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Consumer Perception of Data Capture by AI Tools

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Master Dissertation presented as partial requirement for obtaining the

Master's degree in Data-Driven Marketing in Digital Marketing and Analytics

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Consumer Perception of Data Capture by AI Tools

by

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Master thesis presented as partial requirement for obtaining the Master’s degree in Data-Driven Marketing, with a specialization in Digital Marketing and Data Analytics

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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 or 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.

Bruno Guilherme Peres Teixeira

Lisboa, 2025

DEDICATION

As we come to the end of this academic journey, I would like to say a heartfelt thank you to all the people who, directly or indirectly, helped make this work possible.

My eternal thanks go to my mother. She was the one who taught me never to give up, to believe in myself and to keep going, even when the path seemed most difficult. All that I am, I owe in large part to the strength, care, and values you passed on to me.

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ABSTRACT

Artificial Intelligence has been transforming the way consumers interact with digital products and services, especially through data capture that allows experiences to be personalized and preferences to be anticipated. This research sought to analyze how the perception of consumers is influenced by the collection of data by AI systems, while exploring the role of the perception of value generated by AI and expectations of transparency in building algorithmic trust. To this end, an online experimental study was conducted with a between-subjects questionnaire, in which participants were randomly exposed to two different scenarios - high versus low data capture - in the context of a streaming platform. The results showed that although the manipulation was effective in changing perceptions of the volume of data collected, it had no direct impact on users' trust in AI systems. Only the perception of value generated by AI proved to be a determining factor in increasing trust, regardless of the amount of data captured or expectations of transparency. These results suggest that perceived value plays a central role in consumer attitudes towards algorithmic technologies, more so than the level of data collection or clarity about this process. This study contributes to understanding the paradox between personalization and privacy, offering relevant insights for companies and institutions seeking to balance the effectiveness of their AI systems with building trusting relationships with users.

KEYWORDS

Artificial Intelligence; Algorithmic Trust; Consumer; Consumer Perceptions; Data Capture; Data Transparency Expectations; Perceived Value.

Sustainable Development Goals (SDG):

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF ABBREVIATIONS AND ACRONYMS

AI	Artificial Intelligence

1. INTRODUCTION

We live in an era in which digital technologies have profoundly transformed the way people interact, work, consume and make decisions in their daily lives. The growing integration of systems based on artificial intelligence (AI), recommendation algorithms and digital platforms has changed not only organizational processes, but also individual and social behaviors (Davenport et al., 2020). From personalizing content on social networks to automating financial and health services, these technologies have become an integral part of modern life, shaping expectations, consumer habits and relationships of trust with digital systems. This technological acceleration, while bringing significant gains in efficiency and convenience, also raises new challenges related to privacy, transparency and user trust (Shin, 2021). In this context, it is becoming increasingly relevant to understand how individuals perceive and interact with AI-based systems, particularly regarding managing personal data and building trust in digital environments (Liu & Shi, 2025).

When it comes to the process of creating value, data capture has increasingly become a strategic factor, as algorithms have become a strategic tool for collecting and processing data (Mazurek & Małagocka, 2019). These algorithms are now used by Artificial Intelligence (AI), which makes decisions based on data elements (Fan & Liu, 2022). The scientists who started working on the development of AI aimed to create machines that would be able to perform tasks like humans, tasks that would need to be performed intelligently (McCarthy et al., 2006). That's why it was necessary to begin by better understanding cognitive processes so that they could be replicated by algorithms. The use of AI is something that can bring potential benefits to consumers' life’s, however, there are some concerns regarding the use and exponential growth of artificial intelligence due to privacy, dehumanization and even dependence on these tools (Mariani et al., 2022).

From a business perspective, AI technologies are very useful for companies to get to know their consumers even better, which has meant that most companies have had to restructure their sales strategies to apply AI to them (Aytekin et al., 2021). Seen as a powerful tool, capable of responding quickly and effectively to what has been the evolution of consumer demand, artificial intelligence has been used more in online companies and social networks (Yeo et al., 2022). A study carried by IBM (2022), estimated that 35% of companies are already using artificial intelligence and 42% are exploring this technology. Nevertheless, with its ability to make transactions faster and access large databases, is reaching a level that people cannot fully control (Aytekin et al., 2021).

For this reason, many scientists and business leaders are becoming concerned about this rapid development and argue that it is important to take urgent measures to prevent this technology from becoming a threat to humanity. This is a very important issue to be aware of, as AI's exponential risk of harming humanity is growing (Brockman, 2015).

This is an extremely important issue, because as AI grows exponentially, we will see fewer human-to-human connections and more human-to-AI connections (Dwivedi et al., 2023). This phenomenon will create a new form of loneliness because the introduction of these technologies risks alienating consumers (Puntoni et al., 2021).

It's then important to realize, that algorithms can help a lot with data overload, to filter it better and present more concrete results when it comes to processing it. From another point of view, consumers can also overcome behavioral biases and cognitive limits, making more rational choices and thus empowering them against manipulative marketing techniques (Abrardi et al., 2022).

Most of the studies carried out focus on the advantages of AI to the companies (Chen et al., 2024; Davenport et al., 2020; Ransbotham et al., 2020; Wirtz et al., 2023) and to its application in marketing, such as improving the efficiency of campaigns or increasing sales through personalized recommendations (Haleem et al., 2022). However, there is a need to understand how consumers react to this type of invisible influence, especially regarding issues of trust and data privacy (Bjørlo et al., 2021). It is therefore essential to understand how consumers perceive data capture by artificial intelligence systems, since the literature shows a lack of studies that critically explore the potential associated risks, such as the manipulation and exploitation of personal data (Cheng et al., 2022). At the same time, it is also important to analyze how these perceptions influence consumers' willingness to use these tools. Although existing research consistently addresses the disadvantages and ethical concerns associated with AI, Mariani et al. (2022) argue that there is also a need to deepen understanding of the benefits that these technologies can offer users, especially from the perspective of perceived value and trust.

Since AI is incapable of making social judgments, it was shown in a study that consumers prefer AI to service delivered by humans in potentially embarrassing situations (Mariani et al., 2022). To better understand the potential consumer benefits of AI, it is important to understand consumer perceptions of artificial intelligence and how this influences its use. Exploring the impact of the algorithmic decision autonomy perspective on consumer purchasing decisions is also something that is still underexplored (Fan & Liu, 2022).

This gives rise to a research question: "How does the perception of data capture influence consumer trust in artificial intelligence-based systems?"

Therefore, the underlying objectives of this research are the following:

1. To analyze how data capture influences the perception of value generated by artificial intelligence systems.

2. To investigate the impact of the perception of value generated by AI on building consumer trust in algorithmic systems.

3. To assess whether consumers' expectations of transparency moderate the relationship between data capture and algorithmic trust.

4. Examine, in an integrated way, how the combination of data capture, AI-driven value perception and data transparency expectations influences consumer trust in artificial intelligence tools.

It is therefore important to take into account the consumer's purchasing process and see how AI influences it.

In order to meet the proposed research objectives, this study adopted a quantitative methodological approach, based on the application of an online questionnaire developed as part of an experimental design. The questionnaire was distributed to a sample of consumers, who were randomly exposed to one of two experimental scenarios: one representing a situation of high data capture by an artificial intelligence system, and another illustrating low data capture. The aim of this manipulation was to understand how different levels of information collection influence consumer perception. This methodology makes it possible to rigorously assess the impact of the manipulated variables on consumers' perceptions and levels of trust towards AI. The questionnaire will include questions on the frequency of use of AI platforms, overall satisfaction with the recommendations and the perceived impact of AI on the purchasing decision. The results will be analyzed using a data analysis platform SPSS.

This study makes several contributions to literature and practice. Firstly, there is a gap in studies focused on consumer experiences and their perception of data capture by AI (Puntoni et al., 2021). This is because the role of the consumer as a stakeholder in the debate on AI has not yet been adequately studied, which is essential for the responsible adoption of these technologies (Cheng et al., 2022). Secondly, this study is very pertinent for companies to understand how they should correctly and responsibly apply the use of artificial intelligence in their activity, as well as improving the consumer experience since understanding the consumer's perspective is essential to mitigate concerns and increase acceptance of AI (Aytekin et al., 2021). Finally, this study has a positive contribution in terms of raising consumer awareness, so that they understand their rights regarding privacy and data capture (Mariani et al., 2022) and can also help to explore ethical issues such as manipulation and power asymmetry, shaping a public debate on the ethical limits of AI, promoting a more responsible and humane use of technology (Bjørlo et al., 2021).

This research analyzes how consumers perceive the influence of artificial intelligence during the purchasing process. Through people's opinions on this subject, it seeks to understand how the use of these new technologies is affected by their perceptions. Begins by presenting the context of the dissertation, identifying the gap in existing research and outlining the questions and objectives of the study

Next is the literature review, which is divided into 5 parts, which refer to the theoretical part that supports the empirical study based on existing literature. The first part briefly covers the history of artificial intelligence and consumer contact with this technology. The second part focuses on data capture by AI tools. The third part builds on the previous one by addressing privacy concerns and trust issues in relation to data capture by AI tools. The fourth point of the literature review concerns ethical questions about data capture. And finally, the fifth point concerns the impact that data capture has on consumer autonomy.

This is followed by the study's conceptual model, which presents the hypotheses suggested for the research. Next, the methodology used to understand consumers' perceptions of the use of AI tools by companies to capture their data is presented. This is followed by an analysis of the results and their discussion. Finally, the main conclusions of the study and its contributions are described.

2. LITERATURE REVIEW

2.1 AI AND CONSUMER INTERACTION

Over the last few decades, artificial intelligence (AI) has profoundly transformed the way people interact with the digital world (Liu & Shi, 2025). Originally developed in the 1950s, AI described computer systems capable of performing tasks that, until then, depended exclusively on human intelligence (Cukier, 2021). More broadly, AI can be understood as a non-human tool capable of collecting, analyzing and interpreting data, while learning from this information to improve responses and offer more efficient solutions (Kietzmann et al., 2018; Puntoni et al., 2021).

Over time, these systems have become increasingly sophisticated and widely integrated into different economic and social sectors (Wirtz et al., 2023). The advance is largely due to the transition from rule-based models to models supported by statistics and machine learning, which rely on large volumes of data to optimize their results (Yuan et al., 2022). As Cukier (2021) points out, one of the most notable features of these systems is their ability to process huge amounts of raw data, without any preconceptions about which variables would be most relevant in the first place - something which, paradoxically, makes them more effective than human judgment in certain contexts.

It is therefore not surprising that, in several tasks, AI is now capable of outperforming humans, especially in terms of speed, scale, precision and reducing operating costs (Cukier, 2021; Haleem et al., 2022). Furthermore, the evolution of these technologies has allowed them to replicate not only human actions, but also social behaviors and, in some cases, almost human characteristics in interaction (Čaić et al., 2020).

People's reactions to these technologies are not exactly new. Studies have shown that individuals tend to respond socially to machines long before the sophisticated development of AI today (Flavián et al., 2024). However, this response takes on a new dimension when it comes to AI-equipped agents capable of listening, communicating, predicting behavior and even showing simulated emotional expressions (Belk et al., 2020; Puntoni et al., 2021).

It is important to recognize, however, that for these interactions to take place effectively, continuous collection of user data is necessary (Wirtz et al., 2023). This collection is often accepted - consciously or unconsciously - by consumers when they choose to use certain services or platforms (Cukier, 2021).

In this context, a dynamic exchange is established: on the one hand, algorithms process data to provide personalized experiences; on the other, consumers benefit from more relevant services tailored to their preferences (Cukier, 2021; Puntoni et al., 2021). This balance is particularly evident on free platforms, such as Google or Facebook, where user data is the main bargaining chip that sustains the operation of services (Cukier, 2021).

Today, through constant interaction with digital platforms, consumers leave a trail of information - whether through searches, comments, likes, shares or other online behavior - that reflects their needs, interests and motivations (Yeo et al., 2022). And while, on the one hand, users benefit from this personalization, with more accurate recommendations or more relevant content (Flavián et al., 2024; Yuan et al., 2022), on the other hand, there is debate about the extent to which this operating model represents a fair practice or a form of exploitation in disguise (Cukier, 2021).

In short, understanding how AI works, its data collection mechanisms and the perceptions that consumers develop in relation to these practices is essential. After all, if on the one hand these systems rely on the massive collection of data to offer value, on the other they raise important ethical questions about privacy, transparency and trust.

2.2 DATA CAPTURE IN AI TOOLS

According to Puntoni et al. (2021) data capture can be defined as the experience of providing data to AI. It is important to note that the capture experience can either serve or exploit the consumer. Although the consumer's perspective on data capture can be seen as “exploitation”, the efficiency provided by these systems can create quite significant value, such as personalization and reducing cognitive overload (Wirtz et al., 2023).

Data capture can be explicit or implicit. Explicit capture is where the information is provided directly by consumers, such as on forms and occasions that are voluntarily declared. Implicit capture is data obtained indirectly, such as browsing history and interactions on digital platforms (Abrardi et al 2021).

From a business perspective, the ethical and transparent use of data capture can minimize the feeling of exploitation, thus harnessing the potential of AI for mutual benefits between companies and consumers (Czarnitzki et al., 2023).

In this way, AI algorithmic agents rely on data capture to make decisions in a way that assimilates with consumers. Predictive analytics plays a key role in this process, since by processing data it is possible to predict future consumer behavior and offer accurate recommendations (Fan & Liu, 2022).

As mentioned earlier, AI collects behavioral data, such as clicks on ads, responses to campaigns and interactions on social networks, to create detailed profiles about consumers. AI-based recommendation systems use this data to carry out personalized interaction and target campaigns, thus increasing marketing efficiency (Mariani et al., 2022). Of particular note are machine learning systems, which seek to analyze structured and unstructured data in order to identify patterns and predict consumer preferences (Abrardi et al., 2021).

The use of big data and machine learning algorithms allows AI to process information on a scale impossible for humans (Chen et al., 2024), providing highly personalized recommendations based on consumer behavior, reducing consumers' cognitive overload and enabling faster and more accurate decisions (Yuan et al., 2022).

2.3 PRIVACY AND TRUST ISSUES IN AI DATA CAPTURE

Companies are currently facing the challenge of managing the psychological and social costs that consumers associate with data capture by Artificial Intelligence systems (Puntoni et al., 2021). Although this process is fundamental to the functioning of AI tools, it generates an obvious tension: on the one hand, consumers recognize the benefits that come from the personalization, efficiency and convenience offered by AI - translating into a greater perception of value generated by AI; on the other hand, they often feel uncomfortable and even exploited, especially due to the lack of transparency associated with the way data is collected and processed (Velasco et al., 2024).

This discomfort becomes particularly evident when consumers do not clearly understand the working principles of AI and algorithms, nor do they know exactly how their data is being used (Grafanaki, 2017). This asymmetry of information feeds a sense of loss of control, directly related to the concept of perceived autonomy - that is, the perception that decisions and events are guided by oneself and not by external forces (Richard DeCharms, 1968). Thus, when data capture becomes excessively opaque or intrusive, it threatens not only privacy, but also this basic sense of individual control.

On the other hand, the perception of value generated by AI acts as a mechanism capable of smoothing over these tensions. When consumers recognize clear benefits - such as more accurate recommendations, faster services or more personalized experiences - they tend to more naturally accept the transfer of their data (Flavián et al., 2024; Puntoni et al., 2021). However, this balance is extremely sensitive to the moderating variable in this model: transparency expectations. Consumers who attach high importance to transparency will evaluate data collection more critically. In these cases, any perception of a lack of clarity in communication about how data is handled significantly compromises the development of algorithmic trust ((Grafanaki, 2017; Velasco et al., 2024)).

In fact, although AI is capable of predicting preferences and behaviors, distrust arises when consumers feel that there is insufficient clarity about how data is aggregated, processed and used (Puntoni et al., 2021). However, it should be noted that this lack of trust does not stem so much from the technical capabilities of AI, but rather from the business practices surrounding data management and the lack of transparency about these processes (Wirtz et al., 2023).

Concrete examples illustrate this tension well. As mentioned by Puntoni et al. (2021), in the case of a sex worker whose clients appeared in Facebook's "People you might know" feature, it becomes clear how algorithms can generate unwanted or even harmful situations. Although this type of suggestion technically stems from legitimate data analysis standards, the lack of transparency regarding the criteria used means that consumers perceive these situations as violations of privacy and exploitation (Cukier, 2021). This type of perception inevitably undermines algorithmic trust.

In addition, the digital ecosystem exacerbates these dynamics, since most data intermediaries - known as data brokers - operate in a poorly regulated environment, which further compromises transparency and accountability (Grafanaki, 2017). In this context, it becomes essential for companies to develop strategies that reduce this asymmetry and strengthen trust, namely through more empathetic practices that involve active listening to consumers (via sentiment analysis and digital observation), a critical assessment of data collection practices, and ongoing support for studies and research that help to better understand the impact of AI on different communities (Puntoni et al., 2021).

2.4. ETHICAL CONCERNS AROUND DATA CAPTURE

Consumers tend to like and be satisfied with frontline agents, as they are often seen as solving their problems (Flávian et al., 2024). As already mentioned, AI is seen as a good tool for solving problems (Yeo et al., 2022), however, some studies highlight the challenges that AI can pose when investigating psychological issues that evolve with human-AI interactions. These problems are extremely relevant as the technology is more disruptive than others seen in previous technological revolutions (Flávian et al., 2024).

In general, the lack of ownership over personal data has been associated with a loss of personal control due to the technological threat. Due to the lack of privacy and constant surveillance, people can no longer control their destiny. This means that data capture can sometimes violate expectations of privacy, especially when it is done implicitly (Wirtz et al., 2023).

This creates a risk of overexploitation of consumer data, where companies prioritize profit over ethics (Czarnitzki et al., 2023),which can manifest social inequalities and reinforce stereotypes, creating significant ethical impacts (Cheng et al., 2022). Such dystopian concerns arise when one considers Google's move in the early 2000s to transform consumer data from a by-product into an economic asset that generated a new type of commerce driven by the ability to colonize the consumer's private experience (Puntoni et al., 2021).

An ethical dilemma then arises between personalization and privacy (Mariani et al., 2021). The excessive use of personal data for AI-generated recommendations creates a conflict over what is acceptable between the collection and use of this data (Cheng et al., 2022). This problem intensifies when there are algorithmic decisions based on biased data, which can generate discrimination as well as social inequalities, negatively impacting consumers from vulnerable groups (Fan & Liu, 2022).

Hence the importance of companies being transparent in the way they handle data so as not to damage consumer trust, since invasive practices can be perceived as disrespectful and manipulative (Mariani et al., 2021).

This tension is fueled by the real or perceived loss of personal control, which leads to significant psychological consequences. The loss of control induces feelings of demotivation and powerlessness. For individuals in vulnerable positions (e.g. victims of domestic violence, political activists), for some, violations of privacy can be life-threatening (Wirtz et al., 2023). There is a lack of clear consent as a central concern, where the vast majority of consumers do not know to what extent their data is collected (Fan & Liu, 2022). An example that describes this situation well happened in the USA, where Danielle, a consumer who trusted Amazon's Echo devices until one day she recorded and sent a private conversation to a random contact, without their consent. She understandably felt invaded and refused to use the device again (Puntoni et al., 2021).

2.5. Impact of Artificial Intelligence on Consumer Choice

Not long ago artificial intelligence was considered science fiction, but today it is changing the way consumers eat, sleep, work and even have fun. If we look at examples such as Amazon's speaker devices, as well as Google Photo's editing suggestions and even Spotify's playlists, it is possible to see the interactions that consumers have throughout the day with AI (Puntoni et al., 2021).

It is common for algorithmic tools that use captured data to make decisions automatically, which reduces the role of the consumer during the choice process. Once consumers perceive that their choices are being limited by data-based systems, there may be a rejection of recommendations and distrust in technology (Fan & Liu, 2022).

That said, marketers tend to work in organizations with cultures defined by computer science, which can break with the objectives of software developers who want to create technical excellence, while marketers want to create valued consumer experiences (Puntoni et al., 2021). As consumer choices are guided by algorithms, they lose autonomy, since these tools prioritize corporate objectives over freedom of choice (Cheng et al., 2022). It is therefore clear that the personalization offered by AI is of great convenience to the consumer, but it raises concerns about consumer autonomy, especially when this personalization is excessive, which can limit the consumer when looking for alternatives (Mariani et al., 2021).

It is therefore clear that AI is a very useful tool when it comes to facilitating navigation and saving consumers time, but it limits exploration and spontaneous discovery. The tension between automation and human control is evident (Gonçalves et al., 2024), which is why privacy is a pillar of consumer autonomy, and its violation, through massive data collection, compromises their ability to make independent decisions (Bjørlo et al., 2021).

3. CONCEPTUAL MODEL

After a review of the most relevant topics on the subject and taking into account the objectives and an answer to the research questions, a conceptual model was developed for this study. The model proposed for this research contributes to understanding consumer point of view, in terms of trust, transparency expectations and value perception of data capture by artificial intelligence systems. The model is made up of factors that can positively or negatively influence consumer trust in AI technologies.

In the last years, artificial intelligence has been widely used strategically by companies to personalise services and optimise consumer experiences (Haleem et al., 2022c). However, there are consumers who have concerns about the way their data is captured and used, which can be an influencing factor when it comes to trust in AI systems (Mariani et al., 2022). Previous studies show that the perception of transparency and fairness in the use of data is strongly associated with the acceptance of AI tools and trust in their decision-making processes (Wang et al., 2022).

The relationship between data capture and consumer trust is not linear, as it depends on the perception of fairness in the use of data and the value that consumers perceive in using personalised AI-based services (Bjørlo et al., 2021). When consumers perceive that the use of their data is done ethically and beneficially, trust in AI tends to increase (Wang et al., 2022). On the other hand, privacy concerns and a lack of transparency can result in lower acceptance and greater resistance to the use of these technologies (Darina Vorobeva et al., 2025).

Based on these ideas, the conceptual model investigates the impact of data capture on consumer trust in AI systems, analyzing the factors that can mediate and moderate this relationship. The aim is to provide insights for companies and policymakers on how to balance personalization and privacy order to increase consumer trust.

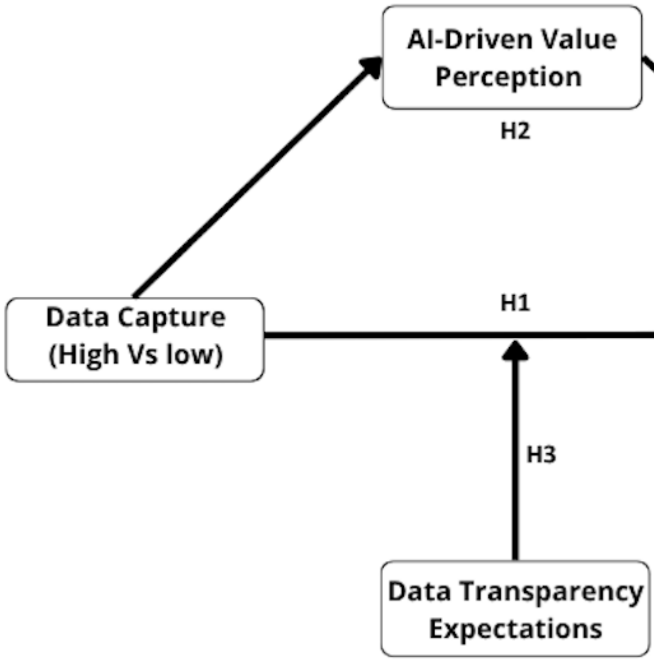

Figura 1- Conceptual Model (Sourse: Author)

Data capture by artificial intelligence systems is integrated into the model as an independent variable, being the main factor that can influence consumer perception. AI-Driven value perception is used as a mediating variable, since it can explain the impact of data capture on algorithmic trust. Finally, the expectation of data transparency acts as a moderating variable, since it can change the way consumers interpret the use of their data and influence the relationship between data capture and trust in algorithms.

3.1 Data Capture (High vs Low)

Consumers increasingly have access to all the information they need to make their purchasing decisions, allowing them to compare products or services and prices in order to acquire the most appropriate solution (André et al., 2018). There is therefore a need for companies to personalize the way they communicate and redesign their marketing strategies, as product or service differentiation is no longer enough to capture consumers' attention (Wang et al., 2022).

In this way, artificial intelligence has emerged as a very useful tool for companies where they can use a large volume of data to offer highly personalized content for each consumer (André et al., 2018). Companies like Netflix and Amazon regularly use this type of tool to segment content according to the needs and interests of their users (Gonçalves et al., 2024).

In order for these artificial intelligence tools to work, data must be captured so that the results are as accurate as possible. As already mentioned, this data capture can be done in various ways, such as through data provided by consumers, either intentionally or unintentionally (Puntoni et al., 2021).

However, not all consumers are extremely happy with the personalization of the content generated for them through these tools, as there are concerns about the privacy of their data and the ethics of the companies in the way they handle it (Cheng et al., 2022). Increased personalization and customer engagement extend the interaction between the customer and technology across touchpoints. This raises challenges when it comes to customer experience management, as customers have high expectations of having effective and seamless experiences (Ghesh et al., 2024). These expectations are sometimes difficult to meet, as implicit personalization does not have the filters chosen by the customers themselves and personalized messages can emerge that provoke less positive reactions in people (Abrardi et al., 2022). There are therefore high expectations of AI-enabled systems facilitating personalization of customer experiences (Mariani et al., 2022). This is how we see the importance and value of data: through captured data companies can improve the consumer experience by creating products, interactive websites, etc. according to their needs and expectations (Yeo et al., 2022), and in this sense artificial intelligence tools are crucial, because the supply of consumer data is always increasing in volume, speed, variety and accuracy. AI can transform this abundance of data into useful information about customers (Cukier, 2021b).

In this way, there is an idea that consumers want to have a personalized experience that meets their expectations as far as possible. However, there is also a question of trust in companies, a high level of concern about ethics and privacy in the way they use artificial intelligence tools to obtain and work with their customers' data. With this in mind, the following hypothesis is proposed:

H1: The high (vs. low) use of data capture by companies to collect information from their customers influences their level of trust.

3.2 AI-Driven Value Perception

Consumer opinions can vary, and indeed the existence of privacy concerns can result in a lack of trust in algorithms, however, when there are perceived benefits that outweigh the risks, the consumer tends to be in the position of the consumer and understand what perceived benefits AI presents to consumers. in the position of the consumer and understand what perceived benefits AI presents to consumers.

Artificial intelligence has also brought benefits to the consumer: the provision of personal data allows consumers to enjoy the convenience of personalized services, information and entertainment, sometimes representing more value than the associated privacy concerns (Bjørlo et al., 2021). In general, companies can reduce the level of exploitation perceived by consumers by playing an active role in educating them about the costs and benefits of AI data capture experiences. For example, Google Home clearly communicates which user data is stored and why. By being transparent, the company helps to maximize the perceived value of the product, so data capture is not seen as something negative, but rather as a benefit that consumers are served by AI (Puntoni et al., 2021).

Sometimes the value of AI is not realized by consumers because they don't tend to incorporate the time, cognitive and emotional costs of research. However, this is something that is directly associated with customer satisfaction; the time that a person wastes to find what they want and that fulfils their needs can cause the customer to become dissatisfied to a certain extent, and this is where AI algorithms are an asset (André et al., 2018).

It is therefore relevant to study the value perceived by consumers about AI, because although it may be a tool that presents privacy concerns, it is a technology that has its benefits that may or may not be seen as a greater good over the concerns associated with AI, with greater confidence in these technologies. Following this logic, the following hypothesis was formed:

H2: AI-driven value perception mediates the relationship between data capture and algorithmic trust.

3.3 DATA TRANSPARENCY EXPECTATIONS

Companies increasingly value the collection and processing of customer data. This will bring many benefits to the company and can also bring benefits to the consumer when these are realized. However, for this to happen, companies must be clear and transparent in the way they collect, process and use their customers' data. It's natural, especially nowadays when there are consumers who already feel that there is a low level of control over the autonomy of their data (Gonçalves et al., 2024), that they want to know how data is collected, what practices are used by brands, who they share it with and how their data is protected (Puntoni et al., 2021). With the use of AI technologies, the story is no different; in fact, there may even be a need for greater transparency, since artificial intelligence acts almost 'invisibly'. Although the vast majority of people already know about it, there is no general knowledge of how algorithms work and how they present the answers they give (Ghesh et al., 2024).

The idea of companies being transparent in the way they use AI technologies to communicate how the process of collecting and processing data works is something that is increasingly inherent in the literature, however, there are some studies that demonstrate the opposite idea. According to Schmidt et al. (2020) it is not always beneficial for companies to be highly transparent in showing how AI systems work, as it can sometimes have a negative effect on trust behaviour.

It is therefore important to understand consumers' perceptions of the transparency of data capture by AI tools, so that companies can increase the level of trust in data capture. The following hypothesis is proposed:

H3: Data transparency expectations moderate the relationship between data capture and algorithmic trust.

3.4 ALGORITHMIC TRUST

In an increasingly digitized context, where personalization is largely driven by algorithms and Artificial Intelligence tools, it becomes essential to understand how consumers build their trust in these systems. The use of AI to collect, analyze and apply personal data raises questions about the extent to which consumers believe these technologies operate fairly, ethically and reliably. This trust is often influenced by individuals' perception of how companies capture and use their data, and the clarity with which these practices are communicated. When this perception is positive, trust tends to strengthen; however, when there is a sense of invasion of privacy or lack of control, trust in algorithmic systems can be significantly undermined.

The relationship between data capture and algorithmic trust is particularly relevant, since the perception of how data is obtained and used can reinforce or undermine this trust. When consumers perceive that companies collect large volumes of data without their explicit knowledge, or without transparency as to the purpose of that collection, they tend to develop fears associated with invasion of privacy and loss of control over their personal information (Cheng et al., 2022; Puntoni et al., 2021). This perception can lead to mistrust of automated systems, even when they are technically effective.

On the other hand, when consumers recognize clear benefits resulting from personalization such as useful recommendations, simplified experiences or time savings, and feel that their data is treated with transparency and respect, trust in algorithms tends to increase (Bjørlo et al., 2021; Mariani et al., 2022). Algorithmic trust, in this sense, depends not only on the quality of the technology, but also on how the data capture experience is communicated and perceived.

Based on this framework, algorithmic trust is considered to result from the way consumers interpret the balance between the risks associated with data collection and the benefits offered by AI-based solutions.

4. METHODOLOGY

In order to answer the research questions proposed by the study and taking into account the literature review previously carried out, a quantitative study was carried out using an online questionnaire. It was decided to carry out quantitative research, as quantitative data allows quantitative or numerical descriptions of trends, attitudes or opinions of a given population through the study of a sample (Creswell & Creswell, 2017). It is an approach to collecting data by asking respondents questions in order to obtain information about their expectations, behaviors, knowledge and so on (Huang & Yongquan, 2025).

In order to ensure transparency and scientific rigor, this study was pre-registered on the AsPredicted platform (study #219872), guaranteeing alignment with good research practices. The methodology adopted corresponds to a between-subjects experimental design, in which the perception of data capture by artificial intelligence systems was manipulated. The experiment includes two different experimental conditions: high data capture (High) and low data capture (Low). Data was collected via an online questionnaire, designed on the Qualtrics platform and made available via a link, allowing participants to answer autonomously on any device with internet access. This online approach is justified by its accessibility, efficiency and the possibility of reaching a more diverse sample in geographical and demographic terms.

Prior to data collection, the study was submitted to and approved by the NOVA Information Management School Ethics Committee (NOVA IMS Ethics Committee), ensuring that all procedures complied with the ethical principles applicable to research with participants. The respondents were previously informed about the objectives of the study and participated voluntarily, ensuring the anonymity and confidentiality of their responses.

The questionnaire was designed using a nine-point Likert scale (ranging from “Strongly disagree” to “Strongly agree”). It will be divided into sections covering different dimensions related to consumers' perceptions of data capture by AI. These dimensions will include questions related to ethical concerns, control over personal data, trust in companies using AI, and the impact of these practices on consumer decision-making.

The data collected relates to consumers who live in Portugal and are over 18 years of age, since it is assumed that from this age onwards, they are more likely to use the internet and in turn AI tools, even if they don't buy the product or service themselves.

This questionnaire is organized into 3 main parts, arranged in a logical way so that the answers and data collected flow smoothly.

On the first page of the questionnaire, respondents are shown information about their participation in the questionnaire. Each respondent is informed of the conditions of participation in the study and then asked if they accept these conditions. If they accepted, they went on to the next part of the questionnaire; if they didn't agree to take part, the questionnaire ended at that point. It is important to note that the questionnaire was completely anonymous, guaranteeing the privacy and confidentiality of the answers. Participants were informed about the purpose of the study and the issues mentioned above, as well as the possibility of withdrawing at any time.

The second part concerns the study itself. It is divided into five sections that correspond to the four hypotheses proposed in the conceptual model.

The first section focuses on consumer awareness of data capture, assessing respondents' level of knowledge about how data is collected and used by AI tools. In order to assess this, a situation was presented concerning a company that had just developed an AI tool (“InsightAI”) with the main aim of improving the consumer experience on streaming services by personalizing content that appeared as a suggestion to the user. In this situation, respondents were randomly assigned one of two scenarios (high data capture or low data capture). The high data capture scenario consists of analyzing the following user information: search history, film and series preferences, content they started watching but didn't finish, the devices they use and even the times they usually watch content. The low data capture scenario, as the name suggests, works as a safer model that recommends content based on information the user provides, such as the films and series they have rated or added to their list.

The second section explores the AI-driven perception of value, examining the extent to which consumers believe that the use of AI and data capture brings relevant benefits. This includes perceptions about the personalization of content or services, convenience, relevance of recommendations and whether using their data transparently actually improves their user experience.

The third section evaluates expectations of data transparency, assessing the degree to which consumers expect companies to be clear and open about their data practices. This includes expectations regarding data access, control, consent mechanisms and visibility into how AI tools work when using personal information.

The fourth section measures algorithmic trust, assessing the level of trust consumers place in AI systems. This includes beliefs about whether AI-based decisions are fair, impartial and reliable, and whether consumers trust companies to use AI responsibly when personal data is involved.

Finally, the fifth section refers to the manipulation check, to measure the number of respondents who understood the scenario presented to them at the beginning of the questionnaire, in which they had to state whether the scenario presented a high volume of captured data or a low volume of captured data.

Then, the last part of the questionnaire focuses on collecting socio-demographic information from the participants, in order to be able to segment the responses and analyze possible differences in the perception of data capture by AI based on demographic factors such as age, gender and occupation.

The sample was non-probabilistic, which allowed for a variety of demographic profiles. To enrich and segment the analysis, data on respondents’ age, gender, and profession was collected.

The data collected was then analyzed using statistical methods, using the appropriate software for data processing, SPSS.

5. RESULTS AND DISCUSSION

The data for the design was collected from 27 March to 15 May, obtaining a total of one hundred and nine responses. All the responses were valid for analysis, and there was no need to exclude any. It was therefore possible to achieve the minimum figure of one hundred respondents.

5.1 Respondents Profile

Of the 109 responses, 45% were from women and the remaining 55% from men, with no non-binary/third gender respondents. The respondents' ages ranged from 19 to 81, with the average age being 32 and the highest percentage being 23 (20%). As for occupation, the vast majority of respondents are employed (71%).

The results were obtained using descriptive statistics to analyze the frequency of items related to demographic aspects.

5.2 Measurement Model

In order to test the hypotheses and the model presented, SPSS (Statistical Package for the Social Sciences) a software programme used to carry out statistical analyses (IBM, n.d.). Firstly, Cronbach's alpha coefficient as used to analyze the quality of the questions for measuring each variable. Then Independence Sample T-Test was carried out to analyze the Main Effect, namely the relationship between data capture (High vs Low) (independent variable) and the manipulation question. The General Linear univariate model was then used to explore the significant effects of the independent variable (Data Capture: High vs Low). The moderator and mediator were tested using Hayes Regression to measure the correlation between these variables. The PROCESS macro for SPSS, developed by Hayes (2022), regression model 4 (mediation analysis) and regression model 1 (moderator analysis) were used to analyze the mediator as well as the moderator. Through the analyses presented, it was possible to accept or reject the three hypotheses developed earlier.

Tabela 1- Constructs and Measurement

Construct	Items	*Items* **Measurement items**	Sources
AI-Driven Value Perception	DVP1	DVP1. I understand the way AI helps me with the decisions I want to make.	Adapted from Baah et al., 2025
	DVP2	DVP2. I understand why AI gives me the answers it does.	
	DVP3	DVP3. I understand the mechanisms that AI uses to form its responses.	
	DVP4	DVP4. I believe that transparency in data capture increases my trust in digital services.	
Data Transparency Expectations (DTE)	DTE1	DTE1. Using AI helps me acquire knowledge.	Adapted from Wanner et al., 2022
	DTE2	DTE2. I feel that the use of AI tools by companies is ethical.	
	DTE3	DTE3. I have no problem providing my information, since through AI I can have a better online experience.	
	DTE4	DTE4. AI improves my online experience by offering content and products aligned with my interests.	
	DTE5	DTE5. I believe that the benefits provided by AI outweigh the concerns about data capture.	
Algorithmic Trust	AT1	AT1. Artificial Intelligence can be trusted.	Adapted from Cabrera-Sánchez et al., 2021
	AT2	AT2. I trust that companies use AI ethically and responsibly.	
	AT3	AT3. I'm concerned about the risk of manipulation through AI algorithms.	
	AT4	AT4. AI algorithms are reliable and do what they promise.	
	AT5	AT5. I believe that the transparency and perceived value of AI increases my trust in algorithms.	
Manipulation Check	MC	MC1. Based on the scenario presented at the beginning of the questionnaire, how would you describe the way the AI system collects and uses user data?	Morales et al., 2017
Demographic	D1	D1. What is your gender?	Adapted from Arora et al., 2024
	D2	D2. What is your occupation?	
	D3	D3. What is your age?	

5.3 ALPHA DE CRONBACH

To assess the internal consistency of the scales used in this study, Cronbach's Alpha was calculated for each variable made up of its multiple items. Cronbach's alpha quantifies the degree of homogeneity between questions measuring the same construct, with a minimum value of 0.7 being acceptable to guarantee adequate reliability (Edelsbrunner et al., 2025). The results obtained were as follows:

About Algorithmic trust, the initial scale made up of five items, recorded a Cronbach's Alpha of 0.662, a value considered "questionable" but still suitable for exploratory use, especially given the small number of items. The "Alpha if item deleted" analysis revealed that item 3 substantially compromised internal consistency: by excluding this item, the Alpha increased to 0.796, exceeding the recommended minimum threshold. For this reason, it was decided to remove the third item from the scale, keeping only four items to measure Algorithmic Trust. With this correction, the scale showed good internal reliability, justifying the use of the composite index at subsequent levels of analysis. AI - Driven Value Perception had a Cronbach's alpha of 0.811, which indicates good internal consistency. This result confirms that the grouped questions consistently measure the variable. For Data Transparency Expectations, a Cronbach's alpha of 0.837 was obtained, also classified as good (Malkewitz et al., 2023). This value shows that the questions selected are highly homogeneous, which demonstrates that they correctly assess the variable.

Tabela 2- Internal Consistency of Scales (Cronbach's Alpha)

Construct	Measurement items	Cronbach's Alpha if item Deleted	Cronbach's Alpha
AI-Driven Value Perception	DVP1. I understand the way AI helps me with the decisions I want to make.	.741	.521
	DVP2. I understand why AI gives me the answers it does.	.806	
	DVP3. I understand the mechanisms that AI uses to form its responses.	.778	
	DVP4. I believe that transparency in data capture increases my trust in digital services.	.848	
Data Transparency Expectations (DTE)	DTE1. Using AI helps me acquire knowledge.	.770	.811
	DTE2. I feel that the use of AI tools by companies is ethical.	.769	

	DTE3. I have no problem providing my information, since through AI I can have a better online experience.	.773	
	DTE4. AI improves my online experience by offering content and products aligned with my interests.	.755	
	DTE5. I believe that the benefits provided by AI outweigh the concerns about data capture.	.803	

Algorithmic Trust	AT1. Artificial Intelligence can be trusted.	.551	.662
	AT2. I trust that companies use AI ethically and responsibly.	.543	
	AT3. I'm concerned about the risk of manipulation through AI algorithms.	.796	
	AT4. AI algorithms are reliable and do what they promise.	.532	
	AT5. I believe that the transparency and perceived value of AI increases my trust in algorithms.	.541	

5.4 T-TEST INDEPENDENT SAMPLE (MANIPULATION VS IV) MODEL

To check the effectiveness of the experimental manipulation, a t-test was carried out (table 2 and 3) to compare the participants' perception of the amount of data collected by the system, depending on the condition they were exposed to (high vs. low data capture).

The test showed that the variations in responses between the two groups were not equal, so the version of the test that does not assume equal variances was used. The results indicate that the participants who saw the low data capture scenario clearly perceived that less data was being collected (Mean = 5.41; SD= 2.81), compared to those who saw the high data capture scenario (Mean = 7.44; SD = 1.90). This difference was statistically significant ($t(104.79) = -4.48$; $p < 0.001$), with a mean difference of -2.03 and a 95% confidence interval between -2.93 and -1.13.

This shows that the manipulation worked as intended: the participants did notice the difference between the two scenarios, which validates the quality and clarity of the experimental design.

Tabela 3- Group Statistics

IV	N	MEAN	Std. Deviation	Std. Error Mean
Low	61	5,41	2,81	0,36
High	48	7,44	1,9	0,27

Tabela 4- Independence Sample T-test Manipulation Check

		Levene's Test for Equality of variances		T-Test for Equality of Means				
		F	Sig.	t	df	Unilateral p	Mean Difference	Std. Error Difference
Manipulation Check (Data Capture high vs low)	Equal variances assumed	11,995	<,001	-4,28	107	<,001	-2,028	0,474
	Equal variances not assumed			-4,48	104,79	<,001	-2,028	0,453

5.5 General Linear Univariate Model

The Univariate Regression Model (Table 3) was used to explore the significant effects of the independent variable (Data Capture High vs Low) on the other variables related to respondents' perceptions of IA systems. The analysis indicated that the independent variable had a statistically significant effect on the manipulation question which assesses how the AI system collects consumer data according to the scenario that appeared to them at the beginning of the questionnaire. The results were $F(1,35) = 19.95$, $p<.001$, which indicates a strong effect on the part of the independent variable.

None of the other variables showed statistically significant differences ($p> .10$), although there was a trend towards significance in the statement ‘I understand the mechanisms that AI uses to form its responses’, $F=(1,35) = 3.07$, $p = .088$. This result shows that there are no clear differences between the variables; however, there are interesting indications that may be worth exploring in future research.

Tabela 5- General Linear Univariate Model: Marginal Effect

Dependent Variable	Sum of Squares	df	Average Square	F	Sig.
I understand the mechanisms that AI uses to form its response	43,44	1	3,811	3,071	0,88
Manipulation Question	171,179	1	97,549	19,945	<,001

5.6 MEDIATION ANALYSIS

To analyze whether the perception of value generated by artificial intelligence (AI-Driven Value Perception) mediated the relationship between the amount of data captured (Data Capture) and trust in algorithms (Algorithmic Trust) mediation analysis was carried out using Hayes model 5 (Hayes, 2022), with 5000 bootstrap samples and a 95% confidence interval.

The analysis revealed that the independent variable (Data Capture) did not have a significant effect on the mediating variable (AI-Driven Value Perception), with a coefficient of $\beta = 0.038$, $p = .902$. This indicates that the different levels of data capture did not significantly influence the perception of value attributed to artificial intelligence.

On the other hand, AI-driven value perception (mediator) had a positive and significant effect on trust in algorithms, with a coefficient of $\beta = 0.898$, $p < .001$. This result suggests that the greater the perception of value attributed to AI, the greater the participants' trust in algorithms.

The direct effect of data capture on algorithmic trust was not significant ($\beta = -0.106$, $p = .661$), and the indirect effect (via AI-Driven Value Perception) was also not statistically significant, with a bootstrap confidence interval that includes zero (95%CI = [-0.341, 0.306]).

5.7 MODERATION ANALYSIS

A moderation analysis was carried out using Hayes model 1 of the (Hayes, 2022), with the aim of testing if data transparency expectations moderate the relationship between data capture independent variable) and algorithmic trust (dependent variable).

The model proved to be statistically significant ($R^2 = .284$, $F(3, 105) = 13.891$, $p < .001$), explaining approximately 28.4% of the variance in algorithmic trust. There was a significant effect of data transparency expectations on algorithmic trust (coef. = .736, SE = .228, $p = .002$), indicating that participants with higher transparency expectations tend to have higher levels of trust in algorithmic systems.

However, the main effect of the Data Capture variable (coef. = 1.031, SE = 1.022, $p = .315$) was not statistically significant, suggesting that, in isolation, the level of data capture does not influence algorithmic trust.

Similarly, the interaction between data capture and data transparency expectations was not significant (coef. = -.187, SE = .156, $p = .235$), which indicates that transparency expectations do not significantly moderate the relationship between perceived data capture and algorithmic trust.

5.8 Discussion

The results obtained reveal an interesting point. Although the participants can tell when a system is collecting more or less data, this perception does not automatically translate into distrust or a lower valuation of the AI system. In other words, the mere fact that the system collects a lot of data does not, in itself, seem to undermine trust in the algorithms or change the perception of the value of AI.

This is partly contrary to what is argued by authors such as Cukier (2021) and Puntoni et al. (2021), who argue that the perception of data intrusion can undermine consumer confidence. In our case, there was no such direct impact. This result may indicate that, despite awareness of the amount of data collected, users do not yet feel that this negatively affects the usefulness of the system, perhaps because they are already used to this type of dynamic in the digital environment or because they do not fully understand what happens “behind the screen”.

Furthermore, the absence of significant mediation of value perception (AI-driven value perception) raises questions about the real importance of personalization when evaluating AI systems. Although the literature insists on the benefits of the value generated - such as more tailored recommendations and less cognitive overload (Wirtz et al., 2023; Yuan et al., 2022) - participants do not seem to automatically value the system more just because it collects more data. This reinforces the idea that personalization alone is not synonymous with perceived value. Value may depend more on the type of interaction and the context than just the amount of data used.

Another relevant point is that the expectation of transparency did not show a statistically significant moderating effect either. This is curious, since several authors (such as Grafanaki, 2017, and Velasco et al., 2024) draw attention to the critical role of transparency in building trust in AI systems. One possible explanation is that the study participants did not have a very /clear idea of what “transparency” meant in the context of the data - or else that the way the manipulation was presented was not concrete enough to activate this kind of more critical judgment.

This scenario reinforces the argument of Flavián et al. (2024) and Gill (2020): the feeling of exploitation arises above all when the consumer clearly perceives that something is being done “behind their backs”. If there is no such feeling of invasion or lack of clarity, even intense data collection can go unnoticed or even be tolerated, as long as the system works well.

Finally, it is worth noting that the results suggest a separation between the judgment of the amount of data and other more affective and cognitive dimensions of the relationship with AI. In simple terms, participants realize that there is more data to be collected, but this is not enough to change what they think or feel about the system. This is in line with the idea that the most critical effects of data collection do not happen immediately, but rather when negative experiences accumulate or when the perception of loss of control becomes evident (Belk et al., 2020; Wirtz et al., 2023).

6. CONCLUSIONS AND FUTURE WORKS

The aim of this study was to explore consumer perceptions of data capture by AI systems. Rather than confirming hypotheses or validating statistical results, this research sought to shed light on how consumers understand and trust Artificial Intelligence systems in a scenario where data collection is becoming increasingly ubiquitous. By testing the impact of data capture - at high and low levels - and analyzing the perception of value generated by AI, as well as the moderating role of transparency expectations, it was possible to reveal relevant insights that help understand the emotional, cognitive and ethical context that shapes the relationship between users and technology.

The empirical evidence gathered suggests that consumers do not react negatively to the volume of data captured per se, but that algorithmic trust is only built when the system delivers real and perceived value. This reveals an interesting deviation from what is sometimes assumed in the public discourse on AI: it's not so much the collection of data that generates distrust, but the lack of clear and tangible return on that collection for the consumer. Data only becomes “invasive” when it is not useful.

This insight has relevant implications for theory: it reinforces the centrality of perceived value as a critical mediating variable in the formation of trust in algorithmic systems, calling into question approaches that treat trust as a direct consequence of transparency or the volume of data collected. In fact, the results of this study indicate that transparency alone is not enough to generate trust if it is not accompanied by an experience that is perceived as advantageous, relevant and personalized.

Furthermore, this work invites reflection on the role of companies in building more empathetic and user-centered AI ecosystems. The challenge is not just to moderate data collection or comply with privacy regulations, but to build clear and coherent value narratives around the use of artificial intelligence. In doing so, organizations not only increase their customers' trust, but also create longer lasting and more sustainable relationships with them.

6.1 Theoretical Contributions

On a theoretical level, this study aims to provide insights into consumer perceptions of data capture by artificial intelligence tools. This study reinforces the importance of perceived value in the formation of trust in AI. The literature on trust in artificial intelligence systems often emphasizes factors such as transparency, explainability and risk perceptions (Benk et al., 2024). This study empirically demonstrates that, despite variations in the volume of data collected, it is above all the perception of value generated by the system (“AI-Driven value perception”) that explains algorithmic trust. This finding contributes theoretically by shifting the focus from traditional variables (amount of data or mere transparency practices) to the actual experience of perceived value, suggesting that models of trust in AI should explicitly incorporate the construct 'perceived value' as a central antecedent.

Although there are studies that speculate on the negative influence of high levels of data capture on user trust (Leschanowsky et al., 2024), the results obtained here do not support a direct or indirect effect of the data capture variable on algorithmic trust. Instead, the absence of mediation and moderation by perceptions of transparency reinforces the idea that simply reducing or increasing the volume of data collected is not enough to change trust, unless these changes translate into tangible gains in value for the user. This development theoretically broadens the understanding of privacy and trust, indicating that the relationship between data collection and trust is more complex and depends on how consumers perceive the benefits.

This study shows that "Data Transparency Expectations", although validated as a construct, do not significantly moderate the effect of data capture on algorithmic trust. This suggests that, from a theoretical point of view, the role of transparency may be conditional on the perception of value, i.e. only when users recognize concrete benefits does transparency strengthen trust. This contributes to refining theories of transparency in AI, alerting us to the need to consider it in conjunction with other subjective perceptions, rather than in isolation.

One of the most relevant debates in digital consumer behavior is the 'privacy calculus' - the idea that users weigh privacy costs (e.g., more data collection) against utility benefits (e.g., more effective recommendations) (Cloarec et al., 2024; Leschanowsky et al., 2024). By showing that perceived value (perceived usefulness) stands out as a predictor of trust, even in contexts of high or low data collection, this study provides empirical support for the privacy-utility trade-off model. In practice, users are willing to accept greater or lesser data collection to the extent that they perceive concrete benefits. This reinforces the theoretical relevance of this approach to studies of AI adoption and digital behavior.

In short, this study contributes to the theory by emphasizing the pre-eminent role of perceived value in algorithmic trust and questioning the direct influence of data capture and data transparency expectations.

6.2 Managerial Implications

The results obtained in this research provide several important reflections for professionals and managers who work with Artificial Intelligence systems, especially in contexts where capturing user data is essential for the technology to work.

First, consumers are attentive to the volume of data they are asked to provide. The experimental manipulation was effective in this regard, which means that, even in digital environments, users can tell when a system is collecting information. This finding aligns with prior research that highlights growing consumer awareness and concern about data practices in AI-mediated interactions (Belk et al., 2020; Cukier, 2021). However, this perception alone does not directly affect levels of trust in the system. This is particularly relevant: trust is not automatically undermined by data capture, but rather by how the consumer interprets the value they get from this interaction, a notion supported by Wirtz et al. (2023), who emphasize that trust emerges when users perceive AI as beneficial and purposeful.

Therefore, brands should not only be concerned with how much they collect, but above all with what they offer in return. If the user feels that AI provides them with a useful, personalized and efficient experience, the perception of value increases - and with it, trust in the system. This reinforces the findings of Yuan et al. (2022), who demonstrate that personalization enhances user engagement and trust, particularly when the benefits are tangible and relevant. In our study, the perception of value generated by AI proved to be the main factor in building algorithmic trust, which suggests that investing in the practical usefulness of technology should be a strategic priority (Flavián et al., 2024).

On the other hand, although transparency expectations did not show a statistically significant moderating effect in this study, this does not mean that they should be ignored. On the contrary: in an increasingly scrutinized digital environment, the way a company communicates its data handling practices can make all the difference in building (or losing) credibility. This is consistent with the literature emphasizing that transparency, while conceptually complex, plays a symbolic role in user perceptions (Grafanaki, 2017). Even if consumers don't always understand the mechanisms behind AI, they expect clarity, honesty and control. In this sense, being transparent in an accessible way - avoiding technical jargon and explaining in plain language what is done with the data - is an opportunity for brands to differentiate themselves positively.

It is important to stress that the relationship between companies and consumers in the context of AI is delicate and must be managed with balance. Personalizing the experience without invading, communicating without alarming, and collecting data responsibly are essential pillars for guaranteeing a long-term relationship of sustainable trust (Gill, 2020; Puntoni et al., 2021).

In this sense, the implications for management include valuing the user experience as a central strategic axis. Specifically, organizations must invest in AI solutions that not only work well technically, but also generate benefits that are recognizable and valued by consumers (Wirtz et al., 2023). Likewise, they must develop an organizational culture oriented towards ethics in data processing, where respect for privacy and transparency are not just legal obligations, but commitments made to their audiences. Trust in digital environments is built on repeated, consistent and meaningful interactions, where perceived value and ethics go hand in hand.

Finally, this research reinforces that trust in Artificial Intelligence systems is not only built with good algorithms, but with conscious, human decisions about how these algorithms interact with people (Belk et al., 2020).

6.3 Limitations and Future Research

This study faces some limitations. The sample included 109 participants, most of whom were young. Given that it favored younger, employed users, the results may not be representative of older populations, students without work experience or people less familiar with technology. Future studies should expand the profile of respondents, incorporating greater age diversity, levels of digital literacy and varied professional backgrounds.

The distinction between "high" versus "low" data capture was presented through a single descriptive scenario. Although this was sufficient for internal validation, as the manipulation proved successful, it did not capture all the possible complexity of interactions with AI systems in a real context. Future research could use multiple scenarios such as different types of service, levels of interactivity, or degrees of personalization to assess whether the effects found are maintained in more varied situations.

Although direct, indirect and moderating effects of data capture, AI-driven value perception and data transparency expectations were tested, the model did not cover other potentially relevant variables, such as perception of control, user satisfaction or emotional factors. Future research could expand the model to include these dimensions, seeking to understand alternative indicators that influence trust in AI.

In short, this work has shown that, in the context of AI systems, it is not just the volume of data collected or isolated transparency practices that determine user trust, but above all the perception of value provided to them. By showing that 'AI-Driven value perception' is the main predictor of algorithmic trust, we have helped redefine how companies and researchers should approach the design and communication of AI-based solutions. These results reinforce the need to focus efforts on creating perceived value, guaranteeing concrete and relevant benefits for the user, while maintaining an adequate level of clarity about the use of their data. Finally, although there were limitations inherent to the type of experimental design and the profile of the sample, I believe that this study lays the foundations for future research that explores more diverse contexts, emotional dimensions associated with the adoption of AI and complementary methodologies that deepen understanding of the complex relationship between privacy, perceived usefulness and trust in emerging technologies.

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8. APPENDIX A

8.1 NOVA ETHICS COMMITTEE

NOVA IMS Information Management School

This is to certify that
Project No.: **DDMKT2025-3-188022**
Project Title: **Consumer Perception of The Influence of Artificial Intelligence**
Principal Researcher: **Bruno Guilherme Peres Teixeira**

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 3/27/2025.

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, 3/27/2025

NOVA IMS Ethics Committee
ethicscommittee@novaims.unl.pt

8.2 ONLINE QUESTIONNAIRE

The images presented below represent the questionnaire completed by the respondents in the study and both scenarios.

English (United Kingdom)

Hello! My name is Guilherme, I am currently a master's student in Data-Driven Marketing at Universidade Nova de Lisboa, Information Management School (NOVA IMS).

The purpose of this survey is to explore consumer perceptions of how Artificial Intelligence (AI) collects and processes data. **Your participation in this research study is completely voluntary, and you may exit the questionnaire at any time without any penalty.** The survey takes approximately 5 minutes to complete. Please be assured that all responses will be kept anonymous and confidential, and will be used only for academic purposes.

By proceeding with this survey, **you confirm that you have 18 or over, and that you read and understood the purpose of this study and voluntarily agree to participate**.

- Yes, I agree to participate in this study
- I do not agree to participate

English (United Kingdom)

Please read carefully and imagine the following scenario (this information will be important for answering a question at the end of the qustionnaire):

At our company we are always looking to innovate and provide the best possible experience for our users. That's why we developed InsightAI, an advanced artificial intelligence system that improves recommendations and personalises the user experience as much as possible.

InsightAI analyses your search history, your preferences for films and series, the content you started watching but didn't finish, the devices you use and even the times you usually watch content. Based on this detailed analysis, we can predict what you'll want to watch next, guaranteeing highly personalised suggestions for each user.

What's more, our artificial intelligence tools also automatically adjust the covers and descriptions of films and series to highlight the aspects that interest you most.

Please read carefully and imagine the following scenario (this information will be important for answering a question at the end of the questionnaire):

In our company we are always looking to innovate and provide the best possible experience for our users. That's why we developed InsightAI, an advanced artificial intelligence system that improves recommendations and personalises the consumer experience as much as possible, **with a low data capture.**

InsightAI works with a secure and transparent model, using only the information that the user provides directly. Instead of analysing your search history, the devices you use or behaviour patterns, with a low level of data capture our artificial intelligence tool recommends content based on the films and series you rate or add to your list.

In this way, we offer personalised suggestions through low data collection, without the need to collect additional information about your viewing habits, guaranteeing greater privacy and control for the consumer.

Please assess how much you agree with the following statements (1 = strongly disagree; 9 = strongly agree):

	Strongly Disagree (1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	Strongly Agree (9)
Using AI helps me acquire knowledge.	○	○	○	○	○	○	○	○	○
I feel that the use of AI tools by companies is ethical.	○	○	○	○	○	○	○	○	○
AI improves my online experience by offering content and products aligned with my interests.	○	○	○	○	○	○	○	○	○
I believe that the benefits provided by AI outweigh the concerns about data capture.	○	○	○	○	○	○	○	○	○
I have no problem providing my information, since through AI I can have a better online experience.	○	○	○	○	○	○	○	○	○

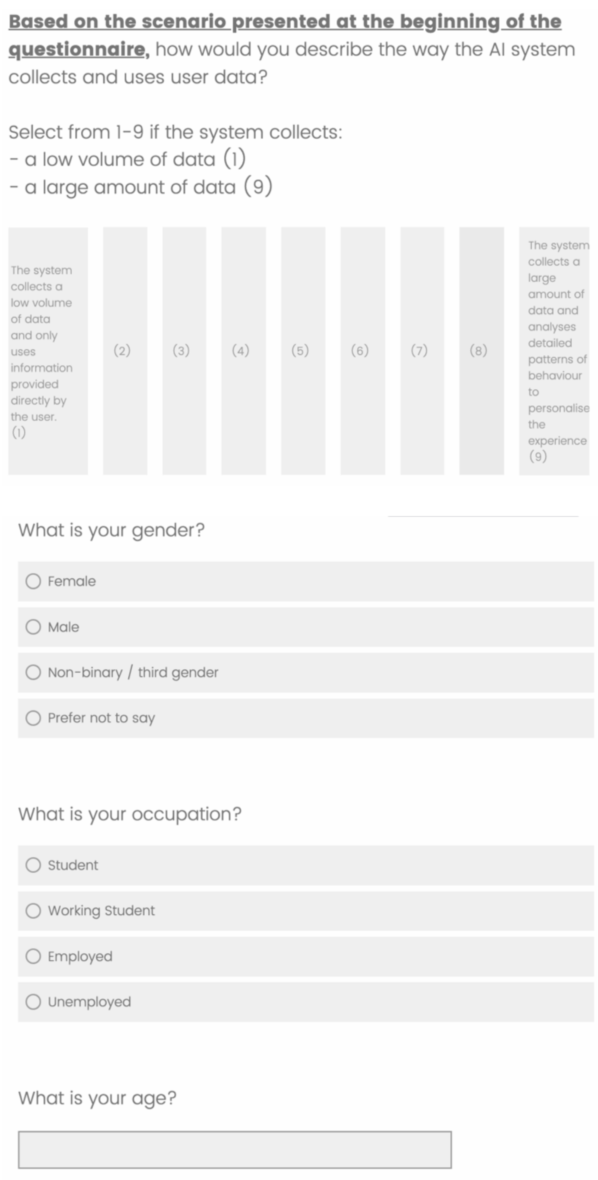
Please assess how much you agree with the following statements (1 = strongly disagree; 9 = strongly agree):

	Strongly Disagree (1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	Strongly Agree (9)
I understand the way AI helps me with the decisions I want to make.	○	○	○	○	○	○	○	○	○
I believe that transparency in data capture increases my trust in digital services.	○	○	○	○	○	○	○	○	○
I understand why AI gives me the answers it does.	○	○	○	○	○	○	○	○	○
I understand the mechanisms that AI uses to form its responses.	○	○	○	○	○	○	○	○	○

English (United Kingdom)

Please assess how much you agree with the following statements (1 = strongly disagree; 9 = strongly agree):

	Strongly Disagree (1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	Strongly Agree (9)
Artificial Intelligence can be trusted.	○	○	○	○	○	○	○	○	○
I trust that companies use AI ethically and responsibly.	○	○	○	○	○	○	○	○	○
I'm concerned about the risk of manipulation through AI algorithms.	○	○	○	○	○	○	○	○	○
AI algorithms are reliable and do what they promise.	○	○	○	○	○	○	○	○	○
I believe that the transparency and perceived value of AI increases my trust in algorithms.	○	○	○	○	○	○	○	○	○



Based on the scenario presented at the beginning of the questionnaire, how would you describe the way the AI system collects and uses user data?

Select from 1-9 if the system collects:
- a low volume of data (1)
- a large amount of data (9)

The system collects a low volume of data and only uses information provided directly by the user. (1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	The system collects a large amount of data and analyses detailed patterns of behaviour to personalise the experience (9)

What is your gender?

- Female
- Male
- Non-binary / third gender
- Prefer not to say

What is your occupation?

- Student
- Working Student
- Employed
- Unemployed

What is your age?

8.3 Mediation Analysis

Run MATRIX procedure:

**************** PROCESS Procedure for SPSS Version 4.2 ****************

Written by Andrew F. Hayes, Ph.D.   www.afhayes.com

Documentation available in Hayes (2022). www.guilford.com/p/hayes3

****

Model : 4

Y : Algorith

X : IV

M : AIDriven

Sample

Size: 109

****

OUTCOME VARIABLE:

AIDriven

Model Summary

R	R-sq	MSE	F	df1	df2	p
.012	.000	2.506	.015	1.000	107.000	.902

Model

	coeff	se	t	p	LLCI	ULCI
constant	5.717	.465	12.286	.000	4.794	6.639
IV	.038	.305	.123	.902	-.568	.643

****

OUTCOME VARIABLE:

Algorith

Model Summary

R	R-sq	MSE	F	df1	df2	p
.637	.406	1.562	23.906	3.000	105.000	.000

Model

	coeff	se	t	p	LLCI	ULCI
constant	.099	1.371	.072	.943	-2.618	2.816
IV	1.014	.969	1.046	.298	-.908	2.936
AIDriven	.898	.229	3.922	.000	.444	1.352
Int_1	-.195	.162	-1.199	.233	-.517	.127

Product terms key:

Int_1 : AIDriven x IV

Test(s) of highest order unconditional interaction(s):

	R2-chng	F	df1	df2	p
X*M	.008	1.437	1.000	105.000	.233

Focal predict: AIDriven (M)

Mod var: IV (X)

Conditional effects of the focal predictor at values of the moderator(s):

IV Effect se t p LLCI ULCI

1.000	.703	.093	7.549	.000	.519	.888
2.000	.509	.133	3.821	.000	.245	.772

****

OUTCOME VARIABLE:

Algorith

Model Summary

R	R-sq	MSE	F	df1	df2	p
.027	.001	2.577	.079	1.000	107.000	.780

Model

	coeff	se	t	p	LLCI	ULCI
constant	5.247	.472	11.119	.000	4.311	6.182
IV	-.087	.310	-.281	.780	-.701	.527

************************ COUNTERFACTUALLY DEFINED ***********************

************** TOTAL, DIRECT, AND INDIRECT EFFECTS OF X ON Y **************

Total effect of X on Y

Effect	se	t	p	LLCI	ULCI
-.087	.310	-.281	.780	-.701	.527

(Pure) Natural direct effect of X on Y

Effect	se	t	p	LLCI	ULCI
-.106	.241	-.440	.661	-.584	.372

Controlled direct effect of X on Y

Effect	se	t	p	LLCI	ULCI
-.109	.241	-.453	.651	-.587	.369

(Total) Natural indirect effect(s) of X on Y:

IV -> AIDriven -> Algorith

Effect	BootSE	BootLLCI	BootULCI
.019	.157	-.341	.306

********************** ANALYSIS NOTES AND ERRORS ***********************

Level of confidence for all confidence intervals in output:

95.0000

Number of bootstrap samples for percentile bootstrap confidence intervals:

5000

Direct, indirect, and total effects are counterfactually defined

assuming X by M interaction and with the following reference (x_ref)

and counterfactual (x_cf) states for X:

x_ref 1.000

x_cf 2.000

NOTE: Standardized effects are not available when using the XMINT option.

WARNING: Variables names longer than eight characters can produce incorrect output when some variables in the data file have the same first eight characters. Shorter variable names are recommended. By using this output, you are accepting all risk and consequences of interpreting or reporting results that may be incorrect.

------ END MATRIX -----

8.4 Moderation Analysis

Run MATRIX procedure:

***************** PROCESS Procedure for SPSS Version 4.2 *****************

Written by Andrew F. Hayes, Ph.D.   www.afhayes.com

Documentation available in Hayes (2022). www.guilford.com/p/hayes3

****

Model : 1

Y : Algorith

X : IV

W : DataTran

Sample

Size: 109

****

OUTCOME VARIABLE:

Algorith

Model Summary

R	R-sq	MSE	F	df1	df2	p
.533	.284	1.881	13.891	3.000	105.000	.000

Model

	coeff	se	t	p	LLCI	ULCI
constant	.697	1.487	.468	.640	-2.252	3.645
IV	1.031	1.022	1.009	.315	-.995	3.058
DataTran	.736	.228	3.231	.002	.284	1.188
Int_1	-.187	.156	-1.195	.235	-.496	.123

Product terms key:

Int_1 : IV x DataTran

Test(s) of highest order unconditional interaction(s):

	R2-chng	F	df1	df2	p
X*W	.010	1.429	1.000	105.000	.235

Focal predict: IV (X)

Mod var: DataTran (W)

Data for visualizing the conditional effect of the focal predictor:

Paste text below into a SPSS syntax window and execute to produce plot.

```
DATA LIST FREE/
  IV        DataTran   Algorith   .
BEGIN DATA.
     1.000     4.556     4.232
     2.000     4.556     4.413
     1.000     6.303     5.191
     2.000     6.303     5.047
     1.000     8.049     6.151
     2.000     8.049     5.680
END DATA.
GRAPH/SCATTERPLOT=
 DataTran WITH     Algorith BY       IV       .
```

********************** ANALYSIS NOTES AND ERRORS ***********************

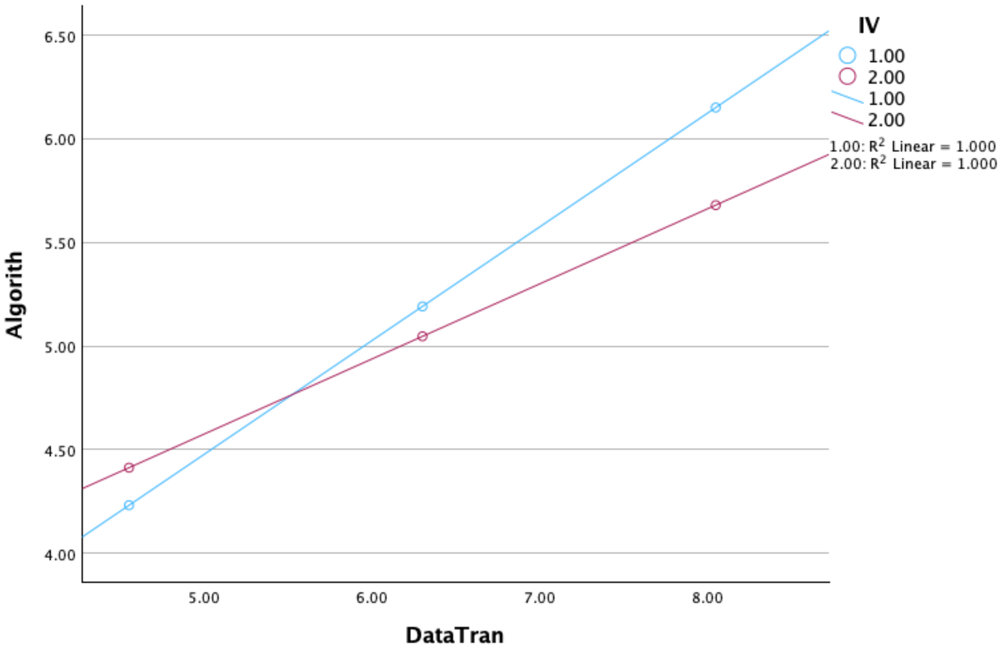
Level of confidence for all confidence intervals in output:

95.0000

WARNING: Variables names longer than eight characters can produce incorrect output when some variables in the data file have the same first eight characters. Shorter variable names are recommended. By using this output, you are accepting all risk and consequences of interpreting or reporting results that may be incorrect.

------ END MATRIX -----

Graph



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