacity of transform decision making processes within an organization, by enhancing transparency and improve performance (Mcafee & Brynjolfsson, 2012; Wamba-Taguimdje *et al*., 2020). According to Zhu *et al*. (2019) recently this trend topic is the most popular data process techniques, including Machine Learning and intelligent systems.

2.1.1.2 "BIG DATA" and ARTIFICIAL INTELLIGENCE

One of the innovative aspects of intelligent systems is the emergence of new technologies to manage data and analytics, which allow organizations to increase the volume of data in their business processes (Gandomi & Haider, 2015). A study conducted by McKinsey (Brown *et al*., 2011) shows the importance of data processed by Artificial Intelligence. Artificial Intelligence, as one of the essential components of "Big Data" allows the creation of new ways of data processing, becoming the main drivers of "Big Data" revolution. Data mining is a term used to describe the act of extracting the desired information from "Big Data" that will hence support in decision making processes (Sabarmathi & Chinnaiyan, 2019). Data mining methods emerge as a response to intractable amounts of data to be analyzed by individuals. Specifically, data mining emerges as a potential for advances and avoid control failures, and thus improve more dynamic decision-making processes (Meyer *et al*., 2014).

"Big Data" has hence become one of the new sources in Artificial Intelligence applications hereby developing processes at a level of performance that was not possible before. The architecture level increased at some point where it's easier to manage large scale of data, while simultaneously it's more efficient. Comparing to data analytics, "Big Data" proved to be more efficient when dealing with a large amount of data (Ostrowski, 2018). This new era of accessibility proved that Artificial Intelligence could solve most problems with more potential when compared to the past attempts. "Big Data" has been gathering information from many sources, as a result management field finds it difficult to manage and process such amount of data. Artificial Intelligence emerges as a provider of accurate data analysis, giving a full and effective use of available resources (N. Wang *et al*., 2020). Nevertheless, when it comes to management, IT technicians need to concern about monitoring quality of "Big Data", as it is important in nowadays data management systems, considering the amount and variety of data available (Nelson, 2018). "Big Data" has the capability to collect and store many amounts data that seems to be limitless.

Artificial Intelligence appears as a mean of access and improve the potential of the collected data, through growth and enrichment in many fields (Smith, 2019). Sharma *et al*. (2014), state that in recent years, interest in the subject of "Big Data" and analytics has increased by organizations and researchers in the areas of Artificial Intelligence, and management due to it's potential to increase the organizational performance. According to the same authors, while automated Artificial Intelligent systems process the data, they also generate a significant amount of information. This information can, and should be, used to make better decisions. This is one of the main benefits for business looking to grow using technology and data analytics sources to their advantage.

2.1.2. ARTIFICIAL INTELLIGENCE

2.1.2.1 ARTIFICIAL INTELLIGENCE DEFINITION

Since its announcement in 1960, Artificial Intelligence (AI) has been a topic of trends not only for its remarkable progress but also because of its performance that proved to exceed human actions (Fouse *et al*., 2020). Recently and according to the to the Stanford University's Artificial Intelligence Index Report of 2021 (D. Zhang *et al*., 2021), Artificial Intelligence has seen a substantial increase on journal publications written for a wider audience. The amount of several articles published had an international impact over the last decade.

Nilsson (1998) state that AI "is concerned with intelligent behavior in artifacts", which comprises "perception, reasoning, learning, communicating, and acting in complex environments". Poole & Mackworth (2010) describe AI as "computational agents that act intelligently". According to the same authors intelligence is the act of being able to act in accordance with circumstances, easily adjust to new and uncertain environments, be able to gain from experience and know-how and therefore benefiting from decision making. N. Wang *et al*. (2020) described Artificial Intelligence as a new technology science that can be used as a simulator of human intelligence. This technology uses natural, social and technology sciences to simulate the information processed by people's apprehension.

Li (2021) foresees Artificial Intelligence development as an integration of computer expertise and human brain. It is also described by the English Oxford Living dictionary as "*the theory and development of computer systems able to perform tasks normally requiring human intelligence, such as visual perception, speech recognition, decision-making, and translation between language*."

Artificial Intelligence has proved to be the new technological science, that along with natural and social science is used to simulate the application of human intelligence. This new way of thinking acts in a very similar way as human intelligence, and it is a simulation of people's conscience and way of thinking (N. Wang *et al*., 2020). Artificial Intelligence has been doing considerable improvements (Cigref, 2018; PWC, 2019), as it can access to much more amounts of data helping business activities.

The appearance of Artificial Intelligence regained strength in business activities because of three relevant events in recent years named the presentation of new and developed algorithms, changes, and new arrival to the market, improving performances, and the introduction of sophisticated databases learning from intelligent systems (Jain *et al*., 2004; Khashman, 2008; PWC, 2019).

2.1.2.2 ARTIFICIAL INTELLIGENCE AND MANAGEMENT

Organizations have become more conscious about the value of Artificial Intelligent technologies as they need tools to exploit better the data they have at their disposal. This awareness is reassured by digitalization and automation as it is the fuel to emerge business value and performance of organizations (Anand *et al*., 2013; Wamba-Taguimdje *et al*., 2020). Those advances impact not only organizations but also knowledge of workers, as it plays a key role in organizations while it produces visible impacts in several areas such as improvements on process level performance.

Some recent and remarkable achievements in the robotics world, made Artificial Intelligence replace some highly repetitive tasks. This replacement has not only saved labor cost and reduced the probability of manual error on repetitive tasks of daily business, but it also improved efficiency in a positive way (Ganapathy, 2021). The continuous development of Artificial Intelligence has thus transformed some processes by replacing it with intelligent processes. This effectiveness is mainly due to the emergence of Artificial Intelligence technology that improves not only accuracy, but also effectiveness of internal and external risk control (Wamba-Taguimdje *et al*., 2020; N. Wang *et al*., 2020). According to Schrettenbrunnner (2020) innovation of technology needs to be taken seriously within an organization as the competitiveness will highly depend on Artificial Intelligence. Artificial Intelligence systems are now seen as a way of progress to business functions. These tools will involve improvements in daily tasks and can be perceived as a competitive factor. Although the adoption of Artificial Intelligence in organizations highly depends on their structures, resources, and characteristics, it is also perceived as a technological innovation that will overtake many tasks.

Artificial Intelligence has affirmed itself as usual and commonplace in some fields such as communication management (Zerfass *et al*., 2020). It is described as a supplement to some professional activities, on the one hand affirming opportunities and on the other hand challenging by not replacing human activities or way of thinking. Artificial Intelligence is viewed as a grown factor, since it allows organizations to achieve efficiency, optimization, and improvement of employee's daily work.

Managers and analysts nowadays have at their disposal a huge number of analytical tools such as data analysis, data mining, and data visualization. However, to process the data and gather the information from these systems, analysts and managers are critical (Sharma *et al*., 2014). According to Li (2021) there is a "man-machine" relationship that ensures the interaction between humans from their social, physical, and informational space and computers. Regardless, studies have proved that the success of Artificial Intelligence within the organizations needs three bilateral elements: AI Management Capabilities, AI Personal Expertise, and AI Infrastructure Flexibility. Regarding the first one, studies have demonstrated that organizations have a significant impact, whereas the other two depend on other factors. (Wamba-Taguimdje *et al*., 2020).

Artificial Intelligence has made significant advances on management field as it is now capable of replacing financial workers that handle with repeated issues. (Ganapathy, 2021).

2.1.2.3 ARTIFICIAL INTELLIGENCE IN DECISION MAKING PROCESS

Nowadays, organizations that cannot accelerate and predict future with new products and processes will have a very hard path to survive. The ability to forecast and the willingness to change are extremely essential as it can make an organization thrive (Schrettenbrunnner, 2020). However, the amount of documentation that organizations have access to make it difficult to predict. Some remarkable progresses of Artificial Intelligence systems, such as elimination of some processes and centralization of others, reductions of errors and enablement of real time visibility contributed to the improvement of management decision making processes through automation. It also has an impact on organizational structures, whereas some basic decisions can be made by anyone, rather than just managers for example, hence, contributing to better administrative performance. The outcome is a better and more efficient capacity of response aligned with the available resources (Wamba-Taguimdje *et al*.,2020).

Organizations have at their disposal significant amounts of data, through which workers need to have knowledge to perform data driven decisions. Workers need to have better understanding to manage information under great complexity as it can enable them to take informed decisions (Smuts & Smith, 2021). According to the same authors, organizations base their decisions making processes on evidence of data, rather than on subjective intuition. Artificial Intelligence intends to help abstract organizational knowledge despite the constraints. Some constraints can be more difficult to surpass than others, such as old processes in historical organizations, various stakeholders, and traditional organization processes. According to the same authors, organizations with too many concerns when it comes to implementation of technology will become history in a shorter period. The growing potential of Artificial Intelligence has been proving its influence on firms as it has automated budgeting and planning processes, using efficient resources, and eliminating inadequate costs and resources (Wamba-Taguimdje *et al*., 2020).

The constant economic evolution leads to new and better competitiveness concerns which involve improvements and changes of information devices in organizations (di Vaio *et al*., 2020). The capacity of innovation within a very dynamic market is the key factor for the challenge's organizations face nowadays. Globalization, competition, along with the skill and capacity to compile the strategic information are essential to value creation. Therefore, it is crucial that organizations seek to innovation to have strategical resources (Malik Badan *et al*., 2019). Thus, Artificial Intelligence seems to be the new response to market acceleration and competitiveness, as the fixed forecast has become unrealistic and gives insufficient answers to innovations. Lack of forecasting along with inadequate planning leads to unsatisfactory competitive decisions.

According to Schrettenbrunnner (2020), decision making processes are automatized and virtualized, as the impact of Artificial Intelligence in organizations at a management level is related to *PDCA - plan, do, check, act*—cycle and this is progressively being implemented, as some leaderships' tasks are being replaced by Artificial Intelligence driven management. This virtualized performance evolution made Artificial Intelligence a decisive factor for innovation within an organization, not only costs saving opportunities but also rigor in decision making processes.

As Costa *et al*. (2020) concluded in 15 interviews with commercial managers from distinct organizations that most of the interviewers consider AI tools a support and benefit for their daily decisions as it can make automated decisions. The quality of the processed information was preferred to quantity of it as it could increase an added value to discussions with costumers, as well as the real-time access. This allow commercials on negotiation processes as they are better prepared. On the one hand, replacing commercials was considered a difficult task as there are some skills and techniques challenging to replicate. On the other hand, some industrial areas could with daily tasks be more easily replaced or supported. However, the lack of motivation and guidance can compromise many projects.

According to Wamba-Taguimdje *et al*. (2020) organizations are increasingly prone to use automatic learning. The study conducted by the authors show that 31,20% of their sample uses it within the organizations, because it not only reduces human intervention in the processes, but also technological systems become more intelligent. Use of automated learning becomes more attractive when the system becomes more accurate, and efficient in its results.

According to Zerfass *et al*. (2020), technological innovation in decision-making depends on three different causes: 1) Internal organization (its structure and communication), 2) external environment (regulations from government, technological infrastructure, and industry characteristics), and 3) availability and technological characteristics. According to Kuzey *et al*. (2014), this growth factor that is Artificial Intelligence not only improved and accelerated automated transformations in market conditions, but also introduced new business models. This automation improved the quality of management in decision making processes.

Wamba-Taguimdje *et al*. (2020) conclude that an association of IT resources with automated and intelligent processes improve the quality of management decisions. Employees are affected in the processes when their needs are expressed, pointing out the data used to sustain the algorithms, whereas managers are more concerned about the outcomes. The performance of the organization can be better if managers and leaders manage solutions between IT resources and organization's processes and resources. All this combined could lead to the achievement of business value. Even though most case studies conducted by the authors conclude that some organizations still have insufficient and unoptimized resources for the implementation and success of Artificial Intelligence.

For management teams it is crucial that recruitment and retainment of talent needed for Artificial Intelligence technologies is a priority combining with training tools and readjust organizational decisions (Wamba-Taguimdje *et al*., 2020). For instance, Artificial Intelligence requires qualified workers, capable of adapting to business activities and to new and existing Artificial Intelligent techniques. In fact, research shows that most organizations need more than one Artificial Intelligent solution. Therefore, managers should be responsible for investigating the benefits of using multiple AI technologies. Regardless, and despite all advantages of Artificial Intelligence resources, most studies don't consider in its approach the time and costs of implementing this technology. So, it still faces some unsolved challenges (Dwivedi *et al*., 2021).

The recent decision-making processes have been focusing on decision making by Artificial Intelligence algorithms. AI uses computer algorithms to perform human functions as it can provide predictions generally more rigorous than observed in routine practice. The assurance of faster, detailed, accurate and cheaper decisions with human's intelligence quality has accelerated recent developments in AI as different professions have been taking important decisions based on AI algorithms (Shrestha *et al*., 2019). However, managers that make decisions based in AI algorithms are still responsible for the outcomes. Their judgment as stated by Abdul *et al*. (2018) opens a discussion on whether managers evaluate, discuss and finally present explanations about the decisions taken.

The prompt improvement in AI is progressively implementing algorithmic decision makers as crucial and decisive organizational actors. Managers need to design the most appropriate decision-making structure based on human's judgement and interpretability as AI have been proving its effectiveness when it comes to predicting with high accuracy. Key performance indicators provide prompt information that will support managers to make decisions. As a result, those decisions could improve efficiency and effectiveness of the process (Wamba-Taguimdje *et al*., 2020). As stated by the same authors "*The automation effect has a significant positive impact at the process level, which is positively associated with the influence of AI at the organizational level*". The authors suggest that an evaluation of aggregated data will improve decision quality referring to value added on the effectiveness perspective driven from the use of Artificial Intelligence to replace human's interaction. Also, predictiveness suggests in its functionality and impact an improvement in decision quality concerning standardization of investment scenario analysis. Mooney *et al*. (1996) suggests the scope of informational and automation effects of management. Data is a fuel for Artificial Intelligence technologies and is used by algorithms to deliver reliable, fast, accurate, relevant, recent, timely and renewed information. Hence, the higher the quantity of processing data and the capability of driven quality, the more efficient the organization can make better decisions (Abijith & Wamba, 2012). As a result, Wamba-Taguimdje *et al*. (2020) concluded that "*the informational effect has a significant positive impact at the process level, which is positively associated with the influence of AI at the organizational level".* Informational effect is described as the capability of Artificial Intelligence to gather, store, process and publish information inside organizations Furthermore, the transformational effect introduces the value created by Artificial Intelligence capacity that assists the progress and empower innovation and transformation (Wamba-Taguimdje *et al*., 2020).

According to Shrestha *et al*. (2019) decision making processes should recognize five dimensions "*specificity of the search space, interpretability of the decision-making process and outcome, size of the alternative set, decision-making speed, and replicability*." The AI based decision making requires accurate objectives while human decision making defines it as general. When it comes to interpretability, decisions can be complex and difficult to explain to AI as humans can be understandable and explainable. The size of alternatives is large to AI and limited to human decision making. Regarding the speed of decision-making, it is proved to be faster in AI and slower in humans. The outcomes are eminently higher with computational actions, whereas humans are susceptible to individual causes and factors (Shrestha *et al*.,2019). According to the same authors, the structure of aggregating human and AI considers it as a member of the group to make decisions. It can be helpful to minimize risky errors of both AI and humans. Nevertheless, Artificial Intelligence has some limitations like human understanding (Shrestha et al., 2019). Having one without the other might not be the desired solution. Some problems of bias and reliability can occur if the decisions were to be taken in accordance with some preferences. Artificial Intelligence can manipulate data as it can be hard to find, therefore regulations and audit processes are still required. Some level of transparency and interpretability of data must be achieved by the organizations therewith managers have to internally build capacities to establish on the inputs to the algorithm and, thus, the interpretation of its prediction.

Personal expertise is characterized as professional skills and know-how of Artificial Intelligence domains and business functions, usually mandatory by organizations for design and/or adopting an intelligent performance in a technology to manage business assigned to it (Wamba-Taguimdje *et al*., 2020). Therefore, it allows employees to be more effective with Artificial Intelligence resources and technologies at their disposal. As a result, organizations with capable employees are expected to fit with conditions of uncertain and changing environments through adjusting Artificial Intelligence with strategies and advantageous intelligent systems. So, Wamba-Taguimdje *et al*. (2020) concluded that "*AI personal expertise has a significant positive effect on AI capabilities, which are positively associated with the influence of AI at the process level".*

In fact, Artificial Intelligence has been adjusting mainly through its technologies the business itself and all organization processes. All those changes require some developments within the internal organization, not only the culture but also skills of employees (Wamba-Taguimdje *et al*., 2020).

2.1.2.4 ARTIFICIAL INTELLIGENCE AND BUSINESS ANALYTICS IN DECISION MAKING PROCESS

H. Simon (1947); H. A. Simon (1956) research set some theoretical foundations about the influence of decision-making processes on technologies and even the connection between processes of decision making and the performance of organizations. The main purpose is to discover how can organizations base and take better decisions once they have better analytical tools. Organizations do not need to have big structural and processes changes to acquire enhancement opportunities from the use of enterprise systems (M. L. Markus, 2004; M. Markus & Tanis, 2000; H. A. Simon, 1979). Those significant structure changes might come when its necessary to achieve advantages from such systems (Sharma *et al*., 2014). Hence, resource allocations can occur if organizations want to take improvements of performance from their used inform decision. The potential value that organizations could create by using business analytics is one of the arguments used by organizations to invest in technologies as intelligent systems as they can create many benefits. Although, those investments could not always create added value, organizations with better information management capabilities achieve improved performance in many ways (Schryen, 2010; Sharma *et al*., 2014). As a matter of fact, the outcome value depends not only on the method in which organizations set up technologies, but also the transformation of decision-making processes. Managers should look out to this to capture value to the organizations using business analytics such as resource allocation and transform decision making processes.

It is crucial to develop relevant insights as it is crucial transform them into valuable decisions. Thus, Swami & Gangadharan (2004) argues that business intelligence enables a better understanding of business by analysis of opportunities, revenues, and costs. But it is not clear that better advances would be recognized with that condition.

Another issue identified in this investigation is related with organizational decision making - how effective are insights converted into final decisions. Sharma *et al*. (2014) argues that despite the insights some specific decisions are influenced by a "host or other factors". Decision making processes that are taken under complex situations have been settled to have significant impacts on the outcomes as suggested by (Bok *et al*., 2012). Furthermore Gavetti (2005) specify how structures of organizations may be responsible to influence business units' managers under some circumstances.

The focus on generating value through business analytics leads to a trivial question that is "how organizations can create value from those decisions". With this question, we can associate two uncertainties- "the uncertainty of successfully implementing decisions and the uncertainty associated with the success of strategic actions." (Miller *et al*., 2004). The successful implementation of quality decisions may come from two fundamental aspects that is his acceptance by subordinates and relevant stakeholders along with the capability of achieving its main objectives. In fact, it's also referred that business analytics have a role on improvement of quality decisions. Nonetheless it's still not clear that it can be used as a way of acceptance of decisions. As a matter of fact, according to Shanks *et al*. (2010), key stakeholders who are responsible for implementing those decisions are not usually involved on the decision-making processes. This raises a negative correlation between the step of decision making and thereafter implementing.

2.1.3 MACHINE LEARNING

2.1.3.1 MACHINE LEARNING DEFINITION

Machine Learning (ML) is defined as a computational mechanism used to improve and enhance performance with high predictive accuracy. The electronic data collected is used for efficient analysis with accurate algorithms related to data analysis and statistics (Mahmood & Wang, 2021).

According to Han & Jochum, (2020) this way of programming computers serves to optimize system performances of data management, avoiding repetitive manual tasks and being a cost saving opportunity. Machine Learning plays an active role on the study of architecture computer programs capable of automatically improving their efficiency. The machines learn to recognize patterns and can deliver results through predictions and accurate information.

Nelson (2018) describes Machine Learning as a branch of Artificial Intelligence, as it acts "autonomously or semi-autonomously" as a response to what it has learned from data. According to the same author, organizations that do not adopt strategies to utilize Machine Learning will fail in modern days. Similarly, Schweyer & Advisor (2018) states Machine Learning as "components of AI", and Kaplan & Haenlein (2019) claim that Machine Learning "is an essential part of AI, but AI is broader than Machine Learning since it also covers a system's ability to perceive data (e.g., natural language processing or voice/image recognition)". It can be said that Machine Learning is part of the Artificial Intelligence interface, which means that when it meets new data sources, Machine Learning software is able to learn, grow, change, and develop new solutions by itself. As the term means, machine learns through exact programming, where the system receives the algorithms and data, crosses the information received and has a complete analysis.

The emerge of Machine Learning proved the need of constant predictions over the continuous business processes, as it learns to predict future trends. The algorithm behind it doesn't really know if the connection really exists or if the prediction doesn't make an intuitive sense, in fact it only cares about the accuracy of the prediction itself. Algorithms behind Machine Learning are supposed to be continuously updating as new data arrives in the system and thus the machine itself can learn. This data driven machine can continuously emerge and therefore predict trends over time as the algorithms allow data to prescribe information contained in input variables and forecasts values for an output variable (Coglianese *et al*., 2016).

Machine Learning has been used to different techniques such as predicting the future of current trends, along with explaining deviations on business processes behavior (di Francescomarino & Maggi, 2020).

According to the Stanford University's Artificial Intelligence Index Report of 2021 (D. Zhang *et al*., 2021), in recent years Machine Learning advances have significantly improved performances over many tasks, as it is possible to train systems to perform them sufficiently good. Organizations in 2020 change at least one business function to an automation process.

2.1.3.2 MACHINE LEARNING AND MANAGEMENT

Nelson (2018) found a connection between Machine Learning and data management considering the number of daily tasks that management have and then highlighted some functions of Machine Learning such as forecasts, classify identical effects, establish patterns, identify irregularities. Given those functions, Nelson (2018) conclude that traditional methods of managing data are no longer efficient, as it reveals poor data quality.

Machine Learning techniques have been proven extremely useful for daily basis decisions as it can collect "Big Data", organize information, and consequently optimize and prevent trends. Those trends are often very accurate and conclusive (Selim, 2020). With software capable of obtaining data relevant to a company, Machine Learning allows a complete analysis of all the information and delivers valuable insights to work on it. In addition to the strategic part, where it is possible to act without taking great risks, with the ideal tool it is possible to increase the team's productivity, as you will not need to waste time analyzing all the raw data received separately. Being able to think fast, make quick decisions in real time is the best way to improve the efficiency of a business through the constant learning of intelligent systems, with the advantage that the success rates tend to increase with the constant learning of the machine and its updates. Using the large volume of data as a strategy and being able to extract valuable insights is the great differential of Machine Learning (Jordan & Mitchell, 2015).

Nowadays we have access to available data from many sources and powerful data visualization tools (T. Davenport *et al*., 2010; T. H. Davenport & Harris, 2007). However, an upgraded knowledge about the active process between analysts and business results on a better understanding of relationship between business analysis and improves in performance.

The process of generating data involves several departments of organizations. Those departments are usually segmented into existing structures to generate insights. But there are some cases where teams don't see full relevant information although the access because of failures in teams' compositions (Henderson & Clark, 1990). This deficiency generates information gaps that could have been gather from the available information. Therewith, a crucial area of improvement is effectiveness as it can improve value for organizations. Machine Learning algorithms can be responsible for detections and consequently improvements on business analytic tools, as seen by Lycett (2013) in Netflix's case. Nonetheless human understanding is still needed to valid and accept the algorithms generated.

2.1.3.3 MACHINE LEARNING IN DECISION MAKING PROCESS

Brehmer (1992) listed some aspects such as deferment feedback or, deficiency of transparency that could decrease an organization's performance. Even though, and according to the same author Machine Learning appears as a mean of solve of those problems, such as anticipate feedback, or the decision maker can base their decisions on assumptions or forecasts made by the machine.

Nelson (2018) states that Machine Learning have been responding to challenges of data management for at least two decades and as more organizations have confident on data for key decision-making process, the ability to acquire prosecutable insights will be more and more important for their prosperity and progress. The level of automation of informational systems is crucial to be better succeed when analyzing large amounts of data and thus implementing a decision-making process, as the process of decision making might monopolize much time if there's no use of computational methods (Ahmed & Malik, 2020). Knowing how to act properly, minimizing risks and losses is the ideal way to make an organization develop according to its needs, taking advantage of trends, behaviors, and opportunities of great value through this technology. Machine Learning systems gave the possibility through *PROCEDO ("PRediction of Control Errors in* Dynamic Contexts"), on the Diabetes care example, to be more cost-effective, and developing better conclusions (Meyer et al., 2014). According to the same authors, this system can be replicated in several environments, to hence made some changes in management control strategies. *PROCEDO*, proved to be a model for development of control enhancement. Moreover, when we can list all the accessible improvements to a control strategy, as it can be possible to develop access in such way that improvements are made automatically by the machine (Meyer et al., 2014; Sharma et al., 2014).

Therefore, Machine Learning technology helps by predicting future actions based on the past actions (Obukhov *et al*., 2019). To take advantage of all the benefits of Machine Learning, it is necessary to understand how it can help the organization, and thus, choose the ideal software, hire a responsible team, and analyze them, then elaborate exact strategies with the information obtained. Obukhov *et al*. (2019), considered five approaches of organizations when considering decision making processes. The first one considers that human interaction is the base for decisions; secondly, authors suggested a partial recommendation from the system to facilitate some tasks; on the third approach the authors considered that human's interaction can only be necessary for *verification* and *confirmation*; the fourth consists on more technical approach where the employee can only check and stop the solution that was previously generated and executed automatically; the last one doesn't consider human interaction as the decision is completely formed automatically. It was found by the same authors that Machine Learning techniques can effectively automate decision making processes as it, not only, reduces the negative control of employees, but also accelerate the processes. Machine Learning techniques can automatically collect data about employees' tasks, store and train them. It forecasts future user's tasks and define scenarios that keep from happening inconsistent tasks by the machine (Obukhov *et al*., 2019). The tool analyses, crosses and separates the data obtained and then delivers, through a report, the information necessary for managers to take the necessary decisions.

It is, regardless, important that data is constantly being updated to improve its accuracy. The emerge of problems within the decision-making process can be due to lack of information about data quality (de Hoog *et al*., 2019). According to the same authors data quality can be measured using different key performance indicators and the quality of context (QoC). At this point is clear that the closer to the QoC the information is, better the quality of data. Hence, to integrate data quality in Machine Learning, the information should also be updated. Actual data, namely information received few seconds ago, is closer to the reality than the previous one (de Hoog *et al*., 2019). Decisions should be based on the information required by the desired data and not similar information. Also, to improve the quality of outcomes, organizations should make a better use of available resources (Meyer *et al*., 2014). With this information, organizations can follow the right directions, be less likely to make mistakes and make an investment doomed to failure. According to the same authors, an environment of dynamic decision-making process was first created to respond to some challenges, such as time feedback- deferred and diversified relations between variables. Better outcomes can come from control strategies improvement; however, the desired outcomes can result for some and fail for others (Meyer *et al*., 2014).

Sharma *et al*. (2014) suggest that decision making processes are not clear to lead always into good or bad decisions, despite the valuable insights. The desired decisions are not always succeeded in dynamic environments of decision strategies. Frisk *et al*. (2013) in case of Swedish Fire and Rescue Service conclude that decision making processes should include much more people, as the interaction between more roles would not only increase the quality but also the acceptance of decisions.

2.2. MANAGEMENT CONTROL

Antony (1965) defined management control as "the process by which managers assure that resources are obtained and used, effectively and efficiently, in the accomplishment of the organization's objectives". Traditionally management control was associated with accounting, providing managers relevant information in different situations of decision-making processes. However, this correlation started to rise controversy for not paying attention to employees' behavior (Malmi & Brown, 2008; Otley, 1999).

Simons (2000) add that management control systems grant financial and non-financial key performance indicators, that organizations can manage in distinct fields. Speklé (2001) described management control as a series of actions taken by managers to achieve predetermined objectives, influencing their individual and group behavior. All those definitions have in common planning, organizing, and controlling, each one of them playing a vital role on management control success.

According to Veltri *et al*. (2007), management control is supposed to be recognized into two different optics. The first correlates the accomplishment of adequate control over subordinates, through objectives. The second one evaluates the objective, comparing it to the desired outcome, and then making corrections, if required.

Management control is used to manage organizations on the desired direction and in line with its strategical planning (Svensson & Funck, 2019). Nevertheless, estimations on management control are supposed to head to the desired results, unlike strategic planning that is supposed to show the expected results. However, changes in strategy or business must be in line with management control to be coherent with new objectives and strategies (Ferreira & Otley, 2009). Management control is vital on the implementation and establishment of new approaches to business models or strategies.

Management control can hence be defined as being responsible for giving the most accurate information and heading organization through their environment to accomplish their goals (Otley & Soin, 2014). Otley (2016) state that management control focus was only forecasting, budgeting, other relevant controls, or performance measures. While Malmi & Brown (2008), propose five different types of control mechanisms – culture controls; planning controls; cybernetic controls; rewards and administrative controls. Decision making processes were a part of administrative controls, while, budgeting, forecasting a part of cybernetic controls. In addition, incentives, and bonus on rewards control; strategic planning on planning and finally values and organizational guidance's on cultures. (Malmi & Brown, 2008).

2.3 DECISISON MAKING PROCESSES

In accordance with H. A. Simon (1979), rational decision making is the action of choosing an option that is expected to result in the most favored result. This process implicates analyze and classify the alternatives, estimation of consequences, and match the accuracy and efficiency of each of these aftereffects. Organizations fight to choose the most appropriate decision-making structures, as it affects its performances and therefore their accomplishments. Decision making process act as a support system to deal with crucial and decisive dilemmas. As stated by B. Zhang & Xiang (2010), decision making processes are detached into three stages. First one is the disintegration of the decision task itself, secondly data processing of decision process and last appoint the decision task. Organizations tend to adopt decision strategies, by efficiently, disqualify or selecting between options (Beach & Mitchell, 1978; H. A. Simon, 1979). According to Edwards (1962) a decision to be dynamic is constrained by time as well as conditional to a series of other decisions to achieve a goal.

Organizations base their decision-making process on strategic planning concerning S.W.O.T. analysis, its strengths, weaknesses, opportunities, and threats, hence prioritizing the best strategical plan (Ahmed & Malik, 2020). Therefore, strategical plans, focuses on future situations and demands, with the aim of profitable objectives, that will help organization thrive besides market fluctuations. The process of taking uncertain decision, also entails the analysis of decisions against the desirable assumption. Moreover, organizations that make strategic plans need to have suitable and enough organizational responses and capabilities, also because long term strategies are based on goals and objectives previously planned (Ahmed & Malik, 2020).

Nowadays, decision making processes of organizations rely on data tools, extracting data from intelligent systems and thus analyzing effects as they become more accurate than the traditional processes. Those methods have proved to be effective along with higher performance and capabilities (Ahmed & Malik, 2020).

According to Mökander *et al*. (2021), decision making systems include a decision-making configuration, an algorithm that decipher this configuration into intelligent systems code and data. This code uses as an input to the system. The automated decision-making systems (ADMS) can enhance be more efficient and hence implement advance solutions.

Chenhall & Morris, (1986) & Pyritz et al. (2011) state that decentralization is the process of empower decision-making process to below levels of management, such as independence in controlling, achieving information and planning capacity. The larger and decentralized the organization, the more proper, precise, and advanced are management control systems. Those systems with modern technologies diminish the loss of control and act as key to access appropriate and relevant information for management control systems purposes, such as planning, controlling and decision-making processes (Abdel-Kader & Luther, 2008). However, centralized organizations use lean sophisticated controls, in fact those organizations are committed to hierarchy and cooperation between employees (Merchant, 1981).

CHAPTER 3 - THEROTHICAL APROACH

3.1 OBJETIVES AND RESEARCH QUESTIONS

According to the literature, some questions have arisen, which are pertinent to move forward with this study. The objective of the literature review is to analyze *the role of intelligent systems on decision making processes*, namely Artificial Intelligence, and Machine Learning systems.

As mentioned on chapter II, we tried to analyze how Artificial Intelligence could impact management control of 21^{st} organizations while also asking if those systems can bring value to organizations.

As stated by Mikalef & Gupta, (2021) the number of organizations investing in AI systems exponentially increased (270%) from 2014 to 2019 and tripled in 2020, although some recognize advantages, others are still dealing with a productivity paradox (Brynjolfsson *et al*., 2017). Therefore, the critical role that Artificial Intelligence plays, generates business value to the organizations as it leaded to serious improvements in some key performance indicators of organizations (Syam & Sharma, 2018).

It was based on the various authors approached that the first research question emerged:

(RQ1) - How do Artificial Intelligence systems improve decision making processes of organizations?
For which the three hypotheses emerged: Influence of perception by users of Artificial Intelligence; Influence of benefits generated by Artificial Intelligence and Influence of challenges generated by Artificial Intelligence.

Artificial Intelligence can manage together with Machine Learning much more in better efficient way becoming part of techniques of decision-making processes (Selim, 2020). While Artificial Intelligence is described as the science of problem solving via automation, Machine Learning appears as potential of exploring Artificial Intelligence, through powerful insights capable of deliver reliable data-driven predictions to management control. Despite the traditional decision-making processes, Machine Learning could help by introducing predictive models and have cost-benefit trade-offs. (Baer, T., & Kamalnath, V., 2017).

The second research question emerged:

(RQ2) How do Machine Learning systems improve decision making processes of organizations?

For which, similarly to the previous one, three test hypotheses emerged: Influence of human interaction on decision making process; Influence of benefits generated by Machine Learning and Influence of challenges generated by Machine Learning.

The following table 3.1 shows the relation between the literature review, the objective of this study and the research questions abovementioned.

Table 3.1 - Relation between literature review, objectives, and research questions

OBJECTIVE – Intelligent Systems **Analyze the role of intelligent systems on decision making processes of 21st century organizations.**		
RESEARCH QUESTIONS	**HYPOTHESES**	**REFERENCES**
(Q1) How do Artificial Intelligence systems improve decision making processes of organizations?	Influence of perception by users of Artificial Intelligence	(Abdul *et al*., 2018; Li, 2021; Smuts & Smith, 2021)
	Influence of benefits generated by Artificial Intelligence	(Anand *et al*., 2013; Schrettenbrunnner, 2020; Wamba-Taguimdje *et al*., 2020; N. Wang *et al*., 2020; Ganapathy, 2021)
	Influence of challenges generated by Artificial Intelligence	(Shrestha *et al*., 2019; Wamba-Taguimdje *et al*., 2020)
(Q2) How do Machine Learning systems improve decision making processes of organizations?	Influence of human interaction on decision making process	(Frisk *et al*., 2013; Obukhov *et al*., 2019)
	Influence of benefits generated by Machine Learning	(Ahmed & Malik, 2020; Kaplan & Haenlein, 2019; Nelson, 2018a; Obukhov *et al*., 2019; Selim, 2020)
	Influence of challenges generated by Machine Learning	(De Hoog *et al*., 2019; Lycett, 2013; Obukhov *et al*., 2019; Sharma *et al*., 2014)

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CHAPTER 4 - METHODOLOGY

4.1 RESEARCH MODEL

After the literature review, a conceptual model was made for the two research questions. Each with the dependent and independent variables. To analyze the responses to the online survey, a Structural Equations Model (SEM) was used, which enable us to establish relationships between the independent and dependent variables. From the conceptual model, hypotheses with direct and indirect effects emerged, which were tested using the Smart PLS 3 program. SmartPLS 3 uses a *Partial Least Squares* (PLS) path with estimated materials considering an analysis between the variables.

PLS-SEM is a “flexible” technique capable of estimating complex models, with many constructs and paths (Sarstedt *et al*., 2019). According to Ringle *et al*. (2015), to test the conceptual model, a SEM must be used through partial least squares (PLS), which is a technique for modeling structural equations based on variance. The analysis and hence the interpretation of results has been split into two parts. Firstly, the reliability and validity of the measurement model was evaluated and, later, the structural model was analyzed. Secondly, to access the quality of the model, the indicators of reliability, convergent validity, internal consistency reliability and discriminant validity have been reviewed, all procedures in accordance with literature (Sarstedt *et al*., 2017).

The methodology used in this dissertation was quantitative, concerning its approach, therewith I looked for cause effect relationships capable of describing characteristics of an online survey. In relation to procced, the research was bibliographic and documental. This study was conducted with a conceptual nature and the purpose was to choose our target public. Therefore, I collected research quantitative data, through surveys conducted to our target public. Our target public included management controllers from different ages and organizations. Identification questions were asked throughout the survey, with the aim of identifying the respondents over age and organizations (multinationals or not). Regarding the online survey (Annex A), it was designed considering the literature review and using *Google Forms* resource, which, after validation by the supervisors of the present study, was shared through a link on *LinkedIn*. The online survey consisted of two sections, the first section was related to Artificial Intelligence and the second one to Machine Learning. Both formed by a multiple-answer question using Likert-type scales with seven levels (Nemoto & Beglar, 2014). An initial question was carried out to ensure that only people linked to management control could advance in the online survey. Regarding, the second one the purpose was to find out the ages of the respondents. At the beginning of each section, a yes or no question was asked concerning the familiarity of respondents with both systems studied.

4.2. CONCEPTUAL MODELS

The construction of conceptual models was done in two steps. Firstly, we conducted a literature review in Artificial Intelligence impact on decision making processes and, secondly, in Machine Learning impact on decision making processes.

4.2.1 THE CONCEPTUAL MODEL 1ST RQ

The first research question is - How do Artificial Intelligence systems improve decision making processes of organizations?

Table 4.1 shows the conceptual model and hypothesis for the first research question. As previously mentioned, we identified three independent variables, as well as the dependent variable on which this study was based. In front of each independent variable, an indicator was identified, which was the basis for the questions in the survey, as we can see on the below table.

Table 4.1 - Conceptual Model and hypothesis test 1st RQ

RQ1 - How do Artificial Intelligence systems improve decision making processes of organizations?		
Dependent variable	Interest in Implementing Artificial Intelligent systems on decision making process of management control of 21st century organizations.	
	Questionary (rate 1-7) Are you willing to implement Artificial Intelligent systems on decision making process of your organization?	
Independent variable	**Indicator**	**Questionary (rate 1-7)**
Perception of users and its implication on daily business	Knowledge and understanding concepts. (Smuts & Smith, 2021)	Are you familiar with Artificial Intelligence?
		Do you know the concept and application of Artificial Intelligence?
		Rate the impact you believe Artificial Intelligence may have in your work.
	Interpretability of provided information by managers. (Abdul *et al.*, 2018; Li, 2021)	Do you believe it is possible to train machines to perform complex functions with excellent hit rates and accuracy?
		Do you believe the quality of future jobs will be guaranteed in a context of man-machine interaction?
		Do you believe Artificial Intelligence can effectively eliminate many processes that were previously done manually?
	Organizations base their decisions making processes on evidence of data, rather than subjective intuition. (Smuts & Smith, 2021)	Do you believe organizations base their decisions on evidence of data rather than subjective intuition?
Benefits generated by Artificial Intelligence	Improve process performance: Better analytical and problem-solving skills based on simulation tools. (Wamba-Taguimdje *et al.*, 2020)	Do you believe Artificial Intelligence can improve a processes' performance based on simulation tools? - Better analytical tools - Better problem-solving skills
	Improve organizational performance: Financial performance like forecasting, planning capacity, cost saving opportunities, market value. (Anand *et al.*, 2013; Schrettenbrunnner, 2020; Wamba-Taguimdje *et al.*, 2020)	Do you believe Artificial Intelligence can improve organizational performance based on simulation tools? - Forecasting - Planning capacity - Cost saving opportunities
		Do you believe better analytical tools can improve the market value of organizations?
		Do you believe decision capabilities are positively associated with the influence of Artificial Intelligence?
		Do you believe this automation can improve the quality of management in decision making processes?
	Reduction of errors by employees. (Ganapathy, 2021; Wamba-Taguimdje *et al.*, 2020; N. Wang *et al.*, 2020)	Do you believe that Artificial Intelligence can help reducing the number of errors on daily tasks by employees?
	Real-time visibility. (Wamba-Taguimdje *et al.*, 2020)	Do you believe that transparency is one of the added values of Artificial Intelligence?
Challenges generated by Artificial Intelligence	Human understanding. (Shrestha *et al.*, 2019)	Do you believe human understanding is not a challenge to Artificial Intelligence?
	Manipulation of data and Risk perception. (Shrestha *et al.*, 2019)	How do you perceive the fact of some organizations not having an internal control on ethical issues related to data and algorithms to ensure trust? Ex: To avoid manipulation of data
		How do you perceive decision making process being made with the help of Artificial Intelligence systems that manipulate data?
	Some organizations have resources that are still insufficient and unoptimized for the implementation and success of Artificial Intelligence. (Wamba-Taguimdje *et al.*, 2020)	Do you consider that organizations have resources that are sufficient and optimized for the implementation and success of Artificial Intelligence?

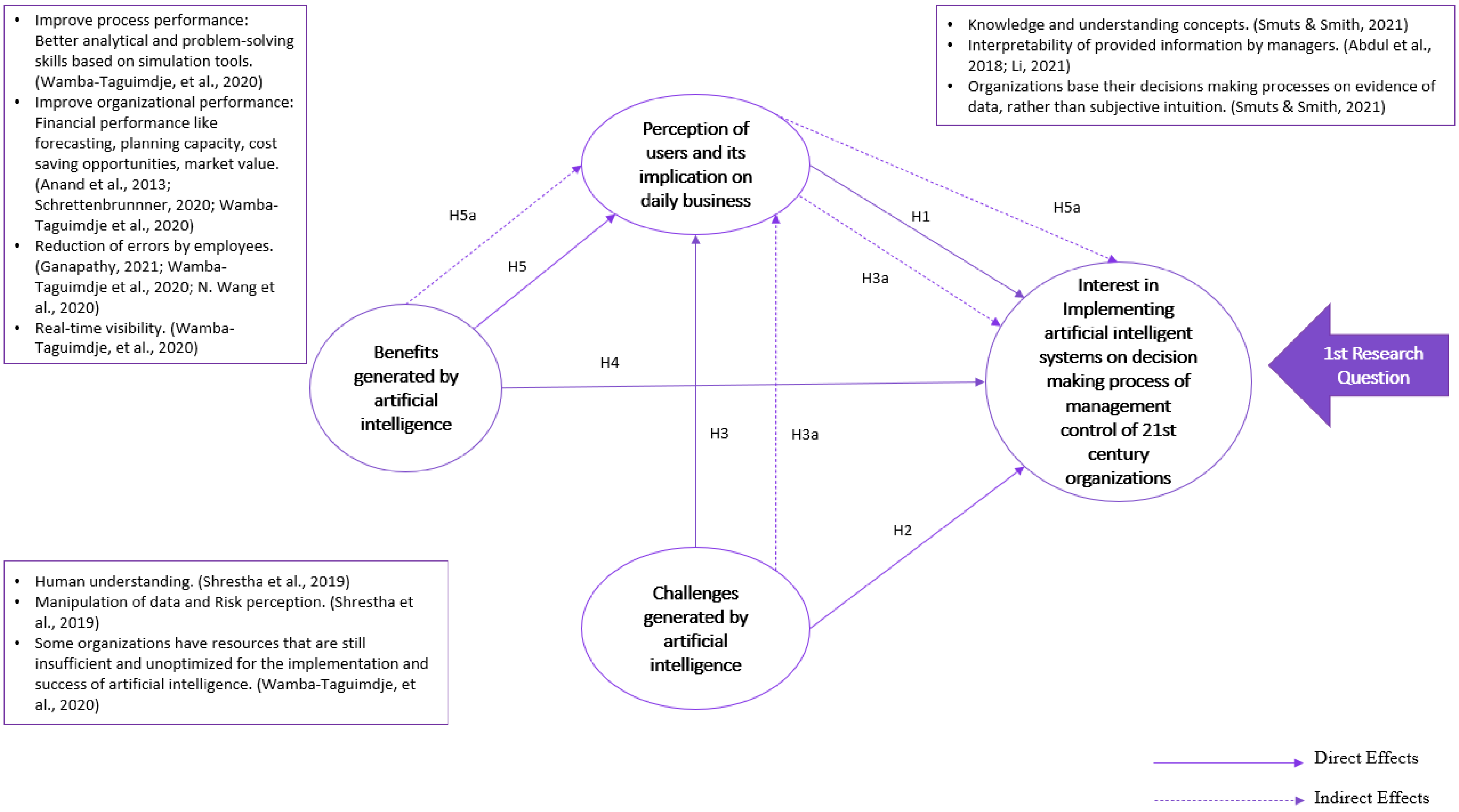
AUTHOR'S ELABORATION

Hypotheses for the 1st Research Question – How do Artificial Intelligence systems improve decision making processes of organizations?

- ***H1:*** *The perception of users and its implication on daily business positively influences the Interest in Implementing Artificial Intelligent systems on management control of 21st century organizations.*
- ***H2:*** *The challenges generated by Artificial Intelligence influences negatively the Interest in Implementing Artificial Intelligent systems on management control of 21st century organization.*
- ***H3:*** *The challenges generated by Artificial Intelligence influences negatively the perception of users and its implication on daily business.*
- ***H3a:*** *The perception of users and its implication on daily business mediates between the challenges generated by Artificial Intelligence and Interest in Implementing Artificial Intelligent systems on management control of 21st century organizations, negatively.*
- ***H4:*** *The benefits generated by Artificial Intelligence systems positively influence the possibility of interest in implementing Artificial Intelligent systems on management control of 21st century organizations.*
- ***H5:*** *The benefits generated by Artificial Intelligence systems positively influence perception of users and its implication on daily business.*
- ***H5a:*** *The perception of users and its implication on daily business mediates between the benefits generated by Artificial Intelligence systems and Interest in Implementing Artificial Intelligent systems on management control of 21st century organizations, positively*

Figure 4.1 shows the conceptual model of the first research question, with the hypothesis described above.

Figure 4.1 - Conceptual model of 1st RQ



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4.2.2 THE CONCEPTUAL MODEL 2ND RQ

The second research question is - How do Machine Learning systems improve decision making processes of organizations?

Table 4.2 shows the conceptual model and hypothesis for the second research question. As previously mentioned, we identified three independent variables, as well as the dependent variable on which this study was based. In front of each independent variable, an indicator was identified, which was the basis for the questions in the survey, as we can see on the below table.

Table 4.2 - Conceptual Model and hypothesis test 2nd RQ

RQ2 - How do Machine Learning systems improve decision making processes of organizations?		
Dependent variable	Interest in Implementing Machine Learning systems on decision making process of management control of 21st century organizations	
	Questionary (rate 1-7) Are you willing to implement Machine Learning systems on decision making process of your organization?	
Independent variable	**Indicator**	**Questionary (rate 1-7)**
Interest of human interaction on decision making process	Decision making processes should include much more people. (Frisk *et al.*, 2013)	Decision making processes should include much more people, as the interaction between more roles would not only increase the quality but also the acceptance of decisions. (Frisk *et al.*, 2013)
	Human interaction and decision-making process (Obukhov *et al.*, 2019).	Do you believe Machine Learning can influence decision making process?
		How do you perceive human interaction on decision making processes? - that human interaction is the base for decisions - partial recommendation from the system to facilitate some tasks. - human's interaction can only be necessary for verification and confirmation. - Human interaction can only check and stop the solution that was previously generated and executed automatically. - doesn't consider human interaction as the decision is completely formed automatically
Benefits generated by Machine Learning	Complete analysis of all the information and delivers valuable insights. (Kaplan & Haenlein, 2019)	Do you believe Machine Learning delivers valuable insights?
	Trends generated by ML techniques are often very accurate and conclusive. (Selim, 2020)	Do you believe that Machine Learning techniques lead to trends that are often very accurate and conclusive?
	Traditional methods of managing data are no longer efficient, as it reveals poor data quality. (Nelson, 2018)	Do you believe that Machine Learning can replace traditional methods of managing data?
		Do you believe traditional methods reveals poor data quality?
	Ability to acquire prosecutable insights will be more important for organizations' progress. (Nelson, 2018)	Do you believe that prosecutable insights are important for an organization's prosperity and progress?
		Do you believe Machine Learning can have the ability to acquire prosecutable insights?
	The process of decision making might monopolize much time if there's no use of computational methods. (Ahmed & Malik, 2020)	Do you believe decision making process might monopolize much time if there's no use of computational methods?
	ML techniques can automate decision making processes as it reduces the negative control of employees and accelerates the processes. (Obukhov *et al.*, 2019)	Do you believe Machine Learning can accelerate the process of decision making?
		Do you believe Machine Learning can reduce the negative control of employees?
	It forecasts future user's tasks and define scenarios that keep from happening inconsistent tasks by the machine. (Obukhov *et al.*, 2019)	How do you perceive the ability of Machine Learning to forecast users' tasks?
		Do you believe that Machine Learning can avoid inconsistent tasks by forecasting users' tasks?
Challenges generated by Machine Learning	Decision making processes are not clear to lead always into good or bad decisions. (Sharma *et al.*, 2014)	Do you believe decision making processes are clear to lead always into good or bad decisions, despite the valuable insights?
	Human understanding is still needed to valid and accept the algorithms generated. (Lycett, 2013)	Do you believe human understanding is not necessary to validate and accept generated algorithms?
	Bad input data and lack of information about data quality thus bad decisions are made. (de Hoog *et al.*, 2019)	Do you believe bad inputs can lead to accurate decisions?
		Do you believe lack of information about data quality can always lead to accurate decisions?
	Decisions should be based on the information required by the desired data and not similar information. (de Hoog *et al.*, 2019; Obukhov *et al.*, 2019)	Do you believe decisions based on similar information can be effective?

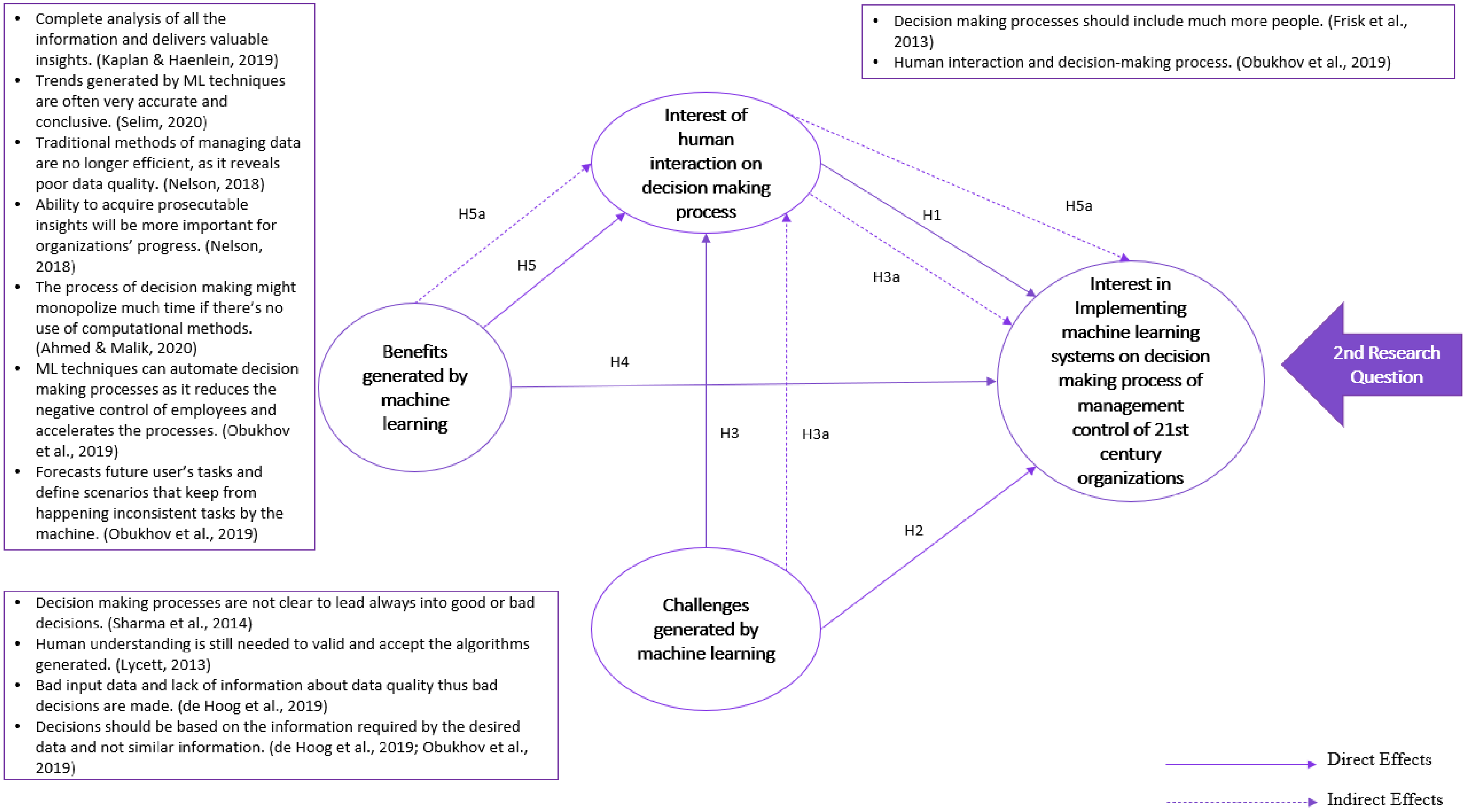
AUTHOR'S ELABORATION

Hypotheses for the 2nd Research Question – How do Machine Learning systems improve decision making processes of organizations?

- ***H1:*** *The Interest of human interaction on decision making process positively influences the Interest in Implementing Machine Learning systems on management control of 21st century organizations*
- ***H2:*** *The challenges generated by Machine Learning influences negatively the Interest in Implementing Machine Learning systems on management control of 21st century organizations*
- ***H3:*** *The challenges generated by Machine Learning negatively influences the interest of human interaction on decision making process*
- ***H3a:*** *The Interest of human interaction on decision making process mediates between the challenges generated by Machine Learning systems and Interest in Implementing Machine Learning systems on management control of 21st century organizations, negatively.*
- ***H4:*** *The benefits generated by Machine Learning positively influence the interest in implementing Machine Learning systems on management control of 21st century organizations*
- ***H5:*** *The benefits generated by Machine Learning systems positively influences the interest of human interaction on decision making process.*
- ***H5a:*** *The Interest of human interaction on decision making mediates between the benefits generated by Machine Learning systems and Interest in Implementing Machine Learning systems on management control of 21st century organizations, positively.*

Figure 4.2 shows the conceptual model of the second research question, with the hypothesis described above.

Figure 4.2 - Conceptual model 2ND RQ

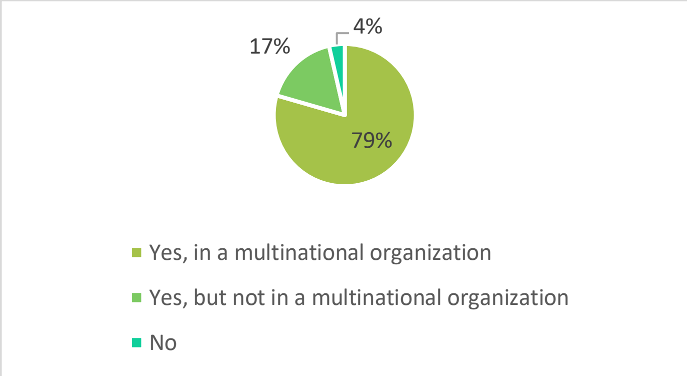


AUTHOR'S ELABORATION

4.3 SAMPLE DESCRIPTION

The survey was answered by 112 individuals. However, for analytical purposes only 100 responses were used, randomly chosen. The survey is anonymous, so all information shared is confidential. The first question which was purposely made to avoid biasing the responses, and to ensure that individuals who were not part of the target public could not advance in the survey. Hence, regarding the organizations, 89 (79%) of the respondents were controllers in multinational organizations, while 19 (17%) were controllers but not in a multinational organization. The remaining respondents, 4 (4%) were not controllers, as we can see on figure 4.3. If the answer to this question (Annex A.) was "No", the survey did not advance. Thus, there were 112 initial responses to the first question and only 108 to the remaining ones, given that 4 people who answered the first question were not eligible. As previously mentioned, only 100 responses were considered, out of 108 valid ones.

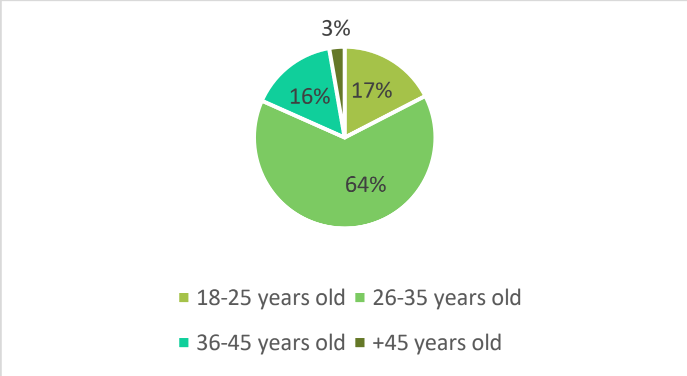
Figure 4.3 - Organization's distribution of controllers



AUTHOR'S ELABORATION

The ages of individuals varied between 18 and +45 years old, of which, 17 (17%) were "18-25 years old"; 64 (64%) were "26-35 years old"; 16 (16%) were "36-45 years old"; and 3 (3%) were "+45 years old", as presented in figure 4.4 below.

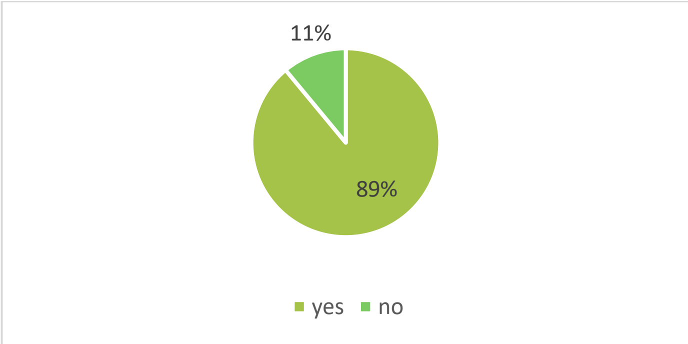
Figure 4.4 - Age distribution of respondents



AUTHOR'S ELABORATION

Regarding the familiarity with Artificial Intelligence, 89 (89%) are familiar with Artificial Intelligence, while 11 (11%) are not familiar with the subject, as shown on the figure 4.5 below.

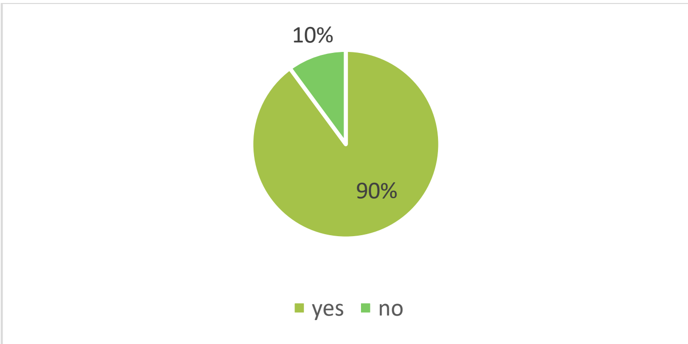
Figure 4.5 - Distribution of familiarity with Artificial Intelligence



AUTHOR'S ELABORATION

Regarding the concept and applicability, 90 (90%) know the concept and applicability of Artificial Intelligence, while 10 (10%) don't, as represented in figure 4.6.

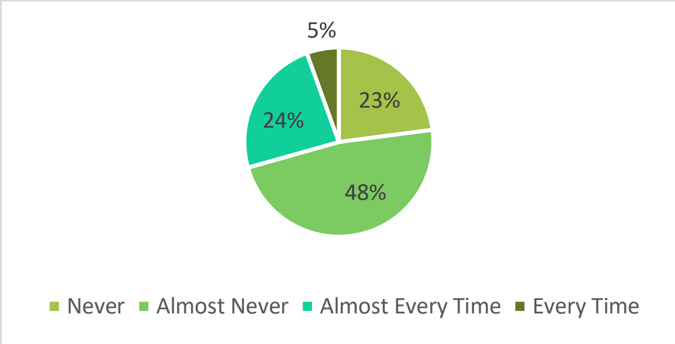
Figure 4.6 - Distribution of knowledge of concepts and applicability of Artificial Intelligence



AUTHOR'S ELABORATION

Concerning the usage of Artificial Intelligence assistances on their smart phones (Apple Siri, google assistant, smart replies, Microsoft pix, Elsa), in respondents' everyday life 23 (23%), never uses; 48 (48%) almost never uses; 24 (24%) uses almost every time and 5 (5%) uses it every time, as shown in figure 4.7 below.

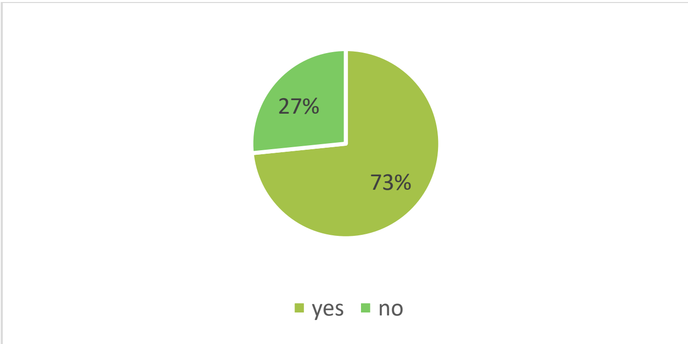
Figure 4.7 - Distribution of usage of Artificial Intelligence assistances



AUTHOR'S ELABORATION

Regarding the familiarity with Machine Learning, 73 (73%) are familiar with Machine Learning, while 27 (27%) are not familiar with the subject, as shown in figure 4.8 below.

Figure 4.8 - Distribution of familiarity with Machine Learning



AUTHOR'S ELABORATION

CHAPTER 5 - RESULTS

5.1 RQ1 – HOW DO ARTIFICIAL INTELLIGENCE SYSTEMS IMPROVE DECISION MAKING PROCESSES OF ORGANIZATIONS?

5.1.1 STATISTICAL ANALYSIS

The online survey - *Interest in Implementing Intelligent systems in Decision Making Process of Management Control of 21st century Organizations* was conducted using a Likert Scale. This Scale was used to categorize and store responses within a limited range of items in a scale of 1 to 7 requiring agreement or disagreement. (1. Strongly Disagree; 2. Disagree; 3. Somewhat Disagree; 4. Neither Agree nor Disagree; 5. Somewhat Agree; 6. Agree; 7. Strongly Agree) (Nemoto & Beglar, 2014). Our target public were controllers from different ages and organizations. The age of respondents varied between 18-25 years old; 26-35 years old; 36-45 years old and +45 years old. After collecting the results, the Partial Least Squares based Structural Equation Modeling (PLS-SEM) was tested relating relationships between dependent and independent variables. PLS-SEM is a "flexible" technique capable of estimating complex models, with many constructs and paths (Sarstedt *et al*., 2019).

The modeling of structural equations with partial least squares estimation (PLS-SEM), evaluates how adequate are the questions used on the hypothetical-defined construct (Ab Hamid *et al*., 2017).

The software used to obtain results of this analysis was SmartPLS 3.

According to Sarstedt *et al*. (2017), we should start by having a quality criteria test of reliability and validity and then evaluate the structural model. Hence, we had to eliminate one indicator since it didn't exhibit discriminant validity, as some authors suggest a threshold of 0.85 (Kline RB, 2011). According to the same authors, values nearest to 1 reveals lack of discriminant validity. That indicator was related with "Benefits generated by Artificial Intelligence". After eliminating that indicator, the discriminant validity was assured.

The results showed that the standardized factor of most items was above 0.6, and were significant when $p<0.001$, which showed the reliability of the individual indicator (Sarstedt *et al*., 2017).

After, we evaluate the individual indicators to assess the quality of the measurement model, which are composite reliability (CR) (Brunner & Süß, 2016) and Cronbach's alfa (α), we conclude that constructs' values were above 0.7, showing internal reliability was confirmed (Sarstedt *et al*., 2017), as represented in table 5.1. Convergent validity was confirmed by fulfilling three criteria, since the Average Variance Extracted (AVE) for each construct was above 0.5 (Bagozzi & Yi, 1988). Therefore, convergent and discriminant validity and reliability are adequate, except for one construct (Benefits generated by AI), in which the value is less than 0.5 (0.420). Nevertheless, the authors (Fornell &

Larcker, 2018) confirm the convergent validity since the composite reliability (CR) is significant to lighten the lower value (0.876).

To access the discriminant validity test, the authors suggest an evaluation by two approaches.

Firstly, the criterion of (Fornell & Larcker, 2018), requires the square roots of AVE must be greater than its highest correlation with any construct ($\sqrt{AVE} > r\text{LV}$), as seen in the table 5.1.

Secondly, the criterion of the HTMT ratio (heterotrait-monotrait ratio) (Henseler *et al*., 2015; Sarstedt *et al*., 2017), according to which the authors state that these values must be less than 0.85 for the model to offer more evidence of discriminant validity, which can be seen in table 5.1

In table 5.1 it is observed that, for all latent variable (LV), AVE > 0.5 and $\sqrt{AVE} > rVL$, as well as CR > 0.7, therefore, convergent and discriminant validity and reliability are adequate.

Regarding the structural model, and according to Sarstedt *et al*. (2017), it must be measured through the sign, magnitude, and significance of the structural path coefficients; through the magnitude of the R2 value for each endogenous variable as a measure of the model's predictive accuracy; and through the Stone-Geisser's Q2 values as a measure of the model's predictive relevance. The values for R2 should be, according to the literature (Falk & Miller, 1992), bigger than the minimal value of 10%. The Interest in Implementing Artificial Intelligent systems on decision making process of management control of 21st century organizations (latent 1) were 68% and for Perception of users and its implication on daily business (latent 2) were 51%. For Q2, Interest in Implementing Artificial Intelligent systems on decision making process of management control of 21st century organizations (latent 1) were 0.701 and Perception of users and its implication on daily business (latent 2) were 0.297. Both, above zero, which indicates predictive relevance of the model (Sarstedt *et al*., 2017).

According to Hair *et al*. (2017), variance inflation factor (VIF) should be all bellow 5, as it shows the collinearity Statistics. All outer VIF's are below the critical value of 5.

Table 5.1 - Cronbach Alpha, Composite Reliability, Average Variance Extracted, Correlations, and Discriminant Validity

Latent Variable	α	CR	AVE	1	2	3	4
(1) Interest in Implementing AI systems	1,000	1,000	1,000	**1,000**	0,755	0,563	0,842
(2) Perception of users and its implication on daily business	0,776	0,849	0,532	0,667	**0,730**	0,588	0,821
(3) Challenges generated by AI	0,837	0,891	0,671	-0,518	-0,498	**0,819**	0,440
(4) Benefits generated by AI	0,841	0,876	0,420	0,773	0,658	-0,371	**0,648**

Note: α-Cronbach Alpha; CR-Composite Reliability; AVE-Average Variance Extracted; ***Bold****-Square roots of AVE; Below diagonal elements-correlations between the constructs; Above diagonal elements-HTMT ratios*

AUTHOR'S ELABORATION

5.1.2 QUANTITATIVE RESULTS

The bootstrapping algorithm is used to determine the path coefficients and Path coefficients Histogram. It is necessary to assess whether the histograms of the bootstrapping are unimodal, because if they are not, it is necessary to go back to the beginning and evaluate the presence of atypical data (outliers) or indicators with little variability (Bido & da Silva, 2019).

According to the same authors, to assess whether there is mediation, and whether it is total or partial, the direct effects are evaluated. The direct effect is significant if ($p < 0.05$), also the indirect effect is significant if ($p < 0.05$). The mediation is total if the direct effect has no significance ($p > 0.05$), and the indirect effect has significance ($p < 0.05$). The mediation is partial if the direct effect has ($p < 0.05$), and indirect effect has ($p < 0.05$). And there is no mediation if the direct effect ($p < 0.05$) and the indirect effect ($p > 0.05$).

The results in table 5.2, show that the Perception of users and its implication on daily business has a positive impact on Interest in Implementing AI (β=0.185; p=0.018), confirming hypothesis H1. The benefits generated by AI also have a positive impact on the Interest in Implementing AI (β=0.572; p=0.000), confirming hypothesis H4. A similar effect also happens with, Benefits generated by AI with the Perception of users and its implication on daily business (β=0.549; p=0.000), validating hypothesis H5. Finally, we can see that the challenges generated by AI have the opposite effect and negatively affect with Interest in Implementing AI (β=-0.214; p=0.003), thus supporting hypothesis H2 and with the Perception of users and its implication on daily business (β=-0.294; p=0.000), supporting hypothesis H3.

Table 5.2 - Direct relationships between constructs

Path	Original Sample (O)	Standard Deviation (STDEV)	t statistics	p values
Perception of users and its implication on daily business -> Interest in Implementing AI	0.185	0.078	2.369	0.018
Challenges generated by AI -> Interest in Implementing AI	-0.214	0.071	3.008	0.003
Challenges generated by AI - > Perception of users and its implication on daily business	-0.294	0.080	3.656	0.000
Benefits generated by AI -> Interest in Implementing AI	0.572	0.073	7.779	0.000
Benefits generated by AI -> Perception of users and its implication on daily business	0.549	0.076	7.258	0.000

AUTHOR'S ELABORATION

In order to test the specific indirect effects between constructs, we used a bootstrapping procedure on SmartPLS 3. This enabled us to conclude two indirect effects, supporting, thus our indirect hypothesis.

Table 5.3 shows the indirect relationships between constructs, in which we can see that the indirect effect of the Challenges generated by AI on the Interest in Implementing AI through the Perception of users and its implication on daily business is significant (β=-0.054, $p<0.037$), thus supporting hypothesis H3a of a negative correlation. With a positive correlation, our second hypothesis H5a of indirect effect is further supported with Benefits generated by AI on Interest in Implementing AI through Perception of users and its implication on daily business (β=0.102, $p<0.034$).

Table 5.3 - Indirect relationships between constructs

Path	Original Sample (O)	Standard Deviation (STDEV)	t statistics	p values
Challenges generated by AI ->Perception of users and its implication on daily business -> Interest in Implementing AI	-0.054	0.026	2.084	0.037
Benefits generated by AI -> Perception of users and its implication on daily business -> Interest in Implementing AI	0.102	0.048	2.120	0.034

AUTHOR'S ELABORATION

5.1.3 RESULT DISCUSSION

The conceptual model was tested using Smart PLS 3 to answer to the first RQ of the present study

How do Artificial Intelligence systems improve decision making processes of organizations?

Based on the literature review, three main factors were identified in the construction of the conceptual model, which are identified below. Firstly, the perception of users and its implication on daily business; secondly challenges generated by Artificial Intelligence and the benefits generated by Artificial Intelligence. The three variables then constituted the independent variables of the tested model. The dependent variable was added - Interest in Implementing Artificial Intelligence systems on decision making process of management control of 21st century organizations. All those variables were latents used to test our model, using Partial Least Squares Algorithm with 500 iterations and with a path weighting scheme. With PLS Algorithm we were able to test our quality criteria, as shown on the previous section. We also used the Bootstrapping to test the statistical significance of various PLS-SEM, with 1000 subsamples and a significance level of 0.05. Besides the previous tests, we also used Blindfolding to calculate Stone-Geisser's Q^2 (Ringle *et al.*, 2015).

Regarding the perception of users and its implication on daily business two indicators were used Knowledge and understanding concepts (Smuts & Smith, 2021) and Interpretability of provided information by managers (Abdul *et al*., 2018; Li, 2021). Several questions were made on the online survey to test the mention indicator. The results of the online survey were also in accordance with the literature review.

Concerning the second independent variable, we used three indicators to test our hypothesis, Human understanding (Shrestha *et al*., 2019); Manipulation of data and Risk perception (Shrestha *et al*., 2019) and Some organizations have resources that are still insufficient and unoptimized for the implementation and success of Artificial Intelligence (Wamba-Taguimdje *et al*., 2020). The results were in line with the work of the authors studied.

Regarding the third independent variable we used improve process performance: Better analytical and problem-solving skills based on simulation tools (Wamba-Taguimdje *et al*., 2020); Improve organizational performance: Financial performance like forecasting, planning capacity, cost saving opportunities, market value (Anand *et al*., 2013; Schrettenbrunnner, 2020; Wamba-Taguimdje *et al*., 2020); Reduction of errors by employees (Ganapathy, 2021; Wamba-Taguimdje *et al*., 2020; N. Wang *et al*., 2020) and Real-time visibility (Wamba-Taguimdje *et al*., 2020). Some indicators had more than one question.

At the end of the online survey, we asked if respondents were willing to implement Artificial Intelligent systems on their organizations. This question was purposely made at the end of the survey so, they could have in consideration all the previous answers, also it helped us to more effectively, understand the willingness to develop this intelligent system. The intentionally to develop the previous mention system constituted our final and dependent variable.

After identifying the three variables to improve decision making processes of organizations through Artificial Intelligence systems, we proceeded to test the hypotheses formulated in the methodology chapter. The conceptual model is composed by direct and indirect effects, all sustained by the results.

The first direct effect H1, the perception of users and its implication on daily business positively influences the Interest in Implementing Artificial Intelligent systems on management control of 21st century organizations, is confirmed by hypothesis H1 of the study. Thus, we can conclude that factors like the willing of respondents to train machines, the believe that quality of future jobs will be guaranteed are factors that determine the intention of users to implement Artificial Intelligence systems on their organizations (Abdul *et al*., 2018; Li, 2021; Smuts & Smith, 2021). The question "Rate the impact you believe Artificial Intelligence may have in your work" had 0.523 correlation with the dependent variable, being the indicator with the higher correlation within this hypothesis.

The second direct effect H2, challenges generated by Artificial Intelligence with the Interest in Implementing Artificial Intelligent systems on decision making process of management control of 21st century organizations, is confirmed with a negative correlation. That is, the greater the limitations identified by the organizations, the lower the possibility of implementing AI to decision making processes. Despite all the added value that AI can bring to organizations, there are still some limitations associated with it, like human understanding, risk of data manipulation and insufficient resources for the implementation of AI (Shrestha *et al*., 2019; Wamba-Taguimdje *et al*., 2020).

The challenges generated by Artificial Intelligence also correlated negatively with the perception of users and its implication on daily business, which validates our third hypothesis, H3. The greater the challenges', the lower the Interest in Implementing AI and the Perception of users and its implication on daily business, which support our hypothesis H3a for indirect effect. Perception of users and its implication on daily business mediates challenges generated by Artificial Intelligence with Interest in Implementing Artificial Intelligent systems on decision making process of management control of 21st century organizations, also with a negative correlation.

Regarding the fourth direct effect H4, the results show that there is a positive influence of Benefits generated by Artificial Intelligence on the Interest in Implementing Artificial Intelligent systems on decision making process of management control of 21st century organizations. Factors like evidence of data; improvement of process and organizational performances; reduction the number of errors by employees and real time visibility of data (Anand *et al*., 2013; Schrettenbrunnner, 2020; Smuts & Smith, 2021; Wamba-Taguimdje *et al*., 2020; N. Wang *et al*., 2020), contribute to this positive effect.

Our fifth hypothesis H5, benefits generated by Artificial Intelligence positively influences the perception of users and its implication on daily business was also supported by our results and therefore validates our hypothesis, which means that the greater the benefits, the more respondents feel influenced to use AI systems on daily business. The indirect hypothesis H5a was also tested and thus validated, which shows that Benefits generated by Artificial Intelligence are indirectly correlated with Interest in Implementing Artificial Intelligent systems on decision making process of management control of 21st century organizations, through Perception of users and its implication on daily business, meaning that the more benefits AI has to offer to organizations, the more perception users will have and consequently the more interested organizations are to implement AI systems. The greater the benefits, the higher the Interest in Implementing AI and the Perception of users and its implication on daily business.

The model studied shows that, taking into consideration the main benefits, characteristics of AI and its limitations, respondents still choose to implement intelligent systems in decision making processes. Also, the limitations and benefits influence the perception of users, as a result, the more benefits AI has, the better the perception of users and its implication on daily business is. The opposite also occurs, the more challenges AI has, the lowest the perception of users and its implication on daily business is. The intention to establish a correlation between the variable's studied was to validate our hypothesis, which was proven.

5.2 RQ2 - HOW DO MACHINE LEARNING SYSTEMS IMPROVE DECISION MAKING PROCESSES OF ORGANIZATIONS?

5.2.1 STATISTICAL ANALYSIS

The online survey conducted was the same as the first research question, as well as the scale used to categorize responses. After collecting the results, the Partial Least Squares based Structural Equation Modeling (PLS-SEM) was tested relating relationships between dependent and independent variables, as previously mentioned. The software used to estimate all analysis was Smart PLS 3.

Firstly, and according to Sarstedt *et al*. (2017), we started by having a quality criteria test of reliability and validity and then evaluate the structural model. Therefore, we had to eliminate some indicators to exhibit an adequate level of reliability above 0.6 of all indicators.

Those indicators were related with "Interest of human interaction on decision making process" and "Challenges generated by Machine Learning". After eliminating those indicators, the reliability was assured. The results showed that the standardized factor of most items was above 0.6, and were significant when $p<0.001$, which showed the reliability of the individual indicator.

Secondly, we checked the individual indicators to assess the quality of the measurement model, which are composite reliability (CR) (Brunner & Süß, 2016) and Cronbach's alfa (α). Constructs' values were above 0.7, showing internal reliability was confirmed (Sarstedt *et al*., 2017). Convergent validity was confirmed by fulfilling three criteria, since the Average Variance Extracted (AVE) for each construct was above 0.5 (Bagozzi & Yi, 1988), except for latent variable 4 (Benefits generated by ML*)* in which the value is very close to what the literature considers fulfilling the validation criterion (0.475). Therefore, convergent and discriminant validity and reliability are adequate as the authors (Fornell & Larcker, 2018) confirm the convergent validity since the composite reliability (CR) is significant to mitigate the lower value (0.908).

To access the discriminant validity test, the authors suggest an evaluation by two approaches.

Firstly, the criterion of (Fornell & Larcker, 2018), requires the square roots of AVE must be greater than its highest correlation with any construct ($\sqrt{AVE} > r\mathrm{LV}$).

After, the criterion of the HTMT ratio (heterotrait-monotrait ratio) (Henseler *et al*., 2015; Sarstedt *et al*., 2017), according to which the authors state that these values must be less than 0.85 for the model to offer more evidence of discriminant validity, as we can see in table 5.4. At the same table, we can observe that, for all latent variable (LV), AVE > 0.5 and $\sqrt{AVE} > rVL$, as well as CR>0.7, therefore, convergent and discriminant validity and reliability are adequate. Also, the correlations between all LVs are quite high.

Regarding the structural model, and according to Sarstedt *et al*. (2017), it must be measured through the sign, magnitude, and significance of the structural path coefficients; through the magnitude of the R2 value for each endogenous variable as a measure of the model's predictive accuracy; and through the Stone-Geisser's Q2 values as a measure of the model's predictive relevance. For the R2, Interest in Implementing Machine Learning systems shows 72.6%, while Interest of human interaction on decision making process shows 54.7%, according to the literature (Falk & Miller, 1992), bigger than the minimal value of 10%. Regarding Q2, the values were 1 and 0.277 for Interest in Implementing ML systems; Interest of human interaction on decision making process, respectively. Both, above zero, which indicates predictive relevance of the model (Sarstedt et al., 2017).

According to the same authors, variance inflation factor (VIF) should be all bellow 5, as it shows the Collinearity Statistics, which has been proven in this model.

Table 5.4 - Cronbach Alpha, Composite Reliability, Average Variance Extracted, Correlations, and Discriminant Validity

Latent Variable	α	CR	AVE	1	2	3	4
(1) Interest in Implementing ML systems	1.000	1.000	1.000	**1.000**	0.838	0.828	0.811
(2) Interest of human interaction on decision making process	0.741	0.837	0.563	0.723	**0.750**	0.838	0.832
(3) Challenges generated by ML	0.792	0.857	0.546	-0.745	-0.657	**0.739**	0.748
(4) Benefits generated by ML	0.889	0.908	0.475	0.771	0.680	-0.638	**0.689**

*Note: α-Cronbach Alpha; CR-Composite Reliability; AVE-Average Variance Extracted; **Bold**-Square roots of AVE; Below diagonal elements-correlations between the constructs; Above diagonal elements-HTMT ratios*

AUTHOR'S ELABORATION

5.2.2 QUANTITATIVE RESULTS

The bootstrapping algorithm is used to determine the path coefficients and Path coefficients Histogram. It is necessary to assess whether the histograms of the bootstrapping are unimodal, because if they are not, it is necessary to go back to the beginning and evaluate the presence of atypical data (outliers) or indicators with little variability (Bido & da Silva, 2019).

According to the same authors, to assess whether there is mediation, and whether it is total or partial, the direct effects are evaluated. The results in table 5.5, show that the Interest of human interaction on decision making process has a positive impact on Interest in Implementing ML systems (β=0.228; p=0.004), confirming hypothesis H1. The Benefits generated by ML also have a positive impact on the Interest in Implementing ML systems (β=0.399; p=0.000), confirming hypothesis H4. A similar effect also happens with, Benefits generated by ML with the Interest of human interaction on decision making process (β=0.440; p=0.000), validating hypothesis H5. Finally, we can see that the Challenges generated by ML have the opposite effect with Interest in Implementing ML systems (β=-0.340; p=0.001), thus supporting hypothesis H2 and with the Interest of human interaction on decision making process (β=-0.377; p=0.000), supporting hypothesis H3. The greater the limitations, the lower the Interest in Implementing ML systems and the Interest of human interaction on decision making process.

Table 5.5 - Direct relationships between constructs

Path	Original Sample (O)	Standard Deviation (STDEV)	t statistics	p values
Interest of human interaction on decision making process -> Interest in Implementing ML systems	0.228	0.078	2.911	0.004
Challenges generated by ML -> Interest in Implementing ML systems	-0.340	0.099	3.446	0.001
Challenges generated by ML -> Interest of human interaction on decision making process	-0.377	0.087	4.338	0.000
Benefits generated by ML -> Interest in Implementing ML systems	0.399	0.064	6.259	0.000
Benefits generated by ML -> Interest of human interaction on decision making process	0.440	0.092	4.762	0.000

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In order test the specific indirect effects between constructs, we used a bootstrapping procedure on SmartPLS 3. This enabled us to support our indirect hypothesis.

Table 5.6 below, shows the indirect relationships between constructs, in which we can see that the indirect effect of the Challenges generated by ML on the Interest in Implementing ML systems through the Interest of human interaction on decision making process is significant (β=-0.086; p<0.005), thus supporting hypothesis H3a with a negative correlation. With a positive correlation, our second hypothesis H5a, where the indirect effect is further supported with Benefits generated by ML on Interest in Implementing ML systems through Interest of human interaction on decision making process (β=0.100; p<0.028).

Table 5.6 - Indirect relationships between constructs

Path	Original Sample (O)	Standard Deviation (STDEV)	t statistics	p values
Challenges generated by ML -> Interest of human interaction on decision making process -> Interest in Implementing ML systems	-0.086	0.030	2.839	0.005
Benefits generated by ML -> Interest of human interaction on decision making process -> Interest in Implementing ML systems	0.100	0.045	2.205	0.028

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5.2.3 RESULT DISCUSSION

The conceptual model was tested using Smart PLS 3 to answer to the second RQ of the present study

How do Machine Learning systems improve decision making processes of organizations?

Based on the literature review, three main factors were identified in the construction of the conceptual model, which are identified below. Firstly, the Interest of human interaction on decision making process; secondly Challenges generated by Machine Learning and the Benefits generated by Machine Learning. The three variables then constituted the independent variables of the tested model. The dependent variable was added - Interest in Implementing Machine Learning systems on decision making process of management control of 21st century organizations. All those variables were latents used to test our model, using Partial Least Squares Algorithm with 500 iterations and with a path weighting scheme. With PLS Algorithm we were able to test our quality criteria, as shown on the previous section. We also used the Bootstrapping to test the statistical significance of various PLS-SEM, with 1000 subsamples and a significance level of 0.05. Besides the previous tests, we also used Blindfolding to calculte Stone-Geisser's Q^2 (Ringle *et al*., 2015).

Regarding the first independent variable, Interest of human interaction on decision making process two indicators were used- Decision making processes should include much more people, as the interaction between more roles would not only increase the quality but also the acceptance of decisions (Frisk *et al* (2013); Human interaction and decision-making process (Obukhov *et al*., 2019). Several questions were made on the online survey to test the mention indicator. As stated before, we had to eliminate some indicators to exhibit an adequate level of reliability above 0.6 of all indicators. Those indicators were related with "Interest of human interaction on decision making process" and "Challenges generated by Machine Learning".

Concerning the second independent variable, challenges generated by machine learning, we used three indicators to test our hypothesis, Decision making processes are not clear to lead always into good or bad decisions, despite the valuable insights (Sharma *et al*., 2014); Human understanding is still needed to valid and accept the algorithms generated (Lycett, 2013); Bad input data and lack of information about data quality thus bad decisions are made (de Hoog *et al*., 2019), Decisions should be based on the information required by the desired data and not similar information (Obukhov *et al*., 2019). As also applies to the previous indicator, we had to eliminate some indicators to exhibit an adequate level of reliability above 0.6 of all indicators. The results were in line with the ideas of the authors studied.

Regarding the third independent variable, benefits generated by Machine Learning, we used - Machine Learning allows a complete analysis of all the information and delivers valuable insights to work on it (Kaplan & Haenlein, 2019); Machine Learning techniques have been proven extremely useful as they can optimize and prevent trends. Those trends are often very accurate and conclusive (Selim, 2020); Traditional methods of managing data are no longer efficient, as it reveals poor data quality (Nelson, 2018); Ability to acquire prosecutable insights will be more and more important for organizations prosperity and progress (Nelson, 2018); The process of decision making might monopolize much time if there’s no use of computational methods (Ahmed & Malik, 2020); Machine Learning techniques can effectively automate decision making processes as it, not only, reduces the negative control of employees, but also accelerate the processes (Obukhov *et al*., 2019); ML forecasts future user’s tasks and define scenarios that keep from happening inconsistent tasks by the machine (Obukhov *et al*., 2019). Some indicators had more than one question.

At the end of the online survey, we asked if respondents were willing to implement Machine Learning systems on their organizations. This question was purposely made at the end of the survey so, they could have in consideration all the previous answers, also it helped us to more effectively, understand the willingness to develop this intelligent system. The intentionally to develop the previous mention system constituted our final and dependent variable.

After identifying the three variables to improve decision making processes of organizations through Machine Learning systems, we proceeded to test the hypotheses formulated in the methodology chapter. The conceptual model is composed by direct and indirect effects, all sustained by the results.

The first direct effect H1, Interest of human interaction on decision making process positively influences the Interest in Implementing Machine Learning systems on decision making process of management control of 21st century organizations, is confirmed by hypothesis H1 of the study. A partial recommendation from the system to facilitate some tasks had 0.588 correlation with the dependent variable, being the indicator with the higher correlation within this hypothesis.

The second direct effect H2, Challenges generated by Machine Learning with the Interest in Implementing Machine Learning systems on decision making process of management control of 21st century organizations, is confirmed with a negative correlation. That is, the greater the challenges identified by the organizations, the lower the possibility of implementing ML to decision making processes. Despite all the added value that ML can bring to organizations, there are still some limitations associated with it, like Decision making processes are not clear to lead always into good or bad decisions, despite the valuable insights (Sharma *et al*., 2014); Human understanding is still needed to valid and accept the algorithms generated (Lycett, 2013); Bad input data and lack of information about data quality thus bad decisions are made (de Hoog *et al*., 2019); Decisions should be based on the information required by the desired data and not similar information (Obukhov *et al*., 2019).

The challenges generated by Machine Learning also correlated negatively with the Interest of human interaction on decision making process, which validates our third hypothesis, H3. The greater the challenges', the lower the Interest of human interaction on decision making process and the Interest in Implementing ML, which support our hypothesis H3a for indirect effect. Interest of human interaction on decision making process mediates Challenges generated by Machine Learning with Interest in Implementing Machine Learning systems on decision making process of management control of 21st century organizations, also with a negative correlation.

Regarding the fourth direct effect H4, the results show that there is a positive influence of Benefits generated by Machine Learning on the Interest in Implementing Machine Learning systems on decision making process of management control of 21st century organizations. Factors like ML delivering valuable insights to work on it (Kaplan & Haenlein, 2019); optimize and prevent trends (Selim, 2020); replacing traditional methods of managing data (Nelson, 2018); being responsible for organizations' prosperity and progress (Nelson, 2018); the fact that without computational methods, the process monopolizes much more time (Ahmed & Malik, 2020); the fact that ML techniques effectively automate decision making processes as it, not only, reduces the negative control of employees, but also accelerate the processes (Obukhov *et al*., 2019); and also by forecasting user's tasks and define scenarios that keep from happening inconsistent tasks by the machine (Obukhov *et al*., 2019).

Our fifth hypothesis H5, Benefits generated by Machine Learning positively influences the Interest of human interaction on decision making process was also supported by our results and therefore validates our hypothesis, which means that the greater the benefits, the more respondents feel interest in having interactions with ML systems, hence the greater the benefits, the more significant are man machine interactions are. The indirect hypothesis H5a was also tested and thus validated, which shows that Benefits generated by Machine Learning are indirectly correlated with Interest in Implementing Machine Learning systems on decision making process of management control of 21st century organizations, through Interest of human interaction on decision making process, meaning that the more benefits ML has to offer to organizations, the more organizations will be interested in man-machine interactions, therefore the more interested organizations are to implement ML systems.

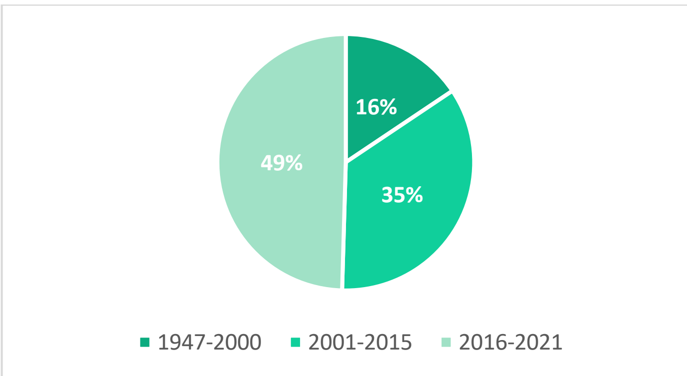
The greater the benefits, the higher the Interest of human interaction on decision making process and thus increases the Interest in Implementing ML systems on decision making processes.

Our literature suggests that on the one hand the benefits from Machine Learning systems are essential in the interest of man machine interaction, and hence the increase of interest in implementing ML systems on decision making processes. On the other hand, challenges from Machine Learning systems act as a brake on their further development as it precludes the interest of man-machine interaction, and hence the interest in implementing ML systems on decision making processes. The intention to establish a correlation between the variable's studied was to validate our hypothesis, which was proven.

5.3 NUMBER OF ARTICLES PUBLISHED BY YEAR

During our research, we always looked for the most recent articles that were closer to representing the reality of organizations in the present century. Figure 5.1 presents the distribution of articles cited in this study by year. As shown on the figure below, most of the articles were published in the last six years (2016-2021), representing 49%, followed by the period between 2001-2015 with 35% of the articles cited in this study. Finally, 16% of the articles published between 1947-2000. This analysis provides a better understanding from the study itself, that intelligent systems have been increasingly a trend topic, namely in the past few years (D. Zhang *et al*., 2021). The publication of articles cited in this study, increased 42% when comparing the years between 2001-2015 and the last six years. The difference is even more significant if we compare it to the years between 1947-2000, in which 53 years elapsed and it increased 218%. Figure 5.1 shows the number of articles cited in this study published by year.

Figure 5.1 - Number of Articles Published by Year



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CHAPTER 6 - CONCLUSIONS

6.1 FINAL CONSIDERATIONS

The objective of this study was to analyze the role of intelligent systems on decision making processes, namely Artificial Intelligence, and Machine Learning. The study was conducted using two research questions "*How do Artificial Intelligence systems improve decision making processes of organizations?*" and "*How do Machine Learning systems improve decision making processes of organizations?*". The hypothesis regarding research questions, were made on basis of literature review. Moreover, we can conclude that the greatest advances in developing intelligent systems have been achieved over the last recent years as suggested by the Stanford University's Artificial Intelligence Index Report of 2021 (D. Zhang *et al*., 2021).

As suggested by (D. Zhang *et al*., 2021), we were able to conclude that for the objective of this study organizations are increasingly investing in computational resources at a faster rate than before. At the same time indicating further development for intelligent systems technologies. This new era of intelligent system technologies has been developing the way organizations manage data, analyzing and creating rigorous and proper strategies through a notable analysis with the information obtained.

One hundred answers were considered to this study on the online survey, in which most respondents work in multinational organizations. 89% of respondents are familiar with Artificial Intelligence, proving that 90% knows its concept and application. Nevertheless, when asked about the usage of AI assistances on their smart phones, the majority state that never uses (23%) or almost never uses (48%). The evidence of usage limits can be seen when respondents recognize the importance of intelligent systems and are willing to implement in their organizations but don't use it on everyday life. Regarding familiarity with Machine Learning systems, a smaller percentage recognized it a familiar 73%. However, it is still most of the answers. Based on the online survey we can also conclude that there is a consensus regarding the need for growth and development of these systems, as more people are willing to use it on daily business. Therefore, we can conclude that intelligent systems are on the right path toward the more digitalized world and the new working concept that we are currently living.

Some remarkable literature refers that nowadays, organizations that cannot accelerate and predict future with new products and processes, like Artificial Intelligence systems will have a very hard path to survive (Schrettenbrunnner, 2020; Smuts & Smith, 2021). Nelson, (2018) also states that organizations that do not adopt strategies to utilize Machine Learning will fail in modern days. It's clear that the literature refers that nowadays organizations must have intelligent systems on their daily business, as it can bring many benefits. Also, intelligent systems should be considered carefully with proper risks whereas some challenges also remain to be clarified. Although some recognize advantages, others are still dealing with a productivity paradox (Brynjolfsson *et al*., 2017).

It was proved by this study that the use of intelligent systems becomes more attractive when the system becomes more accurate, and efficient in its results (Wamba-Taguimdje *et al*., 2020). According to our results, the more interest of human interaction on decision making process, the more Interest are respondents in Implementing Machine Learning systems on decision making process of management control of 21st century organizations. Also, the better perception of users and its implication on daily business, the more interested are respondents in implementing Artificial Intelligent systems on decision making process of management control of 21st century organizations. This was also validated with the indicators of benefits and challenges. The more benefits generated by both intelligent systems, more willing are respondents to implement them on decision making processes of their organizations. Furthermore, the converse has also occurred. The more challenges generated by both intelligent systems; the least interest respondents have to implement them on decision making processes of their organizations.

Moreover, organizations that make strategic plans need to have suitable and enough organizational responses and capabilities, also because long term strategies are based on goals and objectives previously planned. Nowadays, decision making processes of organizations rely on data tools, extracting data from intelligent systems and thus analyzing effects as they become more accurate than the traditional processes. Those methods have proved to be effective along with higher performance and capabilities (Ahmed & Malik, 2020).

The Stanford University's Artificial Intelligence Index Report of 2021 (D. Zhang *et al*., 2021) states that Organizations in 2020 change at least one business function to an automation process. It is common for organizations to aim for growth and even having stability in the market.

But for that, it is necessary to follow the right path, that is, knowing where to go. As much as the manager of a business knows what its goals are, it cannot depend on it alone, it is necessary to know exactly the market needs and new opportunities. It is therefore necessary, to follow the constant and actual evolution of technologies. That's where Machine Learning and Artificial Intelligence come in, as they are responsible to deliver the necessary information to be applied in the future.

Nowadays various technologies and types of Intelligent systems are used by organizations to support decision making processes. Organizations use automized tasks or modern processes by merge intelligent transformation. When it comes to big transformations or big changes people always believe that it is the end of a cycle and the beginning of a new completely different. People can have better performances if they combine their daily activities with this bigger access to data, having better analytical and problem-solving skills based on simulation tools. On the one hand, if you can describe your work, it probably can be automized, but, on the other, more complex activities that require knowledge and analysis capacity are more far from being automatized.

Artificial Intelligence can manage together with Machine Learning much more in better efficient way becoming part of techniques of decision-making processes (Selim, 2020).

6.2 LIMITATIONS

Some limitations during this study were found, that reflects some constraints. The sample size of the present study was reduced. Although the results are accurate, they cannot be considered as representative, as they only represent a sample of controllers. Also, non-multinational organizations only represent 17% of respondents. Thus, we can consider that most of the online survey was answered considering the multinationals reality, therefore representing a significant entry barrier for the perception of differences between multinational and non-multinationals reality. Thus, more studies and developmental work are necessary to explain some differences, also more time would be favorable for this study.

6.3 SUGGESTIONS FOR FUTURE STUDIES

Notwithstanding the above limitations, it may be concluded that further studies are required.

Also, studies for determining the role of deep learning systems to achieve a proper version of intelligent systems development are recommended. The recent success of Machine Learning and Artificial Intelligence for many remarkable applications and the progressively adoption of structure and transparent algorithms, demands another wave of interest to improve these systems, thereby gaining a better understand of them.

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Annexes

Annex A. Online survey for RQ1 and RQ2: Interest in Implementing Intelligent Systems in Decision Making Process of Management Control of 21st century Organizations.

Interest in Implementing Intelligent Systems in Decision Making Process of Management Control of 21st century Organizations.

The objective of my master dissertation is to analyze the role of intelligent systems in decision making processes of an organization. The first sector aims to analyze the interest in implementing artificial intelligence systems in decision making process of management control of 21st century organizations. The second sector aims to analyze the interest in implementing machine learning systems in decision making process of management control of 21st century organizations.

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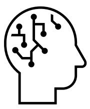
*Obrigatório

1. Are you a controller? *

Marcar apenas uma oval.

- Yes, in a multinational organization — *Avançar para a pergunta 2*
- Yes, but not in a multinational organization — *Avançar para a pergunta 2*
- No



ARTIFICIAL INTELLIGENCE

2. How old are you? *

Marcar apenas uma oval.

- 18-25 years old
- 26-35 years old
- 36-45 years old
- +45 years old

3. Are you familiar with artificial intelligence? *

Marcar apenas uma oval.

- Yes
- No

4. Do you know the concept and application of artificial intelligence? *

Marcar apenas uma oval.

- Yes
- No

5. Rate the impact you believe artificial intelligence may have in your work. *

Marcar apenas uma oval.

	1	2	3	4	5	6	7	
Very Unlikely to Impact								Very Likely to Impact

6. Do you believe it is possible to train machines to perform complex functions with excellent hit rates and accuracy? *

Marcar apenas uma oval.

- Strongly Disagree
- Disagree
- Somewhat Disagree
- Neither Agree nor Disagree
- Somewhat Agree
- Agree
- Strongly Agree

7. Do you believe the quality of future jobs will be guaranteed in a context of manmachine interaction? *

Marcar apenas uma oval.

- Strongly Disagree
- Disagree
- Somewhat Disagree
- Neither Agree nor Disagree
- Somewhat Agree
- Agree
- Strongly Agree

8. Do you believe artificial intelligence can effectively eliminate many processes that were previously done manually? *

Marcar apenas uma oval.

- Strongly Disagree
- Disagree
- Somewhat Disagree
- Neither Agree nor Disagree
- Somewhat Agree
- Agree
- Strongly Agree

9. Do you believe organizations base their decisions on evidence of data rather than subjective intuition? *

Marcar apenas uma oval.

- Strongly Disagree
- Disagree
- Somewhat Disagree
- Neither Agree nor Disagree
- Somewhat Agree
- Agree
- Strongly Agree

10. Do you use AI assistances in your everyday life? Example: Apple Siri, google assistant, smart replies, Microsoft pix, Elsa *

Marcar apenas uma oval.

- Never
- Almost Never
- Almost Every Time
- Every Time

11. Do you believe artificial intelligence can improve a processes' performance based on simulation tools? *

Marcar apenas uma oval por linha.

	Strongly Disagree	Disagree	Somewhat Disagree	Neither Agree nor Disagree	Somewhat Agree	Agree	Strongly Agree
Better analytical tools							
Better problem-solving skills							

12. Do you believe artificial intelligence can improve organizational performance based on simulation tools? *

Marcar apenas uma oval por linha.

	Strongly Disagree	Disagree	Somewhat Disagree	Neither Agree nor Disagree	Somewhat Agree	Agree	Strongly Agree
Forecasting	⬭	⬭	⬭	⬭	⬭	⬭	⬭
Planning capacity	⬭	⬭	⬭	⬭	⬭	⬭	⬭
Cost saving opportunities	⬭	⬭	⬭	⬭	⬭	⬭	⬭

13. Do you believe better analytical tools can improve the market value of organizations? *

Marcar apenas uma oval.

- ⬭ Strongly Disagree
- ⬭ Disagree
- ⬭ Somewhat Disagree
- ⬭ Neither Agree nor Disagree
- ⬭ Somewhat Agree
- ⬭ Agree
- ⬭ Strongly Agree

14. Do you believe decision capabilities are positively associated with the influence of artificial intelligence? *

Marcar apenas uma oval.

- Strongly Disagree
- Disagree
- Somewhat Disagree
- Neither Agree nor Disagree
- Somewhat Agree
- Agree
- Strongly Agree

15. Do you believe this automation can improve the quality of management in decision making processes? *

Marcar apenas uma oval.

- Strongly Disagree
- Disagree
- Somewhat Disagree
- Neither Agree nor Disagree
- Somewhat Agree
- Agree
- Strongly Agree

16. Do you believe that artificial intelligence can help reducing the number of errors on daily tasks by employees? *

Marcar apenas uma oval.

- Strongly Disagree
- Disagree
- Somewhat Disagree
- Neither Agree nor Disagree
- Somewhat Agree
- Agree
- Strongly Agree

17. Do you believe that transparency is one of the added values of artificial intelligence? *

Marcar apenas uma oval.

- Strongly Disagree
- Disagree
- Somewhat Disagree
- Neither Agree nor Disagree
- Somewhat Agree
- Agree
- Strongly Agree

18. Do you believe human understanding is not a challenge to Artificial Intelligence? *

Marcar apenas uma oval.

- Strongly Disagree
- Disagree
- Somewhat Disagree
- Neither Agree nor Disagree
- Somewhat Agree
- Agree
- Strongly Agree

19. How do you perceive the fact of some organizations not having an internal control on ethical issues related to data and algorithms to ensure trust? Ex: To avoid manipulation of data *

Marcar apenas uma oval.

- Strongly Disagree
- Disagree
- Somewhat Disagree
- Neither Agree nor Disagree
- Somewhat Agree
- Agree
- Strongly Agree

20. How do you perceive decision making process being made with the help of artificial intelligence systems that manipulate data? *

Marcar apenas uma oval.

- Strongly Disagree
- Disagree
- Somewhat Disagree
- Neither Agree nor Disagree
- Somewhat Agree
- Agree
- Strongly Agree

21. Do you consider that organizations have resources that are sufficient and optimized for the implementation and success of artificial intelligence? *

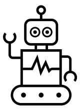
Marcar apenas uma oval.

- Strongly Disagree
- Disagree
- Somewhat Disagree
- Neither Agree nor Disagree
- Somewhat Agree
- Agree
- Strongly Agree

22. Are you willing to implement artificial intelligent systems on decision making process of your organization? *

Marcar apenas uma oval.

- Strongly Disagree
- Disagree
- Somewhat Disagree
- Neither Agree nor Disagree
- Somewhat Agree
- Agree
- Strongly Agree



MACHINE LEARNING

23. Are you familiar with machine learning? *

Marcar apenas uma oval.

- Yes
- No

24. Decision making processes should include much more people, as the interaction between more roles would not only increase the quality but also the acceptance of decisions. Frisk et al (2013) *

Marcar apenas uma oval.

- Strongly Disagree
- Disagree
- Somewhat Disagree
- Neither Agree nor Disagree
- Somewhat Agree
- Agree
- Strongly Agree

25. Do you believe machine learning can influence decision making process? *

Marcar apenas uma oval.

- Strongly Disagree
- Disagree
- Somewhat Disagree
- Neither Agree nor Disagre
- Somewhat Agree
- Agree
- Strongly Agree

26. How do you perceive human interaction on decision making processes? *

Marcar apenas uma oval por linha.

	Strongly Disagree	Disagree	Somewhat Disagree	Neither Agree nor Disagree	Somewhat Agree	Agree	Strongly Agree
Human interaction is the base for decisions	⬭	⬭	⬭	⬭	⬭	⬭	⬭
Partial recommendation from the system to facilitate some tasks.	⬭	⬭	⬭	⬭	⬭	⬭	⬭
Human's interaction can only be necessary for verification and confirmation.	⬭	⬭	⬭	⬭	⬭	⬭	⬭
Human interaction can only check and stop the solution that was previously generated and executed automatically	⬭	⬭	⬭	⬭	⬭	⬭	⬭
Doesn't consider human interaction as the decision is completely formed automatically	⬭	⬭	⬭	⬭	⬭	⬭	⬭

27. Do you believe machine learning delivers valuable insights? *

Marcar apenas uma oval.

- Strongly Disagree
- Disagree
- Somewhat Disagree
- Neither Agree nor Disagree
- Somewhat Agree
- Agree
- Strongly Agree

28. Do you believe that machine learning techniques lead to trends that are often very accurate and conclusive? *

Marcar apenas uma oval.

- Strongly Disagree
- Disagree
- Somewhat Disagree
- Neither Agree nor Disagree
- Somewhat Agree
- Agree
- Strongly Agree

29. Do you believe that machine learning can replace traditional methods of managing data? *

Marcar apenas uma oval.

- Strongly Disagree
- Disagree
- Somewhat Disagree
- Neither Agree nor Disagree
- Somewhat Agree
- Agree
- Strongly Agree

30. Do you believe traditional methods reveals poor data quality? *

Marcar apenas uma oval.

- Strongly Disagree
- Disagree
- Somewhat Disagree
- Neither Agree nor Disagree
- Somewhat Agree
- Agree
- Strongly Agree

31. Do you believe that prosecutable insights are important for an organization's prosperity and progress? *

Marcar apenas uma oval.

- Strongly Disagree
- Disagree
- Somewhat Disagree
- Neither Agree nor Disagree
- Somewhat Agree
- Agree
- Strongly Agree

32. Do you believe machine learning can have the ability to acquire prosecutable insights? *

Marcar apenas uma oval.

- Strongly Disagree
- Disagree
- Somewhat Disagree
- Neither Agree nor Disagree
- Somewhat Agree
- Agree
- Strongly Agree

33. Do you believe decision making process might monopolize much time if there's no use of computational methods? *

Marcar apenas uma oval.

- Strongly Disagree
- Disagree
- Somewhat Disagree
- Neither Agree nor Disagree
- Somewhat Agree
- Agree
- Strongly Agree

34. Do you believe machine learning can accelerate the process of decision making? *

Marcar apenas uma oval.

- Strongly Disagree
- Disagree
- Somewhat Disagree
- Neither Agree nor Disagree
- Somewhat Agree
- Agree
- Strongly Agree

35. Do you believe machine learning can reduce the negative control of employees? *

Marcar apenas uma oval.

- Strongly Disagree
- Disagree
- Somewhat Disagree
- Neither Agree nor Disagree
- Somewhat Agree
- Agree
- Strongly Agree

36. How do you perceive the ability of machine learning to forecast users' tasks? *

Marcar apenas uma oval.

	1	2	3	4	5	6	7	
Very Unlikely	◯	◯	◯	◯	◯	◯	◯	Very Likely

37. Do you believe that machine learning can avoid inconsistent tasks by forecasting users' tasks? *

Marcar apenas uma oval.

	1	2	3	4	5	6	7	
Very Unlikely	◯	◯	◯	◯	◯	◯	◯	Very Likely

38. Do you believe decision making processes are clear to lead always into good or bad decisions, despite the valuable insights? *

Marcar apenas uma oval.

	1	2	3	4	5	6	7	
Very Inaccurate	◯	◯	◯	◯	◯	◯	◯	Very Accurate

39. Do you believe human understanding is not necessary to validate and accept generated algorithms? *

Marcar apenas uma oval.

- Strongly Disagree
- Disagree
- Somewhat Disagree
- Neither Agree nor Disagree
- Somewhat Agree
- Agree
- Strongly Agree

40. Do you believe bad inputs can lead to accurate decisions? *

Marcar apenas uma oval.

- Strongly Disagree
- Disagree
- Somewhat Disagree
- Neither Agree nor Disagree
- Somewhat Agree
- Agree
- Strongly Agree

41. Do you believe lack of information about data quality can always lead to accurate decisions? *

Marcar apenas uma oval.

- Strongly Disagree
- Disagree
- Somewhat Disagree
- Neither Agree nor Disagree
- Somewhat Agree
- Agree
- Strongly Agree

42. Do you believe decisions based on similar information can be effective? *

Marcar apenas uma oval.

- Strongly Disagree
- Disagree
- Somewhat Disagree
- Neither Agree nor Disagree
- Somewhat Agree
- Agree
- Strongly Agree

43. Are you willing to implement machine learning systems on decision making process of your organization? *

Marcar apenas uma oval.

- Strongly Disagree
- Disagree
- Somewhat Disagree
- Neither Agree nor Disagree
- Somewhat Agree
- Agree
- Strongly Agree
