Smart Systems Adoption in Management

Sara Las Cunha, Ph.D. Student
ISCTE - Instituto Universitário de Lisboa
Lisbon, Portugal
saralascunha@gmail.com

Renato Lopes da Costa, Ph.D.
Business Research Unit – BRU-IUL
ISCTE - Instituto Universitário de Lisboa
Lisbon, Portugal
renatojlc@gmail.com

Rui Gonçalves, Ph.D.
PIAGET Almada
Almada, Portugal
ruiahgoncalves@gmail.com

Leandro Pereira, Ph.D PMP
BRU-Business Research Unit
ISCTE - Instituto Universitário de Lisboa
WINNING LAB
Lisbon, Portugal
leandro.pereira@iscte-iul.pt

Álvaro Dias, Ph.D
Universidade Lusófona de Humanidades e Tecnologias
ISCTE - Instituto Universitário de Lisboa
Lisbon, Portugal
alvaro.dias1@gmail.com

Rui Vinhas da Silva, Ph.D.
Business Research Unit – BRU-IUL
ISCTE - Instituto Universitário de Lisboa
Lisbon, Portugal
Rui.Vinhas.Silva@iscte-iul.pt

Sara Las Cunha is Ph.D. student from ISCTE Business School in the field of Strategic Alliances. She is also coordinator at CIEE Council on International Educational Exchange Lisbon. She is also Master Science from ISCTE in Business Administration and General Management.

Renato Lopes da Costa. PhD in General Management, Strategy and Business Development by ISCTE (Portugal) has articles published in several specialized journals in the East, the United States, Canada, Africa, South America and Portugal. He is currently a researcher and member of BRU-UNIDE and a professor at INDEG where he holds the post of director of the MScBA (Master in Business Administration) and guides students in the development of master's and PhD theses. Teaches business strategy modules in executive and post-graduate master's degrees. Since 2013 he has also accumulated teaching duties as an invited professor at the Military Academy where he teaches the Knowledge Management.

Rui Gonçalves holds a PhD in Management from Lisbon School of Economics & Management, with research in information systems for operational risk management, master in Statistics and Information Management from NOVA Information Management School, with research in Intelligent Agents and graduated in Management by Universidade Internacional. In the academic area, he is full professor at Instituto Piaget and an invited assistant professor at ISCTE, NOVA IMS and ESCS. Professionally, he regularly collaborates with different consultant firms in the areas of management consulting and analytical models applied to decision making. Previously, he coordinated the Business Analytics, Operational Risk, Compliance, Fraud, Audit and Money Laundering areas at SAS Portugal.

Leandro Pereira is Professor of Strategy and Management at ISCTE Business School. He holds a Ph.D. in Project Management. He is also CEO and Founder of WINNING Scientific Management. Dr. Pereira is also former President of Business Case Institute, PMI Portugal Chapter and Training Specialist of the Court of Auditors. As CEO, Dr. Pereira receives from Best Teams Leaders the award of Best Team Leader and CEO of Portugal in 2017 in Portugal. He is also PMP from PMI and ROI certified. As researcher, he published more than 80 scientific publications and 10 books. As student, he received the best student award from University of Minho. Dr. Pereira is an international expert in Strategic Management, Project Management, Benefits Realization Management, and Problem Solving.

Álvaro Dias is Professor of Strategy at Instituto Superior de Gestão and ISCTE-IUL, both in Lisbon, Portugal. He got his PhD in Management from Universidad de Extremadura, Spain, after an MBA in International Business. Professor Dias has over 24 years of teaching experience. He has had several visiting positions in different countries and institutions including Brazil, Angola, Spain, Poland and Finland. He regularly teaches in English, Portuguese, and Spanish at undergraduate, master and doctorate levels, as well as in executive programs. Professor Dias has produced extensive research in the field of Tourism and Management, including books, book chapters, papers in scientific journals and conference proceedings, case studies, and working papers.

Rui Vinhas da Silva is Full Professor ISCTE-IUL and Member of the Executive Board INDEG-ISCTE Exec Ed. He was also President of COMPETE 2020 (2014-2016) and Associate Professor at the University of Manchester, Manchester Business School, UK (since April 2008) and subsequently at ISCTE since April 2010, with Aggregation since September 2011-Present. Dr. Vinhas da Silva was also Assistant Professor from September 1999 to April 2008 and Research Fellow (Post Doc.) from 1998 to 1999 at the University of Manchester and Director of the Master in Corporate Communications and Reputation Management (2004-2006). From 1998 to 2010, taught the Full-Time and Executive MBA and PhD programs at Manchester Business School.

Abstract

Information technologies play an essential role in creating additional sources of value creation for customers. Artificial Intelligence (AI) has been on the top of this technological wave and has the potential to help companies to overcome their obstacles. The goal of this article was to assess the key factors that influence manager’s intentionality to implement smart systems in their businesses. For this purpose, a quantitative approach using survey data analyzed through modeling of structural equations, allowing to identify the main factors influencing manager’s decision to implement smart systems are the perception and knowledge about them, the benefits generated by the implementation of smart systems and, finally, the challenges associated. This research is truly innovative in the way that assesses the reasons that lead companies to implement smart systems in the medium term in Portugal.

Keywords: Artificial Intelligence, Smart Systems Implementation, Portuguese Companies

1. Introduction

In the past decade, Europe, as well as some of the most advanced economies in the world, has experienced a decline in productivity, leading to political upheaval and growing uncertainty about the future (Atkinson, 2019). Information technologies have played an essential role in correcting this scenario, making the world closer, more interconnected and highly competitive. Due to the use of sophisticated technologies, companies are increasingly able to improve their efficiency and the performance of their businesses (Antonova, 2014).

Information technologies play an essential role in increasing transaction cost reductions, allowing for the emergence of new business models, and creating additional sources of value creation for customers, as well as encouraging companies to become more direct, without frontiers, entrepreneurial, oriented to processes and projects and to develop global, complex and innovative business models (Antonova, 2014; Dias et al., 2020). In this way, we have witnessed a recent production revolution, made possible in part using smart systems, and which gives rise to a new wave of technologies (Atkinson, 2019).

The implementation of smart systems in the medical, transportation and manufacturing sectors has grown exponentially in recent years and, as such, there is an increased need to understand how these systems should be designed to promote effective interactions (Cummings & Stimpson, 2019). For Stone and his colleagues (2016), the main measure of success for applications of smart systems is the value they create for human lives. In this perspective, these systems must be designed in a way that allows people to understand them with confidence and participate in their use. That said, public policies should help to facilitate society's adaptation to the use of smart systems, extending their benefits and mitigating the errors and failures that may arise from this (Stone *et al.*, 2016).

Even so, and although most companies are optimistic about the future developments of smart systems, they remain cautious with their investments and with the pace of possible changes that may result from this (Simon, 2019). The author stresses that there is still a long way to go until we reach the full potential of this type of technology: among the main challenges, are the learning of new skills and the training of work teams, making them able to interact with the new technological tools (Duque et al., 2020). On the other hand, there is also the issue of security and privacy in the collection and use of data, which will certainly put policy makers in a delicate situation between promoting innovation and respecting acceptance by the public and society (Simon, 2019).

In the short term, education, training and the invention of new goods and services can mitigate these effects (Stone *et al.*, 2016). However, and according to these authors, in the long run, smart systems can be considered a radically different mechanism of wealth creation, in which everyone should be entitled to a part of the income produced in the world, and it is therefore important to start the social debate about these themes. In this sense, the theoretical objective of this study is to investigate what are the factors that influence the intention of business managers to implement smart systems to benefit their business in the next 5 years. Empirically, this article aims to understand how managers can use smart systems tools to help their businesses fulfil the gaps of technology, increasing their chances of success. Finally, we also aim to contribute to the development of the state of the art by discussing a set of knowledge around the topic of smart systems, addressing the main benefits and risks, as well as the potential consequences that these can have on the management field.

This article is organized as follows: 2) literature review on the topic of smart systems, 3) methodology used, namely a quantitative approach, 4) data analysis 5) Discussion of the results and 6) main conclusions of the study, limitations of the study and finally and suggestions for future research.

2. Literature Review

The concept of Artificial Intelligence (AI) is based on the premise that some aspects of human thought can be mechanized (Wasilow & Thorpe, 2019; Lopes da Costa *et al*., 2019) having emerged as an area of academic studies in the middle of the 20th century (Bosse & Hoogendoorn, 2015). Since it emerged, AI is expected to be one of the most widespread disruptive technologies worldwide (Simon, 2019). The first works in the area focused on the development of computers with program storage capacity, with the aim of reproducing the functioning of the human brain and raising questions about the nature of induction (Minsky, 1961).

However, there is no real consensus on the definition of AI, which has changed a lot over time, involving multiple points of view. Interestingly, the lack of a definition accepted by the entire scientific community was precisely what enabled the development of this area at the pace we are seeing today (Stone *et al.*, 2016). According to Nilsson (2010, p. 13) *"Artificial intelligence is that activity devoted to making machines intelligent, and intelligence is that quality that enables an entity to function appropriately and with foresight in its environment"*. For other authors, AI is a science that uses computational techniques that "take inspiration" from the way people use their bodies and nervous systems to feel, learn, reason and act, but that operate in a very different way (Bosse & Hoogendoorn, 2015; Simon, 2019; Stone *et al.*, 2016). AI differs from general information technologies in the sense that it involves a type of technology that can learn, connect and adapt to the environment (Huang & Rust, 2020). Still, and according to these authors, although AI may be able to learn on its own, the objectives and results of AI applications depend exclusively on the needs for which they were designed and may not always be designed to learn.

Although the concept is not new, AI has seen an exponential development in the last decade, largely due to the big data era in which we live (Nguyen *et al.*, 2019). Big data presents itself as a consequence of the importance that the digital world has had in our lives, growing at a speed never seen before (Faroukhi *et al.*, 2020). The concept is defined as the ability to process large amounts of data (Bughin, 2016) using 7 different criteria, also known as the 7Vs: volume, speed, variety, veracity, value, variability and visualization (Faroukhi *et al.*, 2020). In this way, the new paradigm ceased to see data as something static and punctual, and transformed it into raw material for companies and the economy, allowing society to take advantage of information in ways never before explored to produce useful contributions in the development and innovation of products and services with the potential to create value for humanity (Mayer-Schönberger & Cukier, 2013).

Although, for many, it is seen as a disruptive innovation, creator of new technologies and services, others argue that the phenomenon consists of a mere increase in innovation, which only takes data processing methods on a massive scale (Lugmayr *et al.*, 2017; Pinheiro et al., 2021). Either way, nowadays, data is an essential resource for companies in creating value and obtaining competitive advantage (Tian & Liu, 2017), making investment in big data directly linked to better results in making decision-making and business management (Bughin, 2016).

2.1 Practical applications and impact on the business world

The AI area is currently in a period of rapid change, large-scale growth and increasing innovation applied to the industry (Amini *et al.*, 2020). As this area of research grew, the scientific community began to distinguish sub-themes within AI, with specific objectives in solving real problems (Bosse & Hoogendoorn, 2015). There are several sectors that can benefit from the development of autonomous technologies: transport, medicine, education, public security, entertainment, among others (Antonova, 2014; Atkinson, 2019; Simon, 2019; Stone *et al.*, 2016). In fact, there are so many AI applications today and they are so present in our lives, that many of us have grown accustomed to interacting with screens and smartphones, as stated by Stone and his colleagues (2016, p. 6): *"People's future relationships with machines will become ever more nuanced, fluid, and personalized as AI systems learn to adapt to individual personalities and goals."*

In most cases, the use of these technologies focuses essentially on positive tasks, such as helping children to learn, making driving safer, helping in the diagnosis of diseases and improving the quality of life of each individual (Stone *et al.*, 2016). For example, humanitarian organizations use AI to provide psychological support to Syrian refugees, and several doctors use this technology to develop personalized treatments for cancer patients (Castro & New, 2016). In terms of safety, technology that performs critical functions - such as cars that drive without the need for a driver and surgical robots - can potentially reduce errors and human accidents, increasing the productivity of tasks (Cummings & Stimpson, 2019).

There are clear examples of industries in which digital technologies have had profound economic impacts (Russell *et al.*, 2015) and other sectors in which automation is likely to make major changes in the near future (Stone *et al.*, 2016). According to these authors, it is complicated to know exactly whether such economic impacts were driven by the application of AI systems or by the use of other "routine" digital technologies, including business planning resources and information processing and research networks. According to the report of the European Center for the Development of Vocational Training (CEDEFOP, 2018) despite the high levels of unemployment that have been felt in European countries in recent years, especially in the younger strata, there is a large gap between skills necessary for companies and those that are available in the labor market, with 40% of employers admitting that they are unable to fill the vacancies available because they do not find people with the right skill set. These data make the discussion on the subject relevant, especially with regard to the use of AI tools in the business world.

Although it is too early to assess the real consequences of AI, experts believe that technology will replace only concrete tasks in the short term, not jobs, and will also create new types of jobs, still difficult to imagine in advance (Atkinson, 2019). Changes in employment will appear gradually, starting with the replacement of small amounts of work, until, in extreme cases, resulting in the total replacement of jobs (Stone *et al.*, 2016).

It is difficult to predict exactly which tasks will be immediately affected by automation (Furman *et al.*, 2016). According to these authors, since AI is not a single technology, but a set of technologies applied to specific tasks, the effects of AI will be felt unevenly in the economy, that is, some work tasks will be more easily automated than others, and some will be more affected than others. Even so, it is expected that the AI will gradually, and in an optimization logic, integrate most of the employment sectors we know (Stone *et al.*, 2016), especially those whose cognitive needs are lower, such as driving cars or cleaning services (Furman *et al.*, 2016).

In this segment, one of the great current concerns is that the development and the sharp technological revolution that we are experiencing is contributing to an increasingly polarized society (Goos *et al.*, 2014). In other words, since the machine is becoming able to easily replace routine tasks, even if they have a high responsibility, people end up being pushed to perform tasks that are less qualified and less likely to be mechanized, as is the case of home delivery services and dog walkers, for example. As such, it is possible to look at the organizations around us, as well as their processes and methodologies, and understand exactly what the role of AI is in this scenario (Huang & Rust, 2018). According to these authors, the machine will start by replacing the mechanical and routine tasks, and it will also have relevance with regard to the performance of some analytical tasks. However, in areas where tasks are more intuitive and empathic, the machine will have more difficulty in performing such functions, since the use of AI still only pays off financially in a massification strategy (Huang *et al.*, 2019).

Therefore, people and workers with intermediate qualifications are at risk of being pushed into less qualified jobs, if there is no investment and development of their skills, in order to make them different and valuable. In other words, it becomes increasingly important to bet on a strategic approach aimed at personalizing the service, giving workers the possibility of acquiring skills oriented towards information technologies, and making them climb the value pyramid (Huang & Rust, 2020).

Previous studies suggested that the effects of AI on the labor market would continue the trend of being more intense depending on the degree of capacity of innovations, however researchers have different perspectives regarding the direct impact that automation can have on the need of human labor. Frey and Osbourne (2013) studied the likelihood that 702 professional occupations will be replaced by technology in the near future, concluding that 47% of jobs in the USA are at serious risk of being replaced by AI technologies in the next two decades. On the other hand, Arntz, Gregory and Ulrich (2016) emphasize that automation is more likely to be applied to specific tasks, not necessarily affecting professions completely, and estimate that only 9% of jobs will be seriously affected by the replacement of automation. Regardless of the numbers, the authors predict that these consequences will have a greater impact on less qualified workers, which is why it is very important that governments create a safety net that protects these populations from unequal opportunities, betting heavily on their training (Arntz *et al.*, 2016; Furman *et al.*, 2016).

AI can also influence the size and location of the workforce, as many organizations perform functions that can only grow with the addition of human labor (Stone *et al.*, 2016). In this case, with the help of technology, companies will be able to obtain economies of scale more easily and without requiring so much manpower. Another important point defended by the authors is the possibility of using the resource to AI to create new markets, lowering barriers to entry and increasing participation, resulting in an alternative with the potential to drastically reduce production costs and, consequently, prices to the consumer, making the general population, in a way, richer.

In this follow-up, Russell and colleagues (2015) argue that it is urgent to advance the research in order to determine the maximization of the benefits that AI can bring in an economic aspect and to mitigate possible adverse effects, namely in the following four areas: 1) forecasting the evolution labor market and potential effects of AI on less qualified human resources; 2) disruption of current markets, which have become obsolete due to AI; 3) policies to encourage and support unemployment protection, for example, through Unconditional Basic Income (RBI) programs and 4) updating economic measures, such as Gross Domestic Product (GDP), to reflect the benefits of AI.

According to McAfee's analysis (2019) the big issue is not related to the fact that technology can replace human work, but rather to the impact that this can have on the increase or decrease of competences on the part of qualified labor. In other words, will AI be seen as a complementary or substitute tool for the acquisition of professional skills? According to Kai-Fu Lee (2018) one of the great pioneers in the field of AI, this type of technology works more as a tool for amplifying human intelligence, rather than as something that intends to replace this experience.

Still, Lee (2018) highlights the fact that over the next 15 to 20 years, AI will gradually dominate the performance of routine tasks, which is why it is very important to invest in the education and training of the younger strata and in the review of social values for the new technological age. The author believes that it is necessary to create new jobs, of a more human character, where aspects such as sensitivity and compassion, impossible to reproduce by machines, are valued. It is, therefore, essential that joint research between industry and academia go hand in hand, to generate a significant development in AI. For Amini and colleagues (2020), this success must be perceived by both parties and, since AI is a disruptive technology with the potential to create value on a large scale, the search for talent and market share is quite high. That is, a successful collaboration model between the two must include industrial investments in academia, making them sustainable in the long term and capable of promoting the advancement of science, as well as impacting the adoption of technology (Amini *et al.*, 2020).

Promoting joint efforts between research and industry can also be beneficial for 1) understanding which projects have the greatest potential to impact the market, 2) realizing what advances can be critical in the transfer of new technology for a product or service, and 3) determine the best way to obtain corporate sponsorships (Amini *et al.*, 2020; López-Mendoza & Mauricio, 2021). As such, companies are immersed in an environment influenced by business strategies, market growth and competitive differentiation, which can be very useful to achieve these goals (Mitropoulos, 2021).

In sum, the application of these technologies is already capable of saving the lives of many drivers with cars that drive alone, helping doctors to diagnose serious illnesses, recognizing suspicious objects in hundreds of thousands of video surveillance frames, and performing dangerous tasks in the service of army forces (Wasilow & Thorpe, 2019). In their investigation, Castro and New (2016) list the potential benefits of AI applied to different categories: accessibility, agriculture, business operations, consumer convenience, disaster prevention and response, education, energy and environment, health care, industrial operations, public security, social causes and transport.

2.2 Main challenges and associated risks

In the words of Microsoft creator Bill Gates, *"A.I. is like nuclear energy - 'both promising and dangerous"* (Gates, 2019). During his participation in a symposium dedicated to AI, at Stanford University, Gates also mentioned that the power of AI is so strong that he will be able to change society in a very profound way and at different levels. Despite the many gains that can result from these types of technologies, and as exemplified in current political debates, fears of the consequences of AI development are more salient for people (especially those directly affected) than the associated economic gains, which is reflected in a more threatening approach than in an advantage and an improvement in living standards (Stone *et al.*, 2016). On one hand, technologies bring new and unexpected dynamics to economic and social processes. On the other hand, they threaten public priorities, as well as social, community and educational systems (Antonova, 2014), resulting in widespread fears as machines replace humans in large numbers (Atkinson, 2019). But is this the reality we face?

In some sectors, there is a fear that progress will be so rapid that it will replace all human work in a single generation, including those that are largely cognitive or that involve judgment (Stone *et al.*, 2016). Many fears, such as the elimination of jobs, the flight of skilled labor to other countries and the possibility that current society will be dominated by AI (Antonova, 2014; Atkinson, 2019; Simon, 2019; Stone *et al.*, 2016), stem from the belief that strong artificial intelligence is viable and imminent, as is the case with Kurzweil (2005) who states that in 2045 AI will be infinitely more powerful than all human intelligence combined.

Other authors have a more skeptical perspective (Atkinson, 2019; Wladawsky-Berger, 2015) arguing that, at least in the near future, computer systems will not be able to fully mimic the human brain, and that current fears are not strong. reason for being (Amini *et al.*, 2020). Even the smallest progress in this area has been achieved slowly and gradually, and research has had several "winters" over the years (Castro & New, 2016).

Although there are some very promising applications, such as in the areas of development for human interaction actions, AI approaches are still relatively recent and lack the necessary robustness and rigor for automatic security applications (Atkinson, 2019; Cummings & Stimpson, 2019; Zhao & Flenner, 2019; Shokoohyar, et al., 2021). According to Gupta (2018), 99% of AI techniques used today still require human work, being far from becoming autonomous in the short term. In addition, the author draws attention to the large amounts of data that need to be categorized manually, to fine tune the accuracy of the algorithms and generate satisfactory results.

With the advancement of scientific research, the area of smart systems is currently facing a crisis of reproducibility, since many of the codes used and the conditions of tests carried out in the laboratory are, in most cases, omitted from scientific articles (Houtson, 2018). It is necessary to close these gaps and produce research that can be reproduced in full, if we want to achieve successful scientific progress (Chen *et al.*, 2019) and maintain confidence in science (Gundersen & Kjensmo, 2018).

However, the advance in the academic level is still far superior to the practical application of the technology itself (Stone *et al.*, 2016). The high costs of implementing this type of systems are one of the main reasons that delay demand and cause them to lose some of their value when leveraging companies' productivity (Atkinson, 2019). For Wladawsky-Berger (2015), our main concern should not be the creation of super intelligent machines that will surpass the human race, but, and in a perspective closer to reality, find ways to make existing systems and technologies autonomous that we have been incorporating into our day-to-day lives and on which we are completely dependent.

According to Atkinson (2019), we should not be afraid of industrial changes. The author argues that AI will take on some tasks, but it will not happen suddenly and there will be a lot of work for humans. As with past waves of technological advances, automation is causing disruptions and adjustments in the labor market, but economic theory suggests that if there were no strong gains from innovations, they would not be adopted (Furman *et al.*, 2016) . Thus, restricting or slowing the development of new technologies will not help the world economy - instead, nations must find ways to help people adapt to technically advanced jobs (Atkinson, 2019).

Even though technology is a source of several benefits to society, it also raises important ethical and social issues, including privacy concerns (Wasilow & Thorpe, 2019). The authors argue that it is very important to adopt an ethical framework even when creating and developing emerging technologies, proposing a set of guidelines that aims to help technicians, regulators and decision-makers to mitigate potential violations of ethical issues that may arise with the use of this type of technology.

The fact that this type of technology evolves very quickly, presents additional challenges for traditional regulatory systems, which will consequently have to adapt to the measure of scientific progress (Hagemann *et al.*, 2018). In their study, the authors address this issue, showing how the law will have to adjust to emerging technologies, starting to resort to more “informal” processes and tools, in order to operate quickly in decision-making in the various sectors affected. The education sector also faces real challenges in this area and should focus more on "21st century skills", such as teamwork and critical thinking (Atkinson, 2019).

The American government's report on AI, prepared by a team of the President's executive (Furman *et al.*, 2016), focuses mainly on 3 strategies that aim to respond to the challenges imposed by the new technological wave in the labor market: 1) invest in AI and develop this technology, betting on its countless benefits, 2) educate and train the population to better adapt to the jobs of the future, and 3) help workers in this transition and train them in order to guarantee a widely shared growth .

Stone *et al.* (2016) underline that, as a society, we are now at a crucial moment in determining how to implement technological solutions in such a way that they promote, and do not hinder, democratic values such as freedom, equality, and transparency. In other words, in the coming years, the quality of research on this topic, the development of adequate systems and the approach adopted by social and regulatory structures will be primarily responsible for shaping how the benefits will be perceived by the population in terms of their costs and risks (Russell *et al.*, 2015; Stone *et al.*, 2016).

From the point of view of Zhao and Flenner (2019), one of the main problems with regard to the use of this technology in the area of security, has to do with the issue of trust, both on the part of the end users, but also of the specialists who they design the algorithms, since there is no consensus on how or why these algorithms obtain their performance. Some examples of this are the errors easily found in the classification made by the machine, when compared with the human classification, confirming a fundamental instability in the learned functions.

Another important issue to be considered is the fears of individual privacy, as smart systems can perform facial recognition and data collection (Wasilow & Thorpe, 2019). According to these authors, even if these technologies are used with a noble purpose, such as detecting criminal networks or online pedophilia, the truth is that they end up invading the privacy of ordinary people. Despite having some acceptance in people's daily lives, there are still many reservations about major public security issues, since laws and regulations by parts of governments have not kept up with scientific progress in this area (Wasilow & Thorpe, 2019).

3. Methodology

3.1 Research model

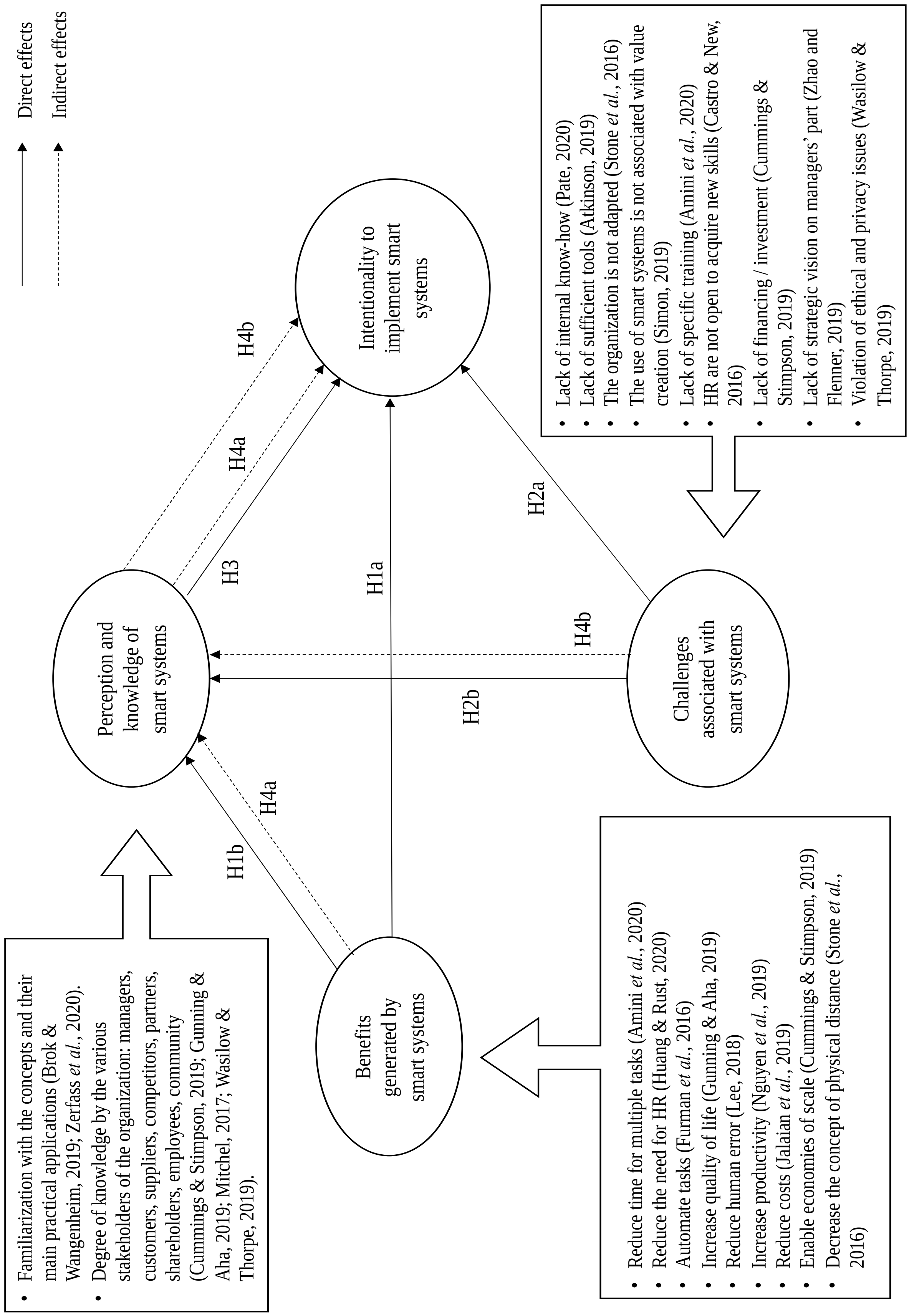
The research question that motivated this article - *What are the factors that influence the intention of business managers to implement smart systems to benefit their business in the next 5 years?* - was answered using a quantitative methodology, namely the modeling of structural equations (Structural Equations Modeling or SEM). SEM originates from the work of Sewall Wright (1918), an American geneticist who used an approach based on path analysis with structural coefficients estimated based on the correlation of observable variables.

SEM applications have increased considerably in recent decades in the social and behavioral sciences (Raykov & Marcoulides, 2006), helping to address the need to explain and predict behaviors of specific individuals, groups or organizations (Tarka, 2018). According to the same author, by recognizing a series of conditions in which the individual, society or organization exists, researchers are able, within certain limits, to identify a particular development trend and describe the details related to their existential sphere. As a result, it is possible to define and discover the vital factors and relationships that define trends in each strategic landscape (Dias et al., 2021; Pereira et al., 2021b). However, since the objective of the social sciences is not only to conduct an elementary statistical description and to recognize individual factors and behaviors, but also to determine the cause-and-effect links between the scientific areas (that is, variables) of interest and the complexity of social reality, sophisticated methods, and techniques of analysis of statistical data are needed, such as SEM (Tarka, 2018).

The target population of the quantitative study were Portuguese individuals who had already professional at least some basic knowledge about smart systems. For data collection, an online questionnaire was developed, accessible through a link. The questionnaire was developed based on the literature review and revised following a two-stage approach: 1) validation by the expert advisors, to assess the content validity of the scales and 2) through a pre-test sent to a sample of convenience, to validate the writing and design of the research. The final questionnaire was then distributed via social networks and e-mail. 280 complete questionnaires were received. Data collection took place between August 24 and October 23, 2020.

In a succinct way, the present investigation was divided into four phases, namely: 1) bibliographic research and information processing; 2) the transfer of the theoretical construct to the field of observation, to obtain the best possible confidence in terms of results; 3) fieldwork and data collection and 4) quantitative analysis (of data received from questionnaires) to give rise to new theoretical conceptual approaches combined with empirical data. In the following figures 1 it is possible to analyze in detail the information that integrated the conceptual model created to answer this research question.

Figure 1 - Conceptual model and hypotheses



Accordingly, the following hypotheses are formulated:

H1a - The benefits generated by smart systems positively impact the intention to implement this type of systems

H1b - The benefits generated by smart systems positively impact the perception and knowledge about smart systems

H2a - The challenges associated with the use of smart systems negatively impact the intention to implement this type of systems

H2b - The challenges associated with the use of smart systems negatively impact the perception and knowledge about smart systems

H3 - The perception and knowledge about smart systems positively impacts the intention to implement this type of systems

H4a - Perception and knowledge about smart systems mediates the effect between the benefits generated by smart systems and the intention to implement this type of systems

H4b - The perception and knowledge about smart systems mediates the effect between the challenges associated with the use of smart systems and the intention to implement this type of systems

In Table 1 is possible to see the relationship between the variables and indicators of the conceptual model

Table 1 - Relationship between the variables and indicators of the conceptual model

Variable	Indicator
Perception and knowledge of smart systems	Familiarization with the concepts and their main practical applications (Brok & Wangenheim, 2019; Zerfass *et al.* 2020) Degree of knowledge by the various stakeholders of the organization: managers, customers, suppliers, competitors, partners, shareholders, employees, community (Cummings & Stimpson, 2019; Gunning & Aha, 2019; Mitchel, 2017; Wasilow & Thorpe, 2019; Abdulmuhsin, et al., 2021).
Benefits generated by smart systems	Reduce time for multiple tasks (Amini *et al.*, 2020) Reduce the need for HR (Huang & Rust, 2020) Automate tasks (Furman *et al.*, 2016) Increase quality of life (Gunning & Aha, 2019) Reduce human error (Lee, 2018) Increase productivity (Nguyen *et al.*, 2019) Reduce costs (Jalaian *et al.*, 2019) Enable economies of scale (Cummings & Stimpson, 2019) Decrease the concept of physical distance (Stone *et al.*, 2016)
Challenges associated with smart systems	Lack of internal expertise (Pate, 2020) Lack of sufficient tools (Atkinson, 2019) The organization is not adapted (Stone *et al.*, 2016) The use of smart systems is not associated with value creation (Simon, 2019) Lack of specific training (Amini *et al.*, 2020) HR are not open to acquire new skills (Castro & New, 2016) Lack of financing / investment (Cummings & Stimpson, 2019) Lack of strategic vision on the part of managers (Zhao and Flenner, 2019) Violation of ethical and privacy issues (Wasilow & Thorpe, 2019)

3.2 Sample description

The present sample includes 280 respondents. An analysis was carried out on all variables that could statistically characterize the sample objectively, especially regarding its demographics, academic background, activity sector and company typology, to understand the existing sample with respect to its nature and the dimension of experience and professional knowledge (Freitas, 2013). Table 2 shows this is detail.

Table 2 - Sample details

Category class	Class description	Total number	Percentage
Role in the management of the partnership	Beneficiary only	43	15%
	Decison maker	94	34%
	Direct management	76	27%
	Indirect management	74	24%
Academic qualifications	High School	37	13%
	Bachelor degree	124	44%
	Master degree	102	37%
	PhD	17	6%
Work sector	Financial and insurance activities	47	17%
	Wholesale and retail trade	38	13%
	Transport and storage	42	15%
	Information tecnologies	45	16%
	Other sectors	69	25%
Type of company	Independent worker	9	3%
	Micro company	42	15%
	Small company	67	24%
	Medium company	102	37%
	Big company	60	21%
Job description	Technician	22	8%
	Specialist	53	19%
	Head of department	81	29%
	Manager/Director	99	35%
	President/CEO	25	9%

4. Data Analysis

The analysis and interpretation of the results of the research question followed a two-step approach. First, the reliability and validity of the measurement model was evaluated and then the structural model was evaluated. To assess the quality of the measurement model, individual reliability indicators, convergent validity, internal consistency reliability and discriminant validity were examined (Hair *et al.*, 2017).

The results showed that the standardized factorial loads of all items were above 0.6 and were all significant when $p < 0.001$, which evidenced the reliability of the individual indicator (Hair *et al.*, 2017). The reliability of the internal consistency was confirmed because all Cronbach's alpha and composite reliability (CR) of the constructs exceeded the minimum value of 0.7 (Hair *et al.*, 2017), as shown in table 3.

Table 3 - CR, AVE, correlations and discriminant validity checks

	Cronbach's Alpha	CR	AVE	1	2	3	4
(1) Benefits	0,890	0,912	0,542	**0,736**	0,316	0,379	0,311
(2) Challenges	0,874	0,889	0,503	0,218	**0,709**	0,205	0,130
(3) Intentionality	0,951	0,976	0,953	0,356	-0,215	**0,976**	0,555
(4) Perception	0,911	0,927	0,542	0,284	-0,113	5,529	**0,736**

Note: Cronbach Alpha; CR -Composite reliability; AVE -Average variance extracted. Bolded numbers are the square roots of AVE. Below the diagonal elements are the correlations between the constructs. Above the diagonal elements are the HTMT ratios.

According to table 3, it can be said that the convergent validity was confirmed for three main reasons. First, and as noted earlier, all items were positive and significant in their respective constructs. Second, all constructs had CR values greater than 0.70. Finally, the average variance extracted (AVE) for all constructs exceeded the minimum value of 0.50 (Bagozzi & Yi, 1988). Discriminant validity was assessed using two approaches. First, the criterion of Fornell and Larcker (1981) was used, which in turn requires that the square root of an AVE construct (shown diagonally with values in bold in table 3) is greater than its greatest correlation with any construct (Fornell & Larcker, 1981), and it can be seen from the table that this criterion is satisfied for all constructs. Second, the HTMT (Heterotrait-Monotrait ratio) criterion (Hair *et al.*, 2017; Henseler *et al.*, 2015) was used. As shown in table 3, all HTMT values are below the most conservative limit value of 0.85 (Hair *et al.*, 2017; Henseler *et al.*, 2015), providing additional evidence of discriminant validity.

The structural model was evaluated using the sign, magnitude and significance of the structural path coefficients; the magnitude of the R^2 value for each endogenous variable as a measure of the predictive accuracy of the model; and Stone-Geisser's Q^2 values as a measure of the predictive relevance of the model (Hair *et al.*, 2017). However, there was still collinearity before evaluating the structural model (Hair *et al.*, 2017). The values of VIF (variance inflation factor) varied between 1,460 and 3,325, all being below the critical indicative value of 5 (Hair *et al.*, 2017). These values did not indicate collinearity. The coefficient of determination R^2 for the two endogenous variables of perception of smart systems and intentionality to implement these systems in the medium term were 15.3% and 37.4%, respectively, exceeding the limit value of 10% (Falk & Miller, 1992). The Q^2 values for the endogenous variables (0.08 and 0.29 respectively) were above zero, which indicates the predictive relevance of the model (Hair *et al.*, 2017).

Table 4 - Direct relationships between constructs

	Path Coefficient	Standard errors	T Statistics	P Values
Benefits -> Intentionality	0,287	0,053	5,421	0,000
Benefits -> Perception	0,325	0,060	5,435	0,000
Challenges -> Intentionality	-0,229	0,068	3,360	0,001
Challenges -> Perception	-0,184	0,070	2,634	0,009
Perception -> Intentionality	0,421	0,054	7,816	0,000

The results in table 4 show that the benefits generated by smart systems have a significantly positive effect on the intention to implement these systems (ß = 0.287, $p < 0.001$) as well as on the perception associated with this type of technologies (ß = 0.325, $p < 0.001$), and these results confirm the hypotheses H1a and H1b, respectively. On the other hand, it is possible to observe that the challenges associated with the use of smart systems have a significantly negative relationship both with the intention to implement these systems, and with their perception and knowledge (ß = -0.229, $p < 0.01$; ß = -0.184, $p < 0.01$, respectively), showing that the greater the challenges identified by users, the lower the incentives for their use, supporting hypotheses H2a and H2b. Finally, it can also be said that the respondents' perception and knowledge of smart systems has a significantly positive relationship with the intention to implement these systems in the medium term (ß = 0.421, $p < 0.001$), thus supporting hypothesis H3.

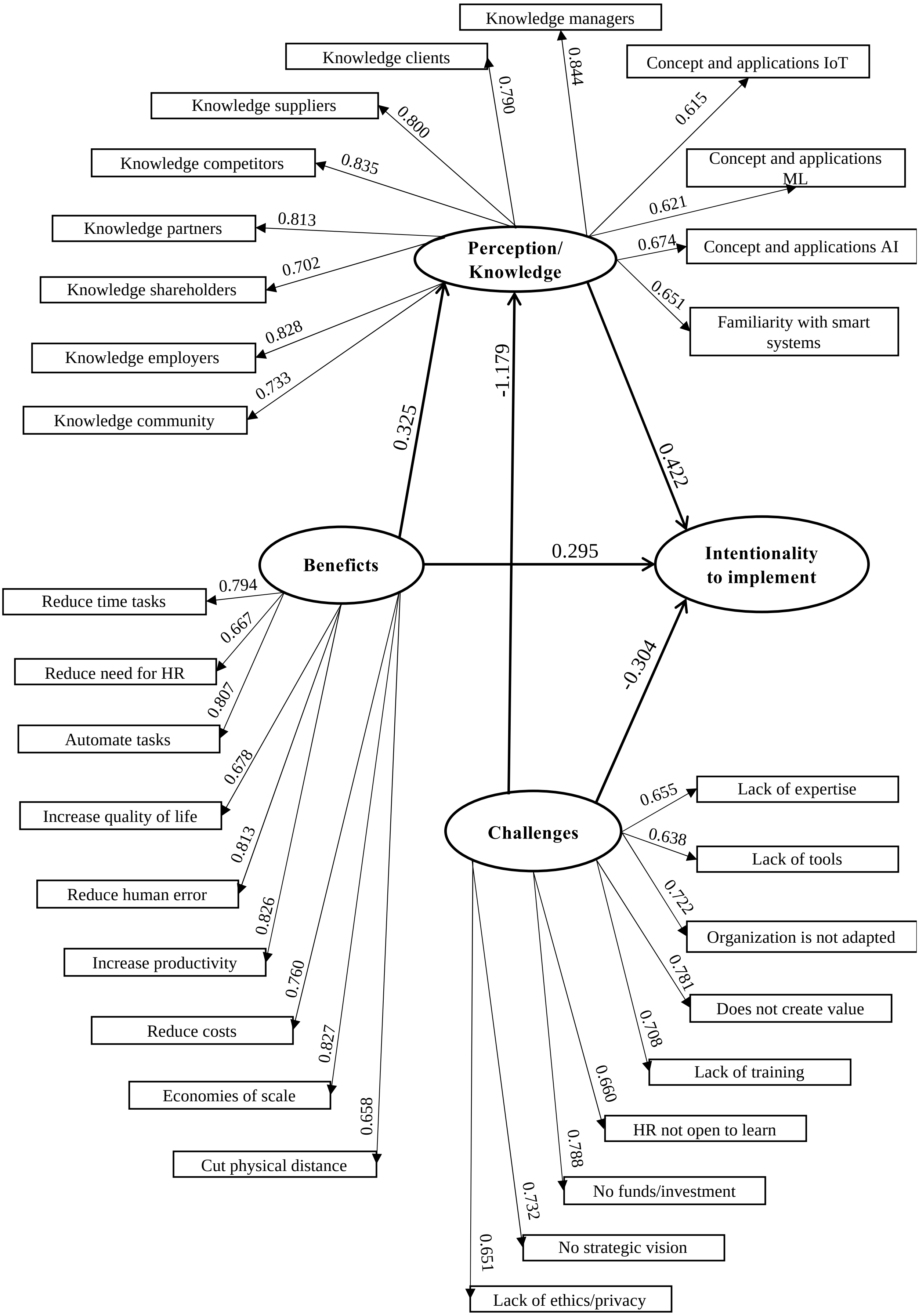
To test the mediation hypotheses (H4a and H4b), the recommendations of Hair *et al.* (2017; p. 232). Thus, a bootstrapping procedure was used to test the significance of indirect effects through the mediator (Preacher & Hayes, 2008). Table 5 shows the results of the mediation effects.

Table 5 - Specific indirect relationships between constructs

	Path Coefficient	Standard errors	T Statistics	P Values
Challenges -> Perception -> Intentionality	-0,077	0,030	2,543	0,011
Benefits -> Perception -> Intentionality	0,137	0,029	4,686	0,000

The indirect effects of the challenges associated with the use of smart systems in the intention of implementing this type of systems through the mediator perception and knowledge about them are significant with ($ß = -0.077$; $p < 0.05$), thus providing support for the H4a mediation hypothesis. In the same vein, the indirect effects of the benefits generated by smart systems in the intention of implementing this type of systems through the mediator perception and knowledge about them are significant with ($ß = 0.137$; $p < 0.001$), thus supporting the mediation hypothesis H4b. Figure 2 shows the testing of the conceptual model with the values obtained.

Figure 2 - Conceptual model tested with SmartPLS 3 with associated values



5. Discussion

The conceptual model under study aims to answer the research question in this paper - *What are the factors that influence the intentionality of business managers in implementing smart systems in order to benefit their business in the next 5 years?* - having been subjected to several tests using SmartPLS 3 (Ringle *et al.*, 2015). Three main factors were identified, namely 1) the perception and knowledge about smart systems (Brock & von Wangenheim, 2019; Zerfass *et al.*, 2020), 2) the benefits generated by the implementation of smart systems (Amini *et al.*, 2020; Cummings & Stimpson, 2019; Furman *et al.*, 2016; Gunning & Aha, 2019; Huang & Rust, 2020; Jalaian *et al.*, 2019; Lee, 2018; Nguyen *et al.*, 2019; Stone *et al.*, 2016) and 3) the challenges associated with the implementation of these same systems (Amini *et al.*, 2020; Atkinson, 2016; Castro & New, 2016; Cummings & Stimpson, 2019; Pate, 2020 ; Simon, 2019; Stone *et al.*, 2016; Wasilow & Thorpe, 2019; Zhao & Flenner, 2019). In order to arrive at these 3 generic categories of factors, the indicators associated with each category were tested individually, through the applied questionnaire, and all of them confirmed to be relevant to the study, when obtaining scores above 0.6, all of which are significant when $p < 0.001$, thus showing its reliability (Hair *et al.*, 2017).

As for the perception and knowledge about smart systems, the results show that these are essentially supported by the interviewees' familiarization with the concepts and their main practical applications, as stated by the studied authors (Brok & Wangenheim, 2019; Zerfass *et al.*, 2020) , as well as the degree of knowledge on the part of the various stakeholders of the organization: managers, customers, suppliers, competitors, partners, shareholders, employees, community, meeting what the authors defend (Cummings & Stimpson, 2019; Gunning & Aha, 2019; Mitchel, 2017; Wasilow & Thorpe, 2019).

Regarding the main benefits generated by smart systems with regard to their application in the business environment, the results are in line with the theory proposed by the authors studied, as the main ones are: reducing the time for various tasks (Amini *et al.*, 2020), reduce the need for human resources (Huang & Rust, 2020), automate tasks (Furman *et al.*, 2016), increase the quality of life of workers (Gunning & Aha, 2019), reduce human error (Lee, 2018), increase productivity (Nguyen *et al.*, 2019), reduce costs (Jalaian *et al.*, 2019), enable economies of scale (Cummings & Stimpson, 2019) and also reduce the concept of physical distance (Stone *et al.*, 2016).

Finally, with regard to the main challenges associated with the implementation of smart systems by business managers, the results once again corroborate the studied literature, since they enumerate the following challenges: lack of internal know-how (Pate, 2020), lack of sufficient tools (Atkinson, 2019), the fact that the organization is not adapted to implement this type of systems (Stone *et al.*, 2016), the use of smart systems is not associated with the creation of value for the organization (Simon, 2019), lack of specific training for the purpose (Amini *et al.*, 2020), human resources are not open to acquire new skills (Castro & New, 2016), lack of financing and / or investment (Cummings & Stimpson, 2019), lack of strategic vision on the part of managers (Zhao and Flenner, 2019) and the possible violation of ethical and privacy issues of workers and the company (Wasilow & Thorpe, 2019).

That said, and once the 3 main factors with a potential impact on the intention of managers to implement smart systems have been identified, the hypotheses formulated in the methodology chapter were tested. With regard to the direct effects of the conceptual model, the results show that the benefits generated by smart systems positively impact the intention of managers to implement these systems, thus confirming the hypothesis H1a of this work. That is, as the authors claim, the greater the emphasis on the added value that this type of technology can bring to the organization, such as cost reduction, automation of tasks and increased productivity, the greater the intention of managers to see these solutions implemented (Amini *et al.*, 2020; Cummings & Stimpson, 2019; Furman *et al.*, 2016; Jalaian *et al.*, 2019; Stone *et al.*, 2016).

Additionally, it is possible to affirm based on the results, that the benefits generated by smart systems positively impact the perception associated with this type of technologies, thus confirming the H1b hypothesis as well. That is, awareness of the potential added value also makes it possible for managers to acquire greater knowledge of what these types of systems truly are, by arousing their curiosity about them. As the authors defend, many people already know the concepts and even potential advantages of use, but it is also necessary to increase in-depth knowledge about these types of technologies, to promote their real use in organizations (Brock & von Wangenheim, 2019; Zerfass *et al.*, 2020; Pereira et al., 2021a). Regarding the challenges associated with the use of smart systems, the results show that these, in turn, negatively impact the intention of managers to implement these systems, confirming the H2a hypothesis and making the greater the challenges identified by users, the smaller the incentives for their use. According to the same authors, despite the numerous advantages that smart systems can bring to organizations, there are still many risks and associated challenges that hinder the speed of their implementation, such as the lack of financing, the lack of know-how and specific training, and also the ethical and privacy issues that arise with this theme (Amini *et al.*, 2020; Atkinson, 2019; Liu *et al.*, 2017; Simon, 2019; Stone *et al.*, 2016; Wasilow & Thorpe, 2019). At the same time, the results also show that these same challenges negatively impact the perception and knowledge of managers about smart systems, since they present themselves as barriers to curiosity and the search for knowledge, indirectly feeding barriers to its use. In other words, according to the same authors, strategic development must be done in two directions: on the one hand, increasing the gains generated by these systems in order to increase the perception and the intention to implement; on the other hand, reducing the associated risks and challenges as much as possible, so as not to negatively affect the knowledge and decision of managers to implement smart systems (Atkinson, 2019; Castro & New, 2016; Cummings & Stimpson, 2019; Pate, 2020; Simon, 2019; Stone *et al.*, 2016).

To end the hypotheses with a direct impact on the decision to implement smart systems, it can also be said that the perception and knowledge that respondents have of these systems positively influences the intention of managers, thus supporting hypothesis H3. However, and as stated by the authors studied, the results confirm that this same knowledge about AI and smart systems must be integrated in organizations and transmitted across most stakeholders in order to become efficient, and not concentrated only on the individual (Brock & von Wangenheim, 2019; Zerfass *et al.*, 2020).

Regarding the indirect effects, hypotheses H4a and H4b were raised. The first, analyzed the impact of the challenges associated with the use of smart systems in the intention of implementing them, through the mediator perception and knowledge about them, in which the results show a significantly negative influence. That is, following the previous assumptions, it is also confirmed here that the greater the risks associated with the implementation of smart systems, the less will be the intention of managers to implement these systems, since that way they will have less knowledge and less aptitude about the system. theme, inhibiting themselves from making the decision and, thus, confirming the H4a mediation hypothesis (Amini *et al.*, 2020; Zerfass *et al.*, 2020).
At the same time and taking into account the indirect effects of the benefits generated by smart systems with the intention of implementing them, through the mediator, perception and knowledge about them, the results show that the impact is positive, thus confirming the

mediation hypothesis H4b. In other words, it is possible to affirm that the efforts put into creating and increasing the benefits generated by smart systems, have the capacity to cause an increase in the level of knowledge of managers of this type of technologies and, with this, positively impact the intention to move forward. its implementation, as stated by the authors studied in the scope of this work (Gunning & Aha, 2019; Huang & Rust, 2020; K.-F. Lee, 2018; Stone *et al.*, 2016).

6. Conclusions

The increasing pressure that markets exert on companies today, in an agitated and unpredictable environment, makes it essential for organizations to rethink their strategies, adapting them to the competitive environment in which we live (Lopes da Costa & António, 2011). This investigation had as main objective to assess the main key factors that influence manager's intentionality to implement smart systems in their businesses. Following an extensive literature review on the topic of smart systems, and after conducting the analysis of a questionnaire with 280 valid responses, it was possible to reach a set of pertinent conclusions about the proposed theme.

It was possible to conclude, through the analysis of the tested conceptual model, that the 3 main factors that influence the intention of managers to implement smart systems in the medium term are: 1) the perception and knowledge about smart systems, 2) the benefits generated by the implementation of smart systems and, finally, 3) the challenges associated with the implementation of these same systems.

As for the perception and knowledge about smart systems, the results show that these are essentially supported by the respondents' familiarization with the concepts and their main practical applications, as stated by the studied authors (Brok & Wangenheim, 2019; Zerfass *et al.*, 2020) , as well as the degree of knowledge on the part of the various stakeholders of the organization: managers, customers, suppliers, competitors, partners, shareholders, employees, community, meeting what the authors defend (Cummings & Stimpson, 2019; Gunning & Aha, 2019; Mitchel, 2017; Wasilow & Thorpe, 2019).
Regarding the main benefits generated by smart systems, the results are in line with the theory proposed by the authors studied, as the main ones are: reducing the time for various tasks (Amini *et al.,* 2020), reduce the need for human resources (Huang & Rust, 2020), automate

tasks (Furman *et al.*, 2016), increase the quality of life of workers (Gunning & Aha, 2019), reduce human error (Lee, 2018), increase productivity (Nguyen *et al.*, 2019), reduce costs (Jalaian *et al.*, 2019), enable economies of scale (Cummings & Stimpson, 2019) and also reduce the concept of physical distance (Stone *et al.*, 2016).

Finally, with regard to the main challenges associated with the implementation of smart systems by business managers, the results once again corroborate the studied literature, in the sense that they enumerate the following challenges: lack of internal know-how (Pate , 2020), lack of sufficient tools (Atkinson, 2019), the fact that the organization is not adapted to implement this type of systems (Stone *et al.*, 2016), the use of smart systems is not associated with the creation of value for the organization (Simon, 2019), lack of specific training for the purpose (Amini *et al.*, 2020), human resources are not open to acquire new skills (Castro & New, 2016), lack of financing and / or investment (Cummings & Stimpson, 2019), lack of strategic vision on the part of managers (Zhao and Flenner, 2019) and the possible violation of ethical and privacy issues of workers and the company (Wasilow & Thorpe, 2019).

It was concluded, therefore, that the perception and knowledge about smart systems, as well as the benefits generated by them, positively affect the intention of managers to implement this type of technologies. Therefore, as the authors claim, the greater the emphasis on the added value that this type of technology can bring to the organization, such as cost reduction, automation of tasks and increased productivity, the greater the intention of managers to see these solutions implemented (Amini *et al.*, 2020; Cummings & Stimpson, 2019; Furman *et al.*, 2016; Jalaian *et al.*, 2019; Stone *et al.*, 2016). That is, although many people already know the concepts and even the potential advantages of using smart systems, it is also necessary to increase the deep knowledge about this type of technologies, to promote their real use in organizations. On the other hand, the associated challenges, and risks, negatively affect the intention of managers to choose the implementation of smart systems in the next 5 years, meaning that the greater the challenges identified by users, the lower the incentives for their use. According to the same authors, despite the numerous advantages that smart systems can bring to organizations, there are still many risks and associated challenges that hinder the speed of their implementation, such as the lack of financing, the lack of know-how and specific training, and also the ethical and privacy issues that arise with this theme (Amini *et al.*, 2020; Atkinson, 2019; Liu *et al.*, 2017; Simon, 2019; Stone *et al.*, 2016; Wasilow & Thorpe, 2019).

Since most companies are forced, nowadays, to constantly rethink their strategy, adapting them to the competitive and unstable environment of today's markets, the context in which organizations operate is characterized by an amazing pace of change. This work aims to contribute to the development of business management by discussing a set of knowledge around smart systems and more specifically on AI, addressing their main concepts, key factors, benefits and associated risks, as well as the potential practical applications and consequences that these technologies can bring to companies. Additionally, this work contributes to the scientific literature by investigating in depth the key factors that influence managers to implement smart systems, thus helping companies to learn about the topic and, consequently, improve their decision-making process.

First, it is important to consider that the findings presented in this research, result from limitations inherent to a reduced investigation in terms of sample size (respondents) and context (Portugal). In this sense, in terms of external validity, that is, the possibility of generalizing the results found to other contexts or samples, although this study has reinforced some of the existing theory regarding the factors that influence managers' decision to implement smart systems, this was only an exploratory study that cannot be generalized or representative. Another limitation was related to the impossibility of observing the interactions and decision-making processes of strategic decision makers (due to the pandemic context in which we live) and, therefore, the consequent particularities, ideas and problem-solving techniques that could result from this same interaction. Finally, the impossibility of following the companies and managers who have demonstrated intention to implement smart systems in the next 5 years, to analyze and evaluate the circumstances and conditions of such implementations.

Some of the limitations mentioned above can be mitigated through changes to be considered in the next studies. Firstly, it would be very interesting to have the opportunity to observe some strategic managers and decision makers *in loco*, allowing for even deeper collection and analysis of quantitative data. Also, the extension of a study of this caliber could be applied to other countries, and some causality and transversality relationship may be established through the comparison of variables between geographic locations. The same could be done with a specific industry as compared to another. It would also be interesting to look for and combine variables that change over time, to carry out a longitudinal study, as it is predicted that in the coming years, many of the outlines of the topic of smart systems will evolve and impact companies.

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