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# Artificial Intelligence applied to Stakeholder Theory

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Master in Business Administration

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## Resumo

A constante evolução e mudança no mundo, tem forçado as organizações a repensar todo o seu modelo empresarial. Os Sistemas Inteligentes têm-se revelado bastante promissores em relação à gestão empresarial, aumentando o desempenho dos negócios através da simplificação de processos, aumento de eficiência e tomada de decisão. A importância da Teoria dos Stakeholders como parte integrante das análises das empresas torna-se evidente na medida em que todos os Stakeholders irão influenciar o ambiente empresarial em algum momento e por isso, torna-se crucial a sua monitorização constante.

Apesar da importância da análise de Stakeholders, continua a ser uma grande lacuna nas organizações. No sentido de encontrar soluções para esta problemática, o principal objetivo desta investigação prende-se com o estudo do impacto dos Sistemas Inteligentes na Teoria dos Stakeholders. Para isso, depois de uma revisão literária, foram levantadas duas questões de pesquisa. A investigação é baseada em uma investigação indutiva, exploratória e foi realizada a partir de uma amostra não probabilística de conveniência. Na obtenção de respostas para as questões de pesquisa foi utilizado uma abordagem mista de métodos qualitativos e quantitativos com análise de 13 entrevistas e 168 questionários *online*, respetivamente.

Os resultados obtidos permitem demonstrar que a utilização de Sistemas Inteligentes relacionada com a Teoria dos Stakeholders nas organizações torna-se relevante e que, a perceção e conhecimento dos indivíduos influenciada ou não pelos benefícios e desafios que a implementação da Inteligência Artificial pode acarretar, se torna crucial na decisão da implementação destes sistemas nas suas empresas.

**Palavras Chave:** Inteligência Artificial, Teoria dos *Stakeholders, Stakeholders*, Sistemas Inteligentes, *Software*

**Classificação JEL:**

C12 – *Hypothesis Testing: General*

O32 – *Management of Technological Innovation and R&D*

M10 – *Business Administration: General*

## Abstract

The constant evolution and change in the world have forced organizations to rethink their business model. Intelligent Systems have proved to be very promising in business management, increasing business performance by simplifying processes, increasing efficiency and decision-making. The importance of Stakeholder Theory as an integral part of business analysis becomes evident as all Stakeholders will influence the business environment at some point, and therefore its constant monitoring becomes crucial.

Despite the importance of stakeholder analysis, it remains a significant gap in organizations. To find solutions to this problem, this investigation's main objective is to study the impact of Intelligent Systems on Stakeholder Theory. For this, after a literary review, two research questions were raised. The investigation is based on an inductive, exploratory study and was carried out from a non-probabilistic convenience sample. To obtain answers to the research questions, a hybrid approach of qualitative and quantitative methods was used, with an analysis of 13 interviews and 168 online questionnaires, respectively.

The results obtained allow us to demonstrate that the use of Intelligent Systems related to the Stakeholder Theory in organizations becomes relevant and that the perception and knowledge of individuals, influenced or not by the benefits and challenges that the implementation of Artificial Intelligence can entail, becomes crucial in the decision to implement these systems in their companies.

**Keywords:** Artificial Intelligence, Stakeholder Theory, Stakeholders, Intelligent Systems, Software

**JEL Classification:**

C12 – Hypothesis Testing: General

O32 – Management of Technological Innovation and R&D

M10 – Business Administration: General

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## Glossary of Acronyms

ADM – Automated Decision Making

AI – Artificial Intelligence

AVE – Average Variance Extracted

BSA – Business Stakeholder Analyzer

CBR – Cased-Based Reasoning

CEO – Chief Executive Officer

CR – Composite Reliability

CRM – Customer Relationship Management

DL – Deep Learning

DLADM – Deep Learning – Augmented Decision - Making

EBIT – Earnings Before Interest and Taxes

FTC – Federal Trade Commission

FTE – Full-Time Equivalent

GDPR – General Data Protection Regulation

HTMT ratio – Heterotrait-Monotrait Ratio

IS – Intelligent Systems

ML – Machine Learning

NGOs – Non-Governmental Organizations

PLS – Partial Least Squares

RDAP – Reactive, Defensive, Accommodative, or Proactive strategies

RQ – Research Question

SEM – Structural Equations Model

SMEs – Medium-Sized Enterprises

SMSS – Stakeholder Management Strategy Support System

ST– Stakeholder Theory

VIF – Variance Inflation Factor

# Introduction

## Framework

Artificial Intelligence (AI) has today the power to overcome most of the world's problems with different degrees of complexity (Edward *et al*., 2000). Despite the ups and downs (Duan *et al*., 2019), AI is a disruptive technology that will significantly change our economy and society in the near future (Li & Zhang, 2017).

Consumers are increasingly using technologies, and companies are taking advantage of their benefits by adopting them in their operations (Miller, 2018), and the results are pretty promising. AI is transforming business (Daugherty & Wilson, 2018). Its correct use can significantly benefit institutions in the long run through growth and savings through increased productivity and innovation. In the globalized and interconnected world in which we live, rapid adaptation and perception of opportunities are necessary (Shabbir & Anwer, 2015).

Freeman (1984, p. 25) described a Stakeholder as "Any group or individual that can affect or is affected by the achievement of the company's objectives." To understand a business is necessary to know how the relationships and interactions between customers, suppliers, financiers, shareholders, managers, and other stakeholders, work and create value. Stakeholder Theory (ST) proposes that value creation is a collaborative effort in relationships, ideally benefiting the focal business and all its Stakeholders (Freeman *et al*., 2010). Therefore, not considering a specific group as an interested party can represent a risk for the company. This group can contribute positively to market opportunities and prevent environmental, social, and economic problems (Gil-Lafuente & Paula, 2013).

Implementing these systems in organizations can contain some obstacles but can be highly beneficial. This research explores the impact of AI implementation on the ST in managing organizations. It is expected that the present investigation will contribute to the development of the community, adding more knowledge about these two areas and their relationship.

## Research Problem

As mentioned above, the focus of this master thesis is to understand the impact of AI implementation on the ST in the management of organizations. Recently, AI and Machine Learning (ML) have aroused much interest. Organizations are starting to rethink their business models, realizing that the activities performed by employees can be carried out productively by adopting these technologies in their operations. These systems can be present and be useful in many business processes (Ramachandran *et al*., 2022), and it will be pertinent to understand whether it is feasible and valuable for organizations to implement Intelligent Systems (IS) that analyze their Stakeholders, once a time that all stakeholders involved will influence the business environment, will provide resources, influence the company and benefit from its growth, efficiency, and impact, whether positive or negative (Donaldson & Preston, 1995).

However, despite all this emerging success and most companies being optimistic about the future of IS developments, AI implementation still has obstacles (Simon, 2019; Vorobeva *et al*., 2022). Only some studies try to apply IS to ST; however, none investigate the various factors that AI entails, the availability of organizations, and the possibility of implementing IS in ST to help organizations to optimize this activity bringing benefits.

In this sense, many sources report how to identify stakeholders manually, but only some studies report how to do it through intelligent systems (Chung *et al*., 2009). Approaching stakeholder analysis based on complex systems and models that assist entrepreneurs in making decisions according to imperative characteristics in each situation and moment is fundamental, given the importance and complexity of identifying stakeholders for companies (Gil-Lafuente & Paula, 2013). The ability to transform data into practical solutions and informed decisions will be a fundamental need of any organization (Sandeep *et al*., 2022).

## Theoretical and Empirical Objectives

The theoretical objective of this dissertation is to contribute to research and scientific knowledge in AI and ST, thus seeking to reduce the literary gap in the relationship between these two themes.

In this way, it is sought to understand whether, with the possibility of implementing IS in ST in organizations, this contribution will be positive. This leads us to the empirical objective of generating evidence of the impact of IS on ST through the facts of lived and witnessed experiences to obtain conclusions. Two research questions resulted from the literature review to respond to the main objective.

**Dissertation Structure**

In order to achieve the proposed objective and answer the research questions presented, the elaboration of this master's dissertation is composed of the Introduction, five main chapters, and the conclusion.

In the introduction, the framework is made, presenting the investigation problem, and the objective that motivated the accomplishment of this investigation. In Chapters I and II, the literature review is carried out. Chapter I is directed to a literature review of IS, namely AI, divided into three fundamental parts: The first defines AI and has as a subchapter its ML and Deep Learning (DL) subcategories, the second explains the concept of Big Data and the third intends to frame AI and its impact on the business world. Chapter II focuses on the Stakeholder Theory and is divided into two parts, the first seeks to define the concept of Stakeholders, and the second to associate AI with the ST.

Chapter III addresses the Theoretical Approach with the objective of the dissertation and the respective research questions resulting from the literature review, which will serve as a basis for the investigation. Chapter IV includes the methodology and explanation of the tools used to collect and analyze the data to answer the research questions identified in the previous chapter. After this chapter, Chapter V follows, where the presentation and discussion of the results are carried out, the analysis of data from the different methodologies of each research question, and the authors of interest to extract significant knowledge.

Finally, the Conclusion describes the final considerations of the scientific investigation, the possible contribution that the investigation will have to organizations and their business management, the study's limitations, and suggestions for future investigations.

# Chapter I - Intelligent Systems

## 1.1. Artificial Intelligence

The emergence of the Artificial Intelligence concept was in 1956, when McCarthy, along with his colleagues Marvin Minsky, Shannon, and Nathan Rochester, organized a conference in Dartmouth and announced that "every aspect of learning or any other feature of intelligence can in principle, be so precisely described that a machine can be made to simulate it" (Cukier, 2019).

There are very different views and opinions regarding AI. Consensus on the definition of AI is far from happening; that is why, over the years, numerous definitions and theories have been developed (Duan *et al*., 2019). A few years after his announcement, McCarthy (1988, p. 308) classified: "AI is concerned with achieving goals in situations in which the information available has a certain complex character. The methods that have to be used are related to the problem presented by the situation and are similar whether the problem solver is human, a Martian, or a computer program".

More recently, Hao (2018) refers that AI can induce machines to learn, ration, and act on their own, making their own decisions when confronted with new situations in the same way that human beings would. ML algorithms allow the use of patterns with the big data known to make predictions about things. Güngör (2020) argues that AI is a generic term for various methodologies designed to provide computers with human-like abilities to see, hear, reason, and learn.

Despite the ups and downs of this technology over time (Duan *et al*., 2019), AI is believed to be a disruptive technology that will change our economy and society significantly soon (Li & Zhang, 2017). The constant development of AI has influenced and improved everyday and modern life. Nowadays, AI can overcome most of the world's problems with different degrees of complexity (Edward *et al*., 2000).

However, only specific results can be expected by AI because it is typically limited to a single frame or type of problem. ML and AI are excellent at extracting a particular pattern. However, the results of ML are easy to misuse. Current AI technology depends on large-scale data and can obtain results using only numerical values, but it does not have the association function like the human brain. AI is only a substitute and does not perform all the functions of the human brain, such as self-understanding, self-control, self-consciousness, and self-motivation (Lu *et al*., 2017).

Several authors distinguish between two distinct types of AI: Weak AI and Strong AI (Amini *et al*., 2020; Atkinson, 2019; Li & Zhang, 2017). Weak AI passively simulates intelligent human processes without accurate understanding, does not intend to imitate the human brain (Li & Zhang, 2017), and has some limitations; namely, it needs large amounts of data and human help to perform its tasks in a viable way (Amini *et al*., 2020). Strong AI is characterized by adapting quickly to the environment, which in turn can match or surpass intelligence at the human level, such as high-level human-like cognition capabilities: common sense, self-awareness, creativity, and applying the problem-solving ability to any issue (Amini *et al*., 2020; Atkinson, 2019).

From a task-solving ability perspective, weak AI is designed to complete a specific task. At the same time, strong AI has generally considered a general AI system that can cater to multiple types of intelligence. Current AI systems are all in the weak AI phase, and Strong AI has yet to exist. It is supposed to take decades for a human to perform strong AI (Li & Zhang, 2017).

The author's Lu *et al*. (2017) realized that there are limitations at the level of AI and have developed a new concept of general-purpose intelligence cognition technology, which merges the benefits of artificial life and AI, called "Beyond AI." Based on this concept, they developed an intelligent learning model called "Brain Intelligence (BI)" that generates new ideas about events without having experienced them, using artificial life with the function of imagining.

Artificial Intelligence is increasingly present in our daily lives. Some examples where we can currently find AI are Fraud Detection - Detect an unknown pattern and warn about it; Resource Scheduling - Efficiently scheduling resources; Complex analysis - Helps in complex analysis, with too many factors to consider; Automation - Automation to handle unexpected changes or events; Customer service - Service by calling, service machines; Security systems - For example in cars, self-surveillance cameras; Machine efficiency - AI can help control a machine for maximum efficiency (Mueller & Massaron, 2018).

In this new era, where information is arriving in every millisecond, Miller (2018) defended that symbiosis between humans and machines is fundamental to increasing individual capacities and strengthening them collectively. Intelligent systems can be used at the level of worker support, helping to support human decision-making, but not replacing or, at the total replacement of the worker in decision-making, where the system makes the final decision. Edward *et al*. (2000) argue that total worker replacement does not necessarily mean leaving a human being without a job; often, a substitute Expert system allows the work to be done by a different, "less expert" person.

First, AI began to replace some mechanical, routine, and analytical tasks. Changes in employment will come about gradually, starting with the replacement of small tasks until, in extreme cases, a total replacement of jobs. AI effects will differ depending on the work sector; some tasks will be more easily automated, and others will be more affected. AI is expected to be introduced gradually and optimally in employment sectors (Stone *et al*., 2016).

However, the introduction of these systems may have some disadvantages since it does not always mean efficient interaction between humans and robots; for instance, the fear of employees being replaced by AI is still a cause for concern, having found that thinking and feeling affect the behavior of employees in the service because AI serves as a benchmark for employees. Another point to mention is that the presence of AI can generate better or worse performance, depending on the task (Vorobeva *et al*., 2022). The team needs to be prepared to work in new ways and in an interdisciplinary way and be motivated, such as aligning employee incentives with the new process and developing reporting tools to provide company-wide transparency to new insights (Fountaine *et al*., 2021).

AI is increasingly ingrained in our lives. Kurzweil (2005) states that in 2045, AI will be infinitely more powerful than all human intelligence combined. Although we want to predict the future, it is still too soon to make predictions. Some experts believe that technology will not replace jobs but only concrete tasks in the short term and will create new types of jobs (Atkinson, 2019). According to the authors Huang *et al*. (2019), the machines will have difficulties performing more intuitive and empathic functions since AI still only pays off financially in a massification strategy.

The benefits that technologies can bring us as a society are well known. For Stone *et al*. (2016), the primary measure of success for IS applications is the value they create for human lives. However, the fears of people (especially those directly affected) prove to be more pronounced when it comes to the consequences of AI development, regardless of the associated economic gains, which is reflected in a more threatening approach than an advantage and improvement in living standards. An empirical study by Woodward (1954) of British manufacturing firms, found that even if the change was implemented slowly and carefully, the reaction of lower supervisors and operators was to resist it. The familiarity of the tasks they perform provides comfort, which prevents them from dealing positively with uncertainty and change, tending to avoid them (Weick, 2001). Also, self-interest, distrust, or preference for a status quo can be factors that will lead employees to question how good the change will be for them (Senge, 1997).

Siau and Wang (2018) report that several factors support people's trust in IS. Transparency and achieving good results and performance are essential to building initial trust. After establishing the initial trust, reliability, security, and interpretability are crucial. The perception of the purpose of IS is essential, as many people may be afraid of losing their jobs or have a derived perception concerning the science fiction aspect of AI – the eventual overcoming of human intelligence and consequent destruction of society (Stone *et al*., 2016).

A study by Holliday *et al*. (2016) demonstrates that users tend to show more confidence in these systems if explanations about how the results are obtained. Another critical factor in user reliability in IS is the perception of the inner workings of AI. From this perspective, these systems should be easily inserted so that people can confidently understand the purpose and benefits of participating in their use (Stone *et al*., 2016). A more recent study by Lozano *et al*. (2021) analyzes AI perception in Spain and the factors associated with it. In short, to get a better attitude and perception towards AI, the individual must think they are good and bring benefits to society (they help carry out tasks). People with a relatively negative attitude towards AI find that it is more challenging to adapt to innovations, that innovations prioritize job losses, and that they worsen the face-to-face mood.

In the research by Araujo *et al*. (2020), one of the points they assess is the extent to which the knowledge, benefits, and concerns about online privacy affect the perception of Automated Decision Making (ADM) by AI as fair, helpful, or risky. The authors found that general knowledge (education) positively correlates with perceptions of ADM benefits. In contrast, domain-specific knowledge (knowledge of computer programming, AI, and algorithms) positively correlates with perceptions of utility and fairness from ADM.

Stone *et al*. (2016) argue that public policies should help to facilitate society's adaptation to the use of IS, extending their benefits and mitigating errors and failures that may arise from this. AI is here to stay and to make our daily life more accessible;

however, it contains some negative points that we must be alert to. AI can be used to steal our private information and launch large-scale network attacks by attackers. This can have ethical consequences, and it is essential to clarify the possible threats in the different areas of AI. AI can bring us efficiency and convenience while simultaneously avoiding harm to humans. It is necessary to discuss ethical and social issues, such as security privacy and that may be raised by AI. The authors believe that despite this, it is possible to use technological advantage to improve security and privacy protection for human society and cyberspace. Building a progressive regulatory system is essential to develop better AI practices (Li & Zhang, 2017).

A technical team must outline specific AI risks, and each adverse event associated with AI must be identified so that the team can detail strategies to mitigate these risks with appropriate standards (Buehler *et al*., 2021); for that, the authors mapped possible risks concerning possible business contexts. The authors recommend that this process consider at least six broad types of AI risk: Privacy, Security, Fairness, Transparency and explainability, Safety and performance, and finally, Third-party risks.

Initially, the main objective of AI was to resemble human beings - it was intended to create intelligent machines capable of reproducing any task of an intellectual and cognitive order (Bosse & Hoogendoorn, 2015). As previously mentioned, many specialists see this technology as a possible threat to the human race and demand an investigation of how the human race can coexist with AI, minimizing its negative impact. The issue of security and privacy in data collection and use raises the need for a balance between promoting innovation and respecting acceptance by the general public and society (Simon, 2019). Continuous efforts are being implemented for society can live in an organized way with technology. Recently, the European Union proposed a set of AI regulations that, if violated, could result in material fines, and the U.S. Federal Trade Commission (FTC) released a warning that could hold organizations accountable for the proliferation of bias or inequality through AI (Buehler *et al*., 2021).

The lack of clarity on how the rules relate to emerging technologies makes it difficult for regulators to apply them in fields such as AI, blockchain, and the internet of things (Espinoza, 2020). An article from the Financial Times newspaper confides that having seen a confidential draft exposed that smaller businesses were particularly affected by the costs of compliance with the General Data Protection Regulation (GDPR) and that medium-sized enterprises (SMEs) faced challenges in implementing this regulation.

Stone *et al*. (2016) underscore that, as a society, we are now at a crucial juncture in determining how to deploy technological solutions in ways that promote, rather than hinder, democratic values such as freedom, equality, and transparency. Atkinson (2019) argues that technological advances must not be restricted or slowed down as this will not help the world economy. Strategies must be created to find ways for people to adapt to technically advanced jobs.

In recent years, AI and ML have gained much attention. Organizations are starting to realize that technologies such as AI and ML are worth adopting; the activities performed by workers can be carried out more quickly and efficiently, resulting in improved productivity. These systems can be present and essential in many business processes (Ramachandran *et al*., 2022).

### 1.1.1. Machine Learning and Deep Learning

The concept of Machine Learning is a subfield of AI, but ML does not fully define AI. ML relies on algorithms to analyze large data sets. The system from a previously experience learns a specific pattern and responding from its learning. In this case, the system becomes smarter, without human involvement (Mueller & Massaron, 2018) and it consists of a methodology normally used for the development of autonomous systems *software* (Cummings & Stimpson, 2019). The basis of ML is math. Algorithms interpret big data in specific ways, depending on what they are formulated for, so they must be adapted according to the intended objective, amount of available data, and data type (Castro & New, 2016).

Big data is unpredictable, and algorithms process input data in specific ways and create predictable outputs based on data patterns. ML deciphers data in such a way that it is possible to see patterns, extract information, and make sense of that data. Its objective is to design algorithms that can create analytical models from new data interactively and automatically without explicitly programming the solution (Castro & New, 2016). According to Panch *et al*. (2018), supervised learning algorithms are programs that learn associations through data analysis defined by a supervisor.

On the other hand, a DL system learns from its experience, but an extensive database or ample information is given in the input. Therefore, DL is suitable for dealing with more extensive data and complexity (Zhang *et al*., 2018). DP is a subcategory of ML. Recent advances in DL algorithms demonstrate benefits for decision-making within organizations as an ally to employees, thus increasing analytical capabilities (Shrestha *et al*., 2021).

Deep Learning refers to real-time environmental data monitoring, which can lead to a proactive or preventive increase in decision-making. Only tiny fractions of the available data are currently being used to support the creation of organizationally relevant knowledge. These new developments in algorithms, data collection and storage, and processing *hardware* and *software* have been reviving the idea of a possible implementation of these systems. The authors found that despite the many advantages of Deep Learning–Augmented Decision-Making (DLADM) for companies, implementing DL requires significant understanding, reflection, and prudence on the part of managers (Shrestha *et al*., 2021). However, Ramachandran *et al*. (2022) found that companies will perform better if AI and ML algorithms can effectively mine large volumes of big data.

## 1.2. Big Data

AI enters our daily lives sometimes without we realize that we are dealing with it. We can find this technology in work, leisure, and even medicine. AI needs tools to reach the goal: the data processing used to achieve that goal and the data acquisition used to understand the goal better. There must be algorithms to achieve an outcome that may or may not be related to human goals or methods of achieving those goals (Mueller & Massaron, 2018).

The internet allows us to generate, distribute and accumulate data and information, which we call Big Data. All these data are related to typical human activities, feelings, experiences, and relationships. The AI can learn by running through this data, how the humane reasoning and action work. One of the biggest challenges in AI is collecting data. The security and consistency of the data are essential to ensure that it is within the parameters, and it must have a specific form. Once stored, data reliability can decrease unless it remains in the desired format. If there is data manipulation by some identity, its reliability is compromised (Mueller & Massaron, 2018).

Gandomi and Haider (2015) state that Big Data can be described in three V's - Volume, Variety, and Velocity. Volume refers to the amount of data. Information storage and analysis structure are needed. A large amount of information is transferred between devices. The variety alludes to the heterogeneity of the data. Using Big Data analytics, the various formats in which data is presented can be analyzed more efficiently than with regular statistics and small data analytic tools. Finally, velocity is the rate at which data is generated and the speed needed to analyze and act on it. With Big Data analytics, real-time intelligence can be built from large volumes of data.

Suppose the data are on a numerical basis. In that case, it is possible to apply mathematical and statistical techniques (called data analysis techniques) to obtain even more information in a helpful way, categorized and organized from those same data. Making an advanced analysis increases the possibility of predicting the future, classifying the information, and thus making decisions in a more efficient way (Mueller & Massaron, 2018).

Interest in Big Data has grown due to its ability to create market value. Big Data enables BI to provide insights that allow companies to understand their customers better, improve marketing technology, enable personalization, and identify problems and opportunities in real-time (Garmaroodi *et al*., 2020). Big data also, with analysis tools allow organizations to solve many current problems and gain greater control over customer loyalty and conduct, which is continually changing, control supply chain risk, build strategic intelligence, and conduct reliable market research to make crucial decisions (Božič & Dimovski, 2019).

### 1.3. Artificial Intelligence in Organizations

With the development of AI, consumers are using these systems more, and consequently, companies are increasingly it taking advantage of its benefits by adopting it in their operations (Miller, 2018) to be able to meet people's needs and, the results are being surprising, AI is transforming business (Daugherty & Wilson, 2018). Haenlein and Kaplan (2019) argued that technological approaches have been increasingly used by companies and the public due to big data and the improvement in computing capacity. High levels of efficiency characterize the different AI approaches that have been developed.

Many businesses have seen increased results and significant growth rates with the implementation of AI. Its correct use can significantly benefit institutions in the long run through growth and economies by increasing productivity and innovation. Rapid adaptation and perception of opportunities are needed in the globalized and interconnected world we live in (Shabbir & Anwer, 2015).

Mckinsey and Company conducted a survey in which nearly half of respondents say their companies have at least incorporated an AI feature into their business, 30% are testing AI, only 21% say their organizations have incorporated AI into various parts of the business, and only 3% of large companies have integrated AI into their complete corporate workflows (Chui & Malhotra, 2018). More recently, Perrault *et al*. (2019) already indicates a higher rate, nearly 60% of large companies, have already adopted AI in at least one function or business unit in 2019.

Year 2020 results from the McKinsey Global Survey on AI suggest that organizations use AI to generate value. Some respondents across industries attributed 20% or more of Earnings Before Interest and Taxes (EBIT) earnings to AI, and more than half of respondents reporting AI adoption say its use in multiple areas has reduced costs. Moreover, while companies in general are making some progress in mitigating the risks of AI, most still have a long way to go (Balakrishnan *et al*., 2020).

AI can be used to improve business performance in areas such as predictive maintenance, where the DL can analyze large amounts of high-dimensional data. Over 400 use cases across 19 industries and nine business functions were analyzed and found that AI improved traditional analytic techniques in 69% of potential use cases (Manyika & Bughin, 2018). Monitoring the data has brought significant changes to the core functions of companies, with nearly half of respondents saying they have significantly changed business practices in the sales and marketing functions. Data monitoring as an ally to growth is still under development, however, companies with a higher growth rate are using data analysis to create value for customers and businesses (Henke & Kaka, 2018).

Despite all the success that AI has experienced in some companies and most companies are optimistic about the future developments of IS, many companies remain cautious when it comes to investments and with the pace of changes that can arise from its implementation (Simon, 2019).

Teams must assess new AI investments and measure the impact of their upstream and downstream decisions, as well as implement measures to address it, companies must work towards a critical objective or challenge - first outlining the steps and details to achieve the objective. AI execution teams must be prepared to spend time figuring out what the optimal process would be to achieve goals and also for potential failures or inefficiencies. Once AI is implemented in the first sectors, it will be easier for organizations to have methodologies and protocols that accelerate AI innovation and its existence in parallel across multiple departments. Ultimately, as companies move from one domain to another, their pace accelerates, their AI capabilities increase rapidly, and the company's future will be built faster (Fountaine *et al*., 2021).

Edwards *et al*. (2000), conducted an analysis of expert systems for business decision making at different levels mainly in two different ways and different roles based on experiments carried out two decades ago: in a support role, giving some suggestions and advice, or in a replacement role, making the solution to a problem. The roles of AI (e.g., expert systems) are examined using the three organizational decision-making levels: strategic, tactical, and operational decisions (Figure 1).

Their study shows that expert systems at the replacement level have limitations at the strategic level but can play an essential and influential role in operational and tactical decision-making. At the support level, they can help make better decisions at a strategic, tactical, and operational level, but actual effectiveness can only be achieved with the user. An expert system acting as user support may not significantly impact user time reduction but acting as a substitute can significantly improve decision-making efficiency. Users who used expert systems in a support role did not believe that they had learned or improved anything by using the system.

The authors believe that when implementing expert systems in companies and organizations, they will benefit from greater effectiveness at the three organizational levels of decision-making, replacing or advising specialists in decision-making. However, a manager replacement system for strategic planning decisions also seems impossible to them, and it is also challenging to develop an advisory system to help decision making, due to the high level of uncertainty and complexity involved at this level (Edwards *et al*., 2000).

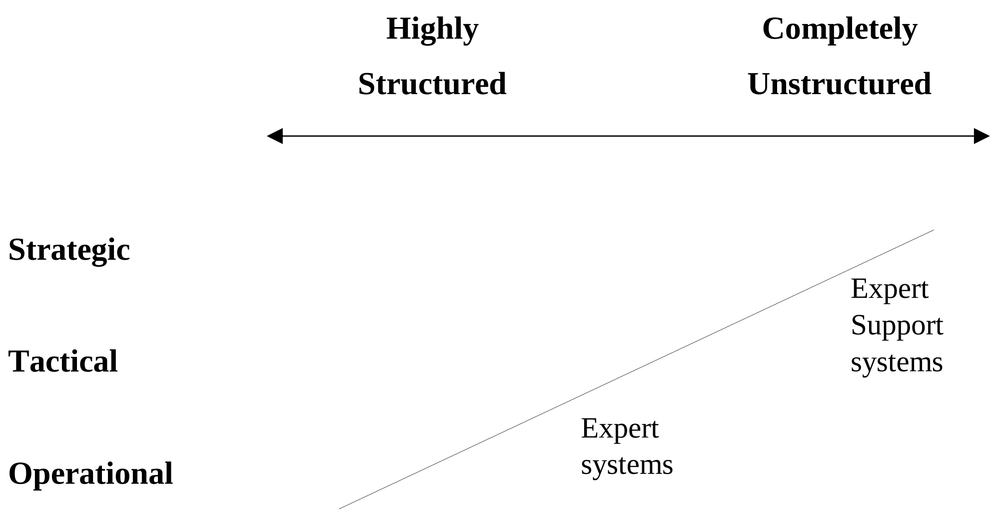


**Figure 1.** The use of expert systems in organizations.
**Source:** Adapted from Edward *et al*. (2000).

The process for achieving AI success starts with a basic understanding of what AI is, how AI will impact the business, current capabilities, and a viable action strategy. Companies that leverage their existing analytical capabilities are likely to get off to a much faster and more effective start with AI (Davenport, 2018).

Some organizations may need more preparation to implement AI or its more complex variants. A more aggressive approach can lead to rapid growth in AI competencies, but any AI strategy must be in the context of the organization's current capabilities (Davenport, 2018a). Source *et al*. (2021) mentioned that organizations are most successful in implementing AI when they start by reimagining a core process, journey, or function (domain). AI can be leveraged to the fullest, reducing development time and costs and starting an organic cycle of change across the organization. Leaders must follow five steps to achieve successful messaging implementation: right-sizing the challenge, assembling and empowering teams, reimagining business as usual, investing in organizational and technological change, and expanding their efforts. Companies can start by honestly evaluating their technology and data infrastructures, so they understand the technology gap between current analytics capabilities and the capabilities needed to use AI successfully.

The organization should conduct a review and assessment in order to understand whether the company culture is geared towards analytics, understand whether the current analytics team will have the ability to identify, define, implement, and maintain analytics use cases across various methodologies and business uses, analyze whether the data and technology infrastructure supports the development and deployment of complex analytics, and finally, assess whether individuals in the organization – including quantitative professionals and managerial champions – are data science, software development and IT expertise to implement AI (Davenport, 2018).

Companies reaping the highest returns from AI have adopted good adaptation management practices. When applying AI, organizations can choose two paths, either apply it to discrete problems to existing processes providing incremental efficiencies but not being enough to drive a change in the way organizations operate or their results, or they overhaul the entire organization. With AI all at once, they typically cannot make a significant impact quickly. The author advises identifying and prioritizing business domains that are broad enough that new AI-enabled ways of working can significantly improve financial performance or customer or employee experiences but are limited enough to deliver results in less than 18 months (Fountaine *et al*., 2021).

Making AI a decision-making tool has been an essential tool in its history; in general, it can help/support humans who are going to make a particular decision or even replace the human decision (Edwards *et al*., 2000). ML effectively manages the data, makes an informed judgment based on the input data and experience, and then takes an action that affects the business process. The ability to turn data into practical solutions and informed decisions is a fundamental need of any organization. With technical advances, technology and IS such as ML and AI are rapidly becoming a way to a business environment; with the adoption of AI-driven systems, companies can improve all their industries (Sandeep *et al*., 2022).

# Chapter II - Stakeholder Theory

## 2.1. Stakeholder Theory

Stakeholder Theory has its origins in the field of strategy when Freeman (1984, p. 25) proposed for the first time the Stakeholder approach as strategic management, classifying it as "any group or individual who can affect or is affected by the achievement of the firm's objectives". One of the central problems in the evolution of ST has been confusion about its nature and purpose. The ST is about how a business can work at its best, value creation and commerce, and managing a business effectively - creating the most significant value (Freeman *et al*., 2010).

Businesses revolve around specific objectives that are a basis for relationships and cooperation between stakeholders and the business. ST proposes that value creation is a collaborative effort in relationships, ideally benefitting the focal business and all its stakeholders (Freeman *et al*., 2010). To understand a business, it is essential create value and to know how the relationships and interactions work between customers, suppliers, financiers, stockholders, managers, etc. (Freeman *et al*., 2010).

Donaldson and Preston (1995) explain that different theories have different purposes and, therefore, different validity criteria and implications. Different types of evidence, criteria, and evaluation methodologies have been used to define the ST, resulting in several interpretations. They also mentioned that the theory has multiple distinct aspects that are mutually supportive: descriptive, instrumental, and normative, and that is why they defend that "the ST is "managerial" and recommends the attitudes, structures, and practices that, taken together, constitute a stakeholder management philosophy" (Donaldson & Preston, 1995, p. 87).

Although the descriptive and instrumental theories are significant aspects of the ST, its fundamental basis is normative and involves acceptance of the stakeholders are persons or groups with legitimate interests in procedural and/or substantive aspects of corporate activity, and the corporation has any corresponding functional interest in them. Furthermore, the interests of all stakeholders are of intrinsic value. That is, each group of stakeholders merits consideration for its own sake and not merely because of its ability to further the interests of some other group, such as the shareowners. The ST identification and salience must account for latent stakeholders to be both comprehensive and valuable because such identification can, at a minimum, help organizations avoid problems and perhaps even enhance effectiveness (Mitchell *et al*., 1997). The ST is unarguably descriptive. It presents a model describing the corporation as a constellation of cooperative and competitive interests possessing intrinsic value. The ST is also instrumental, since it establishes a framework for examining the connections, if any, between the practice of stakeholder management and the achievement of various corporate performance goals. The principal focus of interest here has been the proposition that corporations practicing stakeholder management will, other things being equal, be relatively successful in conventional performance terms (profitability, stability, growth, etc.) (Donaldson & Preston, 1995).

Clarkson (1995) distinguishes stakeholders into primary and secondary stakeholders. Primary stakeholders are those whose continued participation is critical to survival and can significantly and immediately impact the corporation, such as shareholders, employees, customers, and suppliers. Although a secondary stakeholder may be able to influence and be influenced by the corporation, they are not involved in transactions with the corporation and are not essential to its survival, such as non-governmental organizations (NGOs), activists, communities, and governments.

Fassin (2012), argues that Corporate social responsibility should imply corporate stakeholder responsibility and that stakeholder management should contain an ethical component of fair treatment of the company to its various stakeholders, especially the primary stakeholders (Figure 2).

Secondary stakeholders such as NGOs and global activists, through the high visibility they can be subjected to through the media and electronic communication, can mobilize resources, disseminate damaging information about companies and even take action against practices considered offensive to improve corporate responsibility (Waddock *et al*., 2002). Another big thing to consider is the greater awareness in the community and governments about the potential dangers of harmful corporate management.

Also, Clarkson (1995) mentions that in addition to these primary stakeholders, there are secondary stakeholders who are also fundamental for the defense of some interested parties and regulators of laws, official institutions, and control organizations. Strategic stakeholder management has been a great defender of corporate social responsibility and governance.

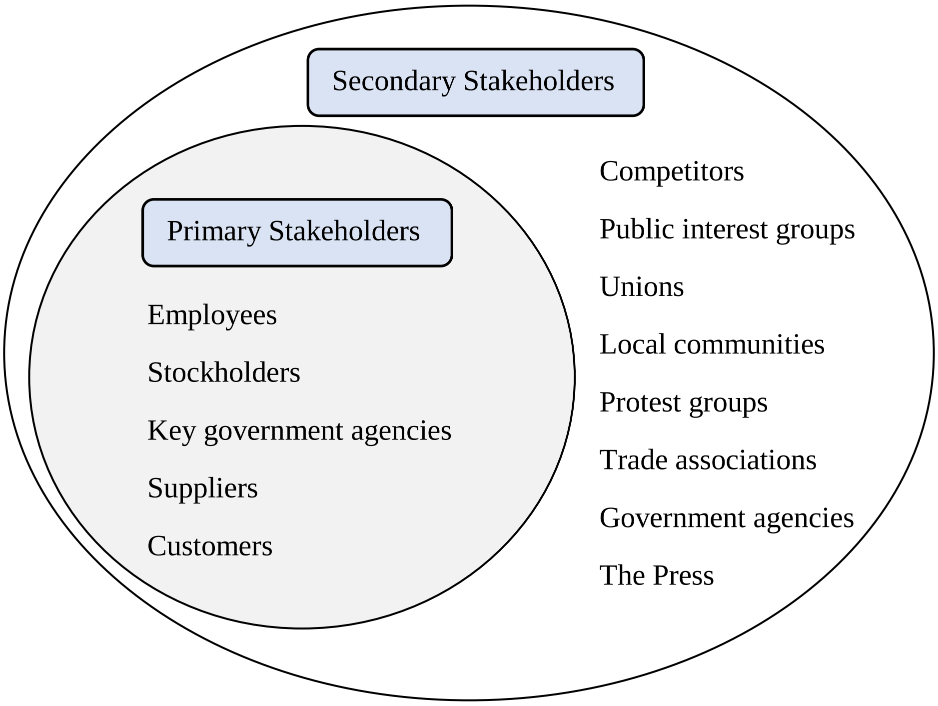


**Figure 2.** Freeman's primary and secondary corporate stakeholders.
**Source:** Adapted from Freeman *et al.* (2010).

All stakeholders will influence the business environment, provide resources, influence the company, and benefit from its growth, efficiency, and impact, whether positive or negative (Donaldson & Preston, 1995). Therefore, it is fundamental and crucial to foster solid relationships with internal and external stakeholders (Freudenreich *et al*., 2019). A company's wealth is sustained over the long term by its relationships with defined stakeholders (Freeman, 1984).

Most frameworks support the view that some stakeholders focus on giving value, while others focus on receiving value. The value that stakeholders receive for their contribution to the business is sometimes unclear, however, their determination is essential for the development and implementation of effective sustainability solutions (Freudenreich *et al*., 2019).

Mitchell *et al*. (1997) proposed a stakeholder identification model that suggests identifying and guiding them by priority and relevance. This stakeholder organization was managed by the *power*, *legitimacy*, and *urgency* of each one. This classification makes it easier for executives to manage responses to the company's various audiences.

A stakeholder has power when he can impose his will in the relationship with the company. This same stakeholder has legitimacy when their actions concerning the company are seen as desirable, proper, or appropriate within society's norms, values, and beliefs. Urgency exists when the firm's attention is urgent, a relationship or complaint is time-sensitive in nature, or when that relationship or complaint is essential or critical to the stakeholder. This model further suggests that executives must meet the demand of a stakeholder organization when each of the three variables is manifested; if only one of the variables is present, the stakeholder will be seen as not being particularly important. If, on the other hand, all three variables are present, an immediate response must be triggered.

For Friedman, the objective of the business is not about social responsibility but about capitalism: "use its resources and engage in activities designed to increase its profits so long as it stays within the rules of the game, which is to say, engages in open and free competition, without deception or fraud" (Friedman, 1962, p. 133), so, ST is about maximizing profits. For Freeman (2010) is different, ST is much more about how to get profits through building good relationships with the customers through great products and services and by building solid relationships with suppliers who keep operations up to date and with employees with a commitment and that improve the company's processes and with communities that allow for the company's prosperous growth.

In a book, the Chief Executive Officer (CEO) of Medtronic, Bill George, reflects on his experience as he summarized the managing for stakeholder's mindset. Serving all stakeholders is the best way to produce long-term results and create a prosperous company. There is no conflict between serving all the stakeholders and providing excellent returns for shareholders. In the long term, having one without the other is impossible. However, serving all these stakeholder groups requires discipline, vision, and committed leadership (George, 2003).

Clement *et al*. (2005, p. 256) conclude that corporations face increasing pressures to respond to their stakeholders. Their literature review article identified five essential lessons from the stakeholder model for business leaders. Corporations have a legal basis for responding to a wide range of stakeholders, are being led by executives in longer guided by the principles of their professions. Ultimately, corporations can improve the bottom line by responding to stakeholder concerns. More value is created as managers focus on creating utility for their stakeholders across both tangible and intangible factors.

Neglect of any stakeholder could set off a downward spiral in the system as the firm's other stakeholders respond to what they observe. Consequently, their position is that the real risk, from a managerial position, is that managers will focus on too few objectives representing too few stakeholder interests rather than too many (Harrison & Wicks, 2013).

For an effective strategy, it is essential to be aware of the environment, past and future changes, and emerging strategic issues and problems. For these reasons, the need for environmental monitoring has increased so that strategies are proactive rather than reactive. Before, companies were concerned with predicting the future environment rather than with changes in the behavior of stakeholders. There began to be a concern with future predictions of the behavior of stakeholders so that the corporation could better predict and plan its response without drastic changes in the actions of the stakeholders. The company's strategy is related to the direction of the company, based on an analysis of organizational capabilities and environmental opportunities and threats (Freeman *et al*., 2010).

## 2.2. Artificial Intelligence applied to Stakeholder Theory

Any company should prioritize the identification of stakeholders because they are the ones who will influence the company's scope of action. A company's stakeholders are individuals and groups that, voluntarily or involuntarily, contribute to its wealth creation capacity and activities and, therefore, are potential beneficiaries and/or risk corridors (Post *et al*., 2002). Therefore, not considering a particular group as an interested party can represent a risk for the company, as this group can contribute positively to market opportunities and prevent environmental, social, and economic problems (Gil-Lafuente & Paula, 2013).

It is impossible to discriminate who the stakeholders of all companies are, not even of a single company. Business strategies and changes in the environment of companies are changing over time, as their objectives and, consequently, those that affect and are affected by the company (Mitchell *et al*., 1997). According to Mohn (2005), the business culture is based on identifying all the people involved in a task. After identifying the stakeholders, the next steps in managing interest groups would be segmentation, prioritization, and dialogue. Many sources report how to identify stakeholders manually, but only some studies report how to do it through IS. Therefore, there is a need for better approaches to uncovering knowledge that can improve understanding of business stakeholder relationships (Chung *et al*., 2009).

Gil-Lafuente and Paula (2013) argue that collecting and processing information will be necessary for successfully identifying stakeholders. Thus, the challenge for companies is to decide which is the best method to identify stakeholders and which tools can be used to process qualitative data and reach a satisfactory result. In a consulting company in Brazil, they used an innovative and helpful tool to identify stakeholders, "the fuzzy logic", more specifically, the "clan theory".

Companies must identify the participants responsible for their sphere of activity. Once companies know their parts, it is essential to characterize them in terms of expectations, issues, geographic areas, their impact on the company's business, and vice-versa. After identifying and segmenting the investigated stakeholders (Stakeholder Map), it is crucial to determine their exact importance and hierarchy to determine their mode of action (Gil-Lafuente & Paula, 2013).

As previously mentioned, there are several methods/criteria to correctly manage the identification of stakeholders (Mitchell *et al*., 1997; Krick *et al*., 2005), including Olcese *et al*. (2008) who suggest how to identify interest groups by analyzing the origin of various financial transactions or business processes.

In the research by Gil-Lafuente and Paula (2013), the stakeholder identification method described by Krick *et al*. (2005) was used according to the type of relationship. They identified stakeholders by the responsibility, that are people with legal, financial and operational responsibilities enshrined in regulations, contracts, policies, or codes of conduct. Influence is those who can influence the organization's ability to achieve its goals. According to the proximity, those are the people with the most interactions with the company. According to Dependency, those are the people most dependent on the organization, such as employees, in some cases, customers, or leading suppliers. Finally, according to Representation, the People are in charge of representing other people through regulatory frameworks.

Chung *et al*. (2009) propose a framework for designing business IS to help managers and analysts to identify and classify their stakeholders on the web, incorporating human knowledge and machine-learned information from web pages and developing a prototype called Business Stakeholder Analyzer (BSA). The framework consists of three steps: intelligence gathering, tagging and feature selection, and automatic classification. The structure's input and output are web and BI data discovered after applying the steps. Each step allows human knowledge to guide the application of techniques.

Research results comparing resource comparison algorithms and a user study showed that the system achieved better in-class accuracies on generalized stakeholder types such as partner/sponsor/vendor and media/reviewer and was more efficient than human classification. Study participants strongly agreed that such a system would save analysts time and help identify and rank stakeholders.

Castro-Herrera and Cleland-Huang (2009) developed a new technique to automatically analyze through ML the contributions and interests of various stakeholders to identify experts in the subject for a topic. Across the *software* lifecycle, the approach has broad applications. During the requirements elicitation phase, it can identify potential stakeholders for new features or inject life into stalled discussions by bringing in new stakeholders. It can also be used to identify stakeholders who might be affected by a proposed change or who might want to participate in product launches. In this way, the approach uses ML techniques to organize stakeholders' contributions into topics and construct profiles that capture their known interests.

This *software* is used to identify three classes of stakeholders for a targeted topic: *Direct stakeholders* who have already contributed ideas to the topic, *indirect stakeholders* who have contributed with ideas for related topics, and *stakeholders inferred* that exhibit patterns of interest that suggest that they may be interested in this topic (Castro-Herrera & Cleland-Huang, 2009).

Lim *et al*. (2005) tested a methodology for stakeholder management strategies in Korean Healthcare IT industry businesses using a stakeholder management strategy support system (SMSS) and using reactive, defensive, accommodative, or proactive (RDAP) strategies. They implement an analysis that consists of four phases: stakeholder analysis, strategy recovery, strategy review, and strategy implementation. Stakeholder management strategies emphasize exploiting conflicting stakeholders to maximize the company's economies of scale. These strategies tend to be formulated using RDAP perspectives (Clarkson, 1995). They used Cased-based reasoning (CBR), a problem-solving technique that reuses past cases, experiences, or tacit knowledge. This methodology is helpful for companies with complicated and profoundly influential stakeholders.

Given the importance and complexity of identifying stakeholders for companies, it is essential to approach the analysis based on complex systems and models that help entrepreneurs in decision-making according to imperative characteristics in each situation and moment (Gil-Lafuente & Paula, 2013).

# Chapter III – Theorical Approach

## 3.1. Objectives and Research Questions

In the previous chapter, two main themes were addressed, Intelligent Systems and Stakeholder Theory, which allowed us to find some gaps in the interconnection of the two themes. Discovering these gaps raised the research questions that will be discussed throughout this chapter. In the literature review, it was possible to find some applications of ST and AI in the business environment. However, the topic can be further explored. As such, it is proposed to answer two research questions to achieve the main objective. As an objective, we will try to understand the impact of IS on ST.

For this, we arrived at the first research question, which tries to clarify the relevance of IS in ST for institutions. On the other hand, in the second research question, the possible factors that can influence the implementation of these IS to the ST in companies/institutions were analyzed through three variables: perception, benefits and challenges.

The way AI is reshaping business, the economy and society are transforming how stakeholders and citizens relate to each other (Nahodil & Vitku, 2013). Several management researchers have been studying the impacts of AI and how this tool may change how we work and relate in an increasingly interrelated and globalized world across customers, businesses, and stakeholders (Huang & Rust, 2018).

The management and categorization of stakeholders in companies have renewed the way companies think about strategic management and improved the utilization and management of resources for formulating appropriate strategies (Lim *et al.*, 2005). Therefore, if there is a good strategy for the planning process, such as stakeholder analysis, it is possible to increase the organization's performance (Mishra & Mishra, 2013).

It is essential to find a model that helps employees in their decision-making (Gil-Lafuente & Paula, 2013). Some authors (Chung *et al.*, 2009; Gil-Lafuente & Paula, 2013); Lim *et al.*, 2005) have tried to create intelligent stakeholder analysis systems. Even Chung *et al.* (2009) demonstrated that this innovative analysis method significantly outperforms the base method.

Readdressing the first question, we try to understand whether corporations will benefit from technologies such as AI in the development of IS to facilitate the process of analysis of stakeholders:

*RQ1 - Is the use of AI relevant in Stakeholder Theory, and does it bring value to companies?*

According to the literature review, the study by Chung *et al*. (2009), using AI to identify, classify and monitor stakeholders obtained better precisions and was more efficient than human classification. Since AI is still not applied to ST regularly, we will try to understand if its implementation can be helpful as a tool for ST and for companies that implement it, giving rise to the second question:

*RQ2 - Which factors linked to Intelligent Systems significantly influence companies' ability to implement Intelligent Systems to analyze stakeholders in their organizational dynamics?*

AI has associated challenges; however, these must be identified so that a team can detail strategies to mitigate these same challenges with appropriate standards (Buehler *et al*., 2021). Miller (2018) argued that the interaction of AI with humans is essential to increase individuals' and collective capabilities. However, there are fears that its presence could replace the full functions of a worker. Although these technologies' benefits are already well-known and demonstrated, some people may fear the consequences they can bring (Stone *et al*., 2016). Therefore, perception becomes an essential element when implementing intelligent systems (Araujo *et al*., 2020).

# Chapter IV – Methodology

Research methodology is a discipline that comes from logic and has as its object the study of the scientific method (Tarski, 1977). This investigation is based on inductive, exploratory research and was carried out from a non-probabilistic convenience sample, constituted according to the availability and accessibility of the elements addressed, which means that the sampling error might be challenging to measure and it is not representative of the population, but with the advantage of being a quick and convenient way to gather the data (Thomas, 2021).

The literature review was based on secondary sources through bibliographic research and information processing, including the systematic study developed in books, magazines, scientific articles, and electronic networks. To have access to scientific papers, searches were carried out in the Scopus and Web of Science databases.

After the Literature Review in this dissertation, an objective and two research questions emerged based on a set of primary sources. To collect and gather the data necessary for the investigation, a mixed approach was chosen between following a quantitative, qualitative, or hybrid system. The hybrid method involves conducting interviews (Annex A) and questionnaires (Annex B). For the first research question, qualitative analysis was selected through semi-structured interviews to understand whether AI becomes relevant in the ST and whether it will add value to companies. Regarding the second research question, the quantitative analysis was selected. The objective was to analyze which factors linked to IS significantly influence companies' ability to implement IS to analyze ST in their organizational dynamics.

Then, in Figure 3, the research model used in this work is described in four steps. The literature review was performed in the first phase, followed by questionnaires and semi-structured interviews. Finally, statistical analysis was performed: quantitative analysis for the questionnaires and qualitative analysis for the interviews:

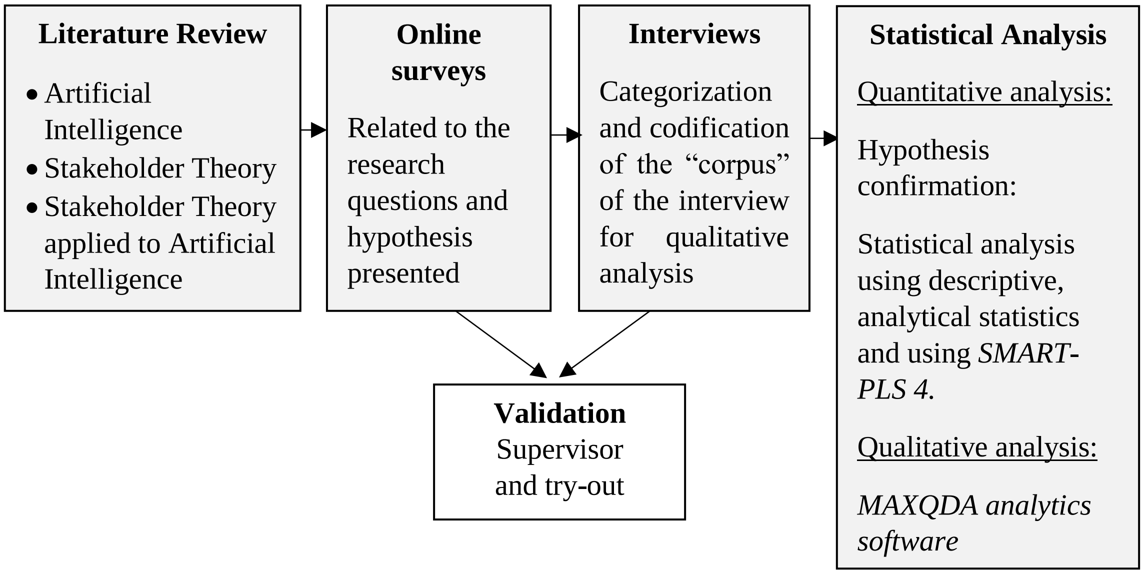


**Figure 3**. Research model design.

**Source:** Author's elaboration.

In Table 1, it is possible to analyze the relationship between the study's objectives, the research questions (RQ) elaborated in the theoretical approach, and the respective connection with the previous literature review.

**Table 1.** Relation between the first objective, research question, methodology and respective references.

<table>
<tr><th>Objectives</th><th>Research Questions</th><th colspan="2"></th><th>Methodology</th><th>References</th></tr>
<tr><td rowspan="5">I.<br>Examine the impact of Intelligent Systems on Stakeholder Theory</td><td>RQ1.<br>Is the use of AI relevant in Stakeholder Theory, and does it bring value to companies?</td><td colspan="2">Interviews</td><td>Qualitative – Interviews with MASQDA 200.1 software</td><td>Vorobeva et al. (2022); Woodward (1954); Senge (1997); Jaiswal et al. (2021); Espinoza (2020); Simon (2019); Balakrishman et al. (2020); Edwards et al. (2000); Miller (2018); Weik (2001); Mueller & Massaron, (2018); Atkinson (2019); Gil-Lafuente & Paula (2013); Buehler et al. (2020); (2021); Li & Zhang (2017).</td></tr>
<tr><td></td><td colspan="2">Hypotheses</td><td></td><td></td></tr>
<tr><td rowspan="3">RQ2.<br>Which factors linked to IS significantly influence companies' ability to implement IS to analyze ST in their organizational dynamics?</td><td rowspan="3">Questionnaires</td><td>Influence of Perception on Artificial Intelligence in the implementation of Intelligent Systems</td><td rowspan="3">Quantitative – SMART – PLS 4</td><td>Holliday (2016); Stone et al. (2016); Simon (2019)</td></tr>
<tr><td>Influence of the Benefits of Artificial Intelligence in the implementation of Intelligent Systems</td><td>Hao (2018); Miller (2018); Daugherty & Wilson (2018); Edwards et al. (2000); Mueller & Massaron, (2018); Atkinson (2019)</td></tr>
<tr><td>Influence of the Challenges of Artificial Intelligence in the Implementation of Intelligent Systems</td><td>Buehler et al. (2020); Shrestha et al. (2021); Mueller & Massaron (2018); Vorobeva et al. (2022); Lu et al. (2017); Li & Zhang (2017)</td></tr>
</table>

## 4.1. Research Model

### 4.1.1. Qualitative Methodology

**1st RQ** - Is the use of AI relevant in Stakeholder Theory, and does it bring value to companies?

The qualitative analysis explores and interprets the collected data, proposing the understanding of social phenomena through inclusion in real experiences (Williams, 2007). This research method relies on dialogue (e.g., by words and experiences), producing qualitative non-quantifiable results through a fundamentally interpretive analysis (O'Leary, 2017). According to Vilelas (2009), acts, comments and gestures can only be understood in their context; an attempt was made to interpret the meaning that people attribute to the analyzed phenomena through observation, collection, and "in loco" analysis of scientific facts and thus, in this way it is possible to analyze the information inductively. During the interview, the interviewer can allow the conversation to proceed fluidly and clarify any issues raised by the respondent or ask probing or follow-up questions (Bhattacherjee, 2012; Carmo & Ferreira, 1998).

On the other hand, it is difficult to group and compare the answers due to the heterogeneity of responses, which can lead to difficulty in synthesizing the data (Vilelas, 2009). Due to this subjectivity and dealing with sample size, projectability is not possible, and it is challenging to apply conventional standards of reliability and validity, so it isn't easy to draw definitive conclusions (Goundar, 2012).

First, a categorization and codification for the interview corpus were created for the qualitative analysis (Fig. 4); after this stage, the interview corpus was formulated, validated by the supervisors, and tested for clarity by a possible participant that met the requirements.

The interviews were semi-structured with open questions and had an intentional character. We invited managers to participate (for free) in a focus group on AI, ML, and Stakeholder theory. They were carried out to 13 participants, managers with more than five years of experience (a prerequisite of the study), and leadership and/or high-level positions in a company that qualifies as a primary source of information. Participants represented various industries (e.g., Banking/Insurance, IT/Technology, Pharmaceuticals) and held different executive positions (e.g., Vice President, Commercial Director, and Inbound Logistic Director). This served to ensure that our propositions and dimensions were adequate, to refine our propositions, and to provide current examples; in addition, we were given a brief description of AI concepts and ST to ensure they mastered the topic.

The objective was to understand their position concerning the relevance of the use of AI in ST and its significance in an organization and, in this way, generate valuable and valid content. Some interviews were conducted online through the *Zoom* platform and others in person between August 20th and September 17th, 2022. The content was recorded for later transcription and content analysis. Its duration was approximately 10-15 minutes. Transcription was in word document format with fidelity to speech.

The number of interviews carried out guarantees a certain degree of reliability; in turn, thirteen interviews were carried out. According to Guest *et al*. (2006), new themes will emerge infrequently and progressively after twelve interviews. Hence, the analysis continued, and therefore a saturation point was reached.

The *MAXQDA Analytics Pro 2022 software* was used to qualitatively analyze the data from the interviews. This software made it possible to categorize the information according to the coding described in Figure 4. A word search was also carried out to analyze all the answers given to specific categories to be able later to present the results in tables with the answers provided by each interviewee, allowing to have an overview of the most frequent answers by the respondents for each of the categories.

Figure 4 below shows the categorization and coding for the interview corpus for further qualitative analysis:

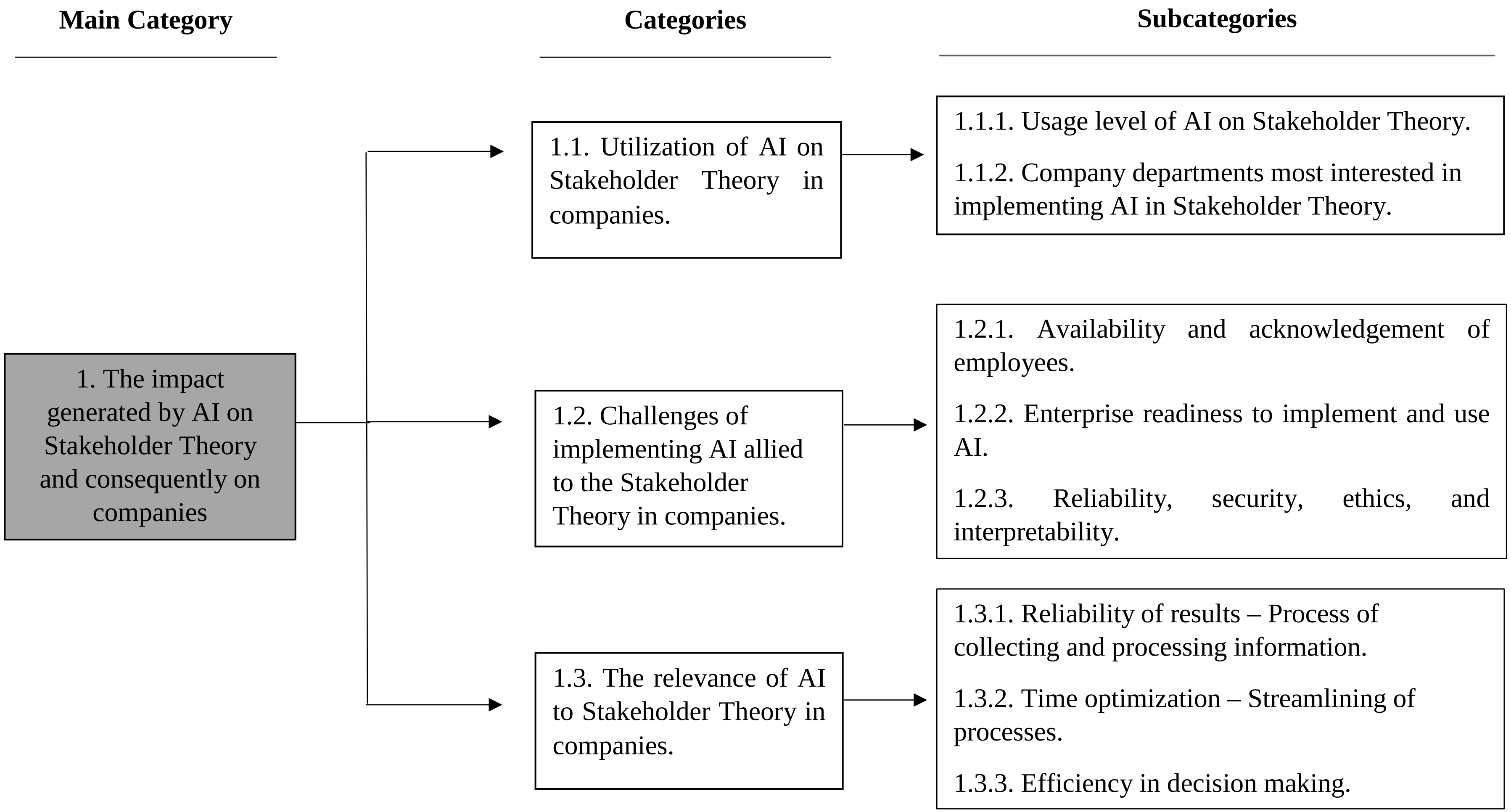


**Figure 4.** Categorization and codification of the interview "corpus" for qualitative analysis.

**Source:** Author's elaboration.

#### 4.1.1.1. Sample description

The sample consists of thirteen participants, and the people interviewed were chosen according to their job position within the companies they work for to get persons that have the necessary experience to become relevant to the study and were invited through the social network via *Linkedin* and personal contacts.

Two (15,4%) of the thirteen interviews were conducted with commercial directors, and two (15,4%) were with store managers. The remaining professional areas are distinct but with a high business position and are represented in Table 2, shown below. Regarding the academic level, ten (76,9%) of the participants have a degree, two (15,4%) have a master's degree, and one (7,7%) doesn't have a degree. The study required that participants had more than five years of professional experience, and the sample consisted of eleven (84,6%) participants with more than ten years of work experience and two (15,4%) participants with professional experience between five and ten years. Three women (23,1%) and ten men (76,9%) participated in the study.

**Table 2.** Sociodemographic characterization of the sample (Interviews).

| | | N | % |
|---|---|---|---|
| **Professional Area** | Business Analyst | 1 | 7,7 |
| | Inbound Logistic Director | 1 | 7,7 |
| | Industrial engineering | 1 | 7,7 |
| | Geospatial engineering | 1 | 7,7 |
| | Commercial Director | 2 | 15,4 |
| | Store manager | 2 | 15,4 |
| | Corporate – Client Management Leader | 1 | 7,7 |
| | General Director | 1 | 7,7 |
| | Product Manager | 1 | 7,7 |
| | Strategy and Business Development - Director | 1 | 7,7 |
| | Manager in public administration | 1 | 7,7 |
| **Academic Level** | No bachelor | 1 | 7,7 |
| | Undergraduate | 10 | 76,9 |
| | Postgraduate | 2 | 15,4 |
| **Years of professional experience** | Less than 5 years | 0 | 0 |
| | Between 5 and 10 years | 2 | 15,4 |
| | More than 10 years | 11 | 84,6 |
| **Gender** | Female | 3 | 23,1 |
| | Male | 10 | 76,9 |

**Source:** Author’s elaboration.

### 4.1.2. Quantitative Methodology

The questionnaire was invented by Sir Francis Galton and is a research instrument that encompasses several questions whose purpose is to capture answers in a standardized way. Structured questions ask respondents to select an answer from a given set of options (Bhattacherjee, 2012), bringing a greater degree of assertiveness as they are understandable to the respondents (Carmo & Ferreira, 2008). This method of analysis has as cons the design difficulties, the fact that it does not apply to the entire population, and a high rate of non-response, but it also has numerous advantages such as a greater probability of data processing and reduction of errors (Vilelas, 2009), becoming capable of effectively translating data into easily quantifiable tables and graphs being extremely dependent on numbers and statistics and therefore offering a greater probability of reliable data that can be projected to a larger population (Goundar, 2012).

The quantitative analysis is controlled and uses numerical data allowing for statistical analysis. The analysis is performed by the relationship of independent variables with dependent variables, based on the hypothesis formulation model, allowing the use of surveys and the performance of descriptive and analytical statistics (Wienclaw, 2021).

The questionnaire was developed through the survey management application released by *Google* - *Google Forms* associated with a *link* that made it possible to fill it out over the *internet*. Before the questionnaire was visible, a pre-test survey was validated by supervisors and applied as a test to four AI professionals to ensure its clarity, relevance, simplicity, errors, extension, and if the questionnaire was adequate for the objective. Its completion was anonymous and voluntary. The data were collected between August 1st and September 10th, 2022, and a total of 168 responses to the questionnaires were obtained. The online questionnaire was published on the *Linkedin* platform through an access *link*, providing a brief introduction to the objectives and descriptions of the concepts and also explaining that the questionnaire was preferably intended for people who had more than five years of professional experience.

The questionnaire was divided into seven sections; the first focused on the professional area, the second assessed the perception and knowledge of IS/AI, the third on the Benefits generated by AI, the fourth on Confidence in AI, the fifth on the Challenges of AI, the sixth in the Possibility of companies to implement IS in their organizational dynamics and, finally, the Sociodemographic Characteristics. The first and the last section were structured with a multiple-answer method to create social clusters, where each respondent is inserted. In the remaining sections, respondents were asked to indicate their degree of agreement with the question. These questions assessed their experience, opinion, and attitude towards a specific subject. For this, the interval-level response was used. Likert response method with seven levels where level 1 corresponded to the answer "I strongly disagree" and level 7 reached the answer "I strongly agree" (Likert, 1932).

To analyze the responses obtained in the surveys, the *Structural Equations Model* (SEM) was used, allowing to establish relationships between the dependent and independent variables, which can be explained as the relationship between multiple regression analyzes of different factors (Ullman & Bentler, 2012; Anderson & Gerbing, 1988). From the conceptual model of RQ2, hypotheses with direct and indirect effects emerged, being tested using the *Partial Least Squares* (PLS) that uses an approach based on the variance of SEM (Hair *et al*., 2017).

Historically, SEM is derived from the hybrid of two different statistical traditions. SEM seeks to represent hypotheses about the means, variances, and covariances of observed data in terms of a smaller number of "structural" parameters defined by an underlying hypothetical conceptual or theoretical model (Kaplan, 2001). According to Tarka (2018), the diagram allows statistically relevant comparisons between theories and models, making understanding relationships between variables instrumental, helping to address the need to explain and predict specific behaviors, groups or organizations.

For questionnaire data analysis, *Excel* editor was used as a data transformer to be transferred later to the *SMART-PLS 4 software* to perform descriptive analyses, regressions, and correlations. To have access to scientific articles, searches were carried out in the Scopus and Web of Science databases. Due to the limited accessibility of articles on the topic that involve both research topics simultaneously, we used all viable articles as support. For the results' analysis and interpretation, the measurement model's reliability and validity were first evaluated, and later, the structural model was analyzed. Second, to assess the quality of the model, the indicators of reliability, convergent validity, internal consistency reliability, and discriminant validity were reviewed (Hair *et al*., 2017).

In order to respond to the main objective of the investigation, the conceptual model represented in Figure 5 and Table 3 was created, considering the hypotheses defined below.

Hypotheses for the 2$^{nd}$ Research Question – **Which factors linked to IS significantly influence companies' ability to implement IS to analyze ST in their organizational dynamics?**

*H1a – The benefits generated by intelligent systems positively impact the perception and knowledge about intelligent systems.*

*H1b – The benefits of AI positively influence the probability of implementing AI.*

*H2a – The challenges from AI influences negatively the probability of implementing AI.*

*H2b – The challenges from AI influences negatively the perception on AI*

*H3a – The perception on AI positively influences the probability of implementing AI.*

*H4a - The perception and knowledge about intelligent systems mediate the effect between the benefits generated by intelligent systems and the intention to implement this type of systems.*

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

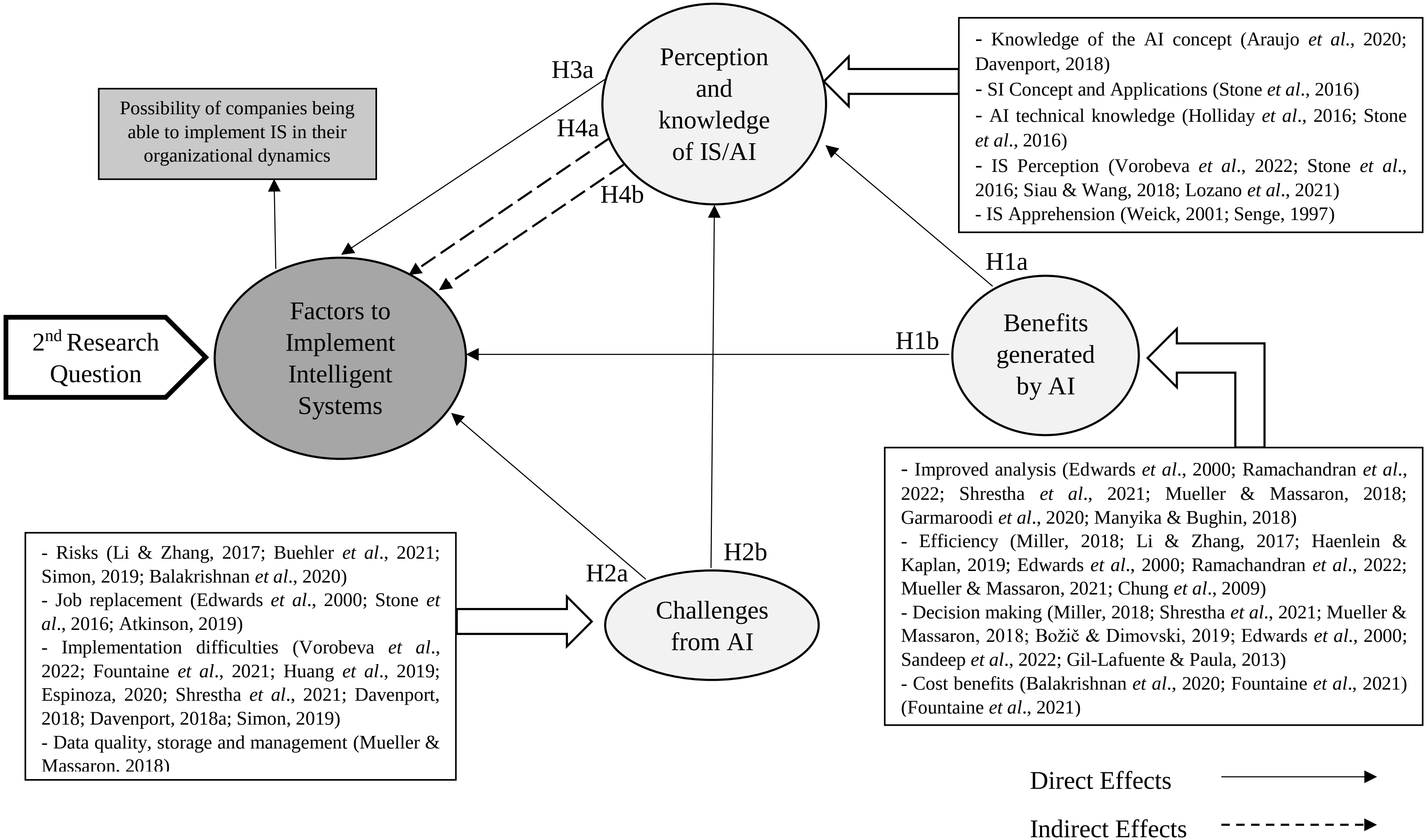


**Figure 5**. RQ2 Conceptual Model.

**Source:** Author's elaboration.

**Table 3**. RQ2 Variables, Indicators and Questions.

| 2. Which factors linked to IS significantly influence companies' ability to implement IS to analyze ST in their organizational dynamics? | | |
|---|---|---|
| **Independent Variable** | **Indicator** | **Questionnaire Questions** |
| **Perception and knowledge of IS/AI** | **Knowledge of the AI concept** (Araujo *et al*., 2020; Davenport, 2018) | - I understand what IS are. |
| | **SI Concept and Applications** (Stone *et al*., 2016) | - I am familiar with the concept and applications of IS. |
| | **AI technical knowledge** (Holliday *et al*., 2016; Stone *et al*., 2016) | - I have the technical expertise to supervise IS activities. |
| | **IS Perception** (Vorobeva *et al*., 2022; Stone *et al*., 2016; Siau & Wang, 2018; Lozano *et al*., 2021) | - AI has more consumers and consequently companies are increasingly taking advantage of its benefits by adopting it in their operations. AI can be advantageous for organizations. |
| | **IS Apprehension** (Weick, 2001; Senge, 1997) | - AI can be an obstacle for companies. |
| **Benefits generated by AI** | **Improved analysis** (Edwards *et al*., 2000; Ramachandran *et al*., 2022; Shrestha *et al*., 2021; Mueller & Massaron, 2018; Garmaroodi *et al*., 2020; Manyika & Bughin, 2018) | - IS can constantly collect, analyze and store a large volume of data and generate more simplified information for the user regarding the ST, consequently simplifying tasks and positively impacting the company. |
| | **Efficiency** (Miller, 2018; Li & Zhang, 2017; Haenlein & Kaplan, 2019; Edwards *et al*., 2000; Ramachandran *et al*., 2022; Mueller & Massaron, 2021; Chung *et al*., 2009) | - The interaction and cooperation at work between humans and IS are advantageous, AI can increase individual work capabilities and strengthening them collectively. |
| | **Decision making** (Miller, 2018; Shrestha *et al*., 2021; Mueller & Massaron, 2018; Božič & Dimovski, 2019; Edwards *et al*., 2000; Sandeep *et al*., 2022; Gil-Lafuente & Paula, 2013) | - Facilitating decision making is a benefit of implementing AI to ST. |
| | **Cost benefits** (Balakrishnan *et al*., 2020; Fountaine *et al*., 2021) | - Cost minimization is a benefit associated with the implementation of AI to ST. |
| **Challenges from AI** | **Risks** (Li & Zhang, 2017; Buehler *et al*., 2021; Simon, 2019; Balakrishnan *et al*., 2020) | - It is hard for an institution to implement an IS that maintains privacy, security, fairness, transparency, explainability, and performance. |
| | **Job replacement** (Edwards *et al*., 2000; Stone *et al*., 2016; Atkinson, 2019) | - The possible human replacement by IS cause me concern. |
| | **Implementation difficulties** (Vorobeva *et al*., 2022; Fountaine *et al*., 2021; Huang *et al*., 2019; Espinoza, 2020; Shrestha *et al*., 2021; Davenport, 2018; Davenport, 2018a; Simon, 2019) | - Implementing IS applied to ST is complicated and challenging at the organizational level. |
| | **Data quality, storage and management** (Mueller & Massaron, 2018) | - Storing and managing a large and diverse amount of data about stakeholders through IS constitutes a challenge and can cause poor-quality data. |
| **Dependent Variable** | **Indicator** | **Questionnaire Questions** |
| **Possibility of companies being able to implement IS in their organizational dynamics** | Interest in Implementing IS | - Considering the Stakeholder Theory, I would like to implement IS in my organizational dynamics. |

#### 4.1.2.1. Sample Description

The sample consists of one hundred and sixty-eight people who responded anonymously and voluntarily to the questionnaire. In the introduction, they were asked to answer the questionnaire only if they had more than five years of professional experience to obtain more viable results that correspond to the reality of the companies. To obtain sociodemographic data, variables such as the business sector and professional work area, gender, age group, and years of professional experience were analyzed. Finally, a quantitative analysis of the responses was carried out to obtain data that would allow later to draw theoretical and empirical conclusions.

Of the one hundred and sixty-eight questionnaires obtained, despite mentioning that it was necessary to have more than five years of experience to answer the questionnaire, fourteen (8,3%) responses were from people with less than five years of experience. However, eighty-one (48.2%) responses were obtained from people with professional experience between five and ten years of experience, and seventy-three (43.5%) responses were from people with more than ten years of professional experience.

Eighty-two (48.8%) participants were female, and eighty-seven (51.8%) were male. Regarding the age of the participants, nine (5.4%) were between eighteen and twenty-five years old, fifty (29.8%) were between twenty-six and thirty-five years old, ninety-four (56%) were between the ages of thirty-six and sixty-five, and finally, fifteen (8.9%) of the respondents were over sixty-five years old.

As for the sector of activity, forty-seven (28%) are from industry, forty-two (25%) people are from production, twenty-three (13,7%) from Wholesale and retail trade, nineteen people (11,3%) from Financial and insurance activities area, eighteen (10,7%) from Human health activities and social support, fifteen (8,9%) from real estate activities, and finally four (2,4%) from the accommodation, catering and similar.

In the question of what is their professional area, forty-five (26,8%) people answered that they work in the area of Strategy and Business Development, and another forty-five people (26,8%) in the area of Human Resources, which are the professional areas with more representation, fifteen (8.9%) in the Commercial area, twenty-four (14,3%) in marketing, fifteen (8,9%) in AI, twenty (11,9%) in finance, one (0,6%) in Information Technologies, one in Operational and finally, two (1,2%) in administrative functions.

**Table 4**. Sociodemographic characterization of the sample (Questionnaires).

| | | N | % |
|---|---|---|---|
| **Business Sector** | Industry | 47 | 28 |
| | Production | 42 | 25 |
| | Wholesale and retail trade | 23 | 13,7 |
| | Financial and insurance activities | 19 | 11,3 |
| | Human health activities and social support | 18 | 10,7 |
| | Real estate activities | 15 | 8,9 |
| | Accommodation, catering and similar | 4 | 2,4 |
| **Professional Area** | Strategy and Business Development | 45 | 26,8 |
| | Human Resources | 45 | 26,8 |
| | Marketing | 24 | 14,3 |
| | Financial | 20 | 11,9 |
| | AI | 15 | 8,9 |
| | Commercial | 15 | 8,9 |
| | Administrative | 2 | 1,2 |
| | Information Technologies | 1 | 0,6 |
| | Operational | 1 | 0,6 |
| **Years of professional experience** | Less than 5 years | 14 | 8,3 |
| | Between 5 and 10 years | 81 | 48,2 |
| | More than 10 years | 73 | 43,5 |
| **Gender** | Female | 82 | 48,8 |
| | Male | 87 | 51,8 |
| | Not identified | 0 | 0 |
| **Age Group** | Between 18 and 25 years old | 9 | 5,4 |
| | Between 26 and 35 years old | 50 | 29,8 |
| | Between 36 and 65 years old | 94 | 56 |
| | Over 65 years old | 15 | 8,9 |

**Source:** Author’s elaboration.

# Chapter V – Results Presentation and Discussion

The results obtained in this section of the dissertation seek to answer the research questions: *Is the use of AI relevant in Stakeholder Theory and does it bring value to companies?* and *which factors linked to IS significantly influence companies' ability to implement IS to analyze ST in their organizational dynamics?*

## 5.1. Qualitative Analysis - Is the use of AI relevant in Stakeholder Theory and does it bring value to companies?

### 5.1.1. AI level used by companies in stakeholder analysis and its usefulness in the organization's departments.

The first generic category 1.1. intended to question the interviewees about the existence of stakeholder analysis in their companies and, if so, whether it is carried out by some intelligent means. This category was subdivided into two subcategories, the usage level of AI on ST (Table 5) and the company departments most interested in implementing AI in ST (Table 6).

**Table 5.** Utilization of AI on Stakeholder Theory in companies.

| Text | Generic Category | Number of times | Interviewed |
|---|---|---|---|
| We use it; however, the processes are supported by database analysis/consultation and manual treatment, but it is manual. | 1.1. | 9 | 2, 3, 4, 5, 8, 9, 10, 11, 13 |
| We use a customer relationship management (CRM) that ends up being a repository of information, but it has to be manually fed. For the remaining stakeholders, it is done manually. | 1.1. | 4 | 1, 6, 7, 12 |

**Source:** Author's elaboration.

All interviewees answered in the affirmative regarding whether the company performed any stakeholder analysis; however, more than half of the respondents responded that they did this analysis manually. Another four participants mentioned using customer relationship management (CRM), a repository of information that has to be fed manually. For other stakeholders, this is done manually *"with sometimes limited results, given the quality of the information available to support these processes"*.

Still related to the previous generic category, it was asked which departments within their company would become more relevant in implementing AI in ST (Table 6).

**Table 6**. Company departments most interested in implementing AI in Stakeholder Theory.

| Text | Generic Category | Subcategory | Number of times | Interviewed |
|---|---|---|---|---|
| Client Management | 1.1. | 1.1.2. | 7 | 1, 2, 8, 10, 11, 12, 13 |
| Marketing | 1.1. | 1.1.2. | 7 | 1, 2, 4, 6, 7, 8, 13 |
| Supplier management | 1.1. | 1.1.2. | 5 | 6, 7, 8, 9, 11 |
| Human Resources | 1.1. | 1.1.2. | 3 | 1, 12, 13 |
| Sales management | 1.1. | 1.1.2. | 2 | 6, 7 |
| All departments | 1.1. | 1.1.2. | 2 | 3, 5 |
| Business Development | 1.1. | 1.1.2. | 2 | 4, 9 |
| Commercial | 1.1. | 1.1.2. | 2 | 1, 6 |
| Strategic management | 1.1. | 1.1.2. | 1 | 4 |
| Operations management | 1.1. | 1.1.2. | 1 | 2 |
| Supply Chain | 1.1. | 1.1.2. | 1 | 2 |

**Source:** Author's elaboration.

The most mentioned departments were client management, *"allowing the segmentation of clients according to their commercial potential, the definition of objectives and directing efforts,"* and marketing *"it would be a great help for analyzing the behavior and connections of clients to the company, an even better analysis of the degree of satisfaction obtained from big data and the various interactions with the company, and their impact. Deeper analysis of customer reactions to the stimuli produced could lead to better products and earlier detection of flops".* Immediately afterward, supplier management was the most mentioned, followed by seven more not-so-repeatedly mentioned mentions.

### 5.1.2. Possible challenges, beneficial factors, and consequent relevance of implementing Intelligent Systems in companies.

The generic category 1.2. resulted in a question posed to the interviewees that aimed to question what challenges companies may face in implementing AI allied to ST. This category was subdivided into three subcategories that were intended to delve deeper into the topic of employees, company availability, and ethics. Table 7 below summarizes the results obtained.

**Table** 7. Challenges from implementing AI in companies.

| Text | Generic Category | Subcategory | Number of times | Interviewed |
|---|---|---|---|---|
| Resistance to change, is mainly due to human resources that do not master IS and who may fear that they will extinguish their jobs or increase the level of demand regarding the results obtained. These factors make teaching employees about AI a difficult task. | 1.2. | 1.2.1. | 7 | 2, 3, 4, 7, 11, 12, 13 |
| Ethical and safety issues GDPR (General Data Protection Regulation). | 1.2. | 1.2.3. | 6 | 1, 2, 2, 4, 7, 11 |
| Ability to update information, collect information and have quality of data/information available in the databases. | 1.2. | 1.2.3. | 5 | 1, 2, 3, 5, 10 |
| Financial resources. | 1.2. | 1.2.2. | 4 | 3, 4, 8, 12 |
| Increased full time equivalent (FTE) - spent on implementing this system. | 1.2. | 1.2.2. | 2 | 3, 4 |

**Source:** Author's elaboration.

Most respondents mentioned the resistance to change, and the fear that AI will extinguish the employees' jobs or increase the level of demand regarding the results obtained as the most significant challenge companies can face when implementing an intelligent stakeholder analysis system. This is in line with Vorobeva *et al*. (2022) point out the fear of employees being replaced by AI as still being a cause for concern, having found that thinking and feeling affect the behavior of employees in the service because AI serves as a benchmark for employees. Often IS allows the work to be done by a different, "less expert" person (Edwards *et al.*, 2000). However, the presence of AI can generate better or worse performance, depending on the task (Vorobeva *et al*., 2022).

Three of the participants pointed out that training decision-makers to make more AI-based and less empirical decisions is a challenge, one of them mentioned that: *"Everything that involves the implementation of new methodologies and changes in procedures, innovation will always face resistance at all levels of the hierarchy in* *companies. It is, therefore, necessary to always go through a process of awareness and training appropriate to the functions and position of each employee"*. In an empirical study by Woodward (1954) of British manufacturing firms, they found that even if the change was implemented slowly and carefully, the reaction of lower supervisors and operators was to resist it. The familiarity of the tasks they perform provides comfort, which prevents them from dealing positively with uncertainty and change, tending to avoid them (Weick, 2001). Also, self-interest, distrust, or preference for a status quo can be factors that will lead employees to question how good the change will be for them (Senge, 1997).

In agreement, Jaiswal *et al*. (2021) and Atkinson (2019) state that organizations must proactively reorganize their policies, practices, and philosophies to accept AI-enabled mechanisms as partners in their operations to take advantage of the benefits of AI. For this, leaders must train employees on AI because companies can prepare to increase their performance in the AI era by increasing their capacity. Adopting AI-enabled services is inevitable; we must understand how to maximize the best service outcomes from human-to-AI interactions (Vorobeva *et al*., 2022; Miller, 2018).

Another of the interviewees points out the age factor as one of the possible causes of this thought: *"the people who work with us, most are over 50 years old. In the era when these workers started to work, little was said about artificial intelligence, it is different from today's generation that was already born with the technology fully implemented"*.

One of the aspects most mentioned by the interviewees as being a barrier to implementing IS in companies was ethical and security aspects. According to Buehler *et al*. (2021), ethical and security issues are two of the possible risks of AI. in the business context, which meets the main concerns of respondents. Nonetheless, as Li and Zhang (2017) mention, technological advantages can be used to improve the regulations of AI practices, such as security and privacy protection.

One of the interviewees specifies: *"Ethical issues are not just about complying with standards but also about implementing them. Ethical and safety issues are a big challenge, and we must ensure that the General Data Protection Regulation (GDPR) was complied with, the data collected were only used internally, and they were not accessed outside the scope for which they were collected. In addition, we would have to ensure that the IS, processes, collection, and use of specific data complied with the Compliance program in force of the company"*. As per the previous comment, an article from the Financial Times newspaper confides having seen a confidential draft exposing that smaller businesses were particularly affected by the costs of compliance with the GDPR. Also, medium-sized enterprises (SMEs) faced challenges in implementing this regulation. The need for clarity on how the rules relate to emerging technologies makes it difficult for regulators to apply them in fields such as AI, blockchain, and the internet of things (Espinoza, 2020).

Next comes up as a challenge, the ability to update information, collect information, and have quality data/information available in the databases. Mueller and Massaron (2018) agree that one of the biggest challenges of AI is collecting value-added data that respects all parameters. Once data is stored or manipulated, it can decrease its reliability. By applying data analysis techniques, it is possible to predict the future and be more efficient in making decisions. Especially in stakeholder analysis, collecting and processing information becomes even more relevant (Gil-Lafuente & Paula, 2013).

Three people mentioned financial resources as a challenge in the implementation of AI. Simon (2019) notes that many companies continue to proceed cautiously when it comes to investments concerning AI, despite feeling optimistic about the development of AI and the success that its implementation has experienced in many companies. While implementing AI comes with an initial cost to the institution, the 2020 results from the McKinsey Global Survey on AI suggest that organizations use AI as a tool to generate value and that its use in various areas reduces costs (Balakrishnan *et al.*, 2020).

Finally, one person mentioned that the implementation of AI could require more time from the employees, either in the development itself or in the adaptation and learning, and this leads to an Increased Full-Time Equivalent (FTE), taking away time that the workers could be spending elsewhere activity.

The generic category 1.3. (Table 8 and Table 9) aimed to question if it would be helpful for companies to have an Intelligent Stakeholder Analysis System. This category was subdivided into three subcategories: Reliability of results, time optimization, and efficiency in decision-making.

**Table 8.** The relevance/ benefits of AI to Stakeholder Theory in companies.

| Text | Generic Category | Subcategory | Number of times | Interviewed |
|---|---|---|---|---|
| Time optimization | 1.3. | 1.3.2. | 7 | 1, 2, 3, 4, 5, 6, 12 |
| Decision making efficiency | 1.3. | 1.3.3. | 6 | 1, 2, 3, 6, 7, 8 |
| Greater security in analyses, projections, and planning. It would allow the use of more robust methods for strategic work. | 1.3. | 1.3.1. | 6 | 2, 4, 4, 7, 9, 12 |
| Anticipate and prevent possible errors and failures | 1.3. | 1.3.1. | 3 | 4, 5, 13 |

**Source:** Author's elaboration.

Time optimization was the factor that interviewees highlighted when asked what the most relevant aspect for the existence of an intelligent stakeholder analysis system in their companies is. In agreement, Ramachandran *et al.* (2022) state that companies want to implement ML and AI because they want precision and time optimization. As an extra, the authors mention that implementing AI improves productivity by reducing repetitive tasks. Implementing AI and ML can be vital tools for any company looking for quantitative help in their decision-making, as it can analyze massive amounts of data. In contrast, Edwards *et al.* (2000) state that when IS are used as support, giving some suggestions and advice may not significantly impact reducing user time, but acting as a substitute can substantially improve decision-making efficiency.

Of the thirteen interviewed, nearly half mentioned efficiency in decision-making, and almost another half had greater security in analyses, projections, and planning as two relevant aspects. As mentioned by the two authors cited in the paragraph above, AI becomes relevant in decision-making since it can collect a large amount of data and translate reliability in analysis and, consequently, confidence in planning. Given the importance and complexity of identifying stakeholders for companies and managers, decision-making must be supported according to imperative characteristics in each situation and moment by complex systems and models (Gil-Lafuente & Paula, 2013). In short, an IS can do an excellent job at the operational and tactical levels and, to some extent, can replace decision-makers and work as a subordinate to senior human managers at the strategic level (Edwards, 2000).

Finally, three interviewees mentioned the anticipation and prevention of errors as relevant to this topic. The study by Shneiderman (2020) corroborates this earlier idea claiming that AI can increase the self-efficacy of users, leading to reliable and safe systems, which can even avoid failures and prevent some human errors and, this way, improves human performance, not meaning that these systems also do not make mistakes.

Still referring to the last generic category 1.3., the last question was asked to understand the fundamental importance that the interviewees give to the analysis of stakeholders using IS, thus directly questioning its usefulness in their companies.

**Table 9**. The impact generated by AI on Stakeholder Theory and consequently on companies.

| Text | Generic Category | Number of times | Interviewed |
|---|---|---|---|
| S.I. would be useful | 1.3. | 11 | 1, 2, 3, 4, 5, 6, 7, 8, 11, 12, 13 |
| S.I. would not be useful | 1.3. | 2 | 9, 10 |

**Source:** Author's elaboration.

Quite significantly, eleven (84,6%) of the respondents answered that the use of IS in the analysis of stakeholders in their companies would be helpful. According to the interviewees, *"The usefulness is immense, and increasingly, through this, it is possible to optimize time and better manage stakeholders' interests. Knowing their interests, companies can invest in areas of greatest interest"* and *"it presents obvious benefits for the organization and consequently for its results and performance"*. This agrees with the authors Manyika and Bughin (2018) and Edwards *et al.* (2000) who consider functional the implementation of IS in organizations. Only two (15,4%) interviewees mentioned that *"in my company, I find the need for an intelligent stakeholder identification system doubtful"*. Simon (2019) referred that some companies cautiously implement AI in organizations.

### 5.2. Quantitative Analysis - Which factors linked to IS significantly influence companies' ability to implement IS to analyze ST in their organizational dynamics?

A theoretical model was constructed to answer the second research question, and an online questionnaire (Annex B) utilizing a 7-point Likert Scale (Likert, 1932). After the results were obtained, we tested the conceptual model using the *SMART-PLS 4 software* (Ringle *et al.*, 2015)., using *Structural Equation Modeling* (SEM). PLS were used, and the analysis and interpretation of the data followed two steps. First, the reliability and validity of the model were tested, followed by the structural model test.

To analyze the model, individual reliability indicators, convergent validity, internal consistency reliability, and discriminant validity were evaluated (Hair *et al.*, 2017). Regarding the reliability of the individual indicators, this is verified since the factor loadings of most items are greater than 0.6 and significant at $p < 0.001$ (Figure 6). As shown in Table 10, rounding of numerical values, all the constructs showed a reliable internal consistency since all the constructs' Cronbach alphas (α) must present values above 0.7 (Hair *et al.*, 2017).

Finally, the Average Variance Extracted (AVE) values must exceed the minimum value of 0.5, a result obtained by performing numerical rounding (Bagozzi & Yi, 1988). Through the Table above, we can verify that the three criteria are verified, and it is thus possible to verify the convergent validity.

Regarding discriminant validity, it was evaluated based on two approaches. The first criterion is that the square root of the AVE of each construct (diagonal values in bold in Table 10) must have a value greater than its highest correlation with any other construct (Fornell & Larcker, 1981). Second, the criterion of the Heterotrait-Monotrait ratio (HTMT ratio) was used, which establishes that all HTMT ratios (values above the diagonal values in bold in Table 10) must be below 0.85 (Hair *et al.*, 2017; Henseler *et al.*, 2015). Once again, Table 10 demonstrates the validity of these criteria.

**Table 10.** CR, AVE, correlations, and discriminant validity checks.

| Latent Variables | α | AVE | 1 | 2 | 3 | 4 |
|---|---|---|---|---|---|---|
| 1) Benefits of AI | 0.818 | 0.641 | **0.800** | 0.302 | 0.236 | 0.696 |
| 2) Challenges of AI | 0.645 | 0.452 | -0.240 | **0.672** | 0.149 | 0.546 |
| 3) Possibility of Implementing AI | | | 0.222 | -0.139 | **1.000** | 0.379 |
| 4) Perception of AI | 0.831 | 0.597 | 0.620 | -0.469 | 0.357 | **0.773** |

*Note: α - Cronbach Alpha; AVE - Average Variance Extracted; Blue-Square roots of AVE; Below diagonal elements - Correlations between the constructs; Above diagonal elements - HTMT ratios.*

**Source:** Author's elaboration.

Hair *et al.* (2017) refer to the primordial need to verify collinearity before evaluating the structural model. For this purpose, the authors refer to the need for the Variance Inflation Factor (VIF) values to be all lower than 5, an aspect verified in this model since the values are in a range of values between 1,000 and 3,014 by turn, did not indicate collinearity.

Once the non-collinearity was confirmed, the structural model was evaluated, and for this purpose, the use of sign, significance, and magnitude of the structural path coefficients was used; the magnitude of the coefficient of determination $R^2$ adjusted for each endogenous variable as a form of predictive accuracy of the model (Hair *et al.*, 2017). The coefficient of determination $R^2$ adjusted for the two endogenous variables of the Factors to implement Intelligent Systems and Perception and Knowledge of IS/AI were equal to 11.3% and 48.6%, respectively, which is higher than the limit of 10%, thus fulfilling the requirement of the authors (Falk & Miller, 1992).

**Table 11.** Direct Effects of the second SEM-PLS Analysis.

| Direct Effects | Path Coefficients β | Standard Deviation | T-Statistics | *p*-values |
|---|---|---|---|---|
| Benefits of AI -> Possibility of Implementing AI | -0.002 | 0.091 | 0.023 | 0.982 |
| Benefits of AI -> Perception of AI | 0.538 | 0.055 | 9.722 | 0.000 |
| Challenges of AI -> Possibility of Implementing AI | 0.037 | 0.083 | 0.443 | 0.658 |
| Challenges of AI -> Perception and Knowledge of IS/AI | -0.339 | 0.047 | 7.201 | 0.000 |
| Perception of AI -> Possibility of Implementing AI | 0.375 | 0.093 | 4.039 | 0.000 |

**Source:** Author's elaboration.

Table 11 shows the direct relationships present in the model, the Benefits of AI, and the Challenges of AI that users feel do not have a significant positive effect on the Possibility of Implementing AI, confirmed by its Path Coefficient (β) and the *p*-value (β = -0.002; *p* = 0.982 and β = 0.037; *p* = 0.658), and these results reject hypotheses H1b and H2a. However, both the Benefits of AI and the Challenges of AI have a significant positive effect on the Perception of AI (β = 0.538; *p* = 0.000 and β = -0.339; *p* = 0.000), showing that the greater the benefits or the challenges identified by users, greater or lesser will be their perception of AI supporting hypotheses H1a and H2b respectively. Finally, it can be said that respondents' perception and knowledge of intelligent systems have a significantly positive relationship with the intention to implement these systems (ß = 0.375; *p* = 0.000), thus supporting hypothesis H3a.

Table 12 presents the results of mediation effects to test the mediation hypotheses (H4a and H4b). Thus, according to the recommendations of Hair *et al*. (2017; p. 232), a bootstrapping procedure was used to test the significance of indirect effects through the mediator (Preacher & Hayes, 2008).

**Table 12.** Indirect Effects of the first SEM-PLS Analysis.

| Indirect Effects | Path Coefficients | Standard Deviation | T-Statistics | *p-values* |
|---|---|---|---|---|
| **Benefits generated by AI -> Perception of AI -> Possibility of Implementing AI** | 0.202 | 0.057 | 3.562 | 0.000 |
| **Challenges of AI -> Perception of AI -> Possibility of Implementing AI** | -0.127 | 0.036 | 3.525 | 0.000 |

**Source:** Author’s elaboration.

The indirect effects of the benefits associated with the use of intelligent systems in the intention to implement this type of system through the mediator perception and knowledge over them are significant with (ß = 0.202; *p* = 0.000), thus providing validation support for the H4a mediation hypothesis. Likewise, the indirect effects of the challenges generated by intelligent systems in the intention to implement this type of systems through the mediator perception and knowledge about them are significant with (ß = -0.127; *p* = 0.000), thus supporting the hypothesis of H4b mediation. Figure 6 shows the testing of the conceptual model with the values obtained.

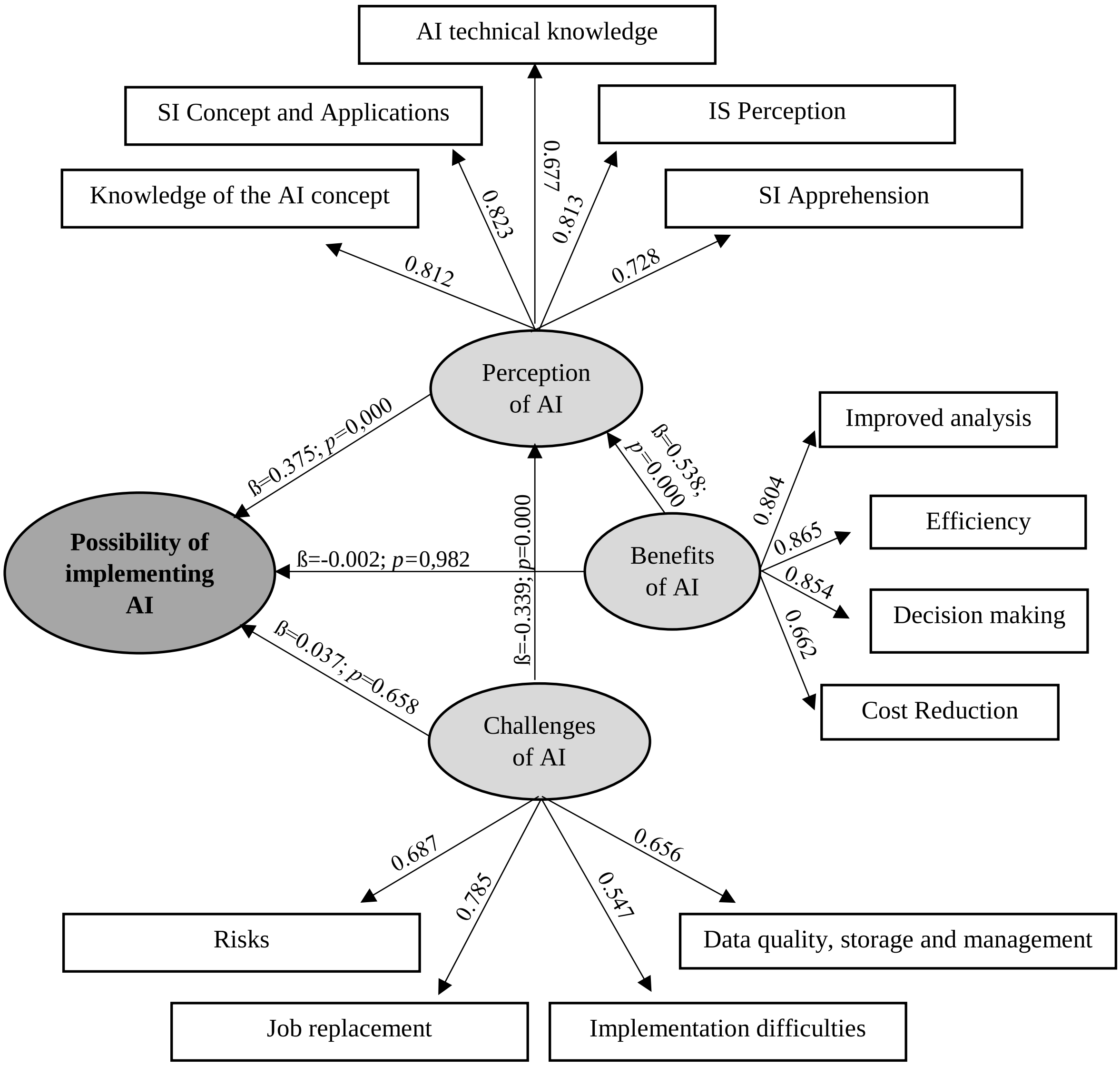


**Figure 6.** RQ2's Conceptual Model results.

**Source:** Author's elaboration.

In order to answer the second research question analyzed in this section, which aims to answer which factors linked to IS significantly influence companies' ability to implement IS to analyze ST in their organizational dynamics, three main factors were analyzed in this section, Perception, and knowledge of AI, the Benefits of AI and the Challenges of AI. Each variable being analyzed used several indicators based on the previous literature review.

As mentioned in the previous paragraph and demonstrated in Figure 6, three main generic categories of factors were identified, through the indicators associated with each category that were tested individually, through the applied questionnaire. The categories found were 1) *perception and knowledge of IS/AI* (Araujo *et al.*, 2020; Davenport, 2018; Stone *et al.*, 2016; Holliday *et al.*, 2016; Vorobeva *et al*., 2022; Siau & Wang, 2018; Lozano *et al*., 2021; Weick, 2001; Senge, 1997), 2) *the benefits generated by the implementation of intelligent systems* (Edwards *et al*., 2000; Ramachandran *et al*., 2022; Shrestha *et al*., 2021; Mueller & Massaron, 2018; Garmaroodi *et al*., 2020; Miller, 2018; Li & Zhang, 2017; Haenlein & Kaplan, 2019; Božič & Dimovski, 2019; Sandeep *et al*., 2022; Gil-Lafuente & Paula, 2013; Balakrishnan *et al*., 2020; Fountaine *et al*., 2021; Stone *et al*., 2016; Manyika & Bughin, 2018; Chung *et al*., 2009) and 3) *the challenges associated with implementing these same systems* (Li & Zhang, 2017; Buehler *et al*., 2021; Simon, 2019; Balakrishnan *et al*., 2020; Edwards *et al*., 2000; Stone *et al*., 2016; Atkinson, 2019; Vorobeva *et al*., 2022; Fountaine *et al*., 2021; Huang *et al*., 2019; Espinoza, 2020; Shrestha *et al*., 2021; Davenport, 2018; Davenport, 2018a; Mueller & Massaron, 2018).

The Perception and knowledge of IS/AI were confirmed to be relevant for the study, as it obtained scores above 0.6, being significant when $p < 0.001$, thus evidencing its reliability (Hair *et al*., 2017). However, the Benefits of AI and the Challenges of AI that users feel do not have directly a significant positive impact on the Possibility of Implementing AI but rather an indirect effect on the Perception of AI, which in turn will influence the possibility of implementing AI.

As for the *perception and knowledge of intelligent systems*, the results show that these are essentially supported by the respondents' familiarization with the concepts (Araujo *et al*., 2020; Davenport, 2018) and their main practical applications, as stated by the authors studied (Stone *et al*., 2016), as well as the degree of technical knowledge (Holliday *et al*., 2016; Stone *et al*., 2016) and IS Perception (Vorobeva *et al*., 2022; Stone *et al*., 2016; Siau & Wang, 2018; Lozano *et al*., 2021) and SI Apprehension (Weick, 2001; Senge, 1997).

Regarding the main *benefits generated by intelligent systems* concerning their application in the business environment, the results are in line with the theory proposed by the authors studied, insofar as the main ones are: improved the quality of analysis (Edwards *et al*., 2000; Ramachandran *et al*., 2022; Shrestha *et al*., 2021; Mueller & Massaron, 2018; Garmaroodi *et al*., 2020; Manyika & Bughin, 2018), brings greater efficiency in performing tasks (Miller, 2018; Li & Zhang, 2017; Haenlein & Kaplan, 2019; Edwards *et al*., 2000; Ramachandran *et al*., 2022; Mueller & Massaron, 2021; Chung *et al*., 2009), assists, guides and aids in decision making (Miller, 2018; Shrestha *et al*., 2021; Mueller & Massaron, 2018; Božič & Dimovski, 2019; Edwards *et al*., 2000; Sandeep *et al*., 2022; Gil-Lafuente & Paula, 2013) and lastly, reduce costs (Balakrishnan *et al*., 2020; Fountaine *et al*., 2021).

Finally, concerning the main *challenges associated with the implementation of intelligent systems* by business managers, the following challenges are listed: Risks that artificial intelligence entails (Li & Zhang, 2017; Buehler *et al*., 2021; Simon, 2019; Balakrishnan *et al*., 2020), the possibility of replacing jobs or tasks (Edwards *et al*., 2000; Stone *et al*., 2016; Atkinson, 2019), the fact that the organization encounters difficulties in implementing this type of system (Vorobeva *et al*., 2022; Fountaine *et al*., 2021; Huang *et al*., 2019; Espinoza, 2020; Shrestha *et al*., 2021; Davenport, 2018; Davenport, 2018a; Simon, 2019) and finally, the difficulty that artificial intelligence may have in the storage, management, and formulation of quality data (Mueller & Massaron, 2018).

Therefore, regarding the direct factors, the main factor with potential impact on managers' intention to implement intelligent systems has identified the perception and knowledge of intelligent systems, thus confirming the H3a. Regarding indirect factors, H4a and H4b were confirmed, as the authors state (Lozano *et al*., 2021; Araujo *et al*., 2020), the greater the emphasis on the added value that this type of technology can bring to the organization and the lower the challenges that entail its implementation, the greater the perception of individuals in relation to AI.

In short, the better the perception of individuals concerning AI, whether they are positively impacted by the benefits or negatively affected by the challenges, the greater the probability of implementing intelligent systems in organizations for stakeholder management.

# Conclusion

## Final Considerations

With the development of AI, consumers and, consequently, companies are increasingly taking advantage of its benefits by adopting it in their operations (Miller, 2018), and, the results are surprising, AI is transforming business (Daugherty & Wilson, 2018). Its correct use can significantly benefit institutions in the long term through growth and economies by increasing productivity and innovation. In the globalized and interconnected world in which we live, rapid adaptation and perception of opportunities are necessary (Shabbir & Anwer, 2015).

This thesis aimed to study the impact of Intelligent Systems on Stakeholder Theory through two objectives, by verifying the relevance of the use of AI in Stakeholder Theory and if it brings value to companies and the other aim is verifying which factors linked to IS significantly influence companies' ability to implement IS to analyze ST in their organizational dynamics. First, an extensive literature review was carried out on the themes of Intelligent Systems, which deepened their most relevant subcategories for this topic and their relevant connection with organizations. The other theme was the Stakeholder Theory, where the theoretical part of the theory was deepened, and finally, the two themes of relevance, AI and ST, were united. The second step consisted of collecting the necessary data and its respective analysis. After conducting a questionnaire analysis with 168 valid responses and 13 interviews, it was possible to reach relevant conclusions about the proposed theme.

First, and taking into account the first research question of this work, referring to the relevance of the use of AI in Stakeholder Theory and its value to companies, it was possible to conclude that the implementation of intelligent stakeholder analysis systems in organizations would be pretty valuable. This agrees with the authors Manyika and Bughin (2018) and Edwards *et al.* (2000) who consider the implementation of IS in organizations useful. This usefulness is mainly due to the optimization of time (Chung *et al*., 2009), efficiency in decision-making (Miller, 2018; Shrestha *et al*., 2021; Mueller & Massaron, 2021; Božič & Dimovski, 2019; Edwards *et al.*, 2000; Sandeep *et al.*, 2022; Gil-Lafuente & Paula, 2013) and in the best and most robust data analysis that would translate into better strategies (Ramachandran *et al*., 2022; Edwards *et al.*, 2000;

Shrestha *et al.,* 2021; Mueller & Massaron, 2021; 2018; Garmaroodi *et al.*, 2020; Manyika & Bughin, 2018).

It was also possible to verify that many of the companies use manual processes of analysis and treatment of data, however, authors refer that with a slow and progressive adaptation of the companies, it will be possible to have a beneficial and consistent implementation of the companies to intelligent systems (Davenport, 2018; Fountaine *et al*., 2021). This implementation will make more sense mainly in the Client Management department, followed by Marketing, Supplier Management, Human Resources, and Sales management. It was also possible to conclude that the most relevant challenges in the implementation of AI are the resistance to change and the whole part involving human resources (Vorobeva *et al.*, 2022; Siau & Wang, 2018; Lozano *et al.*, 2021; Weick, 2001; Senge, 1997; Stone *et al.*, 2016).

Ethical issues have also been shown to be relevant since there are more and more regulations and bureaucracies related to intelligent systems and human rights, such as the General Regulation on Data Protection (Espinoza, 2020). Finally, data quality issues related to updating information, collecting information, and having the quality of data/information available in the databases (Mueller & Massaron, 2021), as well as financial resources, were also relevant (Huang *et al.*, 2019).

Briefly, in most cases, despite possible implementation difficulties, the interviewees' perception was that the implementation of intelligent systems, in the existence of reliable *software* that analyzed and managed the stakeholders, would be beneficial for the theory of stakeholders and organizations.

Moving on to the second research question of this work, which aimed to answer which factors linked to IS significantly influence companies' ability to implement IS to analyze ST in their organizational dynamics. After the Literature Review and subsequent creation of a conceptual model, the variables were divided into three groups: Perception and knowledge of IS, Benefits generated by IS, and Challenges associated with implementing IS.

As for the *perception and knowledge of intelligent systems*, the results show that these are essentially supported by the respondents' familiarization with the concepts (Araujo *et al*., 2020; Davenport, 2018) and their main practical applications, as stated by the authors studied (Stone *et al*., 2016), as well as the degree of technical knowledge (Holliday *et al*., 2016; Stone *et al*., 2016) and IS Perception (Vorobeva *et al*., 2022;

Stone *et al*., 2016; Siau & Wang, 2018; Lozano *et al*., 2021) and IS Apprehension (Weick, 2001; Senge, 1997).

Regarding the main *benefits generated by intelligent systems* concerning their application in the business environment, the results are in line with the theory proposed by the authors studied, insofar as the main ones are: Improved the quality of analysis (Edwards *et al*., 2000; Ramachandran *et al*., 2022; Shrestha *et al*., 2021; Mueller & Massaron, 2021; 2018; Garmaroodi *et al*., 2020; Manyika & Bughin, 2018), Brings greater efficiency in performing tasks (Miller, 2018; Li & Zhang, 2017; Haenlein & Kaplan, 2019; Edwards *et al*., 2000; Ramachandran *et al*., 2022; Mueller & Massaron, 2021; Chung *et al*., 2009), Assists, guides and aids in decision making (Miller, 2018; Shrestha *et al*., 2021; Mueller & Massaron, 2021; Božič & Dimovski, 2019; Edwards *et al*., 2000; Sandeep *et al*., 2022; Gil-Lafuente & Paula, 2013) and lastly, reduce costs (Balakrishnan *et al*., 2020; Fountaine *et al*., 2021).

Finally, about the main *challenges associated with the implementation of intelligent systems* by business managers, the following challenges are listed: Risks that artificial intelligence entails (Li & Zhang, 2017; Buehler *et al*., 2021; Simon, 2019; Balakrishnan *et al*., 2020), the possibility of replacing jobs or tasks (Edwards *et al*., 2000; Stone *et al*., 2016; Atkinson, 2019), the fact that the organization encounters difficulties in implementing this type of systems (Vorobeva *et al*., 2022; Fountaine *et al*., 2021; Huang *et al*., 2019; Espinoza, 2020; Shrestha *et al*., 2021; Davenport, 2018; Davenport, 2018a; Simon, 2019) and finally, the difficulty that artificial intelligence may have in the storage, management, and formulation of quality data (Mueller & Massaron, 2018).

Therefore, concluded that the perception and knowledge about intelligent systems positively affect the intention of managers to implement this type of technology. On the contrary, the benefits and challenges generated by them don’t have influence on the managers' intention to implement this type of technology. Although many people already know the concepts and even the potential advantages and challenges of their use, it is also necessary to increase their in-depth knowledge about this type of technology, in order to promote their real use in organizations.

In short, to get a better attitude and perception towards AI, the individual must think that AI brings benefits. People with a more negative attitude toward AI are more challenged to adapt to innovations (Lozano *et al*., 2021). The greater the general knowledge (education), the greater the positive association with perceptions of benefits, while domain-specific knowledge positively correlates with perceptions of utility and fairness (Araujo *et al.*, 2020).

## Contributions to the Stakeholder Theory

Organizations and companies are forced to rethink their business model as the world is constantly changing and developing. It becomes increasingly important to plan an effective strategy, and for that, it is necessary to be aware of the environment, past and future changes, and emerging strategic issues and problems. For these reasons, the need for stakeholder monitoring has increased so that strategies are proactive rather than reactive (Freeman *et al.*, 2010). All stakeholders will influence the business environment, provide resources, influence the company and benefit from its growth, efficiency, and impact, whether positive or negative (Donaldson & Preston, 1995).

Through this investigation was possible to conclude that there is indeed usefulness in the use of IS related to ST and consequently in organizations and that, although there may be challenges and benefits associated with the implementation of IS in companies, these do not directly influence the possibility of implementing of these systems but influence, indirectly, by first influencing the perception and knowledge of individuals, which, in turn, will directly affect the possibility of implementing these systems.

The results agree with Gil-Lafuente and Paula (2013), who cites the importance for companies of using complex systems and models that help managers in the complexity of the analysis and identification of stakeholders so that decision-making follows the imperative characteristics in each situation and moment.

## Limitations of the study

There are some limiting factors related to the data collection and literature review. The sample obtained, including the number of respondents and responses to the questionnaire, was reduced. Thus, it is necessary to pay attention to the generalization of the results obtained that proves the literature review. The results can also be biased due to several factors, such as a lack of knowledge and attention to the issues. Another factor is that the people who responded work in heterogeneous companies and therefore have different needs in them.

In terms of literature review, the organizations that this master's dissertation intends to study are heterogeneous in their systems and operations, and the implemented IS are sometimes still scarce and, in certain areas and points of interest, the literature review is sometimes limited, which could reduce the benefit of the investigation.

**Suggestions for future investigations**

Future studies that contribute to the ST or the literature would be an asset of a long-term investigation that follows the implementation of IS associated with the analysis of stakeholders and the consequences of this implementation for organizations. Regarding data collection, a larger sample can contribute to more representative results on the subject, and further, carrying out more research at the international level could increase the global reality.

Finally, the last suggestion concerns the benefits and challenges of AI identified in the literature. Since the conceptual model was not able to translate the direct impact of the benefits and challenges of AI on the implementation of AI in organizations, as pointed out by the authors as aspects with positive correlation to the implementation, it would be interesting to deepen this theme to understand if these aspects are a determining factor in its uniqueness for the implementation of these IS.

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# Annex A – Interview Guide

**(Portuguese)**

1. Na sua empresa há algum tipo de análise de stakeholders (assim como identificação, classificação e monitoramento)? Se sim, algum é feito por Sistemas Inteligentes?

2. Quais os departamentos da sua empresa em que se tornaria mais relevante a existência deste Sistema Inteligente? Porquê?

3. Quais os problemas e desafios poderiam ser encontrados na implementação de Sistemas Inteligentes para gerenciamento de stakeholders na sua empresa (como por exemplo, em termos de recursos de implementação, funcionários, questões éticas e de segurança, etc.)?

4. Você acha que seria útil/é útil, um Sistema Inteligente de análise de Stakeholders?

   4.1. Se sim, qual a relevância em termos de confiabilidade de resultados, otimização de tempo e eficiência na tomada de decisão?

**(English)**

1. Does your company have any kind of stakeholder analysis (as well as identification, classification and monitoring)? If yes, is any made by Intelligent Systems?

2. Which are the departments in your company that make the existence of this Intelligent System more relevant? Why?

3. What issues and challenges might you encounter in implementing inteligent systems for stakeholder analysis in your company (in terms of implementation resources, employees, ethical and implementation issues, etc.)?

4. Do you think it would be useful/is it useful, in your company, to have an Intelligent Stakeholder Analysis System?

   4.1. If yes, how effective is it in terms of reliability of results, time optimization and efficiency in decision making?

## Annex B – Structure of the online questionnaire

# Questionário sobre implementação de Sistemas Inteligentes aplicado à Teoria dos Stakeholder

No âmbito da minha Dissertação de Mestrado para obtenção do grau de mestre do curso de Master (MSc) in Business Administration do Instituto Universitário de Lisboa - Business School (Iscte IBS), pedia a sua colaboração no preenchimento deste breve questionário que tem como objetivo principal examinar o impacto dos Sistemas Inteligentes na Teoria dos Stakeholders.

Os dados recolhidos serão usados apenas para fins académicos, sendo o questionário anónimo e confidencial. O questionário tem duração de cerca de 5 minutos e destina-se a pessoas com pelo menos 5 anos de experiência profissional.

Para qualquer esclarecimento adicional, por favor contacte a autora do estudo Ana Rita Montez, através do endereço eletrónico: arhmz@iscte-iul.pt

Muito grata pela sua colaboração!
*Obrigatório

**1. Qual a sua área profissional? ***

- ◯ Recursos Humanos
- ◯ Estratégia e Desenvolvimento Empresarial
- ◯ Inteligência artificial
- ◯ Outra:

**Perceção e conhecimento da Inteligência Artificial**

Questionário sobre Implementação de Sistemas Inteligentes aplicado à Teoria dos Stakeholders.
A Inteligência Artificial é considerada uma tecnologia disruptiva, que mudará significativamente nossa economia e sociedade em um futuro próximo (Li & Zhang, 2017).

Classifique de 1 a 7 o quanto está de acordo com as afirmações.

**2. Compreendo o que são Sistemas Inteligentes. ***

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Discordo totalmente | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Concordo totalmente |

**3. Conheço o conceito e aplicações dos Sistemas Inteligentes. ***

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Discordo totalmente | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Concordo totalmente |

**4. Tenho competências técnicas para supervisionar as atividades de Sistemas Inteligentes. ***

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Discordo totalmente | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Concordo totalmente |

**5. A Inteligência Artificial (IA) tem mais consumidores e, consequentemente, as empresas estão a aproveitar os seus benefícios ao adotá-la nas suas operações. A IA pode ser vantajosa para as organizações. ***

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Discordo totalmente | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Concordo totalmente |

**6. A Inteligência Artificial pode constituir um obstáculo para as empresas.***

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Discordo totalmente | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Concordo totalmente |

## Principais benefícios da implementação de Inteligência Artificial

“Um stakeholder em uma organização é qualquer grupo ou indivíduo que pode afetar ou é afetado pela realização dos objetivos da organização” (Freeman, 1984). A teoria dos stakeholders propõe que a criação de valor é um esforço colaborativo nos relacionamentos, beneficiando idealmente o negócio focal e todos os seus stakeholders (Freeman *et al.*, 2010).

Classifique de 1 a 7 o quanto está de acordo com as afirmações.

**7. Os Sistemas Inteligentes são capazes de recolher, analisar e armazenar constantemente um grande volume de dados e consequentemente gerar informação mais simplificada para o utilizador no que toca à Teoria dos Stakeholders e consequentemente simplificar tarefas e impactar positivamente a empresa. ***

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Discordo totalmente | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Concordo totalmente |

**8. A interação e cooperação no trabalho entre humanos e Sistemas Inteligentes é vantajosa, a IA pode aumentar as capacidades individuais de trabalho e fortalecê-las coletivamente. ***

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Discordo totalmente | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Concordo totalmente |

**9. Facilitar a tomada de decisão é um benefício da implementação de Inteligência Artificial associado à Teoria dos Stakeholders. ***

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Discordo totalmente | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Concordo totalmente |

**10. A diminuição de custos é um benefício associado à implementação de Inteligência Artificial associada à Teoria dos Stakeholders. ***

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Discordo totalmente | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Concordo totalmente |

## Desafios de implementação de Inteligência Artificial associada à Teoria dos Stakeholders

Classifique de 1 a 7 o quanto está de acordo com as afirmações.

**11. É difícil para uma instituição implementar um Sistema Inteligente que mantenha privacidade, segurança, justiça, transparência, explicabilidade e desempenho.** *

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Discordo totalmente | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Concordo totalmente |

**12. A possível substituição humana pelos Sistemas Inteligentes causa-me preocupação.** *

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Discordo totalmente | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Concordo totalmente |

**13. A implementação de Sistemas Inteligentes aplicada à Teoria dos Stakeholders é complicada e desafiadora a nível organizacional.** *

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Discordo totalmente | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Concordo totalmente |

**14. Armazenar e gerenciar uma grande e diversificada quantidade de dados sobre a Teoria dos Stakeholders por meio de Sistemas Inteligentes constitui um desafio e pode originar dados de baixa qualidade.** *

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Discordo totalmente | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Concordo totalmente |

## Possibilidade de implementação de Sistemas Inteligentes nas dinâmicas organizacionais da sua empresa.

Classifique de 1 a 7 o quanto está de acordo com as afirmações e questões.

**15. Tendo em conta todas as entidades que formam o meio envolvente e com que a minha empresa se relaciona, tenho interesse em implementar Sistemas Inteligentes para a sua gestão dinâmica.** *

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Discordo totalmente | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Concordo totalmente |

## Dados Sociodemográficos

Assinale a opção que mais se adequa.

**Género***

◯ Masculino
◯ Feminino
◯ Prefiro não mencionar

**Idade***

◯ Menos de 18 anos
◯ Entre 18 e os 25 anos de idade
◯ Entre 26 e os 35 anos de idade
◯ Entre 36 e os 65 anos de idade
◯ Mais de 65 anos de idade

**Setor de atividade da minha empresa***

◯ Indústria
◯ Produção
◯ Electricidade, gás e água
◯ Construção
◯ Comércio por grosso e a retalho
◯ Transporte e armazenagem
◯ Alojamento, restauração e similares
◯ Actividades financeiras e de seguros
◯ Actividades imobiliárias
◯ Actividades de saúde humana e apoio social

**Experiência Profissional***

◯ Menos de 5 anos
◯ Entre 5 e 10 anos
◯ Mais de 10 anos

**O questionário terminou. Obrigada pela sua colaboração!**