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The trust in AI robots shaping customer decision-making process: impact on the purchase

Ana Filipa Marmeleiro Leite

Master Thesis

presented as a partial requirement for obtaining a Master's Degree in Data-Driven Marketing

NOVA Information Management School
Instituto Superior de Estatística e Gestão de Informação
Universidade Nova de Lisboa

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by

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Master Thesis presented as a partial requirement for obtaining the Master's degree in Data-Driven Marketing, with a specialization in Data Science for Marketing

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STATEMENT OF INTEGRITY

I hereby declare having conducted this academic work with integrity. I confirm that I have not used plagiarism, any form of undue use of information, or falsification of results along the process leading to its elaboration. I further declare that I have fully acknowledged the Rules of Conduct and Code of Honor from the NOVA Information Management School.

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ABSTRACT

Artificial intelligence (AI) includes machines, programs, systems, and robots that have any sign of human intelligence. Despite the benefits, consumers might have negative reactions to AI suggestions since they don’t understand this technology. Robots are growing in this society, acting like entertainers, friends, and advisors, and customers tend to have difficulty trusting these machines, especially when they look like humans. However, this trust is a crucial factor when talking about consumer behavior, especially talking about aspects that lead to making purchase decisions. This study analyzes whether trust in anthropomorphic or non-anthropomorphic AI robots affects consumer purchase decisions. To conduct this research, an experimental study with 100 participants was made where half of the participants were randomly exposed to a video with an anthropomorphic robot, and the other half to a video of a non-humanoid robot (tablet robot). All this analysis was made using FaceReader Facial Expression software, which captured participants’ micro expressions when watching the video and complemented with a questionnaire to understand trust and purchase attributes. Results indicated that the robot's appearance affected specific facial expressions, contrary to basic emotions, and some trust variables proved to influence purchase intentions. This research will aggregate the industry’s understanding of how AI robots’ appearance will impact consumer trust and behavior, providing insights to develop tools, and thinking about customer usability perspective.

KEYWORDS

Artificial Intelligence; Robot; Trust; Decision-making process; Purchase

Sustainable Development Goals (SDG):

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF CHARTS

LIST OF ABBREVIATIONS

AI	Artificial Intelligence
AU	Action Unit
M	Mean
SD	Standard Deviation
DF	Degrees of Freedom
T	T-Value
P	Probability value
CI	Confidence interval
SE	Standard Deviation

1 INTRODUCTION

Artificial intelligence (AI) includes every machine, program, and system that shows any sign of intelligence (Shankar, 2018), more specifically, human intelligence (Huang & Rust, 2018). Sellers use the help of AI to understand the preferences, desires, and needs of their consumers and analyze how customers behave to give them useful recommendations (Davenport et al., 2020; Fernández-García et al., 2019). However, sometimes customers have a negative reaction to the suggestions that AI gives them since they don't understand how these machines know what is best for them (Zimmermann et al., 2023).

Another way where it's possible to see AI is in robots with some physical aspects incorporated (Davenport et al., 2020). Robots are increasingly present in people's lives both humanoid robots and voice-based ones (Wirtx et al., 2024), they can be seen as entertainers, social enablers, friends, or even advisors for customers (Roy et al., 2024).

Whenever a person feels reliability and integrity in another person, object, or situation, they trust in it (Morgan & Hunt, 1994). While shopping, customers trust if they believe that they'll have been understood by the salesperson, company, or product (Plank et al., 1999). Customers feel more comfortable trusting a robot that has physical embodiment than just AI because they can feel empathy with robots (Davenport et al., 2020). The theory of mind explains that there are two mental states and traits that demonstrate how consumers evaluate and respond to non-human operators: agency, connected to the ability to express opinions, and experience, which is the skill to sense emotions (Pitardi et al., 2024). If the salesperson is a robot, then customers tend to have more difficulty trusting (Yagoda & Gillan, 2012).

Customers can benefit from the help of an AI robot while shopping, and if they rapidly decide to make a purchase, it's possible to conclude that they trust the AI algorithm to give them recommendations (Panigrahi & Karuna, 2021; Subbaiah et al., 2024). Robots help customers find the products that they are looking for, making them trust the machines and leading them to make a purchase (Panigrahi & Karuna, 2021).

The trust that consumers have in robots, or the impact of trust on the customers' decision-making process has been widely studied; however, there is a lack of papers regarding the analysis of the physical aspect that the robots have and their impact on the customer's purchase decision. Hence, this project intends to answer the following research question: "Will the trust in AI robots (anthropomorphic or not) shape customer purchase decisions?".

The main goal of this study is to understand, through participants' facial expressions and personal opinions, what they think about the appearance of the robot. Additionally, the study aimed to determine if customers are willing to be helped in-store by an anthropomorphic robot with a face and arms like a human or by a robot that doesn't have physical human characteristics.

To achieve the goal of the project, an experimental study was applied to 100 participants. Using the FaceReader software, 50 participants were randomly exposed to a video where an anthropomorphic robot with physical similarities to humans is helping a young lady to make a purchase and the other 50 participants watched a video of a mechanical robot with no head or arms helping customers make purchases.

After the visualization, all participants answered the same questionnaire, developed with Qualtrics, to understand what plans they have to buy a product and their purchase intentions considering that they would be helped by the robot that they visualize in the videos. This methodology was chosen since consumers tend to have more positive attitudes whenever they interact with a more anthropomorphic robot (Li et al., 2024); however, this can have a negative effect when the machines start to look even more like a human (Mori et al., 2012).

This project has some theoretical and practical contributions for the society. The subject studied helps in the understanding of trust in artificial intelligence agents in the context of consumer behavior and in the analysis of the influence that the appearance of AI robots can have on consumer trust and purchase behavior. Despite that, it's possible to analyze consumers' emotions between both conditions, helping in the understanding of the decision-making process. This thesis also helps give guidance for the design of software that is AI-driven and aims to assist customers in increasing their level of trust in the machines.

The present project starts with an introduction explaining what is going to be studied, followed by a literature review of the main subjects made by authors from top journals, articles, books, and some dissertations about this topic mostly recent literature mostly from the last 10 years. This literature led to the construction and definition of the conceptual model and hypothesis that are going to be tested. Right after, there is an explanation of the methodology used in the study, the results, and a discussion of the data collected. Lastly, the conclusions are presented where the practical and theoretical implications of the study are presented as well as future research.

2 LITERATURE REVIEW

2.1 ARTIFICIAL INTELLIGENCE

In the past years, artificial intelligence (AI) has been growing a lot (Carmody et al., 2021; Du-Harpur et al., 2020), and today has a huge impact on how customers live their lives changing the way they eat, sleep, and work (Puntoni et al., 2021). Some authors defend that AI is an agent that can do difficult tasks and does data analysis, as they are learning at the same time (Gonçalves et al., 2023), other authors define it as a data-driven algorithm (AI agent) that can behave autonomously without the need for human interference and are capable of analyzing customers data (Carmody et al., 2021), with the purpose of facilitate the human's life (Masnita et al., 2024). However, when the term first appeared it was defined as a generation of robots that were rapidly evolving, capable of seeing, reading, speaking, learning, and feeling emotions (Rodgers, 2021). Either way, all definitions state that machines can perform tasks and roles based on commands and adapt to society (Yu, 2022).

AI systems have a lot of applications (Masnita et al., 2024):

- Observe the environment: acting accordingly to what they observed, learning from it;
- Data absorption: as companies usually work with big amounts of data and have to analyze it, being hard for a human to do that;
- Store a lot of information.

There are several fields in which artificial intelligence is used (Cavazza et al., 2023) like marketing, medical, education, law, and manufacturing (Masnita et al., 2024). Nowadays, AI is more present in the customer experience as they begin to trust artificial intelligence to get a greater variety of choices and a higher level of service (Gonçalves et al., 2023). Retailers have in mind their customers' needs and wants when implementing AI in their business so that they can get customer insights and do content creation or AI-powered chatbots (Ameen et al., 2021).

The interaction between customers and AI is something that has the potential to grow and develop some businesses (Ameen et al., 2021). Through the data flow that exists, professionals need to be able to use AI to create valuable insights for customers, since they indicate their needs and wants through searches, conversations, and interactions in social media, which they do through a variety of channels like the web, mobile, and face-to-face (Kietzmann et al., 2018).

Artificial intelligence has the potential to increase organizations' efficiency in almost all areas (Rodgers & Nguyen, 2022) and it can be used to improve the way customers perceive the service quality and the relationship between the brand and themselves (Ameen et al., 2021).

2.1.1 AI Robots

As time goes on, technology has a considerable advance and smart robots are starting to replace humans when it comes to providing contactless services. Organizations are continuously seeking ways to add value to their customers through robotics and AI (Chiang & Trimi, 2020). The combination of AI with robots has been constantly growing in different areas of the world for different purposes (Kamran et al., 2020). When combined, robots will interact with humans through their voice and image recognition, which leads to better performance of the robots when learning different scenarios and offering personalized feedback and directions (Chu et al., 2022).

They are considered powerful machines to support the world daily. Robots can do a lot of actions like pick and move objects or destroy and modify them, simply following what they were told to do (Kamran et al., 2020). These machines can go from being completely independent and doesn’t need human interaction, to being partially autonomous and necessitating to have human-robot integration (Chiang & Trimi, 2020). For robots to independently perform complex tasks, intuition, judgment, and empathy are required (Chiang & Trimi, 2020).

Robots can be organized into two big groups (Nitto et al., 2017):

- Based on functionality:
    - Service robots: mechanical devices that can behave like a human and do some tasks that are more dangerous, dirty, repetitive, and time-consuming (Brengman et al., 2021; Chiang & Trimi, 2020; Song et al., 2022);
    - Industrial robots: are mostly used for manufacturing (Chiang & Trimi, 2020).
- Based on appearance:

- Humanoid robots: robots that are designed with the intuition to appear and behave like a human (Song et al., 2022) and have a face, arms and legs (Brengman et al., 2021);
- Mechanical robots (Nitto et al., 2017).

To guarantee service quality while using service robots in a business, it’s important to take into account the customer inputs and know their expectations, as well as certify that the robots are in the perfect state regarding technical capability (Chiang & Trimi, 2020). This type of robot is considered “smart” whenever AI is involved (Brengman et al., 2021).

Service robots haven't yet incorporated the intuitive and empathetic intelligence of AI to equal or surpass humans, so they are not able to perform services that require experience, emotion, and the human touch when performing services that require authority and experience (Chiang & Trimi, 2020). These machines can be used in several functions like malls, hotels, airports, and other facilities (Tung & Au, 2018) and normally perform activities related to guiding people, and cleaning or moving objects (Tsarouchi et al., 2016). This type of robot can be used in product recommendations (Song et al., 2021) and in sales promotion, since it can be efficient when attracting customers’ attention. However, they usually have a humanlike appearance and use natural language to communicate with customers (Song et al., 2022).

Consumers tend to prefer that robots use text to communicate with them (Law et al., 2021). The level of trust that humans have in humanoid robots, will intensify their emotional connections and their intentions to use the robots according to their needs (Song et al., 2022).

In anthropomorphism, real or imagined non-human objects have human characteristics, properties, or mental states (Hegel et al., 2008). An individual is more likely to accept and like robots as the likeness between them and the robot increases within a range of low to medium levels of visual anthropomorphism (Mara et al., 2022). The more a robot has a similar appearance to a human, the more consumers are likely to have hope for social connections from the robot (Garvey et al., 2023).

Whenever companies think about human-robot interaction, they have the power to program what level of association the robot will have with the customers (Kamran et al., 2020). It’s important that companies that own a robot in customer service guarantee that they are visually acceptable for them because robots that look a lot like humans, tend to be considered "creepy" by customers (Chiang & Trimi, 2020), meaning that the degree of anthropomorphism has an impact on the level of trust that the customers have (Chiang & Trimi, 2020; Song et al., 2022). If they look too much alike to humans, that can lead consumers to feel uncomfortable (Brengman et al., 2021). The main purpose behind the interaction between customers and robots is human satisfaction, comfort, and confidence in the environment created (Kamran et al., 2020). When an offer falls short of expectations, consumers react less negatively towards a robot than if it were a human employee, because the robot's diminished sense of agency makes its offer appear less exploitative (Pitardi et al., 2024).

Some studies state that an increase in the similarity between robots and humans leads to an increase in the expectations that humans have about cognitive capabilities (Pütten & Krämer, 2014), and people are more willing to take advice from them (Phillips et al., 2018). When it comes to the cognitive abilities and the behavior of the robots, it's all related to how they look like to humans (Pütten & Krämer, 2014). Regarding the physical appearance of a robot, some authors find out what aspects the customers value the most:

- The more the robot head has human features like eyes, nose, mouth, etc., the more it is perceived as a human (DiSalvo et al., 2002);
- The width and height ratio of the head has a big impact on how human-like the robot is perceived (DiSalvo et al., 2002);
- A shorter chin makes the eyes look too big for the face (Powers & Kiesler, 2006).

The uncanny valley is described as the increase in the affinity that we have for robots when we try to make them look like humans (Mori et al., 2012) leading to consumers accepting them easily (Pütten & Krämer, 2014). However, when the similarity between the robot and humans is almost perfect, it creates a negative reaction from the humans (Appel et al., 2020).

As a result, the perception of human likeness is influenced by the visual and functional functions of the robot and by the user as long as the environment in which the interaction between the human and robot happens (Appel et al., 2020).

2.2 CONSUMER DECISION-MAKING PROCESS

Consumer decision-making is the understanding of the way consumers behave that will predict and determine their decisions to buy a new product that will satisfy them (Erasmus et al., 2001). The main goal of the consumer decision-making process is to understand what path customers take and when they come in touch with the brand to make it a better experience for them and an obvious choice (Lemon & Verhoef, 2016). The level of complexity of this process depends on the importance that the product has for the customer (Erasmus et al., 2001).

Buying behavior is known as how people search, select, purchase, use, and dispose of products or services to meet their needs and wants (Panwar et al., 2019; Stankevich, 2017) that will help in the development of the decision-making process (Lemon & Verhoef, 2016). Understanding how consumers behave is always a challenge that companies have and want to overcome to improve their marketing and selling strategies to have a successful business (Stankevich, 2017).

There were developed a lot of consumer decision-making models that explain how consumers make their decision to buy a product (Towers & Towers, 2022) and their main goal is to state the cause and effect related to the consumers' behaviors (Erasmus et al., 2001). The traditional model has 5 stages (Mussa, 2020; Stankevich, 2017), however, they can skip one or more stages (Mussa, 2020):

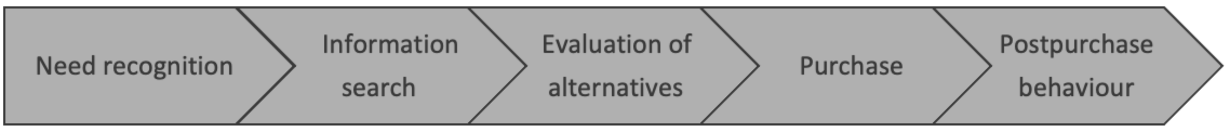

Figure 1- Five stage consumer buying process

2.2.1 PURCHASE BEHAVIOR

To make a purchase, consumers need to know how much a brand is worth to them, and how much they're willing to spend (Kietzmann et al., 2018). Marketers need to know their customers to meet their needs (Stankevich, 2017). In this process, consumers can use physical stores to learn more information about the product and make the actual purchase (Flavián et al., 2016).

The purchase decision happens after a long and complex process that includes an information search, comparing brands, and evaluating them and their products (Stankevich, 2017). However, the probability of the purchase or when and where the purchase will be made will vary based on the reasons that the customer had to buy the product/service (Puccinelli et al., 2009). The majority of customers, like to hear the opinions and experiences that other consumers have about a retailer's product or service before making a purchase decision (Fernandes et al., 2022),

The process of buying a product or service is influenced by price, design, package, knowledge, quality, and trends (Shafiq et al., 2011). Knowledge about the products is considered one of the most important factors when it comes to the purchasing decision (Jayachandran et al., 2004; Rao & Monroe, 1988). Packaging is also very important (Fiore, 2008) and is considered by some companies that it will show the quality of the product (Kumar, 2006). The perceived value is another factor that points customers to the purchase intention (Shafiq et al., 2011) and can establish the relationship between the product and customers (Payne & Holt, 2001), a high perceived value leads to a high intent of actually purchasing (Chang & Wildt, 1994).

A purchase decision algorithm assists marketers in detecting the consumer's needs and activities throughout the purchase decision journey, enabling them to develop the most effective advertising for the most appropriate customer (Rodgers & Nguyen, 2022). Professionals are always seeking ways to lead customers to their products or services influencing them in their purchases (Stankevich, 2017) so that their purchase intentions, that is the preference to buy a particular product/service (Younus et al., 2015), can become actual purchase (Spears & Singh, 2004).

When the customer decides which brand he/she will buy, they have to make the purchase (Stankevich, 2017) and they decide what and where they will make it (Mussa, 2020). A customer's purchase intention is their tendency to purchase a product or service (Sharma et al., 2023); however, having an intention to make a purchase doesn't always mean that the intention will transform into an actual purchase, normally those who have an actual intention to make a purchase, have a higher probability of buying it than those who don't show intention (Wee et al., 2014).

Marketers must guarantee that the customers move from the third to the fourth step of the buying process by showing them the value that their brand has compared to the competitors (Mussa, 2020). Making sure that customers are satisfied during the purchase process is a crucial part of managing customer experiences leading to the purchase (Puccinelli et al., 2009).

2.3 TRUST IN ROBOTS

Trust is considered an attitude that will allow to the person achieve personal goals in an uncertain situation (Lahno, 2001) and a vulnerable situation (Hancock et al., 2011; Lahno, 2001; Yagoda & Gillan, 2012; Zand, 1972), which means that the person is no longer under control (Patrick, 2002). Trust can extend to objects that don't express an intrinsic, self-determined intention and that are not sentient organisms (Schaefer, 2013). In a trust situation, there is an understanding between two people that allows each other to exercise a certain degree of control over certain aspects of their lives that are important to them (Lahno, 2001).

Daily, customers are used to being vulnerable because they trust that the actions the others won't be harmful to them (Patrick, 2002). When humans trust, they feel that they can rely on the trusted person, object, or system (Rotter, 1980). When someone does that, it can be seen as a risky choice (Campellone & Kring, 2013). Trust can be defined as an attitude that demonstrates the confidence (Lahno, 2001) that the customer's weaknesses will not be taken advantage of in a risky situation (Ameen et al., 2021) and behavior that someone has based on their beliefs about the other person, experience, or object (Kim et al., 2008; Lahno, 2001).

The facial emotions that a human shows during social interactions can have an impact on decisions of trust (Campellone & Kring, 2013). When thinking of AI, trust is a crucial factor to be taken into account to guarantee the acceptance, progress, and development of the business (Ameen et al., 2021). It can influence the interaction between humans and robots (Ullman & Malle, 2019) as it is an important feature when using a robotic system, establishing the acceptance and use of it (Yagoda & Gillan, 2012), and accepting that if you trust in the system, you'll stop controlling it directly (Patrick, 2002).

In these interactions, trust is also present in a moment when a human will decide whether or not they give a task to the robot or a human (Hancock et al., 2021) and to share, cooperate, and rely on the results (Khavas et al., 2020). The level of trust that a consumer feels about a service provider depends on two components: cognitive trust and affective trust (Johnson & Grayson, 2005). Cognitive trust arises from an assessment of the service provider's competence and reliability in managing service interactions based on knowledge (Roy et al., 2024). On the other hand, affective trust stems from the emotions experienced during the interaction with service providers (Rempel et al., 1985).

When thinking about human-robot trust, initial trustworthiness can be defined as what the human perceives about the characteristics of the robot as they interact with each other. The robot's appearance (type and level of anthropomorphism) is an important feature regarding trustworthiness (Schaefer, 2013). The less a person trusts in robots, the faster they'll intervene in what the robot is doing (Hancock et al., 2011); however, maximizing their trust in robots does not mean that there's going to perform positive achievements (Kok & Soh, 2020). There are some factors that can be considered antecedents of human-robot trust (Hancock et al., 2011):

Table 1- Trust factors in human-robot interaction

Human-related	**Ability-based**	Expertise, past experiences, competency, engagement
	Characteristics	Personality, attitude, comfort with the robot, self-confidence, propensity to trust
Robot-related	**Performance-based**	Reliability, behavior, frequency of fault, transparency, predictability
	Attribute-based	Proximity, personality, adaptability, anthropomorphism
Environmental	**Team collaboration**	Culture, communication, mental models
	Tasking	Task type, complexity, physical environment, requirements

The higher the level of trust in the technologies, the better the customer experience (Ameen et al., 2021). If someone stops trusting in automation, it can cause disuse of the machines (Billings et al., 2012; Kok & Soh, 2020).

3 CONCEPTUAL MODEL AND HYPOTHESIS

After analyzing all significant literature about the topic, and crossing it with the research question and goals, the model and hypothesis for this project were developed.

The model intends to study what will be the impact of AI robots (anthropomorphic or not) on customers decision-making process to understand if the presence of a robot in store assisting the customer would lead to him to make a purchase, and additionally, see if the trust that consumers have on robots would change their perspective of making the purchase.

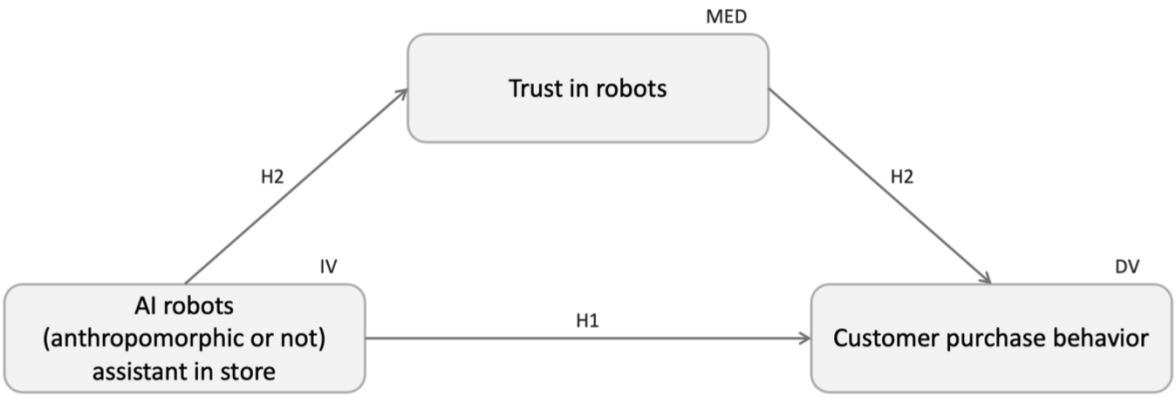

Figure 2- Conceptual model

A robot is a machine that is programmed to do some tasks autonomously while living in the environment (So et al., 2023) following some directions and prior knowledge and experience (Wirtx et al., 2024). These machines can appear like humanoid or non-humanoid robots (Wirtz et al., 2018) and are becoming more present in the daily activities of customers (Wirtx et al., 2024).

For a robot to be anthropomorphic it has to look and behave in a similar way to a human. Normally, when a robot has a higher degree of anthropomorphism, it guides to negative impressions from the customers (So et al., 2023). Robots can drive consumers during their customer journeys (Wirtx et al., 2024)

However, some authors state that anthropomorphism has a positive impact on customer relations with robots in terms of the level of trust and intention to use it (van Pinxteren et al., 2019). There are different opinions regarding the interactions between humans and humanoid robots (So et al., 2023). Some state that the interaction between them, can lead to distress from the consumers (Mende et al., 2019) and impact their perception of the robots based on the perceived strangeness when agents resemble humans too closely (Kim et al., 2019). On the other hand, some authors affirm that human-like attributes like facial expressions, gestures, or voice can have a positive influence on the way that customers respond to robots, leading to increased trust and enjoyment (Choi et al., 2020; van Pinxteren et al., 2019; Yoganathan et al., 2021).

That´s why the first hypothesis was created where artificial intelligence robots (anthropomorphic or not) assistant in store is the independent variable (IV) and customer purchase behavior is the dependent variable (DV).

H1: The use of an AI robot in store (anthropomorphic or not), will affect the customer purchase behavior.

Customers behave and evaluate non-human agents based on their prior experiences and knowledge (Pitardi et al., 2024). The combination of artificial intelligence and human capabilities has the objective of preparing a more personalized service, thinking of the customer's needs and preferences (Adam et al., 2021; Leocádio et al., 2024).

Trust is an important factor when it comes to technology acceptance (Chi et al., 2023; Ha & Stoel, 2009; Wu et al., 2011) and is related to a belief that arises through a cognitive process (Chi et al., 2023; McKnight & Chervany, 2001). For a customer to trust in the robot, they need to believe that the machines can help them achieve their goals and get what they want (Tussyadiah et al., 2020).

Robots must show that they are capable of helping customers (Wirtx et al., 2024) and assisting them with their demands (Leocádio et al., 2024). Aspects inherent to the robot, such as appearance and capabilities (Hancock et al., 2011), their level of communication (Lemaignan et al., 2017), and nonverbal signs like smiling and moving their head (Yu & Ngan, 2019), play a crucial role in building trust with the customers. However, the more a robot looks alike to a human, people tend to feel strange and uncomfortable (Mori et al., 2012) and develop a negative opinion and position toward the robot (S. Y. Kim et al., 2019; Mende et al., 2019; S. Zhang et al., 2023).

Thus, de second hypothesis was developed adding a mediator to the first hypothesis that is responsible for mediating the relationship between the AI robots and the purchase: trust in robots.

H2: The level of trust in the robot will mediate the option to use an AI robot in store (anthropomorphic or not), which will influence the customer purchase behavior.

4 METHODOLOGY

A methodology is the study of which methods will be used giving a work plan of the research (Goundar, 2012). For this project, participants participated in an experimental study in which first they visualized a video through FaceReader software and then answered a short questionnaire regarding the video and related to the research objectives and questions.

4.1 FaceReader Software

FaceReader is a Noldus Information Technology Software that analyzes people's emotions and classifies facial expressions on a scale from 0 to 1 (Lewinski et al., 2014). This software is prepared to classify people's expressions following three steps (Loijens & Krips, n.d.):

1. Face finding: the position that the participant is on the image;
2. Face modeling: based on 468 key points in the participants' faces;
3. Face classification: recognition of the expressions that the face does based on a deep artificial network.

To start the analysis is necessary to do the calibration that uses the frame of the participant to consider that as a neutral expression and can be done in two ways: participant calibration or continuous calibration (Loijens & Krips, n.d.). The preferred method of calibration is the participant's one; however, to facilitate the data collection, for this project, we chose continuous calibration.

There is a 96% to 100% accuracy in the identification of facial expressions (*Facial Expression Analysis - FaceReader | Noldus*, n.d.) based on basic emotions that are: happy, angry, sad, surprised, scared, and disgusted, plus neutral (Terzis et al., 2010).

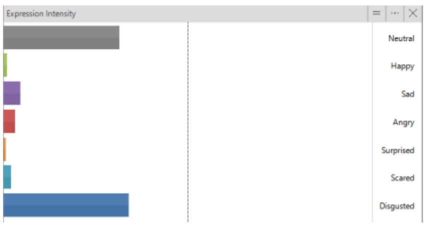

Chart 1- Participants' basic emotion bar chart

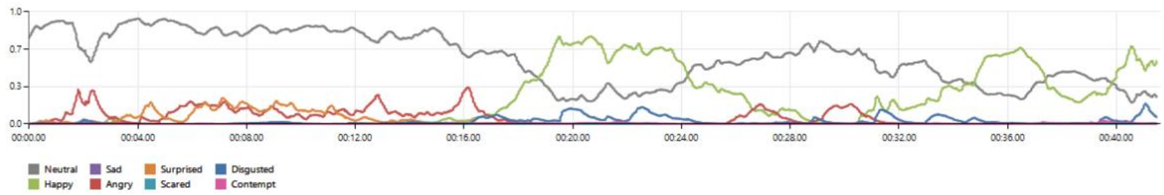

Chart 2- Participants' basic emotions line chart

To differentiate the emotions, the software analyzes the valence, which can go from unpleasant to pleasant, and the arousal, which can vary from not arousing to highly arousing (Höfling et al., 2020).

According to Noldus (*Facial Action Coding System (FACS) | Objective and Reliable | Noldus*, n.d.), 20 facial action units are recognized by the software:

Table 2- Facial Action Units

Action Unit	Contribution
AU1. Inner Brow Raiser	Sadness, surprise, fear and interest
AU2. Outer Brow Raiser	Surprise, fear, and interest
AU4. Brow Lowerer	Sadness, fear, anger and confusion
AU5. Upper Lid Raiser	Surprise, fear, anger and interest
AU6. Cheek Raiser	Happiness
AU7. Lid Tightener	Fear, anger, and confusion
AU9. Nose Wrinkle	Disgust
AU10. Upper Lip Raiser	Non defined
AU12. Lip Corner Puller	Happiness and contempt (when appear unilaterally)
AU14. Dimpler	Contempt (when appears unilaterally) and boredom

AU15. Lip Corner Depressor	Sadness, disgust and confusion
AU 17. Chin Raiser	Interest and confusion
AU18. Lip Pucker	Non defined
AU20. Lip Stretcher	Fear
AU23. Lip Tightener	Anger, confusion, and boredom
AU24. Lip Pressor	Boredom
AU25. Lips Part	Non defined
AU26. Jaw Drop	Surprise and fear
AU27. Mouth Stretch	Non defined

Despite the action units, the software is also capable of analyzing custom expressions created by the combination of some metrics and action units recognized by FaceReader (*Gathering Data - FaceReader | Noldus*, n.d.). The use of custom expressions can lead to a deeper understanding of the behavior that a basic expression can ignore (Hendriks, 2024). For this study, from the 16 default custom expressions that the software provides, only 5 were selected and analyzed based on their description and inputs shown by the software (Table 3); however, only two of them proved to have consistent values that allow them to be interpreted that was Interest and Attention.

Table 3- Custom Expression descriptions and inputs

Custom Expression	Description	Input
Attention	Indicates whether a person is centrally focused (based on the head pose and attentiveness)	- Pitch - Yaw - Depth Position

Interest	Affective Attitude Interest	- AU01- Inner Brow Raiser - AU02- Outer Brow Raiser - AU05- Upper Lid Raiser - AU17- Chin Raiser - AU20- Lip Stretcher - AU26- Jaw Drop
Laughing	Laughing with mouth open	- AU12- Lip Corner Puller - AU06- Cheek Raiser - AU26- Jaw Drop - AU25- Lips Part
Smiling	Smiling (AU6 + AU12) with mouth closed	- AU12- Lip Corner Puller - AU06- Cheek Raiser - AU26- Jaw Drop - AU25- Lips Part
Spontaneous Laughter	Laughing out loud	- AU26- Jaw Drop - AU25- Lips Part - AU12- Lip Corner Puller - AU06- Cheek Raiser

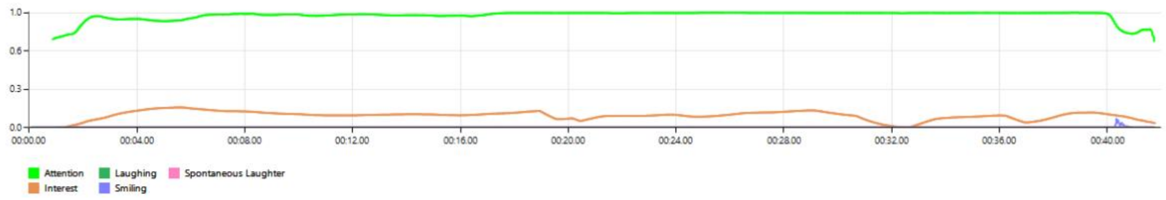

Chart 3- Custom expressions line chart

The videos used as stimulus in the study were searched on YouTube and adapted for the study:

- Anthropomorphic robot: https://www.youtube.com/watch?v=iJ184evAu-I
- Non-human robot: https://www.youtube.com/watch?v=ZsEano0qwcg

4.2 QUESTIONNAIRE

Questionnaires are made to collect data (Marshall, 2005) in a reliable, valid, interesting, and succinct way (Jenn, 2006). When developing one, is important to search for a questionnaire that is already validated to save time and resources (Marshall, 2005).

The questionnaire was a structured-direct survey, once the participants knew the aim of the study and the questions had an order to be answered (Malhotra, 2020).

For the development of this study, all questions were measured with a Likert Scale with nine points (Owuor, 1980). On the question about the plans to buy, the scale ranges from “I am very unlikely to buy it.” (1) to “I am very likely to buy it.” (9), the question regarding the purchase intention ranges from “I would never buy it.” (1) to “I would definitely buy it.” (9), lastly, the questions about trust have a scale that ranges from “Strongly Disagree.” (1) to “Strongly Agree.” (9).

Based on previous studies (Day et al., 1991; Schaefer, 2013; Spears & Singh, 2004; Yagoda & Gillan, 2012), Qualtrics platforms were used to develop the questionnaire, adapted from the following measurement scales (Table 1):

Table 4- Questionnaire measurement items

Construct	Measurements items	Source
Plans to do a Purchase (PP)	PP1. In terms of your plans to buy a product, how likely is it that you will purchase it with the help of the robot that you saw?	Adapted from Day et al., 1991
Purchase Intention (PI)	PI1. What are your intentions in buying a product with the help of a robot like you saw in the video?	Adapted from Spears & Singh, 2004
Trust (T)	T1. The robot is reliable.	Adapted from Yagoda & Gillan, 2012
	T2. The robot will follow my directions.	Adapted from Schaefer, 2013

T3. The robot is friendly.	Adapted from Schaefer, 2013

The questionnaire had a total of 9 questions: 2 of them related to the purchases, 2 were about the trust in the robot present in the video, 1 manipulation-check (that is important to understand if the experimental manipulations were successful (Marett, 2015)), 2 questions about the demographic information (age and gender) and the last one was an open question where participants had the opportunity to write a comment if they wanted (Appendix C).

In total 7 participants wrote a comment about their opinion on the topic:

Table 5- Participants comments

Participant	Stimulus	Comment
Participant 8	Anthropomorphic robot	"You lose the contact with humans that's important for the credibility of the purchase."
Participant 28	Robot without human characteristics	"I don't like the idea of robots in stores."
Participant 29	Robot without human characteristics	"I identify with the topic covered in the video because it is increasingly a reality these days. I agree that there are robots that can be an asset to helping humans, but I also agree that they should in no way change their role. This type of attitude of exchanging computers instead of people is equally negative as unemployment will increasingly be a constant reality, thus being more economically beneficial for structures."
Participant 49	Anthropomorphic robot	"Is the robot representing a male gaze or a female gaze?"

Participant 70	Robot without human characteristics	"I would prefer it not to be such a basic robot, I would prefer the experience to be a little more similar to human contact."
Participant 95	Robot without human characteristics	"It can also be understood as a problem. Hope the function of using this robot could improve store "attendance" and fire people who are a mess in clothing stores, for instance."
Participant 100	Robot without human characteristics	"Robots may help localize what you want."

4.3 PROCEDURE AND MEASURE

The data collection was made with 100 participants and took place at the NOVA Marketing Analytics Lab at NOVA Information Management School. The study consists of three parts: first participants arrive at the lab, a number is assigned to them, to facilitate the identification when doing the data analysis, and they have to read the informed consent which has a brief explanation of the project and the used software, answering if they agree or not to participate in it (Appendix B); second, half of the participants will see a short video of an anthropomorphic robot (Figure 3) interacting with a customer in their decision-making process, and the other part of the participants will see a similar video; however, the robot has a different aspect not having human characteristics (Figure 4) but also helping customers through their decision-making process; the third part is the questionnaire answered with a tablet through a Qualtrics link.

Figure 3- Robot with human characteristics (anthropomorphic)

Figure 4- Robot without human characteristics

4.4 PARTICIPANTS

100 participants participated in the study in a consent way. The data collection started on the 15th of February and lasted until the 2nd of March of 2024, having taken place in NOVA IMS Marketing Analytics Lab at NOVA Information Management School. There were 57 female participants (57%) and 43 males (43%), with ages between 18 years old and 57 years old, with an average of *M*=29,89 years old (*SD*=10,942). The quality of the video recording goes from 0 to 1 and varies from 0.686 to 0.852, with an average of *M*=0.78.

Table 6- Participants profile

Question	**Options**	**Frequency**	**Percentage**
Gender	Male	57	57%
	Female	43	43%
Age	18-21	28	28%

	21-25	45	45%
	26-30	6	6%
	31-35	2	2%
	36-40	4	4%
	41-45	1	1%
	46-50	5	5%
	51-55	8	8%
	56-60	1	1%

5 RESULTS

To understand the significance of a variable, it’s necessary to analyze its p-value, that is measure of the strength of evidence opposite to the null hypothesis (Ludbrook, 2013), which will allow us to understand if the variable is significant or not based on a reference value (Davies & Crombie, 2009) and will traduce a statistical summary of the observed data and our predictions, assuming that all the statistical models are correct (Greenland et al., 2016).

For this study, the values considered were $p < 0.05$ with a confidence interval of 95%, meaning that only 5% of the time can contain a false value of the variable (Davies & Crombie, 2009). This is the value that is normally assumed as a standard level of significance since they eliminate all results that do not meet this criterion, excluding the majority of variations introduced randomly (Fisher, 1966). According to the literature, the two-sided p-value is the better one to be used to understand the significance levels of a variable (Ludbrook, 2013).

The analysis of the results from the FaceReader and questionnaire was done with SPSS. An independent samples t-test was done in all variables considering two groups of observation: Group 1 having participants who observed the video with an anthropomorphic robot and Group 2 with participants who saw the video with a non-humanoid robot (tablet robot). It was possible to observe relevant significance levels in two variables:

- Arousal;
- AU04- Brow Lowerer;

Table 7- Significant variables

		Mean	Standard Deviation	T-Value	P-Value
Arousal	Group 1	0.29	0.04	2.453	.016
	Group 2	0.28	0.03		
AU04- Brow Lowerer	Group 1	0.11	0.05	2.04	.044
	Group 2	0.09	0.02		

Three variables also exhibited marginal significance:

- Sad;
- AU06- Cheek Raiser;
- AU26- Jaw Drop.

Table 8- Marginally significant variables

		Mean	Standard Deviation	T-Value	P-Value
Sad	Group 1	0.05	0.06	1.702	.092
	Group 2	0.04	0.04		
AU06- Cheek Raiser	Group 1	0.07	0.02	1.877	.063
	Group 2	0.06	0.01		
AU26- Jaw Drop	Group 1	0.1	0.03	1.869	.065
	Group 2	0.09	0.02		

Lastly, seven variables based on the literature (Chuah & Yu, 2021; Filieri et al., 2022; Huang et al., 2021; Li et al., 2024; Loijens & Krips, n.d.; Roy et al., 2024; Söderlund, 2022); however, the results demonstrated different scenario for this variables:

- Valence
- Happy;
- Surprise;
- Interest.
- Trust:
    - Trust1- The robot is reliable.
    - Trust2- The robot will follow my directions.
    - Trust3- The robot is friendly.

Table 9- Variables that should be significant

		Mean	Standard Deviation	T-Value	P-Value
Valence	Group 1	-0.03	0.08	-.896	.373
	Group 2	-0.02	0.06		
Happy	Group 1	0.03	0.04	.662	.51
	Group 2	0.02	0.04		
Surprise	Group 1	0.01	0.01	-.147	.884
	Group 2	0.01	0.01		
Interest	Group 1	0.01	0.03	1.096	.276
	Group 2	0.01	0.02		
Trust1	Group 1	6.24	1.66	.398	.691
	Group 2	6.12	1.34		
Trust2	Group 1	6.66	1.76	-1.268	.208
	Group 2	7.08	1.55		
Trust3	Group 1	7.34	1.61	.694	.490
	Group 2	7.12	1.56		

6 DISCUSSION

6.1 SIGNIFICANT VARIABLES

Beginning with variables that showed relevant significance, the variable Arousal, which represents the level of emotional activation or excitement (Yang & Dorneich, 2015), where +1 is active and 0 is not active (Loijens & Krips, n.d.), presented a mean of *M* = 0.29, *SD =* 0.04 for participants who saw the video of an anthropomorphic robot, whereas, for the participants who saw the robot without human characteristics, it was *M* = 0.28, *SD* = 0.03, *t*(98) = 2.453, *p* = .016, revealing that there is a statistically significant difference in Arousal levels between participants from both groups, suggesting that the appearance of the robot has an impact on arousal levels.

A high level of arousal is usually associated with this emotion: happy, glad (Russel, 1980), excited (Lim, 2016; Tsai, 2007), and enthusiastic (Feldman, 1993; Lim, 2016). A low level is present in emotions like calm (Feldman, 1993; Russel, 1980; Tsai, 2007), boredom, depression, sadness, and tiredness (Russel, 1980).

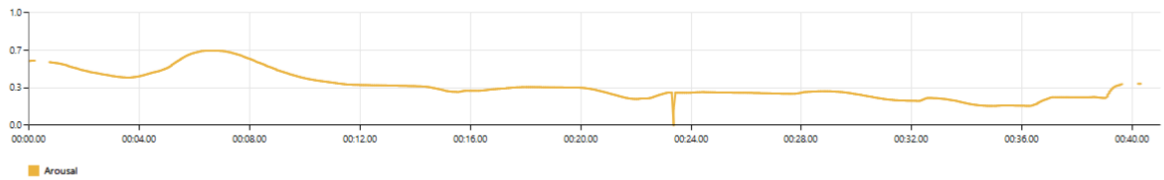

Chart 4- Arousal line chart from participant of group 1

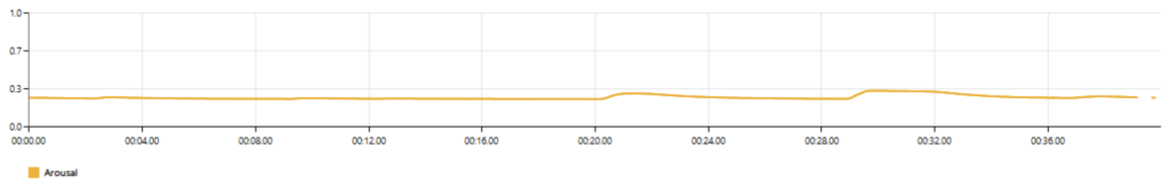

Chart 5- Arousal line chart from participant of group 2

Moving on to the second variable that showed some significance, it was AU04- Brow Lowerer where participants that were in group 1 exhibited a mean of *M* = 0.11, *SD* = 0.05. In the other group, participants had a slightly lower mean of *M* = 0.09, *SD* = 0.02, *t*(98) = 2.04, *p* = .044, suggesting a statistically significant difference in AU04-Brow Lowerer activation between the two groups. Once this action unit contributes to emotions like sadness, fear, anger, and confusion, we can state that participants from group 1 who saw the anthropomorphic robot had higher levels of these emotions compared to the ones who saw the robot with a tablet.

Figure 5- AU04- Brow Lowerer

6.2 Marginal Significant Variables

For a variable to be considered marginally significant, it has to present a significance level a little bit higher than .05 with a p-value between .05 < p ≤.10 (Botella et al., 2021; Olsson-Collentine et al., 2019).

Regarding the variables that are considered marginally significant, starting with the variable Sad, analyzing the significance of the level of sadness between participants from group 1 (*M* = 0.05, *SD* = 0.06) and those from group 2 (*M* = 0.04, *SD* = 0.04, *t*(98) = 1.702, *p* = .092), it's possible to conclude that there was a marginal significance difference in the experience of sadness between participants from both groups, observing that participants exposed to the robot with human characteristics presented slight higher levels of sadness compared to participants that were in group 2.

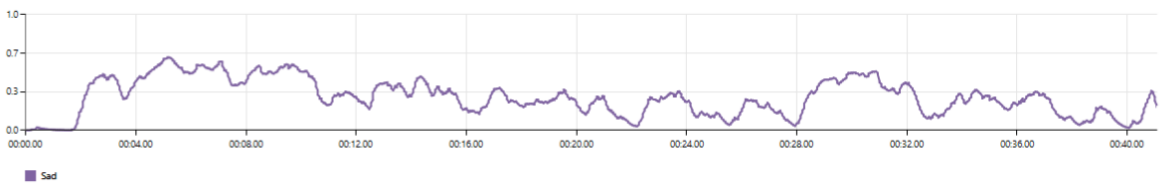

Chart 6- Sad line chart from participant of group 1

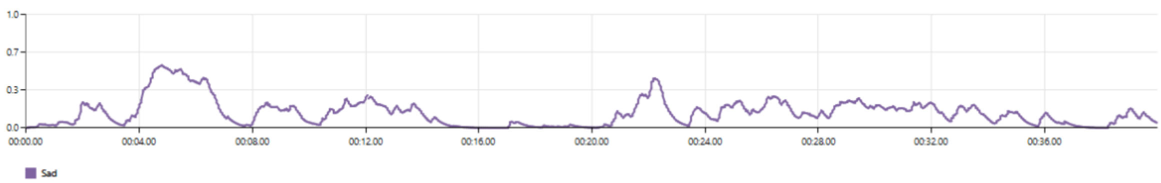

Chart 7- Sad line chart from participant of group 2

The second variable that can be considered marginal significant was AU06- Cheek Raiser, where participants in the robot-human group (M = 0.07, SD = 0.02) presented a higher mean compared with participants in the other group (M = 0.06, SD = 0.01, $t(98)$ = 1.877, p = .063), demonstrating a statistically significant difference in AU06-Cheek Raiser between the two groups. This can lead us to further investigate positive emotions from consumers when interacting with robots.

Figure 6- AU06-Cheek Raiser

The last variable that can present significant values to be marginal significant is AU26- Jaw Drop, where participants in the anthropomorphic robot group (M = 0.1, SD = 0.03) had a slightly higher mean compared to participants in the other group with a robot with a tablet (M = 0.09, SD = 0.02, $t(98)$ = 1.869, p = .065). As stated above, this action unit can indicate surprise and fear, so we can associate that consumers who saw the robot with a tablet presented higher senses of surprise than the ones who saw a robot with human characteristics.

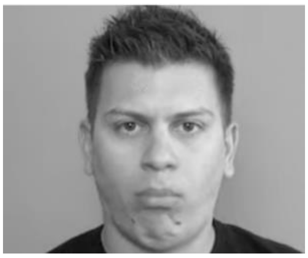

Figure 7- AU26- Jaw Drop

6.3 VARIABLES THAT SHOULD BE SIGNIFICANT

According to the literature, the variable Valence should have shown significant levels since they indicate that the way a consumer feels about the robot, will match the way they feel about the service that the agent will provide, as well as the level of trust that they feel on the machine (Söderlund, 2022). These levels can go from -1 to +1, where a level of 0 means a neutral expression (Chuah & Yu, 2021) and to achieve this value the highest negative emotion is subtracted from the intensity of the emotion "happy" (Loijens & Krips, n.d.). However, after running an independent sample t-test it was observed contrary values proving that there are no significance levels in the Valence variable between group 1 and group 2 (M = -0.03, SD = 0.08) and participants from group 2 (M = -0.02, SD = 0.06, $t(98)$ = -.896, p = .373).

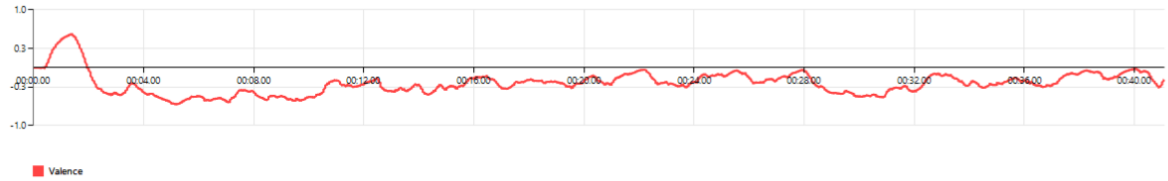

Chart 8- Valence line chart from participant of group 1

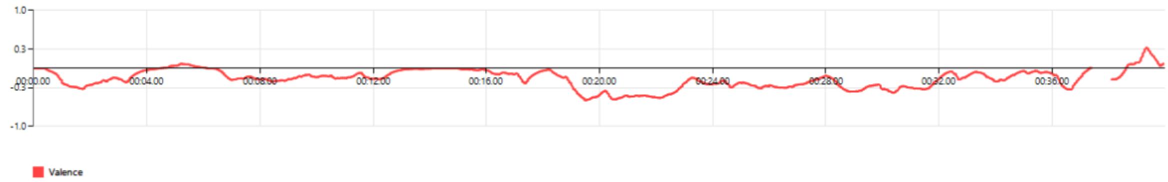

Chart 9- Valence line chart from participant of group 2

The independent sample t-test from the variable Happy showed differences in the level of happiness between the participants who saw the video of a humanoid robot (M = 0.03, SD = 0.04) and those who saw the robot without human characteristics (M = 0.02, SD = 0.04, $t(98)$ = .662, p = 0.51). It's possible to conclude that this variable it's not significant between groups, something that was not expected since there is literature that reveals that happiness is a feeling that is present in consumers' expressions when facing a service robot (Filieri et al., 2022; Huang et al., 2021).

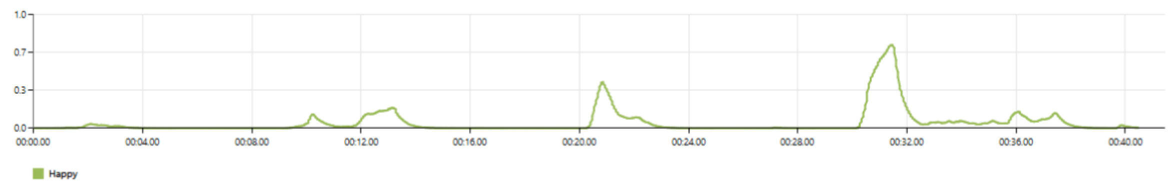

Chart 10- Happy line chart from participant of group 1

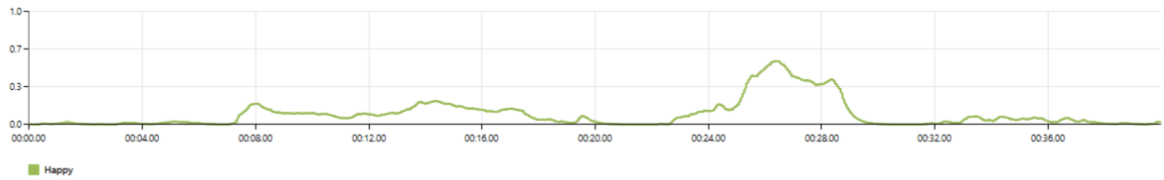

Chart 11- Happy line chart from participant of group 2

According to the literature, the level of Surprise from the participants was supposed to be relevant because people feel amazement when they interact with service robots, and amazement is a feeling of a good surprise (Filieri et al., 2022; Huang et al., 2021). However, the independent sample t-test showed the contrary situation with a non-significant difference between participants from group 1 (*M* = 0.01, *SD* = 0.01) and participants from group 2 (*M* = 0.01, *SD* = 0.01, *t*(98) = -.147, *p* = .884).

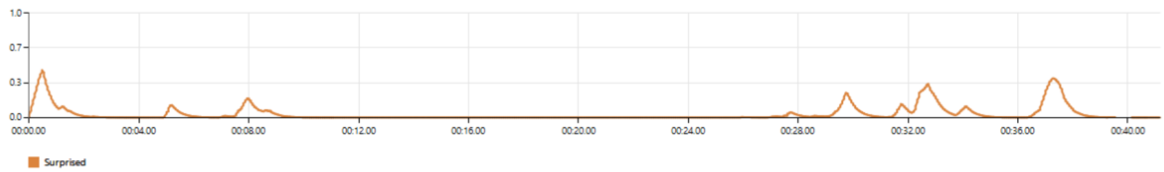

Chart 12- Surprise line chart from participant of group 1

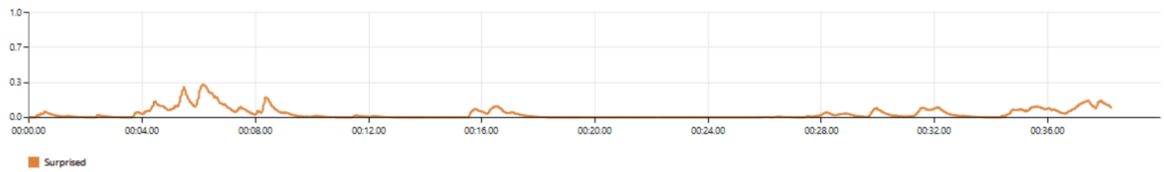

Chart 13- Surprise line chart from participant of group 2

The variable Interest was a variable that had the potential to show significant levels between groups in line with the literature that states that customers feel engaged and curious, emotions of the feeling of interest when dealing with robots (Chuah & Yu, 2021; D. Huang et al., 2021). In contrast, the independent sample t-test conducted yielded a non-significant difference between participants in the robot-human group (*M* = 0.01, *SD* = 0.03) and participants in the robot-tablet group (*M* = 0.01, *SD* = 0.02, *t*(98) = 1.096, *p* = .276).

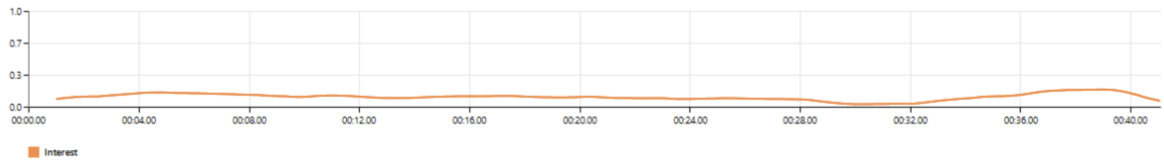

Chart 14- Interest line chart from participant of group 1

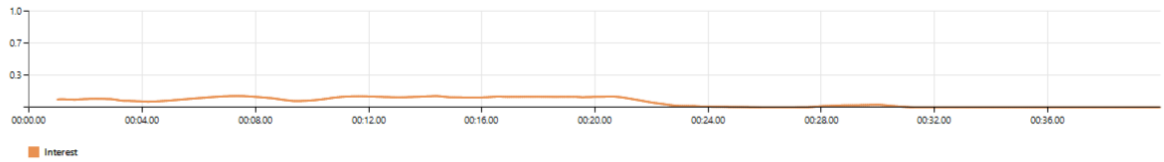

Chart 15- Interest line chart from participant of group 2

Lastly, the variables used to evaluate the level of trust that the consumers felt in the robot were also expected to present significant levels between participants from both groups according to literature that states that the trust that consumers fell in the robot is easily established (Li et al., 2024) and can be perceived as a factor that can mediate the quality that they experience (Roy et al., 2024). However, the independent sample t-test demonstrated different results between participants from group 1 (Trust1- M = 6.24, SD = 1.66; Trust2- M = 6.66, SD = 1.76; Trust3- M = 7.34, SD = 1.61) and group 2 (Trust1- M = 6.12, SD = 1.34, $t(98)$ = .398, p = .691; Trust2- M = 7.08, SD = 1.55, $t(98)$ = -1.268, p = .208; Trust3- M = 7.12, SD = 1.56, $t(98)$ = .694, p = .490), showing that they are not significant variables.

6.4 Mediation Analysis

An analysis of the mediating effect was carried out using the Macro-PROCESS, model 4 (Hayes, 2022) by estimating 5000 bootstraps, and 95% confidence intervals (CI). In a mediation analysis, the results of a study are evaluated to determine whether a causal antecedent variable X transmits its effects to a subsequent variable Y. This analysis is an extension of a linear regression that adds more variables to it where the researcher presumes that the IV (X) will affect the mediator (M), that will impact the DV (Y) (Abu-Bader & Jones, 2021).

In this study the type of robot (anthropomorphic or not) was the independent variable (X), the customer purchase behavior was the dependent variable (Y), and the trust in the robot was the mediator (M). Two variables evaluate the customer purchase behavior: Plans to buy (PlansBuy) and Purchase intention (PurInten). The mediator trust was evaluated in three questions: Robot is reliable (TrustRel M1), Robot will follow my directions (TrustDir M2) and Robot is friendly (TrustFri M3).

The first matrix was conducted to analyze the direct and indirect effects of the IV on the DV (PlansBuy), passing through the Mediators. The direct effect (X → Y) is β = .1910 (SE= .3061, p = .5342, CI [-.4167, 0.7987]), indicating a not statistically significant effect. The indirect effect (X → M → Y) from the M1 (TrustRel) is β = -.0564 (SE= .1473, CI [-.3715, .2140]), from M2 (TrustDir) is β = .0157 (SE= .0572, CI [-.0897, 0.1580]), and from M3 (TrustFri) is β = -.0503 (SE= 0.0883, CI [-.2646, 0.1043]) leading to a non-significant indirect effect as the intervals include zero. Lastly, the total effect (X → Y) is β = .1000 (SE= .3533, p = .7778, CI [-.6012, 0.1043]) meaning that there is not a significant effect on the customers' plans to buy when looking at both direct and indirect effect paths passing through this mediators.

Table 10- First matrix (Stimulus → Trust → Plans to Buy)

Effect	**Path**	**Coefficient (β)**	**Standard Error**	**p-value**	**Confidence Interval (95%)**
Direct Effect	Type of Robot → Plans to Buy	.1910	.3061	.5342	[-.4167, .7987]
Indirect Effect	Type of Robot → TrustRel → Plans to Buy	-.0564	.1473	-	[-.3715, .2140]
	Type of Robot → TrustDir → Plans to Buy	.0157	.0572	-	[-.0897, .1508]
	Type of Robot → TrustFri → Plans to Buy	-.0503	.0883	-	[-.2646, .1043]
Total Effect	Type of Robot → Plans to Buy	.1000	.3533	.7778	[-.6012, .8012]

The second matrix analyzes the direct and indirect effects of the IV on the DV (PurInten), through the Mediators. The direct effect of the type of robot on the customers' purchase intention (X → Y) has a coefficient of β = -.0352 (SE= .3549, p = .8661, CI [-.7644, .6444]) demonstrating that this effect is not statistically significant. Regarding the indirect effect, (X → M → Y) from the M1 (TrustRel) is β = -.0498 (SE= .1317, CI [-.3469, .1850]), from M2 (TrustDir) is β = .0677 (SE= .0800, CI [-.0657, 0.2514]), and from M3 (TrustFri) is β = -.0428 (SE= 0.0837, CI [-.2477, 0.0883]) indicating that there is not a significant indirect effect. The total effect (X → Y) resulted in a coefficient of β = -.0600 (SE= .3549, p = .8661, CI [-.7644, .6444]) suggesting that the type of robot doesn't impact significantly on the customers' purchase intentions considering direct and indirect path passing through the mediators.

Table 11- Second matrix (Type of Robot → Trust → Purchase Intention)

Effect	**Path**	**Coefficient ($\boldsymbol{\beta}$)**	**Standard Error**	**p-value**	**Confidence Interval (95%)**
Direct Effect	Type of Robot →Purchase Intention	-.0352	.3549	.8661	[-.7644, .6444]
Indirect Effect	Type of Robot → TrustRel → Purchase Intention	-.0498	.1317	-	[-.3469, .1850]
	Type of Robot → TrustDir → Purchase Intention	.0677	.0800	-	[-.0657, .2514]
	Type of Robot → TrustFri → Purchase Intention	-.0428	.0837	-	[-.2477, .0883]
Total Effect	Type of Robot →Purchase Intention	-.0600	.3549	.8661	[-.7644, .6444]

7 CONCLUSION

This study investigated the impact that AI robots (anthropomorphic or not) will have on customer purchase behavior, understanding if the level of trust that consumers place in these machines will mediate their purchases. To analyze the effect of that relation, an experimental study with 100 participants was conducted, where each participant was randomly assigned to a video with either a human-like robot or a mechanical one.

The experiment showed that the appearance of the robot can influence some emotional responses from the participants, like arousal levels and brow lower that can be associated with feelings of confusion, sadness, fear, and anger, which proves that participants acted differently to each type of robot. The anthropomorphic robot presented higher levels of emotional arousal and brow lower, indicating that participants demonstrated a higher emotional engagement than those that were exposed to the non-humanoid robot. However, there were some variables like happiness, surprise, and interest, which proved that they were not significant between the two groups that were observed but were supposed to be according to the authors. Additionally, the mediation analysis proved that although trust in the robot's reliability had a significant direct effect on the dependent variable, it didn't mediate the relationship between the IV and DV in a significant way.

Regarding the hypothesis formulated, it was possible to conclude that hypothesis 1 (The use of an AI robot in store (anthropomorphic or not), will affect the customer purchase behavior.) is not verified by the findings of this study, since the type of robots doesn't seem to statistically affect customer purchase behavior significantly in a direct way. The second hypothesis (The level of trust in the robot will mediate the option to use an AI robot in store (anthropomorphic or not), which will influence the customer purchase behavior.) was not validated, once the indirect effect of the type of robot on customers' purchase behavior through trust is not statistically significant.

So, to answer the research question, we can't state that the level of trust, by itself, that consumers feel about the physical appearance of a robot (anthropomorphic or not) will shape customer purchase decisions once there is a lack of significant levels that can support that trust in AI robots.

7.1 THEORETICAL IMPLICATIONS

The results of this study contribute to the understanding of how human likeness, like anthropomorphism, explains the consumers' intention to interact with a robot (Chuah et al., 2021), adding value to the complexity theory that aims to simplify complex systems (Manson, 2001). As a result of this research, the spectrum of applications for goal-oriented decision-making theory is expanded. This theory is based on the assumption that consumers make their decisions as a result of a long process of thinking and analyzing options before making a decision (Alexander, 2012). It is becoming increasingly important to incorporate technology into the daily lives of consumers as technology advances. The Portuguese market already has restaurants that carry out this service using robots to deliver food to customers at their tables, we must now broaden the range of activities in which robots can be incorporated and take into consideration how they can be used in retail stores to optimize the consumer experience. To respond to this need for innovation, it is important to work with consumers and understand what makes them averse to trusting service automation. Therefore, the continuation of this study will be important to understand what other factors may influence consumers and thus contribute to the development of the Innovation Resistance Theory (IRT) (Zhang, 2022).

This leads to some findings like anthropomorphic robots with physical similarities to humans can provoke greater emotions in consumers, compared to more mechanical robots that only have a tablet. It's possible to conclude that the appearance of AI robots (anthropomorphic or not) might influence some emotional responses from the customer like arousal levels and brow lowering that indicate sadness, fear, anger, and confusion, as is explained by the complexity theory that state that the consumer decision process is a complex system and it's influenced by diverse factors (Chuah et al., 2021).

Now it is important to continue developing this study to understand other characteristics of robots, like voice that may influence consumers in their purchasing decisions. Despite that, it was observed that the level of trust in AI robots does not mediate in a significant way the relation between the types of robots and customers' purchase decisions. To continue with this research, there is a need to understand that other mediators may come to play an important role in this relationship to provide development on the part of retail and stores.

7.2 PRATICAL IMPLICATIONS

When the customer decides to proceed with a purchase, they analyze all the brand options that have the product or service they are looking for and that can satisfy their needs. However, consumer confidence is considered the biggest factor that could affect the moment of purchase(Djan & Adawiyyah, 2020). In this evolving world, retailers, managers, and stakeholders should start considering the implementation of more automatization in their stores in more phases of the life cycle of a product or service, especially robots. Anthropomorphic robots that deal with customers can make them feel warm and engaged in a purchase (Huang & Rust, 2021).

Based on this study, customers showed low levels of arousal that usually indicate calm (Feldman, 1993; Russel, 1980; Tsai, 2007), boredom, and tiredness (Russel, 1980). In this case, the 50 participants who visualized the video with a robot with human characteristics presented slightly higher levels compared to those 50 participants who saw the video with the mechanical robot, suggesting that retailers should test the user experience in their customers to understand what type of emotions they feel based on their appearance to make sure that the robot has the right design accordingly to customer experiences and purchase outcomes.

Even though this research didn’t show a significant mediation effect of trust in the robot, it’s important to keep in mind that customers need to trust the opinion that they were given to keep making the purchase, since they don’t want to feel that they are being used and that the opinion is honest and not opportunist (Ginting et al., 2023; Kamtarin, 2012).

7.3 LIMITATIONS AND FUTURE RESEARCH

This study aims to contribute to the development and innovation of retail technologies and AI knowledge in customers. However, there were some limitations faced during the development of this thesis that can be studied later. The research was carried out in a curricular context and realized at NOVA IMS University, making most of the participants students under 30 years old (79%). In a future study, the cultural and demographic factors should be considered when selecting the sample to make a better and more diverse sample. Unfortunately, to save time and ensure that data collection ran as smoothly as possible for participants, the chosen calibration (continuous calibration) was not the best option, since it does not assume the neutral state of each participant but rather assumes a general neutral state, therefore, calibration per participant would be the most suitable for a project like this. Evaluating more mediators that could also mediate the use of AI robots in stores to help customers with their purchase decisions would be interesting, both from the robot's perspective like their gender, their perceived usefulness, and voice tone, from the consumers' perspective like their enjoyment of using the machines, and from the stores' perspective like the type of retail environment and purpose of the purchase. Despite that, there would be a possibility to study and develop a new scale to evaluate either trust or purchase behavior in the context of artificial intelligence and add some different methodologies to hear customers' opinions in the shopping context. All these directions will help improve the analysis and construct a more effective and consumer-friendly robot designed especially for the retail environment.

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APPENDIX

APPENDIX A: ETHICS COMMITTEE REPORT

This is to certify that

Project No.: **DDMKT2024-2-213415**

Project Title: **The trust in AI robots shaping customer decision-making process: impact on the purchase**

Principal Researcher: **Ana Filipa Marmeleiro Leite**

according to the regulations of the Ethics Committee of NOVA IMS and MagIC Research Center this project was considered to meet the requirements of the NOVA IMS Internal Review Board, being considered **APPROVED** on 2/21/2024.

It is the Principal Researcher's responsibility to ensure that all researchers and stakeholders associated with this project are aware of the conditions of approval and which documents have been approved.

The Principal Researcher is required to notify the Ethics Committee, via amendment or progress report, of

- Any significant change to the project and the reason for that change;
- Any unforeseen events or unexpected developments that merit notification;
- The inability of the Principal Researcher to continue in that role or any other change in research personnel involved in the project.

Lisbon, 2/21/2024

NOVA IMS Ethics Committee
ethicscommittee@novaims.unl.pt

APPENDIX B: INFORMED CONSENT

Please enter your participant number:

You are invited to participate in a research study. The purpose of this study is to understand the impact that a robot can have on a customer's purchasing decision.
This study has an approximate duration of 5 to 7 minutes and has two parts. First, you'll watch a short video where the software FaceReader will record your facial expressions, and then you'll answer a questionnaire.
It's important that you answer all the questions and read the instructions carefully. Your participation in this study is entirely voluntary, your responses and the recording will be kept confidential and used only for academic purposes.
By continuing with this study, you indicate that you have read and understood the information provided in this consent form, that you voluntarily agree to participate in the study, and that you have more that 18 years old.

If you have any questions, please contact me:
Ana Filipa Leite
20220040@novaims.unl.pt

- ◯ I agree to participate in this study.
- ◯ I do not agree to participate in this study.

APPENDIX C: QUESTIONNAIRE

Dear participant, you have just watched a short video about the use of an AI (Artificial Intelligence) robot to assist the consumer in-store. The following questionnaire is about the video you watched and the possibility of purchasing in the store. I appreciate your time. Thank you.

Please enter your participant number:

In terms of your plans buy a product, how likely is it that you will purchase them with the help of the robot that you saw?

	1. I am extremely unlikely to buy it	2	3	4	5. I am neither likely nor unlikely to buy it.	6	7	8	9. I am extremely likely to buy it.
Likelihood to do a purchase	○	○	○	○	○	○	○	○	○

What are your intentions in buying a product from a store with the help of a robot like you saw in the video?

	1. I would never buy it.	2	3	4	5. I am uncertain about buying it.	6	7	8	9. I would definitely buy it.
Intention to do a purchase	○	○	○	○	○	○	○	○	○

Please select at what level you agree with the following statements:

	1. Strongly disagree.	2	3	4	5. Neither agree nor disagree.	6	7	8	9. Strongly agree
The robot is reliable.	○	○	○	○	○	○	○	○	○
The robot will follow my directions.	○	○	○	○	○	○	○	○	○
The robot is friendly.	○	○	○	○	○	○	○	○	○

Based on the video that you saw, what was the appearance of the robot?

- ○ Robot with head and arms
- ○ Robot without head and arms

What is your age?

What is your gender?

- Male
- Female
- Non-binary
- Prefer not to say
- Other

We would like to thank you for your participation in this study. If you have any comments that you would like to give about the presence of robots in stores, please feel free to share them in the space below.

NOVA Information Management School
Instituto Superior de Estatística e Gestão de Informação

Universidade Nova de Lisboa