Algorithmic aversion in artificial intelligence co-leadership and the impact of metaphors and comparisons

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Abstract

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The importance of Artificial Intelligence (AI) has been increasing at a fast pace. Besides transforming our lives, these technologies are crucial to improving business operations by conducting tasks faster, better and with lower costs, and by helping in the decision-making process that is an intellectually demanding task. However, despite the advantages AI can offer, people still disbelieve the ability of algorithms, often prefer to decide for themselves and refuse to rely on algorithms after seeing them err. This phenomenon is called algorithm aversion and goes against the best interest of companies that need to gain competitive advantage in a very competitive market. In this way, this dissertation intends to study the potential use of metaphors and comparisons as strategies to reduce algorithm aversion. For this to be done, an experimental study with three experimental groups was conducted. The effect of a language-based metaphor, a visual metaphor and an explicit comparison between human and artificial neurons was studied by relying on a specific type of AI called Artificial Neural Network (ANN) to see if people would prefer this technology that seems to function in a similar way to humans, over a general AI in a leadership position. The results of the study did not corroborate the hypothesis that the metaphors were going to reduce algorithm aversion, as the only difference found in the leadership acceptance was between the general AI group and the human one in which the new leader was a normal person.

Keywords: Artificial Intelligence, Artificial Neural Networks, Algorithm Aversion, Metaphor, Persuasion, Algorithm Leadership, Algorithm Appreciation, Technology

Sumário

Título: Aversão algorítmica na coliderança em inteligência artificial e o impacto das metáforas e comparações

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A importância da Inteligência Artificial (IA) tem aumentado a um ritmo rápido. Além de transformar as nossas vidas, estas tecnologias são cruciais para melhorar operações de empresas, realizando tarefas de modo mais rápido, melhor, com menos custos, e auxiliando a tomada de decisão que é uma tarefa intelectualmente exigente. No entanto, apesar das vantagens que a IA pode oferecer, as pessoas ainda não acreditam na capacidade dos algoritmos, muitas vezes preferem decidir por si mesmas e recusam-se a confiar nos algoritmos depois de os verem errar. Este fenómeno é chamado de aversão ao algoritmo e vai contra o melhor interesse das empresas que precisam de ganhar vantagem competitiva num mercado muito competitivo. Assim, esta dissertação pretende estudar o potencial uso de metáforas e comparações como estratégias para reduzir a aversão a algoritmos. Para isso, foi realizado um estudo experimental com três grupos experimentais. O efeito de uma metáfora linguística, uma metáfora visual e uma comparação explícita entre neurónios humanos e artificiais foi estudado através de um tipo específico de IA chamada Rede Neural Artificial (RNA) para ver se as pessoas prefeririam esta tecnologia que parece funcionar de modo semelhante aos humanos, em vez de uma IA geral numa posição de liderança. Os resultados do estudo não corroboraram a hipótese de que a metáfora incluída na RNA iria reduzir a aversão ao algoritmo, pois a única diferença encontrada na aceitação da liderança foi entre o grupo de IA geral e o humano em que o novo líder era uma pessoa normal.

Palavras-chave: Inteligência Artificial, Rede Neural Artificial, Aversão ao Algoritmo, Metáfora, Persuasão, Liderança por Inteligência Artificial, Apreciação ao Algoritmo, Tecnologia

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Glossary

AI	Artificial Intelligence
α	Cronbach's index of reliability
&	And
ANN	Artificial Neural Network
β	Estimated value of standardized regression coefficient
b	Estimated value of unstandardized regression coefficient
F	F distribution, Fisher's F ratio
IA	Artificial Intelligence
n	Number of cases per condition
N	Total number of cases
p	p-value
r	Estimation of the Spearman's correlation coefficient
R^2	Coefficient of determination
RQ	Research Question
SD	Standard Deviation

> “The rise of powerful AI will be either the best or the worst thing ever to happen to humanity. We do not yet know which” (Hawking, 2016)

1. Introduction

Artificial Intelligence (AI) and other technologies are evolving every day at an ever-faster pace (Haenlein & Kaplan, 2019). Haenlein and Kaplan (2019) noted that this evolution is enabling companies to incorporate these technologies into their processes and decisions, leading to greater competitive advantage and better profits. They also noted that these technological advances are not only profoundly transforming our personal lives, but the way companies explore their processes and how they make wise and difficult decisions. AI is also transforming the workplace and companies will need to adapt to this evolution to establish a lasting competitive advantage to remain in the market (Kaplan & Haenlein, 2019).

Every day, we live in a world surrounded by disruptive advances (such as in science or technology) and massive amounts of information and data (Schwartz, 2004). As the number of options and information increases, decision-making is becoming an intellectually demanding task (Schwartz, 2004). Schwartz (2004) noted that, while it is one of the most important skills one needs to have in life, in the workplace, by governments or companies, decision making is also one of the hardest things to do in a world of so much uncertainty – decisions are both critical and difficult to make.

According to Schwartz (2004) to survive an increasingly competitive world, companies need to make correct judgments about the problems they face, but they are presented with two difficulties: On the one hand, studies show that human beings are inherently irrational, conditioned by psychological factors in decision making and easily manipulated. On the other hand, there is a lot of false information and persuasion made by companies whose sole and ultimate goal is profit (Schwartz, 2004).

In this way, technological advances are here to transform the decision-making processes that must be implemented by companies from different areas and that help in the difficult process of choosing the right decision for a problem, while improving key operations (Kordzadeh & Ghasemaghaei, 2022). Machine learning, smart robots, big data and AI have come to help and should be implemented in work systems to improve task execution and employee performance (Pereira, Hadjielias, Christof, & Vrontis, 2021).

Pereira and collaborators (2021) noted that there is, however, one crucial factor that keeps companies away from the advantages AI can offer: For these revolutionary technologies to reach their full potential to help a company, employees need to accept and understand their underlying benefits and how can they improve processes, productivity, working conditions, and even how they can help with insightful advice that is crucial to answer important questions within a company (Pereira et al., 2021). In addition, AI has the power to contribute to business growth and it is important for employees and managers to adopt these technologies to digitally transform the business (Rampersad, 2020). For this to happen, algorithmic literacy regarding how these technologies work (i.e., teaching statistical concepts such as error and uncertainty, information about the algorithm and training with algorithmic aids) is required for those who run the companies, but also for all employees (Burton, Stein, & Jensen, 2020). Therefore, managers will need to change their leadership style to build trust in employees (Kaplan & Haenlein, 2019). Kaplan and Haenlein (2019) noted that this will require several leadership skills, such as open dialogue, transparency and healthy conflict resolution.

However, there is still a huge disbelief in the ability of algorithms and people are biased against AI. This phenomenon is called algorithm aversion (Dietvorst, Simmons, & Massey, 2015). In other words, it is the preference for human forecasts and recommendations (Reich, Kaju, & Maglio, 2022). Despite the help of these technologies, it can be understood that humans' decisions are irrational and prone to cognitive limitations (Schwartz, 2004). Humans often prefer to have the power to decide over machines, even when AI has proven to be successful at problem solving, decision making and forecasting most of the time (Dietvorst et al., 2015). Decision-making and the need to respond to difficult problems require expertise and unbiased thinking. However, people will more quickly abandon algorithms that make mistakes than humans who make mistakes, and even if humans make bigger mistakes (Dietvorst et al., 2015). Furthermore, humans also ignore the potential of AI technologies because they are afraid of being replaced by these computer systems in their workplace (Jussupow & Benbasat, 2020). This fear has emerged since algorithms and computers have already begun to be applied in tasks previously executed by humans (e.g., computerized tomography of images or deciding whether to keep a prisoner in jail or release; Jussupow & Benbasat, 2020).

Algorithm aversion is an issue that requires attention, as it can be costly for humans, companies and society as a whole to make decisions and let businesses run based on a response or forecast that is not the most profitable and productive (Burton, Stein, & Jensen, 2020; Schwartz, 2004). Minimizing aversion through knowledge, literacy or specific strategies (e.g., potentially persuasive metaphors; Miller & Levine, 2008) is important to remove this additional cost and increase the likelihood of making the right decision (Burton et al., 2020).

Thus, in a world where companies try to survive in an increasingly competitive market, it is important to know how to reduce this fear that employees can have and to study what causes and conditions their aversion to algorithms.

1.1. Problem Statement

This research aims to study and understand, at a mainly managerial level, the use of metaphors and comparisons as strategies that companies can use to reduce aversion to algorithms, changing the perception of employees, and thus increasing the use of these technologies in the work environment. For this to be done, it is important to understand what AI is, what is its potential, what are the reactions of people in general, and employees in specific, to AI and what factors can influence and change this human reaction to AI.

In this thesis, the focus will be on the role of metaphors and comparisons in reducing algorithm aversion. More precisely, the role of a specific type of AI called Artificial Neural Networks (ANNs) will be studied. ANNs are computational models that try to recreate the processes that humans have inside their brains when making decisions (Jain, Mao, & Mohiuddin, 1996). Since this type of AI has "neural" in its name (i.e., a metaphor), how will people perceive this technology compared to others? If people know the similarities between human and artificial neurons, will they feel algorithms are something more natural and therefore be less averse to them?

To substantiate the problem statement, the following research question will be explored:

RQ: Do metaphors and comparisons have an impact on people's perception of algorithms?

1.2. Relevance

This dissertation contributes to the current literature and research on AI, appreciation and aversion to algorithms by analyzing how human and algorithm characteristics contribute to changing people's perception of AI and synthesizing studies that show empirical evidence on the appreciation or aversion to algorithms. Furthermore, this dissertation explores the role of metaphors and comparisons to combat aversion to technologies that are proven to be more efficient than people in forecasting and making decisions (Dietvorst et al., 2015). This is a contemporary discussion, and it is important to research and learn more about the potential impacts that AI will have on the future workplace (Jussupow & Benbasat, 2020).

Understanding how humans perceive and interact with these technologies is important in deciding when to use algorithmic support or not, and in which situations using them will lead to better decisions (Jussupow & Benbasat, 2020). Thus, the findings of this research are relevant to managers that are trying to increase employees' acceptance of AI and to incorporate these technologies within company processes. Since AI technologies are becoming increasingly important and bring productivity increases, companies that use metaphors associated with AI would potentially be able to maintain their competitive advantages in a market that is increasingly competitive and with innovative companies emerging (Makridakis, 2017).

The findings of this research will also be relevant to society as a whole, as these technologies are revolutionizing industries, stimulating economies and creating solutions to address the challenges we face today concerning, for example, the environment, food, water and security (Rampersad, 2020). In addition, companies may have a greater use of AI technologies that can help to improve the efficiency of internal operations (Kaplan & Haenlein, 2019) and the knowledge gained on how to reduce algorithm aversion can be applied not only to employees but also to customers.

1.3. Structure

To answer this thesis' research question and investigate more about AI, this thesis is organized as follows: In the next chapter, the literature review will be useful to summarize previous empirical results and findings on AI, the factors that drive people to have algorithm aversion or appreciation, and what is persuasion and metaphors, what are the characteristics that condition them, and the effects they can have in changing people's attitudes and behaviors. In the third chapter of the dissertation, the methodology of the experimental study will be detailed and explained. In the fourth chapter, the resulting data will be analyzed. In the fifth chapter, the most important results of the study will be explored and discussed. The discussion chapter will also be the stage for limitations and future research. Finally, in the sixth and last chapter, the most important conclusions will be addressed.

2. Literature Review

2.1. Acceptance of AI

2.1.1. What is it?

AI refers to the intelligence of machines and computerized systems that are programmed to interpret and learn from external data (Haenlein & Kaplan, 2019) through flexible adaptation (Kaplan &

Haenlein, 2019), in such a way that they can mimic and simulate the way humans think and act, having the ability to learn, decide and plan (Pereira et al., 2021). AI uses data from the internet of things (i.e., "the idea that devices around us are equipped with sensors and software to collect and exchange data" that is necessary as input for AI; Kaplan & Haenlein, 2019, p.17) and similar sources and, by relying on machine learning, it can identify rules and patterns that help computers to continuously learn (Kaplan & Haenlein, 2019).

According to Kaplan and Haenlein (2019), the types of existing AI technologies are defined considering three types of competencies: cognitive intelligence (e.g., pattern recognition), emotional intelligence (e.g., adaptability and self-confidence) and social intelligence (e.g., empathy). Considering these skills, there are three types of AI (Kaplan & Haenlein, 2019):

a) Analytical AI: It has only characteristics related to cognitive intelligence and it is the most used AI system among firms. It is used to perform, for example, image recognition or financial fraud detection.
b) Human-inspired AI: It has characteristics of cognitive and emotional intelligence. In addition to the activities that analytical AI can perform, this type of AI can also understand human emotions when it is making decisions. Companies use these systems, for example, to recognize customers' emotions when interacting with them.
c) Humanized AI: It has cognitive, emotional, and social competencies. These systems are a project for the future and will be able to be both self-conscious and self-aware in interactions. Progress has already been made in the areas of human recognition and mimicking.

Pereira and collaborators (2021) noted that AI is expected to surpass the way humans work and optimize processes and production within companies, doing tasks that can be replicated and that can potentially harm humans. Besides that, AI technologies allow tasks to be conducted faster, better and with lower costs (Kaplan & Haenlein, 2019). These algorithmic systems can be used to assist humans in the decision-making process by generating information, doing predictive analysis and providing recommendations (Kordzadeh & Ghasemaghaei, 2022). According to Makridakis (2017), it is important for companies to engage in these AI technologies because they can bring the productivity improvements necessary for companies to remain competitive.

AI systems can be used in different areas such as finance (e.g., risk classification; Kordzadeh & Ghasemaghaei, 2022) or medicine (e.g., algorithms that develop medical decisions that are followed by doctors; Jussupow & Benbasat, 2020) and they can already be found in our daily lives in schools, corporations or even being used by the government (Kaplan & Haenlein, 2019). Some schools have already implemented AI-based virtual teaching and used AI to check for plagiarism in academic reviews (Kaplan & Haenlein, 2019). According to Kaplan and Haenlein (2019), in companies, it can be useful in several areas: in marketing and sales to create personalized communication according to customers' preferences, in retail to help manage inventories and in customer service with chatbots that assist the customer and generate responses to their inquiries. Companies also use human-inspired AI that helps identify customers' mood through face recognition (e.g., Walmat) and create personalized recommendations based on customers' taste (e.g., Spotify and Netflix that recommend music and movies, respectively; Kaplan & Haenlein, 2019). In addition, AI is one of the reasons for the emergence of fintech startups that have created, for example, robo-advisors. Finally, these technologies are also being used by governments in smart street lightning or in recruiting soldiers (Kaplan & Haenlein, 2019). AI technology is expected to optimize production processes, improve managerial decisions, to change the way recruitment processes are done (e.g., by making them faster and having a database that selects the right people for a certain position within the company) and help with employee retention or engagement, by being effective and giving employees new challenges to face (Pereira et al., 2021).

In addition, studies have shown that AI technologies can be unbiased and make better decisions (Dietvorst et al., 2015). There are, however, examples of companies that have had to stop using algorithm systems because of algorithm bias. Algorithm bias happens when an algorithm distributes burdens and benefits unevenly due to "differences in individuals' inherent characteristics, talents, or luck", deviating from the principle of equality in a systematic way (Kordzadeh & Ghasemaghaei, 2022, p.394). One example of a company that had to stop using an AI system due to algorithm (gender) bias was Amazon, where men held 75% of the company's management positions. Kordzadeh and Ghasemaghaei (2022) noted that the company was forced to stop using the algorithm for recruitment decisions because algorithm bias was discovered, as the algorithm recommended mostly men for new management positions. Thus, although AI has impressive benefits and help companies to succeed, they can also bring problems and ethical questions.

Furthermore, many scholars (e.g., Choi & Kang, 2019; Haenlein & Kaplan, 2019; Kaplan & Haenlein, 2019; Rampersad, 2020) fear that AI technologies reduce the importance of the role of people in production, that these technologies reduce manual work in sectors with lower productivity rates and fear the general replacement of labor in tasks that can be automated or where there is less need for skills (e.g., low literacy or problem-solving abilities). Some also defend that job loss will affect employees in an emotional level, increasing stress levels and making them less committed to work and less productive (Pereira et al., 2021). To combat the job loss and the potential economic inequality these technologies can create, some advocate the creation of policies to slow job loss (e.g., employee education and training, tax penalties for companies that eliminate jobs and incentives to create startups that increase total employment) and policies to serve societies with high rates of job loss (e.g., a universal income that guarantees access to basic necessities and incentives to volunteer, so that people stay busy and fulfilled; Choi & Kang, 2019).

On the contrary, there are also many scholars who believe that new jobs and skills will be created (e.g., Haenlein & Kaplan, 2019; Kaplan & Haenlein, 2019; Wilson, Daugherty, & Morini-Bianzino, 2017). This is the case since human intervention will be required to ensure that tasks performed by AI technologies are effective and accountable. Therefore, it will be necessary to have people capable of explaining the processes behind the machines and to ensure that activities continue to be ethical and in accordance with human norms, values, and morals (Wilson et al., 2017).

In this way, people will need to develop skills that are crucial for the future and that AI cannot replicate (Rampersad, 2020). Many argue that humans will always have the upper hand in jobs that involve artistic creativity, innovation (Kaplan & Haenlein, 2019) and social and interpersonal skills (Makridakis, 2017). Therefore, workers of the future are expected come up with new ideas to revolutionize industries and possess skills such as: critical thinking, problem solving, communication and teamwork (Rampersad, 2020). Entrepreneurs, innovators and creators will be increasingly important (Kaplan & Haenlein, 2019). It is important for people to develop these skills to ensure that workers can use new technologies effectively and to ensure "that they survive and thrive in a quickly changing workplace" (Rampersad, 2020, p. 68).

However, it is still not obvious that technology advances will generate enough new jobs to accommodate the many employees who will lose their low-skilled jobs (Haenlein & Kaplan, 2019).

2.2. AI reactions

According to previous studies, there are two main ways people react to AI and associated technologies: Algorithm aversion, in which people prefer a human agent over an algorithm to perform a task, and algorithm appreciation, which refers to positive behaviors towards algorithms and shows that people are not exclusively averse to algorithms and sometimes even prefer to use them (Kordzadeh & Ghasemaghaei, 2022).

2.2.1. Algorithm aversion

The literature shows that algorithms can forecast with more accuracy than human forecasters. However, humans generally prefer to decide for themselves rather than putting all their trust in a machine (Dietvorst et al., 2015). This constitutes the concept of algorithm aversion, and, in this subsection, I will examine the particular case of algorithm aversion in terms of employees and managers, leaving customers out. This will happen since the focus of this thesis is on employees' and managers' aversion to the algorithm, not on customers'.

In addition to preferring to decide by themselves, people also refuse to use algorithms after seeing that they are not perfect. This happens even if people's predictions are not perfect either and they get it wrong more often than the algorithms (Dietvorst, Simmons, & Massey, 2018). Jussupow and Benbasat (2020) noted that people assess algorithm and human agent performance differently and there is a biased evaluation of performance. The reason why decision makers struggle so much and give so much importance to algorithms' errors can be explained by the theory of expectation-disconfirmation (i.e., the theory that explains the psychological motivation behind the expectation that the algorithm will perform well; Sohn & Kwon, 2020). According to this theory, individuals often believe that the algorithm is perfect and will not make mistakes, but upon realizing that this is not true (i.e., the disconfirmation of their expectations), they will punish the algorithm much more than they would if a human decision maker failed (Jussupow & Benbasat, 2020). Furthermore, humans are reluctant to use algorithms that they know to be "superior but imperfect", even if they know they will get a bonus and be compensated monetarily if they make a good prediction (Burton et al., 2020, p.222). In other words, most of the time, people miss the opportunity to receive this monetary bonus because they would rather decide for themselves than choose the algorithm to help them in the decision process (Burton et al., 2020). This shows that people will often lose because of their aversion to algorithms, and these costs can also translate to a higher level, affecting companies as well.

The literature shows that there are also lots of factors that influence people's aversion to algorithms. General perceived capabilities, for example, are a reason for algorithm aversion because algorithms are often perceived to lack capabilities for a specific task. This happens more often in tasks that involve moral decisions because algorithms lack empathy and other human characteristics (Jussupow & Benbasat, 2020). In addition, algorithms are also not capable of performing highly subjective tasks (Jussupow & Benbasat, 2020).

Furthermore, people can be averse to algorithms because they can integrate social biases, such as discrimination, stereotypes, or prejudice, thus exacerbating inequalities in the workplace and in society. In this way, algorithm bias can change the perception of fairness and can generate an aversion to algorithms (Kordzadeh & Ghasemaghaei, 2022). If a company uses a biased algorithm, that organizational decision is likely to replicate and reinforce these social biases as they are fed back into the algorithm. These discriminatory outcomes are contrary to norms of justice and equality principles and primarily affect minorities, underprivileged and marginalized groups (e.g., black people and women; Kordzadeh & Ghasemaghaei, 2022).

At the corporate level, it is necessary to explain and prove to employees the importance of these technologies and how they will benefit from them. Not only can employees be algorithm averse, but so can managers, and this aversion needs to be addressed at a higher level (Burton et al., 2020).

Despite the frequency of literature focused on algorithm aversion, the opposite, algorithm appreciation, has also been shown, as seen in the next subsection.

2.2.2. Algorithm appreciation

Studies have shown that humans are more willing to use AI and rely on these technologies to decide and forecast in an incentivized forecasting activity if they had no experience with the algorithm before (i.e., if they had no information about the performance of the algorithm). Thus, the literature shows that people are not always averse to relying exclusively on algorithms (Dietvorst et al., 2018).

According to Kordzadeh & Ghasemaghaei (2022), people are likely to accept algorithmically generated recommendations if the decision involves mechanical tasks that require lower levels of human skills. In tasks that require human skills, such as intuition (e.g., hiring or evaluation of employees' work), people will not think that the algorithm has what it takes to make a fair judgment since it does not have these human qualities (Kordzadeh & Ghasemaghaei, 2022; Lee, 2018).

Furthermore, studies have shown that people are willing and likely to choose algorithms to make predictions when they can modify the algorithm's imperfect prediction, even minimally (Dietvorst, Simmons, & Massey, 2018). By making small adjustments to the algorithms' prediction, they will perceive it as superior, and this will make them satisfied and perform better, since the forecast will be closer to being correct. According to Dietvorst and collaborators (2018) , it is not necessary to give people much control of the algorithm to reduce their aversion because even a small amount of control is enough to make people prefer using an algorithm rather than relying on their own forecasts.

Since the literature shows that people can be both averse to and appreciative of algorithms, it is interesting to understand what factors can influence these AI reactions.

2.3. Factors that influence AI reactions

As mentioned in the introduction, for technologies and AI to have an impact in our lives and to help solve problems, people need to accept and understand their importance. It is essential that employees learn how these technologies can help, so that companies can exploit these emerging technologies to their fullest potential (Makridakis, 2017). Therefore, managers need to show employees the benefits of AI and how it can contribute to a safer and more productive workplace (Pereira et al., 2021). Thus, understanding the reasons behind people's resistance to technological changes and how a company can change the way it is implementing AI to create curiosity and engage employees is very important.

Research on the topic shows that there are many factors that can contribute and influence people's aversion to algorithms. Jussupow and Benbasat (2020), for example, noted that people distinguish between two types of algorithms: Performative algorithms, in which the algorithm has decision authority as it can perform complex tasks autonomously and thus replace human work, and advisory algorithms, in which humans have decision-making power, choosing whether to follow the advice given by the algorithm. It is known that humans like to have more control over the decision process and the technology they are using, and therefore, they are less averse when dealing with an advisory algorithm (Jussupow & Benbasat, 2020).

In addition, people's involvement in the algorithm can influence their AI reaction. If humans can train the algorithm by providing expertise or if they create a "human-algorithm hybrid" (Jussupow & Benbasat, 2020, pp. 8-9) in which the human makes the final decision, this involvement will create the impression that the algorithm is capable of solving the task. Thus, people will perceive it as being a valid source of information, the algorithm will be evaluated more favorably, and aversion will decrease. According to Jussupow and Benbasat (2020), human involvement reduces aversion by making the algorithm an advisory one, and by increasing its perceived capabilities. The authors noted, however, that it is still not clear if a human-algorithm hybrid performs better than algorithms by themselves.

Furthermore, performance information is also a factor that influences AI reactions. This happens since performance information is related to the expectation-disconfirmation theory and can change the way people perceive algorithms (Jussupow & Benbasat, 2020). Thus, the way information is displayed and framed can change how decision makers see and perceive the algorithm. Jussupow and Benbasat (2020) noted that if, for example, a person expects lower degrees of performance and therefore a higher probability of algorithm failure, the aversion will be stronger.

The aversion to algorithms also depends on ease of use, usefulness, and whether people are looking for new experiences and are curious about technology. As AI technologies are in early stages of social acceptance, aversion is also heavily influenced by other people's opinion of trusting these technologies (Sohn & Kwon, 2020).

Furthermore, according to Filiz and collaborators (2021), overconfidence leads to algorithm aversion because people follow their gut and intuition rather than an algorithm to make investment decisions that turn out to be suboptimal. The authors noted that experience and repeated feedback regarding investments and experience helps people to better access their capabilities, reducing their overconfidence. After accessing their abilities more realistically, people gradually delegated their predictions to the algorithm, causing their aversion to decrease over time (Filiz et al., 2021).

Furthermore, as mentioned in the algorithm appreciation subsection, another way to reduce people's aversion to algorithms is to give them control over the algorithm (i.e., the chance of slightly modify the predictions of an imperfect algorithm; Dietvorst et al., 2018).

There are also some authors who try to study ways to make people less averse to algorithms. Reich and collaborators (2022), for example, observed that when people make mistakes and demonstrate learning from them, this initial mistake is seen as beneficial and as experience gained. In this way, the author sought to build a conceptual bridge and studied whether the same would happen with technology. Reich and collaborators (2022) found that people are often afraid of algorithms after seeing them err, because they do not think these technologies can improve their skills through learning. Therefore, by emphasizing that algorithms can learn over time, people will perceive these mistakes as opportunities, trusting technology and being less averse to algorithms (Reich et al., 2022). Berger and collaborators (2021) did a similar study and found that the ability of algorithms to improve and learn over time reduces people's aversion after seeing an algorithm err, avoiding biases and errors in decision making.

In addition, Reich and collaborators (2022) studied the effect of changing the name of an algorithm on consumer confidence in its ability to learn. The authors made a language-based change by calling the algorithm a "machine learning algorithm", which shows the ability to learn in the name. Reich and collaborators (2022) observed that this language-based change shifted consumers' preferences toward the algorithm (i.e., participants chose the technology to make art quality estimates over themselves more often compared to when the algorithm was just labeled “algorithm”). This is a particularly interesting experiment, as in this thesis I am also studying the impact of a language-based change on the name of technology on people's perception of algorithms. Furthermore, the experiment suggested that the aversion decreased when the authors made the machines more similar to humans, showing that they can learn, and in this dissertation I am making a similar comparison, showing participants that the decision process in ANN has a similar basis to what happens in our decision process.

2.4. Persuasion and Metaphors

In this section, a review of the literature on persuasion and metaphors will be helpful in summarizing what they are and how they can change people's attitudes. These are the main focus of the thesis, as I want to study whether metaphors and comparisons can change people's perception of algorithms, making them less averse. This is especially important because if metaphors and comparisons can change algorithm aversion, companies can strategize based on these social influences and make employees and managers want to use these technologies.

In this section, the literature will first be reviewed regarding the concept of persuasion and what are the factors that condition people to be persuaded. The literature review will include the Elaboration Likelihood Model (ELM), which is a model that studies attitude change. Afterwards, a review of the literature on metaphors will be made, explaining what a metaphor is and in which situations it can be useful and act as a persuasion tool, connecting the concept to the ELM. Finally, I will explain my hypothesis and what the main objective of the thesis is.

2.4.1. Persuasion

Persuasion is a type of social influence in which a person tries to influence another one through communication (Miller & Levine, 2008). According to Miller and Levine (2008), a persuasive attempt is successful when it generates “cognitive, affective, or behavioral modification in the target” (p. 261). This attempt to convince others and change their attitudes and behaviors is done in an “atmosphere of free choice” (Kang, Tan, & Miao, 2015, p.61).

Miller and Levine (2008) noted that there are different factors affecting persuasion, such as source effects (e.g., source credibility, perceived competence or authority), message effects (e.g., the quantity and quality of evidence and language intensity) and recipient characteristics (e.g., self-esteem, intelligence, gender and argumentativeness). Argumentativeness, for example, is a personal trait of those who tend to counterargument (i.e., those who try to refute other's ideas; Miller & Levine, 2008). In the limit, counterarguing can even lead to an attitude change in the opposite direction of the message (i.e., the so-called boomerang effect; Miller & Levine, 2008).

In addition, some processes of persuasion are more effective than others in changing people's attitudes. This can be explained by the ELM and the different routes to persuasion.

2.4.1.1. Elaboration Likelihood Model

The ELM is a theory that studies attitude change and the effect of different variables for persuasion (Petty & Cacioppo, 1986). It studies the processes that occur when the persuader tries to change a person's attitude by using persuasive communication (Kang et al., 2015). According to this framework, there are two different routes to persuasion, the central and peripheral route, and several variables can condition the route one takes when thinking about a message (Petty, Barden, & Wheeler, 2009).

The route to persuasion depends on the amount of thinking and cognitive effort that the receiver spends in processing a message (Kitchen et al., 2014). In other words, this effort goes from low to high on an elaboration continuum and the amount of thinking about the message can explain how and if people will be persuaded. Where people are in this continuum depends on several variables, but mainly two: motivation and ability (Kitchen et al., 2014). On the one hand, motivation is conditioned by perceived relevance of the message, the source of the message argument and need for cognition (i.e., whether the person enjoys thinking in general; Petty et al., 2009). On the other hand, ability is influenced, for example, by intelligence, perceived knowledge level, the amount of distraction presented in the persuasion context (Kang et al., 2015), repetitiveness, complexity of message (Kitchen et al., 2014) and number of variables (Petty et al., 2009). Motivation and ability influence the likelihood of elaboration and, ultimately, the route to persuasion. As the probability of elaboration increases, central route processes become dominant in their impact on attitude change (Petty et al., 2009). If the persuaded person is motivated and has the necessary ability, there will be careful processing of the message and an attitude that is well articulated and "integrated into the person's overall belief structure" (Petty et al., 2009, p. 5). Thus, when the recipient's elaboration likelihood is high, there will be careful consideration of the information presented (Petty & Cacioppo, 1986). This thoughtful processing of the information will take place through the central route. Careful consideration of information and message will involve generating positive or negative thoughts about the message position, and this valence of thoughts is related to the direction of persuasion (i.e., depends on whether the thoughts are positive or negative; Petty, Barden, & Wheeler, 2009).

On the contrary, when the recipient's elaboration likelihood is low, change can be driven by simple cues (e.g., if the information source is attractive or if the person is in a good mood when receiving the message and associates positive feeling with it; Petty et al., 2009). In this case there is no need to scrutinize the information (Petty & Cacioppo, 1986), little consideration of the information is required (Petty et al., 2009) and processing occurs through the peripheral route (Petty & Cacioppo, 1986). On the peripheral route to persuasion, attitudes are changed through simple association and the use of mental shortcuts such as heuristics (e.g., people think that experts are always correct and accept their opinion, rather than thoughtful thinking about the information presented; Petty et al., 2009).

Petty and Cacioppo (1986) noted that in the case where persuasion is done through the central route, changes are more lasting because attitudes will persist over time and will resist information to the contrary (Petty et al., 2009). This happens because changes through the central route are due to careful thought about a message, more accessible to memory, persistent over time, resistant to counter-persuasion and predictive of people's behavior (Petty et al., 2009). Although attitude changes through the peripheral route are more likely to happen (Montazeri et al., 2013), they will likely only last in the short term. While attitude changes through the central route are more difficult to achieve, they bring greater benefits (Petty et al., 2009).

Although there is a lot of information about ELM and the different routes to persuasion, there is still little information about through which route metaphors can act as persuasion devices. There are even contradictory results: As will be explored in the next two subsections, some studies indicate that metaphors act as persuasion devices through the central route, while others suggest that this happens through the peripheral route.

2.4.2. Metaphors

A metaphor is an "A is B" comparison between two different objects, in which characteristics applied to one object are transferred to the second object in a way that cannot be literally applicable (Sopory & Dillard, 2002, p. 383). In this way, metaphors will create new meanings through the similarities in the characteristics of different objects (Kim & Kim, 2019). Like comparisons, metaphors are also figures of speech (Kosimov, 2022). However, the literature suggests that there are differences between the two. While comparisons can be defined by words and adverbs (e.g., in comparison with, like, similar), metaphors are used to express an idea through events that occur in our daily lives and do not use adverbs (Kosimov, 2022). Since the time of Aristotle, linguists have considered that metaphors and comparisons could perform the same functions and that a metaphor could be expressed as a comparison or vice versa. However, in modern psycholinguistics there are two different views on the subject (Kosimov, 2022): Those who hold the comparative view see the difference between metaphors and comparisons as an "undifferentiated difference" (i.e., metaphors and comparisons are equivalent; Kosimov, 2022, p. 38), whereas in categorization theories they are different, although they seem similar to the first glance (Haught & Glucksberg, 2006). Given that there is no literature on the difference between the role of metaphors and comparisons in terms of persuasion, this thesis assumes they are equivalent in this regard.

According to Landau, Keefer and Meier (2010), metaphors help people understand and process information related to abstract concepts by shaping how people perceive aspects of the social environment. In other words, "metaphors can explain an abstract concept in a concrete way that people can relate to more readily", helping to better understand the world (Montazeri et al., 2013, p.3). Metaphors are also useful in helping people to better organizing literal information and to create interpretive frameworks and are, therefore, capable of influencing people's actions (Stee, 2018).

In addition, Sopory and Dillard (2002) brought together several theories that defend different effects of metaphors on persuasion according to different conditions (e.g., familiarity of target, novelty of the metaphor or source credibility). The authors concluded that there is a persuasive advantage of metaphors over literal language and that the persuasive effects of metaphors are maximized when: the persuasive message is placed in the message's introduction, it is written and not in audio format, it is novel (i.e., creates new information about the target), it is nonextended (i.e., there are no sub metaphors with the same target), is within a familiar target (i.e., the audience is familiar with the target of the metaphor) and there are fewer metaphors within the message (Sopory & Dillard, 2002).

Furthermore, metaphors can also be used as persuasive devices when the source is credible. This can happen primarily during peripheral processing, as the message recipient uses the communicator's credibility as a cue to accept or reject the message (Stee, 2018). In addition, Stee (2018) noted that the sense of relief people feel when they understand a metaphor can also change attitudes. According to the author, when the message deviates from literal language, people first feel a negative tension that is reversed when they understand the metaphor. Thus, they will accept the message more easily (Stee, 2018).

Finally, Stee (2018) also noted that visual metaphors have a greater persuasive effect over literal messages and that metaphors also proved more persuasive when they are visual rather than written. According to the author, this happens because visual metaphors require the message recipient to understand if he or she is the target of the message beyond all the semantic linkages, and this additional processing of the metaphor provides less opportunity for the recipient to counterargue, increasing persuasion (Stee, 2018).

In sum, the literature has shown that metaphors can be used as persuasive devices to change people's attitudes. However, there are still contradictory results about which route of persuasion do metaphors tap into to influence people.

2.4.2.1. Metaphors and the Elaboration Likelihood model.

According to Montazeri and collaborators (2013), the potential lasting effect of a metaphor will depend on the route taken. However, the literature has not been consistent about the persuasion route of metaphors, as different studies conclude different processes.

Montazeri and collaborators (2013), for example, studied the effect of metaphors to encourage conscious consumption of using napkins in a coffeeshop. The metaphor used consisted of comparing the use of napkins with the consumption of trees, since the napkin dispenser had the design of a tree that disappeared as people used more napkins. In the study, Montazeri and collaborators (2013) hypothesized that making sense of metaphors is a mental activity that requires careful examination of information and a greater cognitive processing. This happens because the recipient needs to make the connection between the presented product and the message, requiring a complex cognitive process (Montazeri et al., 2013). Furthermore, the author defended that, if the argument being presented is congruent with people's beliefs, they are more likely to make a more informed decision about their need for napkins and the processing of the message would be done through the central route of persuasion (Montazeri et al., 2013). The napkin study results suggested a reduction in consumption behavior because of the persuasive visual metaphor (Montazeri et al., 2013). However, the route to persuasion was not identified, only hypothesized. Montazeri and collaborators (2013) suggest that the lasting effect of the persuasive experience may be due to clients' memory and behavior and that the effects of persuasion are longer lasting when persuasion takes place through the central route to persuasion.

Furthermore, Kim and Kim (2019) noted that interpreting visual metaphors in advertisements is more complex than verbal metaphors, requiring more cognitive elaboration. According to the author, the visual metaphors in the ads are decoded by the central route in the ELM, as the recipient needs to be able to process and interpret the ad message (Kim & Kim, 2019).

However, Jeong (2008) defends that visual metaphors can also be processed through the peripheral route. According to the author, this happens because visual metaphors cause a central way of processing the arguments of the message, but images or pictures are considered cues. Thus, after decoding the meaning of the message, visual metaphors are considered heuristic cues that cause peripheral modes of processing information (Jeong, 2008).

Finally, as mentioned in the last subsection, Stee (2018) noted that metaphors can be used as persuasive devices when the source is credible. According to the author, this process will happen through the peripheral processing as this can also be seen as a cue do accept or reject a message (Stee, 2018).

These studies show that there is no consensual route of persuasion through which metaphors can change behaviors and attitudes. Considering that the literature confirms that metaphors are effective as persuasion devices and that literacy or specific strategies (such as persuasive metaphors; Miller & Levine, 2008) can be used change people's perception of AI, an experiment was conducted to see the effect of metaphors and comparisons in minimizing algorithm aversion. Thus, this study has the following main hypothesis:

H1: An implementation of AI that involves ANN, which naturally includes metaphors of AI with human decision making, will lead to lower AI aversion than an implementation of AI that does not include ANN nor an AI-human decision-making metaphors.

3. Methodology

The following chapter describes, step by step, how the study was conducted to test the main hypothesis and answer the research question. The chapter first describes the characteristics of the participants, then the research design, and finally, the materials and procedures used.

3.1. Participants

This study was distributed among family, friends and university colleagues to voluntarily participate. In addition, participants were also recruited through social media (e.g., on Instagram, Facebook, LinkedIn and Reddit on a page called SampleSize, which is dedicated to studies). Although this thesis aims to study perception change in the context of a company, I have accepted responses from people who are not currently working to see if explaining technologies to people helps them feel less averse, even though they did not receive all questions. This happened because people who are currently working were asked questions about their satisfaction in their current workplace and it did not make sense for students, for example, to answer this type of question. The full questionnaire can be found in Appendix A.

The recommended minimum sample size for an experimental study with three conditions is 159 (for a one-way ANOVA, 80% power and a medium effect size, $f = .25$, as calculated by G*Power (Faul, Erdfelder, Lang, & Buchner, 2007). With the objective of increasing power, I collected more than the minimum sample size. In total, I collected 410 answers for this study and obtained a total of 319 valid responses after excluding 91 answers. Of the excluded participants, three did not consent to participate in the study, 12 did not answer to the attention check question asking to select "slightly agree" if the participant was paying attention, 55 failed the attention check, 13 answered "strongly disagree", "disagree" or "slightly disagree" to the statement "I paid enough attention in this study for you to use my data" and eight answered "strongly disagree", "disagree" or "slightly disagree" to the statement "I completed the study without being interrupted". These three attention checks were included to identify careless answers (Meade & Craig, 2012). The statement "If you are paying attention choose "Slightly agree" was inspired after reading both Moreira's (2020) and Marques's (2021) thesis in which participants were asked to select a certain option to show they were attentive. The two remaining attention statements were inspired after reading Moreira's (2020) where participants answered similar questions. The only difference is that in my questionnaire these statements were together with the other statements related to the leadership change and in Moreira's (2020) thesis they were two different questions separated from any statement. I decided to combine the attention checks with the other statements because I wanted to make sure that participants were aware of all the questions in the block.

From the valid answers, 138 were males (43.3%) and 179 were females (56.1%). One person preferred not to identify the gender, and another selected the "other" option. The highest education level between participants was the Bachelor's degree (44.2%). Most participants were employed (70.2%), workers and students (12.5%), or only students (9.4%). Among those participants that were already working, the majority work in the industry of health and medicine (21.1%), business, management, and administration (19.2%) and science and technology (14.3%). The mean age of participants was 38.14 years (*SD* = 14.11) and most participants (51.1%) were between 17 and 39 years old. This sample includes participants from 18 countries, 91.9% of which were from Portugal (88.1%) and Spain (3.8%). For more demographic information broken down by experimental conditions see Appendix B.

3.2. Design

In this research I aimed to test if metaphors and comparisons can be used to change people's perception towards algorithms, making them less algorithm averse. To do that, I designed an experimental study in which I studied the difference in people's perception regarding company leadership changes (human vs. non-ANN AI vs. ANN AI). I chose to conduct an experimental study because it is particularly useful when testing for causality in the case of hypothetical situations (Aguinis & Bradley, 2014). A between-subjects design was conducted to compare participants that are in different scenarios with different conditions (Aguinis & Bradley, 2014). When building the experience design, I inspired my work in a thesis regarding AI technologies from a previous Catolica's student, Moreira (2020), that had a scenario where people would answer questions about their workplace before and after some changes. These changes were related to leadership (AI leader vs. human leader) and manipulations in leaders' perceptions of trust and fairness. The objective was to study the impact and influence of changes on psychological safety and employee turnover intentions (Moreira, 2020). Since I found Moreira's (2020) study to have some similarities to mine, I tried to adapt a similar experience to the context of my analysis.

In the study, I manipulated the leader joining the board to understand both the change in job satisfaction and the change in leadership acceptance. Participants were randomly assigned to one of the three conditions. Of the 319 valid responses, 105 were from participants assigned to the human leader group, 105 to the AI group and the remaining 109 to the ANN group (see Appendix B for demographic information broken down by experimental condition).

3.3. Procedure and materials

The study, designed with Qualtrics (an online survey platform), began with an informed consent explaining the objectives of the research and asking participants if they consented to continue the study (see Appendix A for the full questionnaire). Participants who consented to participate proceeded to answer the demographic questions. These questions were inspired after reading both Moreira's (2020) and Marques's (2021) thesis. Participants who were currently working were further asked 1) to select the sector in which they worked (to analyze whether people in more tech-related industries would be less algorithm-averse) and 2) to rate nine control statements about their satisfaction in their current workplace, in a seven-point Likert-scale ranging from 1 (*Strongly disagree*) to 7 (*Strongly agree*), for example "My salary is good and fair" and "I am recognized whenever I do something well at work". The nine statements that compose the job satisfaction variable were inspired on questions that I answered from several of my professors during my master's degree, as well as on Yanchus and collaborators (2015), as reported in Moreira's (2020) thesis. The full set of questions that compose the variables of this study can be found in Appendix D.

In the case of between-subject design, participants read only one vignette although, during data analysis, comparisons are made between them. As participants do not have other vignettes to serve as reference points for their judgments, it is important that participants receive all possible background information (Aguinis & Bradley, 2014). In this way, participants were randomly assigned to three different groups, as they would receive different testimonials regarding changes in their workplace. In the human group (n = 105), participants received a testimonial in which the company they worked for hired a new human leader to be part of the current board who would be responsible for organizing processes and human resources together with the human leader who was already in the company. In the two remaining groups, the new leader was either a generic AI technology (n = 105) or an ANN (n = 109), respectively. These two AI testimonials also explained that this new technology would be part of the leaders' board and would give its opinion for important decisions about the processes within the company and some human resource decisions, such as the current position of employees, or changes in salary. In addition, these testimonials had a short explanation of what AI or ANN is and how they work. All testimonials were developed by me and were inspired after reading the testimonials included in Moreira's (2020) experimental study. Similar to Moreira's (2020) study, my questionnaire included a testimonial with a hypothetical situation in which a new leader joined the board and what were its responsibilities. The only difference is that in my experimental study I also explained how the leader made decisions. In addition, all the testimonials used in my questionnaire included images because it helps to increase the realism in the case of hypothetical scenarios (Aguinis & Bradley, 2014). In the human leader group, the testimonial had a photo of two human hands in a handshake (Cornejo, 2021), while in the remaining two groups the testimonial had a human and a robot hand in a handshake (Denisismagilov, 2021). Besides that, the ANN group had two additional images that showed the comparison between artificial and biological neurons to emphasize the metaphor that the ANN technology makes decisions in a similar way to the human brain (Jain, Mao, & Mohiuddin, 1996). Furthermore, and as mentioned in the subsection of the literature review on metaphors, these images were also used since visual metaphors have a greater persuasive effect over literal and written messages (Stee, 2018).

After the presentation of the testimonial, participants were asked to answer two sets of statements keeping in mind the previously described scenario and trying to imagine themselves in the new leadership situation. The first set of statements focused on leadership changes (e.g., "This testimony makes me change my perception towards my leadership" or "I can trust this leadership") and included a statement regarding the testimonial realism ("This testimonial seems very realistic to me") and an attention check ("If you are paying attention choose "Slightly agree"). Participants had to rate all the statements of the questionnaire in a seven-point Likert-scale ranging from 1 (*Strongly disagree*) to 7 (*Strongly agree*). The statements in this first set of questions were inspired on questions that I answered from several of my professors during my master's degree. From these statements, two variables were computed: one to measure the acceptance of leadership change and another one that measured the perceived impact of testimony in changing technology acceptance. These two variables were created because the first variable includes statements that were received by all groups, while the second has statements focused on the technological leader itself and were only received by the AI and ANN groups. The second set of questions had statements about the scenario realism (e.g., It was easy for me to imagine the situation described) and two attention checks (e.g., "I completed the study without being interrupted"). After answering these two sets of questions, participants were asked the same questions they had to answer at the beginning of the questionnaire about their job satisfaction. Participants were asked to rate these items a second time to study whether job satisfaction had changed due to the change that occurred in leadership. Participants who were not working did not receive this set of questions (as they also did not receive them before the leadership change).

The experiment ended with a debriefing thanking all participants for their time and effort and explaining the goals of the research.

4. Results

In this chapter the relevant results of the study will be presented along with the statistical methods that were used to analyze the main hypothesis. First, the data transformations that were conducted will be explained, then the scale reliability will be analyzed and finally, the hypothesis will be tested.

The data from the Qualtrics questionnaire was analyzed using IBM SPSS Statistics.

4.1. Data transformation

To test the hypothesis, data was first transformed. Some variables were transformed into dummy variables, such as gender, age, nationality, education, occupation and industry, which are categorical.

Gender was transformed in a dummy that was created to separate men and women. The participant who preferred not to identify the gender and the one who selected the “other” option were represented by zero along with the women (women and the other two participants compose the baseline category). Age was divided into three distinct groups according to the age of participants. Two dummy variables were created: one for the youth group (for participants aged 17 to 39 years), and another one for the adults group (for participants aged 40 to 59 years). The category of seniors (for participants aged 60 to 75 years) is the group represented by zero in both age dummies and is thus the baseline. Age was divided into these three specific limits because I wanted the three age groups to span more or less the same number of years (a span of about 20 years). Additionally, education was divided into dummy variables according to the categories that were presented in the questionnaire. However, participants who chose primary and secondary school as their highest level of education were aggregated in the same dummy variable since there were only two participants in the primary school group. In total, four dummy variables were created for education. The baseline group (which is represented by zero in all four dummies) is composed of those who have a bachelor’s degree and the participant who answered “other” to the education question. Occupation was also divided into dummies according to the six categories presented in the questionnaire, and the retired group is the baseline and is represented by zero in all five dummies. Nationality and industry, which were composed of a lot of categories, were divided into groups according to the majority of participants’ responses. In this way, nationality was divided into three categories: Portugal, Spain and others, while industry was divided into four categories: health and medicine, business, management and, administration, science and technology and others. In both these variables the baseline variable is the one in which participants answered “other” and is represented by zero in all dummies.

In addition, the current study used scales for job satisfaction, scenario realism, leadership change acceptance and perceived impact of testimony in changing technology acceptance, which will be discussed in section 4.3.

4.2. Descriptives and bivariate correlations

The descriptives and bivariate correlations were computed for the variable that measures job satisfaction pre-exposure (i.e., before the leadership change) and the continuous variables that were used in the regressions. By analyzing the table below, we can notice that job satisfaction pre-exposure is a little higher than before the changes in leadership occurred (*M* = 5.05 vs. *M* = 4.91), which explains why the mean change in job satisfaction is negative (-0.14).

Descriptive Statistics

	N	*Min*	*Max*	*M*	*SD*
Job satisfaction pre-exposure	266	1.44	7.00	5.05	1.06
Job satisfaction post-exposure	265	1.67	7.00	4.91	1.02
Change in job satisfaction	265	-3.22	2.33	-0.14	0.67
Leadership change acceptance	319	1.00	6.67	4.00	1.12
Perceived impact of testimony in changing technology acceptance	213	1.00	7.00	3.81	1.42
Scenario Realism	319	1.00	7.00	4.82	1.01
Valid N (listwise)	174				

In addition, by analyzing the correlations table below we notice that there is no significant correlation between the variable of job satisfaction pre-exposure and the variables that measure the leadership change acceptance and the perceived impact of the testimony in changing technology acceptance. However, the table suggests that the variable that measures the change in job satisfaction is correlated to both the leadership change acceptance and the perceived impact of the testimony in changing technology acceptance, and this correlation is statistically significant. The scenario realism is also correlated with the variables that measure job satisfaction post-exposure, leadership change acceptance and the impact of testimony in changing technology acceptance. This correlation is statistically significant.

Correlations

	1	2	3	4	5	6
1. Job satisfaction pre-exposure	-					
2. Job satisfaction post-exposure	0.80^{**}	-				

3. Change in job satisfaction	-0.38**	0.26**	-			
4. Leadership change acceptance	0.01	0.21	0.28**	-		
5. Perceived impact of testimony in changing technology acceptance	-0.01	0.24**	0.33**	0.73**	-	
6. Scenario Realism	0.08	0.17**	0.10	0.40**	0.34**	-

** $p < .01$

4.3. Scale Reliability

To test the reliability of the scales used in the questionnaire, a reliability analysis was performed in which the Cronbach's α was computed. The analysis of reliability was performed for the variables of job satisfaction, for the scenario realism variable, for the variable that measures the leadership change acceptance and for the one that measures the perceived impact of the testimony in changing technology acceptance. The items that were negatively worded were reverse coded (e.g., "I am considering changing my job" and "After this change I would feel distant from leadership") and each variable was computed by averaging the answers to the statements that remained for the variable after the reliability analysis.

The job satisfaction scale presented a Cronbach's α = .87 and was composed of the nine original item. The high Cronbach's α indicates a good reliability of the scale (Field, 2009). The reliability analysis was conducted with the items of the pre-exposure job satisfaction, but an average was also calculated for post-exposure, as was the average difference between pre and post-exposure. For more information regarding the reliability analysis of the scales see Appendix C.

In addition, the items for the scenario realism scale had a Cronbach's α = .79 (which is an acceptable value; Gliem & Gliem, 2003). This variable is composed of two statements out of the three original items since reliability analysis showed an increase in Cronbach's α from .58 to .79 by removing the statement "This testimonial seems very realistic to me".

The items for the leadership change acceptance had a Cronbach's α = .84, which is considered to have a good level of internal consistency (Gliem & Gliem, 2003). This variable is composed of the six original items.

Finally, the items that measure the perceived impact of the testimony in changing technology acceptance had a Cronbach's α = .91, which is considered an excellent coefficient (Gliem & Gliem, 2003). This variable includes only two items out of the four original ones since the reliability analysis suggested an increase in Cronbach's α from .08 to .48 after removing the statement "I do not see myself working in a company headed by artificial intelligence in the future" and an increase in Cronbach's α from .48 to .91 after removing the statement "I would only take advice from an artificial intelligence in I knew it would be the human leader making the final decision". For more detailed information regarding which statements compose each variable see Appendix D.

4.4. Hypothesis testing

My hypothesis predicted that metaphors and comparisons would change people's perception towards algorithms, reducing algorithm aversion. To test this hypothesis, I conducted several statistical inferences.

4.4.1. Effect on job satisfaction post-exposure

To test the effect of treatment on the job satisfaction post-exposure (i.e., after the leadership change), I ran a multiple regression with job satisfaction as the dependent variable, while the predictors were two dummy variables: one for the human group and one for the ANN group.

The regression results indicate that the model explains 1% of the variance and that it is not significant for predict the job satisfaction, $R^2 = .01$, $F(2, 262) = 1.20$, $p = .274$. The dummy for the human group did not contribute significantly to the model, $\beta = 0.23$, $p = .139$, and the same happened with the dummy for the ANN group, $\beta = 0.04$, $p = .813$. For more information regarding the models used to estimate job satisfaction post-exposure, see Appendix E.

I ran the same regression adding the control variables (i.e., dummies for age, gender, industry and education, plus the scenario realism variable). The regression results indicate that the model explains 12.5% of the variance and that it is significant for predicting job satisfaction, $R^2 = .125$, $F(13, 250) = 2.74$, $p = .001$. The regression showed that two of the industry dummies were statistically significant in explaining the job satisfaction post-exposure. These variables are the dummy for business, management, and administration, $\beta = 0.47$, $p = .007$, and for science and technology, $\beta = 0.68$, $p < .001$. In addition, the variable for the scenario realism was also statistically significant to explain the job satisfaction post-exposure, $\beta = 0.13$, $p = .047$. No other predictors were significant, all $p > .05$. Thus, the results show that there is a statistically significant difference in job satisfaction between those who are in the business, management, and administration and science and technology sectors, and those working in other sectors. Furthermore, the positive β indicates that people who work in these sectors have higher job satisfaction than those who do not work in these sectors. In addition, job satisfaction was higher for those who perceived higher testimonial realism.

4.4.2. Effect on change in job satisfaction

To test the effect of treatment on the variable for the change in job satisfaction (i.e., the difference between job satisfaction post-exposure and job satisfaction pre-exposure), I ran a multiple regression with change in job satisfaction as the dependent variable, while the predictors were two dummy variables: one for the human group and one for the ANN group.

The regression results indicate that the model explains 0.8% of the variance and that it is not significant for predicting the change in job satisfaction, $R^2 = .01$, $F(2, 262) = 1.05$, $p = .351$. The dummy for the human group did not contribute significantly to the model, $\beta = 0.12$, $p = .244$, and the same happened with the dummy for the ANN group, $\beta = -0.01$, $p = .901$. For more information regarding the models used to estimate the change in job satisfaction, see Appendix F.

I ran the same regression adding the control variables (i.e., dummies for age, gender, industry and education, plus the scenario realism variable). The regression results indicate that the model explains 4.8% of the variance and that it is not significant for predicting the change in job satisfaction, $R^2 = .05$, $F(13,250) = .97$, $p = .485$. The regression showed that no predictor was significant to explain the change in job satisfaction, all $p > .05$.

4.4.3. Effect on leadership change acceptance

To test the effect of treatment on leadership change acceptance, I ran a multiple regression with the leadership change acceptance as the dependent variable, while the predictors were two dummy variables: one for the human group, and one for the ANN group.

The regression results indicate that the model explains 14.5% of the variance and that it is significant for predicting the technology acceptance, $R^2 = .15$, $F(2, 316) = 26.75$, $p < .001$. The dummy for the human group contributed significantly to the model, $\beta = 0.91$, $p < .001$, but the same did not happen with the dummy for the ANN group, $\beta = 0.01$, $p = .947$. This indicates that there is a difference in leadership acceptance between those in the human group and those in the AI group, such that there is more acceptance in the human leadership condition than in the AI condition, but, against this thesis' main hypothesis, that there is no significant difference between AI and ANN groups. However, this variable allows to test for algorithm aversion, as participants accepted the leadership change better in the human condition than in the AI/ANN conditions. For more information regarding the models used to estimate leadership change acceptance, see Appendix G.

I ran the same regression adding the control variables (i.e., dummies for age, gender, industry and education, plus the scenario realism variable). The regression results indicate that the model explains 34.6% of the variance and that it is significant for predicting leadership change acceptance, $R^2 = 0.35$, $F(13, 251) = 10.23$, $p < .001$. The regression showed that five variables are statistically significant in explaining technology acceptance: the dummy for the human group, $\beta = 0.74$, $p < .001$, the dummies for those who have a primary or secondary degree, $\beta = 0.37$, $p = .028$, high education, $\beta = 0.68$, $p = .035$, doctoral degree, $\beta = -0.59$, $p = .022$ and the variable that measures the testimonial realism, $\beta = 0.39$, $p < .001$. No other predictors were significant, all $p > .05$. Thus, results show that leadership acceptance was higher for the human leader, for those with primary, secondary, high education or doctoral degree and for those who perceived higher testimonial realism. As there was not a difference between the AI and the ANN group, the results do not support the main hypothesis of this study.

4.4.4. Effect on perceived impact of testimony in changing technology acceptance

To test the effect of treatment on the perceived impact of testimony in changing technology acceptance, I ran a multiple regression with this variable as the dependent variable, while the predictor was one dummy variable for the ANN group as the point of this analysis is to compare the AI and the ANN group. The dummy for the human leadership was not included, as this group was not exposed to the statements regarding technology acceptance that compose this variable.

The regression results indicate that the model explains 0.7% of the variance and that it is not significant for predicting perceived impact of the testimony in changing technology acceptance, $R^2 = .01$, $F(1, 211) = 1.45$, $p = .231$. The dummy for the ANN group did not contribute significantly to the model, $\beta = 0.24$, $p = .231$. For more information regarding the models used to estimate the perceived impact of testimony in changing technology acceptance, see Appendix H.

I ran the same regression adding the control variables (i.e., dummies for age, gender, industry and education, plus the scenario realism variable). The regression results indicate that the model explains 21.6% of the variance and that it is significant for predicting technology acceptance, $R^2 = .22$, $F(12, 161) = 3.70$, $p < .001$. The regression showed that three variables are statistically significant in explaining technology acceptance: the dummy for the primary and secondary education, β = 0.61, p = .042, the dummy for the health and medicine industry, β = 0.66, p = .018, and the variable that measures the scenario realism, β = 0.46, $p < .001$. No other predictors were significant, all $p > .05$. Thus, people with primary or secondary education, people in the health and medicine sector and those that self-reported higher scenario realism reported higher perceived impact of the testimony in changing technology acceptance. Yet, as the ANN dummy was not significant, this analysis did not support this thesis' main hypothesis.

5. Discussion

5.1. Research findings and main conclusions

Technologies are revolutionizing the way companies approach their processes and make decisions, and it is increasingly important to incorporate these technologies into activities and to show employees their benefits. Therefore, in this research I wanted to test whether metaphors and comparisons had an impact on changing employees' perception of AI, making them less averse to algorithms.

The results of the study did not corroborate the hypothesis, as the only difference found between experimental groups was between the human group and the AI group in explaining leadership change acceptance. The results showed that, while people better accept a leadership change when the new leader is human instead of an AI, thus revealing algorithmic aversion, there is no difference between the ANN and the AI group as hypothesized.

The results of the study go against the literature, since Reich and collaborators (2022), for example, carried out a similar study to see the effect of changing the name of an algorithm on consumer confidence in the learning ability of that technology by calling it "machine learning algorithm". The researchers found that this language-based change shifted consumers' preferences towards the algorithm as people realized that the algorithm had the ability to learn from its mistakes. In addition, it also goes against the literature that noted that metaphors can have a persuasive effect on people's behaviors and attitudes (Sopory & Dillard, 2002; Stee, 2018) and that visual metaphors have a greater persuasive effect over literal and written messages (Stee, 2018). The results of the study may be different from what is expected by the literature, as it may not be enough that humans are similar to AI technologies to reduce aversion. Perhaps participants needed to be similar to these technologies in a more important way and positive associations could be used between human and artificial neurons for the metaphor to work. Furthermore, the results show that perhaps people are unfamiliar with neurons and using a more common metaphor might work better (e.g., reinforcement that algorithms can learn, as done in the 2022 study by Reich and collaborators).

In terms of covariates, the results suggest that scenario realism is important in explaining job satisfaction, leadership change acceptance and the perceived impact of testimony in changing technology acceptance. Furthermore, it suggests that those in more tech-related industries (e.g., science and technology or business, management, and administration) have higher job satisfaction compared to those in other industries. In addition, the level of education is also important in explaining leadership and technology acceptance.

5.2. Academic and managerial relevance

Although the expected result was not found, this study is relevant in academic and managerial contexts. This study focuses on widely explored themes, such as AI, aversion to algorithms and strategies to implement these technologies in the company's processes to make companies gain competitive advantage in a digital world. Although many studies have already addressed problems related to these subjects, this research adds a new and relevant feature: the impact of metaphors and comparisons in reducing aversion. This is important to study because if metaphors and comparisons really have an impact on reducing algorithm aversion, companies can start using them as a strategy to more easily implement technological innovations within internal processes.

Although the hypothesis of the thesis has not been confirmed, this research can be the starting point to other research that uses a similar experimental method in different conditions. The results of the study showed that there is a difference in leadership change acceptance between the human and the AI group, and when conducting a similar study, Reich and collaborators (2022) found that the metaphor used changed people's perception of algorithms. These results suggest that if my study was conducted differently or using different variables, it would be possible to have other statistically significant differences between the AI and ANN group. However, the results of my experiment do not support the main hypothesis and may have been conditioned by several limitations, as the next section explores.

5.3. Limitations and future research

This research offers valuable information about AI technologies, aversion and appreciation to algorithms, and the impact of metaphors and comparisons as persuasion devices. However, it has limitations that may offer directions for future research in the area. First, the impact of metaphors on changing people's perception of technologies is a novel topic and there is not much literature to support my claims. There is also not a lot of evidence showing that neural networks and the associated metaphors and comparisons can reduce algorithm aversion. This suggests a new problem regarding the way the study was conducted: As there is not much information and studies on the subject, the metaphor may have been incorrectly emphasized and people may have had difficulties in understanding the difference between technology being neural or not. The unexpected result may also have happened because a lot of people from medical or scientific fields answered the questionnaire, and probably they are not averse to AI in leadership positions and know that there is not much difference in a technology being neural or not, and that a general AI technology can do similar tasks as ANN technologies. Future research could explore the effect of metaphors that are simpler to understand, study how algorithm aversion would differ due to different technologies, what would happen if other characteristics or problems of these technologies were identified (e.g., if ethical issues such as algorithmic bias) or what would happen if the AI system played a different role within the organization and not a leadership role. These are interesting to study, as there are a wide range of technologies that can create aversion to algorithms.

A second line of limitations has to do with the sample and its diversity, as most participants were Portuguese, and the sample could have benefited from being diverse. A more diversified sample could even help finding the hypothesized result, since Portugal is one of the countries where the number of digitized companies is still small compared to some EU countries (Eurostat, 2022). Being less digitized than other European countries is relevant, as Portuguese participants may be more averse towards algorithms as these technologies are not as embedded in Portuguese culture and businesses as it is in other countries.

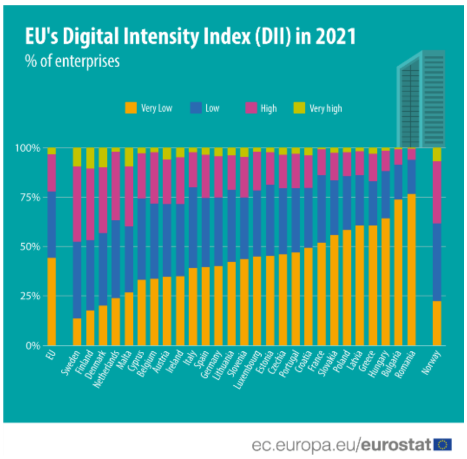

Figure 1: EU's Digital Intensity Index (DII) in 2021 (% of enterprises)

A more demographically dispersed sample with different characteristics and culture would be a good complement in future studies since this thesis is generalizing the results and conclusions to other cultures and realities, although most of respondents were Portuguese.

Furthermore, I may not have measured the variables the right way. I could have asked, for example, what people know and think about the subject, since the literature notes that metaphors have greater persuasive effects if there is target familiarity (i.e., if the audience is familiar with the target of the metaphor, which in this case is the technology itself). In addition, I could have asked participants for their knowledge regarding neurons, as participants may not know much about neurons and may not have positive associations about them as they have for algorithms that can learn, as noted by Reich and collaborators (2022), Berger and collaborators (2021) and mentioned in the subsection on factors influencing AI reactions. Not asking to self-report knowledge of AI and neurons may have been of the biggest flaws of the survey and future studies should certainly consider measuring it. Furthermore, the literature suggested that metaphors can work through the peripheral route and that this route is associative. In this way, a future study could try to create positive associations with neurons (e.g., by showing positive facts about neurons) and see if it improves 1) participants' associations with artificial neurons and 2) the impact of the ANN metaphor. It would also be interesting to see if different persuasion devices (e.g., repetition of a certain idea) could be used to reduce AI aversion.

In addition, even if the study had worked and the hypothesized result was found, it would not be possible to know if it was due to the written or the visual metaphor, or if it was due to the explicit comparison between the human and the artificial neurons. Future research would need to conduct a second study with just one of the metaphors and no explicit comparison.

Finally, although an experimental study is useful for predicting results in hypothetical situations, it will never have the realism of a real-life working situation. In this way, this research could also be conducted in a real working condition to increase the realism and see if the results would have changed. Furthermore, when conducting a between subject experiment, each person only answered one randomized questionnaire regarding one type of leadership. However, if the experiment was not between subjects, perhaps the same person would behave differently in the other scenarios as they would have been able to compare conditions.

6. Conclusion

Technologies improve and evolve at an ever-faster pace. Businesses and consumers can benefit from understanding how these technologies work and how to get the best out of them by implementing them into business processes. Despite all the studies that have already addressed several technology-related issues, this dissertation is a first step towards understanding the impact of metaphors and comparisons on changing people's perception towards algorithm aversion so that managers can implement these technologies in the workplace, giving the company better chances of success. As there is not much information on this topic, I believe this thesis, together with past literature, shows more research is needed into how to reduce algorithm aversion, with metaphors or other persuasion devices.

7. Bibliography

Aguinis, H., & Bradley, K. J. (2014). Best practice recommendations for designing and implementing experimental vignette methodology studies. *Organizational Research Methods, 17(4)*, 351–371. doi:https://doi.org/10.1177/1094428114547952

Berger, B., Adam, M., Rühr, A., & Benlian, A. (2021). Watch me improve - Algorithm aversion and demonstrating the ability to learn. *Business & Information Systems Engineering, 63*, 55–68. doi:https://doi.org/10.1007/s12599-020-00678-5

Burton, J. W., Stein, M.-K., & Jensen, T. B. (2020). A systematic review of algorithm aversion in augmented decision making. *Journal of Behavioral Decision Making, 33(2)*, 220-239. doi:https://doi.org/10.1002/bdm.2155

Choi, D. Y., & Kang, J. H. (2019). Net job creation in an increasingly autonomous economy: The challenge of a generation. *Journal of Management Inquiry, 28(3)*, 300-305. doi:https://doi.org/10.1177/1056492619827372

Cornejo, S. (2021, October 30). *Hand shake.* [Photograph]. Adobe Stock images. Retrieved from https://stock.adobe.com/pt/images/hand-shake/42359394?as_campaign=TinEye&as_content=tineye_match&clickref=1100lwqaeWhC&mv=affiliate&mv2=pz&as_camptype=domain&as_channel=affiliate&as_source=partnerize&as_campaign=tineye

Denisismagilov. (2021). *Man and robot handshake, night city.* [Clipart]. Adobe Stock images. Retrieved from https://stock.adobe.com/images/Man-and-robot-handshake%2C-night-city/173569772?as_campaign=TinEye&as_content=tineye_match&clickref=1101lwsVfqFT&mv=affiliate&mv2=pz&as_camptype=domain&as_channel=affiliate&as_source=partnerize&as_campaign=tineye

Dietvorst , B. J., Simmons, J. P., & Massey, C. (2015). Algorithm aversion: People erroneously avoid algorithms after seeing them err. *Journal of Experimental Psychology: General, 114(1)*, 114-126. doi:https://doi.org/10.1037/xge0000033

Dietvorst, B. J., Simmons, J. P., & Massey, C. (2018). Overcoming algorithm aversion: People will use imperfect algorithms if they can (even slightly) modify them. *Management Science , 64(3)*, 1155-1170. doi:https://doi.org/10.1287/mnsc.2016.2643

Eurostat. (2022, August 26). *How digitalised are the EU’s enterprises?* Retrieved from Eurostat: https://ec.europa.eu/eurostat/web/products-eurostat-news/-/ddn-20220826-1

Faul , F., Erdfelder, E., Lang, A.-G., & Buchner, A. (2007). G*Power 3: a flexible statistical power analysis program for the social, behavioral, and biomedical sciences. In F. Faul, E. Erdfelder, A.-G. Lang, & A. Buchner. Behavior Research Methods. doi:10.3758/bf03193146

Field, A. P. (2009). *Discovering statistics using SPSS: (and sex, drugs and rock 'n' roll)* (3rd ed.). Los Angeles: SAGE Publications.

Filiz, I., Judek, J. R., Lorenz, M., & Spiwoks, M. (2021). Reducing algorithm aversion through experience. *Journal of Behavioral and Experimental Finance, 31*, 1-22. doi:https://doi.org/10.1016/j.jbef.2021.100524

Gliem, J. A., & Gliem, R. R. (2003). Calculating, interpreting, and reporting Cronbach's alpha reliability coefficient for Likert-type scales. *Midwest Research-to-Practice Midwest Research-to-Practice* .

Haenlein, M., & Kaplan, A. (2019). A brief history of artificial intelligence: On the past, present, and future of artificial intelligence. *California Management Review, 61(4)*, 5-14. doi:https://doi.org/10.1177/0008125619864925

Haught , C., & Glucksberg, S. (2006). On the relation between metaphor and simile: When comparison fails. *Mind & Language, 21(3)*, 360–378. doi:https://doi.org/10.1111/j.1468-0017.2006.00282.x

Hawking, S. (2016). Stephen Hawking's speech from the launch of the Leverhulme Centre for the Future of Intelligence on 19 October 2016 [Conference session]. *LCFI Launch.* Cambridge. Retrieved from http://lcfi.ac.uk/resources/cfi-launch-stephen-hawking/

Jain, A. K., Mao, J., & Mohiuddin, K. (1996). Artificial neural networks: A turorial. *Computer, 29(3)*, 31-44. doi:10.1109/2.485891

Jeong, S.-H. (2008). Visual metaphor in advertising: Is the persuasive effect attributable to visual argumentation or metaphorical rhetoric? *Journal of Marketing Communications, 14(1)*, 59-73. doi:https://doi.org/10.1080/14697010701717488

Jussupow, E., & Benbasat, I. (2020). Why are we averse towards algorithms? A comprehensive literature review on algorithm aversion . *28th European Conference on Information Systems* , (pp. 1-16). Atlanta.

Kang, Y., Tan, A.-h., & Miao, C. (2015). An adaptive computational model for personalized persuasion. *24th International Conference on Artificial Intelligence* (pp. 61-67). Buenos Aires, Argentina: AAAI. Retrieved from https://ink.library.smu.edu.sg/sis_research/5531

Kaplan, A., & Haenlein, M. (2019). Siri, Siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence. *Business Horizons, 62(1)*, 15-25. doi:https://doi.org/10.1016/j.bushor.2018.08.004

Kim, S., & Kim, J. (2019). The effect of visual metaphors in advertising. *Visual Communications Journal, 55(2)*, 16-33.

Kitchen, P. J., Kerr, G., Schultz, D. E., McColl, R., & Pals, H. (2014). The elaboration likelihood model: Review, critique and research agenda. *European Journal of Marketing, 48(11-12)*, 2033-2050. doi:https://doi.org/10.1108/EJM-12-2011-0776

Kordzadeh, N., & Ghasemaghaei, M. (2022). Algorithmic bias: Review, synthesis, and future. *European Journal of Information Systems, 31(3)*, 388-409. doi:https://doi.org/10.1080/0960085X.2021.1927212

Kosimov, A. (2022). Figurative language devices and their classification in English. The difference between metaphor and other figurative language devices. *International Journal of Nursing Education, 1(9)*, 35-41.

Landau, M. J., Keefer, L. A., & Meier, B. P. (2010). A metaphor-enriched social cognition. *Psychological Bulletin, 136(6)*, 1045-1067. doi:https://doi.org/10.1037/a0020970

Lee, M. K. (2018). Understanding perception of algorithmic decisions: Fairness, trust, and emotion in response to algorithmic management. *Big Data and Society, 5(1)*, 1-16. doi:https://doi.org/10.1177/2053951718756684

Makridakis, S. (2017). The forthcoming Artificial Intelligence (AI) revolution: Its impact on society and firms. *Futures, 90*, 46-60. doi:https://doi.org/10.1016/j.futures.2017.03.006

Marques, T. (2021). *Overcoming algorithmic bias: The role of bias awareness, knowledge, and minority status on human decision-making.* Lisbon: [Master's thesis, Universidade Católica Portuguesa].

Meade, A. W., & Craig, S. B. (2012). Identifying careless responses in survey data. *Psychological Methods, 17(3)*, 437-455. doi:https://doi.org/10.1037/a0028085

Miller, D. M., & Levine, R. T. (2008). Persuasion. In W. D. Stacks, B. M. Salwen, & C. K. Eichhorn, *An Integrated Approach to Communication Theory and Research* (pp. 261-275). New York: Routledge. doi:https://doi.org/10.4324/9780203887011

Montazeri, S., Finkbiner, D., Papalambros, P., & Gonzalez , R. (2013). Save a napkin, save a tree: The role of metaphors in product design to change behavior. In U. Lindemann, S. V, Y. S. Kim, S. W. Lee, J. Clarkson, & G. Cascini (Ed.), *19th International Conference on Engineering Design*, (pp. 357-366). Seoul, Korea.

Moreira, P. (2020). *How trust and fairness perceptions impact turnover intentions.* Lisbon: [Master's thesis, Universidade Católica Portuguesa].

Pereira, V., Hadjielias, E., Christof, M., & Vrontis, D. (2021). A systematic literature review on the impact of artificial intelligence on workplace outcomes: A multi-process perspective. *Human Resource Management Review, 33(1)*, 1-22. doi:https://doi.org/10.1016/j.hrmr.2021.100857

Petty, R. E., & Cacioppo, J. T. (1986). The Elaboration Likelihood Model of Persuasion. *Advances in Experimental Social Psychology, 19*, 123-205. doi:https://doi.org/10.1016/S0065-2601(08)60214-2

Petty, R. E., Barden, J., & Wheeler, S. C. (2009). The Elaboration Likelihood Model of persuasion: Developing health promotions for sustained behavioral change. *Emerging theories in health promotion practice and research*, 185-214.

Rampersad, G. (2020). Robot will take your job: Innovation for an era of artificial intelligence. *Journal of Business Research, 116*, 68-74. doi:https://doi.org/10.1016/j.jbusres.2020.05.019

Reich, T., Kaju, A., & Maglio, S. J. (2022). How to overcome algorithm aversion: Learning from mistakes. *Journal of Consumer Psychology*, 1-18. doi:https://doi.org/10.1002/jcpy.1313

Schwartz, B. (2004). Decising and Choosing . In B. Schwartz, *The paradox of choice* (pp. 47-75). New York: HarperCollins Publishers.

Sohn, K., & Kwon, O. (2020). Technology acceptance theories and factors influencing artificial Intelligence-based intelligent products. *Telematics and Informatics, 47*, 1-14. doi:https://doi.org/10.1016/j.tele.2019.101324

Sopory, P., & Dillard, J. P. (2002). The persuasive effects of metaphor: A meta-analysis. *Human Communication Research, 28(3)*, 382-419. doi:https://doi.org/10.1111/j.1468-2958.2002.tb00813.x

Stee, S. K. (2018). Meta-analysis of the persuasive effects of metaphorical vs. literal messages. *Communication Studies, 69(5)*, 545-566. doi:https://doi.org/10.1080/10510974.2018.1457553

Wilson, H. J., Daugherty, P. R., & Morini-Bianzino, N. (2017, March 23). *The Jobs That Artificial Intelligence Will Create*, 58(4). Retrieved from MIT Sloan Management Review: https://sloanreview.mit.edu/article/will-ai-create-as-many-jobs-as-it-eliminates/

Yanchus, N. J., Periard, D., Moore, S. C., Carle, A. C., & Osatuke, K. (2015). Predictors of job satisfaction and turnover intention in VHA mental health employees: A comparison between psychiatrists, psychologists, social workers, and mental health nurses. *Human Service Organizations Management, 39(3)*, 219-244. doi:https://doi.org/10.1080/23303131.2015.1014953

8. Appendix

Appendix A: Survey

Welcome and thank you for your participation in this study!

Hello! My name is Carolina Leal and I am conducting this experiment as part of my Master Thesis at Católica Lisbon School of Business and Economics, under the supervision of Prof. Cristina Mendonça. This survey consists of reading a testimonial and answering several questions about leadership change in the workplace. This survey will take about 7 minutes to complete. Please note that your responses will be completely confidential and anonymous. This means that there will be no way to link your responses to your identity. The data collected will be used for research purposes only. Your participation is voluntary and you can stop your participation at any point by leaving the page. Please be honest in your answers and reply to the study in a single sitting with no distractions.

If you have questions about the study, please contact me: Carolina Leal (s-cmsleal@ucp.pt). Thank you very much!

Do you consent to participate in this study?

○ Yes ○ No

Skip To: End of Survey If Do you consent to participate in this study? = No

Thank you for your consent! Please answer some demographic questions before we begin the study.

What is your gender?

○ Male ○ Female ○ Prefer not to say ○ Other

How old are you? ________________

Country of your nationality:

▼ Afghanistan (1) ... Zimbabwe (1357)

What is your highest level of education?

- ◯ Primary education
- ◯ Secondary education
- ◯ High education
- ◯ Bachelor's degree
- ◯ Master's degree
- ◯ Doctoral degree
- ◯ Other (please, specify)

What is your current occupation?

- ◯ Student
- ◯ Worker and student
- ◯ Retired
- ◯ Unemployed
- ◯ Employee
- ◯ Other (please, specify)

(Only for those who were working)

In which industry do you work?

- ◯ Architecture and engineering
- ◯ Arts, culture and entertainment
- ◯ Business, management, and administration
- ◯ Communication
- ◯ Community and social services
- ◯ Education
- ◯ Energy and utilities
- ◯ Science and technology
- ◯ Installation, repair and maintenance
- ◯ Farming, fishing and forestry
- ◯ Government
- ◯ Health and medicine

○ Law and public policy	○ Leisure, sport, and tourism	○ Marketing, advertising and PR	○ Media and Internet

○ Other (please, specify) ________________

(Control questions: Only for those who were working, but for all treatment groups)

Considering your current job, please indicate how much you agree with the following statements:

	Strongly disagree	Disagree	Slightly disagree	Neither agree nor disagree	Slightly agree	Agree	Strongly agree
I am satisfied with the company I am currently working in	○	○	○	○	○	○	○
My superiors care about my problems and opinion	○	○	○	○	○	○	○
I am recognized whenever I do something well at work	○	○	○	○	○	○	○

I like and get along well with my co-workers	○	○	○	○	○	○	○
I like working in this company	○	○	○	○	○	○	○
My salary is good and fair	○	○	○	○	○	○	○
I like and get along with my superiors	○	○	○	○	○	○	○
I am considering changing my job	○	○	○	○	○	○	○
I see myself working at this same company in the future	○	○	○	○	○	○	○

(Only for those in the human leader condition)

Please, imagine the following situation:

Imagine that your company has decided to make some major changes. In particular, a new person will be hired to be in a leadership position. This person will be responsible for organizing processes and human resources together with the leader who was already in the company. This person will give their opinion regarding management processes and, together with the existing leader, he or she will be in charge of hiring employees, choosing your position inside the company, your salary, among other things.

When making decisions, managers use the Vroom-Yetton model and data provided by the company for each situation (e.g., employee KPIs, such as monthly sales or customer engagement). Under this model, managers also considers a set of factors (e.g., whether employees need to be on board for the decision to be successful) to decide on employee participation, which can go from an extreme where employees' opinions will not be considered, to one where they will create a brainstorming session with employees to hear their opinions and concerns until they reach a consensus between both parties.

Figure 2: Photo of two human hands in a handshake

Considering the changes that we asked you to imagine have occurred in your job, please indicate how much would you agree with the following statements:

	Strongly disagree	Disagree	Slightly disagree	Neither agree nor disagree	Slightly agree	Agree	Strongly agree
This testimony makes me change my perception towards my leadership	○	○	○	○	○	○	○
This testimonial seems very realistic to me	○	○	○	○	○	○	○

I would easily accept orders from my new leader	○	○	○	○	○	○	○
I would feel safe knowing that a new leader was helping the first leader making decisions	○	○	○	○	○	○	○
If you are paying attention choose "Slightly agree	○	○	○	○	○	○	○
After this change I would feel distant from leadership	○	○	○	○	○	○	○
This change in leadership is fair	○	○	○	○	○	○	○
I can trust this leadership	○	○	○	○	○	○	○

Please, indicate how much you agree with the following statements regarding the situation described:

	Strongly disagree	Disagree	Slightly disagree	Neither agree nor disagree	Slightly agree	Agree	Strongly agree
It was easy for me to imagine the situation described	○	○	○	○	○	○	○
It was easy for me to understand the questions and testimony	○	○	○	○	○	○	○
I paid enough attention in this study for you to use my data	○	○	○	○	○	○	○
I completed the study without being interrupted	○	○	○	○	○	○	○

(Control questions after leadership change: Only for those who were currently working)

Considering the changes that we asked you to imagine have occurred in your job, please indicate how much would you agree with the following statements (for the group of participants that is currently working only):

	Strongly disagree	Disagree	Slightly disagree	Neither agree nor disagree	Slightly agree	Agree	Strongly agree
I am satisfied with the company I am currently working in	◯	◯	◯	◯	◯	◯	◯
My superiors care about my problems and opinion	◯	◯	◯	◯	◯	◯	◯
I am recognized whenever I do something well at work	◯	◯	◯	◯	◯	◯	◯
I like and get along well with my co-workers	◯	◯	◯	◯	◯	◯	◯
I like working in this company	◯	◯	◯	◯	◯	◯	◯
My salary is good and fair	◯	◯	◯	◯	◯	◯	◯
I like and get along with my superiors	◯	◯	◯	◯	◯	◯	◯

I am considering changing my job	○	○	○	○	○	○	○
I see myself working at this same company in the future	○	○	○	○	○	○	○

(Only for those in the AI leader condition)

Please, imagine the following situation:

Imagine that your company has decided to make some major changes. In particular, an artificial intelligence will be implemented to be in a leadership position. This artificial intelligence will be responsible for organizing processes and human resources together with the leader who was already in the company. It will give its opinion regarding management processes and, together with the human leader, they will be in charge of hiring employees, choosing your position inside the company, your salary, among other things.

To give you some context:

Artificial intelligence (AI) refers to the simulation of human intelligence in machines that are programmed to interpret and learn from external data in such a way that they can mimic and simulate what humans think and act, having the ability to learn, decide and plan. AI is expected to surpass the way humans work and optimize processes and production within companies, doing tasks that can be replicated and that can potentially harm humans.

When making decisions, the artificial intelligence will use a decision tree model and, in each situation, use data provided by the company (e.g., employee KPIs, such as monthly sales or customer engagement). The decision tree model tries to classify/value certain variables based on their attributes and starts at the root with a test. Then the branch with the appropriate result is followed. The process continues until a leaf is found with the correct classification. The leaf is where the decision is made.

When making decisions, the human manager uses the Vroom-Yetton model and data provided by the company for each situation (e.g., employee KPIs, such as monthly sales or customer engagement).

Under this model, the human manager also considers a set of factors (e.g., whether employees need to be on board for the decision to be successful) to decide on employee participation, which can go from an extreme where employees' opinions will not be considered, to one where they will create a brainstorming session with employees to hear their opinions and concerns until they reach a consensus between both parties.

Figure 3: Photo of a human and a robot in a handshake

Considering the changes that we asked you to imagine have occurred in your job, please indicate how much would you agree with the following statements:

	Strongly disagree	Disagree	Slightly disagree	Neither agree nor disagree	Slightly agree	Agree	Strongly agree
This testimony makes me change my perception towards my leadership	○	○	○	○	○	○	○
This testimonial seems very realistic to me	○	○	○	○	○	○	○

I would easily accept orders from my new leader (AI)	○	○	○	○	○	○	○
I would feel safe knowing that an Artificial Intelligence was helping my leader make decisions	○	○	○	○	○	○	○
If you are paying attention choose "Slightly agree"	○	○	○	○	○	○	○
After this change I would feel distant from leadership	○	○	○	○	○	○	○
This change in leadership is fair	○	○	○	○	○	○	○

I can trust this leadership (human + AI technology)	○	○	○	○	○	○	○
This testimonial makes me appreciate AI technologies more	○	○	○	○	○	○	○
This testimonial increases my confidence in AI technologies	○	○	○	○	○	○	○
I do not see myself working in a company headed by artificial intelligence in the future	○	○	○	○	○	○	○

I would only take advice from an artificial intelligence if I knew it would be the human leader making the final decision	○	○	○	○	○	○	○

Please, indicate how much you agree with the following statements regarding the situation described:

	Strongly disagree	Disagree	Slightly disagree	Neither agree nor disagree	Slightly agree	Agree	Strongly agree
It was easy for me to imagine the situation described	○	○	○	○	○	○	○
It was easy for me to understand the questions and testimony	○	○	○	○	○	○	○

I paid enough attention in this study for you to use my data	○	○	○	○	○	○	○
I completed the study without being interrupted	○	○	○	○	○	○	○

(Control questions after leadership change: Only for those who were currently working)

Considering the changes that we asked you to imagine have occurred in your job, please indicate how much would you agree with the following statements (for the group of participants that is currently working only):

	Strongly disagree	Disagree	Slightly disagree	Neither agree nor disagree	Slightly agree	Agree	Strongly agree
I am satisfied with the company I am currently working in	○	○	○	○	○	○	○
My superiors care about my problems and opinion	○	○	○	○	○	○	○

I am recognized whenever I do something well at work	○	○	○	○	○	○	○
I like and get along well with my co-workers	○	○	○	○	○	○	○
I like working in this company	○	○	○	○	○	○	○
My salary is good and fair	○	○	○	○	○	○	○
I like and get along with my superiors	○	○	○	○	○	○	○
I am considering changing my job	○	○	○	○	○	○	○
I see myself working at this same company in the future	○	○	○	○	○	○	○

(Only for those in the ANN leader condition)

Please, imagine the following situation:

Imagine that your company has decided to make some major changes. In particular, an artificial neural network (i.e., a type of artificial intelligence) will be implemented to be in a leadership position. This artificial intelligence will be responsible for organizing processes and human resources together with the leader who was already in the company. It will give its opinion regarding management processes and, together with the human leader, they will be in charge of hiring employees, choosing your position inside the company, your salary, among other things.

To give you some context:

Artificial Neural Networks (ANNs) are computational models that try to recreate the processes that humans have inside their brains. It tries to recreate the network of neurons that constitutes the human brain so that a computer can continuously learn and make decisions, optimizations, and predictions like a human being.

The similarities between biological networks and artificial networks can be seen below:
In biological neural networks, a neuron is a cell capable of processing information. It receives signals from other neurons and transmits the generated signals. At the terminal of its strands are the synapses, which is the place of contact between two neurons. In this way, the cell is able to transmit the information to the next neuron.

In an artificial network, the neuron is composed of layers that are connected through nodes, and these connections form a "network". A node is activated when there are enough stimuli or inputs. This activation spreads through the network, creating a response to the stimulus (outcome). The connections between these artificial neurons act as simple synapses, causing signals to be transmitted from one to the other.

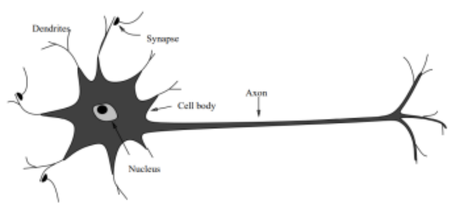

Figure 4: Sketch of a biological neuron

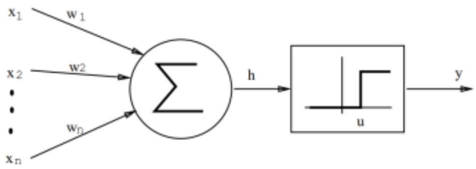

Figure 5: McCulloch-Pitts model of a neuron

When making decisions, this artificial intelligence will, in each situation, use data provided by the company (e.g., employee KPIs, such as monthly sales or customer engagement). When faced with a request or problem to solve, its artificial neurons will do mathematical calculations to decide if there is enough information to send to the next neuron. The neural network output is a value or probability, and the decision is made accordingly and using these values.

When making decisions, the human manager uses the Vroom-Yetton model and data provided by the company for each situation (e.g., employee KPIs, such as monthly sales or customer engagement). Under this model, the human manager also considers a set of factors (e.g., whether employees need to be on board for the decision to be successful) to decide on employee participation, which can go from an extreme where employees' opinions will not be considered, to one where they will create a brainstorming session with employees to hear their opinions and concerns until they reach a consensus between both parties.

Figure 6: Photo of a human and a robot in a handshake

Considering the changes that we asked you to imagine have occurred in your job, please indicate how much would you agree with the following statements:

	Strongly disagree	Disagree	Slightly disagree	Neither agree nor disagree	Slightly agree	Agree	Strongly agree
This testimony makes me change my perception towards my leadership							
This testimonial seems very realistic to me							
I would easily accept orders from my new leader (ANN)							
I would feel safe knowing that an Artificial Intelligence was helping my leader make decisions							

If you are paying attention choose "Slightly agree"	○	○	○	○	○	○	○
After this change I would feel distant from leadership	○	○	○	○	○	○	○
This change in leadership is fair	○	○	○	○	○	○	○
I can trust this leadership (human + ANN technology)	○	○	○	○	○	○	○
This testimonial makes me appreciate AI technologies more	○	○	○	○	○	○	○

This testimonial increases my confidence in ANN technologies	○	○	○	○	○	○	○
I do not see myself working in a company headed by artificial intelligence in the future	○	○	○	○	○	○	○
I would only take advice from an artificial intelligence if I knew it would be the human leader making the final decision	○	○	○	○	○	○	○

Please, indicate how much you agree with the following statements regarding the situation described:

	Strongly disagree	Disagree	Slightly disagree	Neither agree nor disagree	Slightly agree	Agree	Strongly agree
It was easy for me to imagine the situation described	○	○	○	○	○	○	○
It was easy for me to understand the questions and testimony	○	○	○	○	○	○	○
I paid enough attention in this study for you to use my data	○	○	○	○	○	○	○
I completed the study without being interrupted	○	○	○	○	○	○	○

(Control questions after leadership change: Only for those who were currently working)

Considering the changes that we asked you to imagine have occurred in your job, please indicate how much would you agree with the following statements (for the group of participants that is currently working only):

	Strongly disagree	Disagree	Slightly disagree	Neither agree nor disagree	Slightly agree	Agree	Strongly agree
I am satisfied with the company I am currently working in							
My superiors care about my problems and opinion							
I am recognized whenever I do something well at work							
I like and get along well with my co-workers							
I like working in this company							
My salary is good and fair							
I like and get along with my superiors							

I am considering changing my job	○	○	○	○	○	○	○
I see myself working at this same company in the future	○	○	○	○	○	○	○

Appendix B: Sample demographic characteristics

Descriptive Statistics: Age

	N	Minimum	Maximum	Mean	Std. Deviation
Age	319	17.00	72.00	38.14	14.11
Valid N (listwise)	319				

Sample Demographic Characteristics

		HL		AI		ANN		Total	
		Count	Column N %	Count	Column N %	Count	Column N %	Count	Column N %
Gender	Male	43	41.0%	47	44.8%	48	44.0%	138	43.3%
	Female	62	59.0%	57	54.3%	60	55.0%	179	56.1%
	Prefer not to say	0	0.0%	1	1.0%	0	0.0%	1	0.3%
	Other	0	0.0%	0	0.0%	1	0.9%	1	0.3%
Education	Primary education	1	1.0%	0	0.0%	1	0.9%	2	0.6%
	Secondary education	20	19.0%	18	17.1%	20	18.3%	58	18.2%
	High education	3	2.9%	9	8.6%	5	4.6%	17	5.3%
	Bachelor's degree	49	46.7%	48	45.7%	44	40.4%	141	44.2%
	Master's degree	30	28.6%	21	20.0%	33	30.3%	84	26.3%
	Doctoral degree	2	1.9%	8	7.6%	6	5.5%	16	5.0%
	Other	0	0.0%	1	1.0%	0	0.0%	1	0.3%
Occupation	Student	8	7.6%	9	8.6%	13	11.9%	30	9.4%
	Worker and Student	12	11.4%	14	13.3%	14	12.8%	40	12.5%
	Retired	5	4.8%	6	5.7%	2	1.8%	13	4.1%

	Unemployed	2	1.9%	7	6.7%	3	2.8%	12	3.8%
	Employee	78	74.3%	69	65.7%	77	70.6%	224	70.2%
	Other	0	0.0%	0	0.0%	0	0.0%	0	0.0%
Industry	Health and medicine	21	23.3%	16	19.5%	19	20.4%	56	21.1%
	Business, management, and administration	17	18.9%	13	15.9%	21	22.6%	51	19.2%
	Science and technology	14	15.6%	11	13.4%	13	14.0%	38	14.3%
	Other	38	42.2%	42	51.2%	40	43.0%	120	45.3%
Age	Youth	47	44.8%	59	56.2%	57	52.3%	163	51.1%
	Adults	51	48.6%	40	38.1%	48	44.0%	139	43.6%
	Seniors	7	6.7%	6	5.7%	4	3.7%	17	5.3%
Countries	Portugal	96	91.4%	90	85.7%	95	87.2%	281	88.1%
	Spain	2	1.9%	5	4.8%	5	4.6%	12	3.8%
	Other	7	6.7%	10	9.5%	9	8.3%	26	8.2%

Group Frequency

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	HL	105	32.9	32.9	32.9
	AI	105	32.9	32.9	65.8
	ANN	109	34.2	34.2	100.0
	Total	319	100.0	100.0	

Appendix C: Reliability Analysis

Reliability Statistics for Job Satisfaction

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.864	.873	9

Reliability Statistics for change in Job Satisfaction

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.778	.790	2

Reliability Statistics for Leadership Change Acceptance

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.837	.837	6

Reliability Statistics for Perceived Impact of Testimony in changing technology acceptance

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.913	.914	2

Appendix D: Questions used to compute the transformed variables

Questions used to compute job satisfaction before, after testimonial and change in job satisfaction:

a) I am satisfied with the company I am currently working in
b) My superiors care about my problems and opinion
c) I am recognized whenever I do something well at work
d) I like and get along with my co-workers
e) I like working in this company
f) My salary is good and fair
g) I like and get along with my superiors
h) I am considering changing my job
i) I see myself working at this same company in the future

Questions used to compute scenario realism:

a) It was easy for me to imagine the situation described
b) It was easy for me to understand the questions and testimony

Questions used to compute leadership change acceptance

a) This testimonial makes me change my perception towards my leadership
b) I would easily accept orders from my new leader
c) I would feel safer knowing that a new leader was helping the first leader making decisions
d) After this change I would feel distant from leadership
e) This change in leadership is fair
f) I can trust this leadership (human/AI/ANN)

Questions used to compute the perceived impact of testimony in changing technology acceptance

a) This testimony makes me appreciate AI/ANN technologies more
b) This testimonial increases my confidence in AI technologies

Appendix E: The effect of leadership change on Job Satisfaction

	Model 1	Model 2
Group dummy (Human Leadership)	β = 0.23 (*p* = .139)	β = 0.13 (*p* = .405)
Group dummy (ANN Leadership)	β = 0.04 (*p* = .813)	β = -0.04 (*p* = .789)
Education dummy (Primary/Secondary education)	-	β = -0.02 (*p* = .892)
Education dummy (High education)	-	β = -0.41 (*p* = .239)
Education dummy (Master's degree)	-	β = 0.03 (*p* = .823)
Education dummy (Doctoral degree)	-	β = -0.40 (*p* = .147)
Gender dummy (Male)	-	β = 0.16 (*p* = .238)
Industry dummy (Health and medicine)	-	β = -0.10 (*p* = .557)
Industry dummy (Business, management, and administration)	-	β = 0.47 (*p* = .007)
Industry dummy (Science and technology)	-	β = 0.68 (*p* < .001)
Scenario Realism	-	β = 0.13 (*p* = .047)
Age dummy (Youth)	-	β = -0.13 (*p* = .693)
Age dummy (Adult)	-	β = 0.02 (*p* = .942)
R^2	1%	12,5%
F test	$F(2, 262) = 1.20, p = .274$	$F(13, 250) = 2.74, p = .001$

Appendix F: The effect of leadership change on Change in Job Satisfaction

	Model 1	Model 2
Group dummy (Human Leadership)	β = 0.12 (p = .244)	β = 0.06 (p = .547)
Group dummy (ANN Leadership)	β = -0.01 (p = .901)	β = -0.03 (p = .744)
Education dummy (Primary/Secondary education)	-	β = -0.18 (p = .157)
Education dummy (High education)	-	β = -0.24 (p = .300)
Education dummy (Master's degree)	-	β = -0.02 (p = .830)
Education dummy (Doctoral degree)	-	β = -0.35 (p = .061)
Gender dummy (Male)	-	β = -0.01 (p = .958)
Industry dummy (Health and medicine)	-	β = 0.06 (p = .615)
Industry dummy (Business, management, and administration)	-	β = -0.11 (p = .371)
Industry dummy (Science and technology)	-	β = -0.02 (p = .890)
Scenario Realism	-	β = 0.07 (p = .116)
Age dummy (Youth)	-	β = -0.12 (p = .585)
Age dummy (Adult)	-	β = -0.03 (p = .907)
R^2	0.8%	4.8%
F test	$F(2, 262) = 1.05, p = .351$	$F(13, 250) = 0.97, p = .485$

Appendix G: The effect of leadership change in Leadership Change Acceptance

	Model 1	Model 2
Group dummy (Human Leadership)	β = 0.91 (p < .001)	β = 0.74 (p < .001)
Group dummy (ANN Leadership)	β = 0.01 (p = .947)	β = 0.01 (p = .969)

Education dummy (Primary/Secondary education)	-	β = 0.37 (p = .028)
Education dummy (High education)	-	β = 0.68 (p = .035)
Education dummy (Master's degree)	-	β = 0.07 (p = .635)
Education dummy (Doctoral degree)	-	β = -0.59 (p = .022)
Gender dummy (Male)	-	β = 0.20 (p = .111)
Industry dummy (Health and medicine)	-	β = 0.12 (p = .436)
Industry dummy (Business, management, and administration)	-	β = 0.19 (p = .233)
Industry dummy (Science and technology)	-	β = 0.12 (p = .527)
Scenario Realism	-	β = 0.39 (p < .001)
Age dummy (Youth)	-	β = 0.29 (p = .336)
Age dummy (Adult)	-	β = 0.19 (p = .527)
R^2	14.5%	34,6%
F test	F(2, 316) = 26.75, p < .001	F(13, 251) = 10.23, p < .001

Appendix H: The effect of leadership change in Perceived Impact of Testimony in Changing Technology Acceptance

	Model 1	Model 2
Group dummy (Human Leadership)	-	-
Group dummy (ANN Leadership)	β = 0.24 (p = .231)	β = 0.03 (p = .887)
Education dummy (Primary/Secondary education)	-	β = 0.61 (p = .042)
Education dummy (High education)	-	β = 0.47 (p = .396)
Education dummy (Master's degree)	-	β = 0.10 (p = .680)
Education dummy	-	β = -0.65 (p = .108)

(Doctoral degree)		
Gender dummy (Male)	-	β = 0.36 (*p* = .094)
Industry dummy (Health and medicine)	-	β = 0.66 (*p* = .018)
Industry dummy (Business, management, and administration)	-	β = 0.48 (*p* = .092)
Industry dummy (Science and technology)	-	β = 0.22 (*p* = .493)
Scenario Realism	-	β = 0.46 (*p* < .001)
Age dummy (Youth)	-	β = 0.48 (*p* = .435)
Age dummy (Adult)	-	β = 0.44 (*p* = .485)
R^2	0.7%	21,6%
F test	$F(1, 211) = 1.45, p = .231$	$F(12, 161) = 3.70, p < .001$