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Impact of Recommender Agents used in Online Retail on Customer Satisfaction and Purchase Intention

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Master Thesis

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

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by

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Master Thesis presented as partial requirement for obtaining the Master's degree in Data-Driven Marketing, with a specialisation in Digital Marketing and Analytics

Supervised by

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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

Technology has changed how consumers live their lives and make purchases, which has forced businesses to adjust to a more competitive market environment. Artificial Intelligence (AI) is one example of a disruptive technology that has revolutionised corporate processes and offered creative ways to improve customer experiences. In contrast to conventional decision-making processes, this thesis examines the effects of AI-driven Recommendation Agents (RAs), on online retail, with a special emphasis on customer satisfaction and purchase intention. By evaluating customer data and forecasting their preferences, RAs use AI to customise the online purchasing experience, which enhances decision-making and reduces information overload. There is no empirical study on AI personalisation's substantial impact on customer behaviour, despite the industry's increased investment in this area. To close this gap, this study compares consumer responses when supported in making decisions by RAs vs traditional techniques. The main study topic looks at how customer satisfaction and purchase intention are affected by decision-making supported by RAs. Furthermore, the research explores how factors like algorithm aversion, perceived decision autonomy, and trust affect these results. This study attempts to advance knowledge of AI's revolutionary potential in marketing and its function in promoting improved customer interactions by offering insightful information about the strategic implications of RAs for online businesses. To accomplish the intended objective, quantitative analytic research using an online questionnaire with 150 replies was used to develop this thesis.

KEYWORDS

Recommender Agents; Artificial Intelligence; Customer Satisfaction; Purchase Intention; Consumer Decision-Making

Sustainable Development Goals (SDG):

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LIST OF ABBREVIATIONS AND ACRONYMS

AI	Artificial Intelligence
IAs	Intelligent Agents
RA	Recommendation Agent
IT	Information Technology
ADM	Automated Decision-Making
STD	Self-determination Theory

1. INTRODUCTION

Technology advancements and evolving customer preferences are driving constant change in the e-commerce sector (Rahman and Dekkati, 2022). In the current digital era, businesses must adapt to a changing landscape marked by increased competition and more demanding consumers. Adaptation is centred on adopting "new" technologies and having a distinct understanding of customer behaviour (Hidayat et al., 2022).

Customers are searching for more than quick transactions from online shops, they are also seeking more personalised and enriching experiences as these businesses become increasingly integrated into daily life. Artificial intelligence (AI) is viewed as a major game changer in fulfilling these objectives because of its capacity to analyze enormous data sets and identify trends (He and Liu, 2024).

According to Verma et al. (2021), AI is the latest technological disruptor with enormous potential for marketing transformation and for businesses to enhance their approaches. According to an article from PWC (2023), AI will begin to radically alter how business is conducted in 2024. It will affect how businesses generate income, run their daily operations, interact with clients and staff, create new business models, and more.

AI is best described by its ability to interpret and compress data into meaningful information, to notify main objective behaviours (Ameen et al., 2021). In other words, Geisel (2018) describes AI as "A true artificially intelligent system is one that can learn on its own. We are talking about neural networks (...) which can make connections and reach meanings without relying on predefined behavioural algorithms. True AI can improve on past iterations, getting smarter and more aware, allowing it to enhance its capabilities and knowledge" (p.116).

Businesses, such as online retail, are utilizing AI in a variety of ways, including personalizing the online buying experience and increasing engagement based on contextual and behavioural data. This tech helps to react quickly to client's needs, providing consumer insights that are crucial for attracting and maintaining customers (Wirth, 2018). With AI, online retailers may be able to forecast what customers will want (Davenport et al. 2020). This alters the way firms interact with their customers with the potential to achieve better customer-brand relationships (Evans, 2019).

AI applications are driven by Intelligent Agents (IAs), which can be machine agents, such as home robots, or software agents (chatbots or recommender systems) (Soni et al., 2019). This investigation will focus on Recommendation Agents (RAs) because they have become relevant to the customer experience and businesses. According to Nilashi et al. (2016), RAs have a measurable effect on customers' purchasing decisions and can improve their decision-making.

Consumers are facing information overload and to address this issue, RAs are being developed to enhance consumers' information search and ability to make decisions (Pratibha & Xiaojing, 2012).

RAs are used in online marketplaces to analyze a customer’s past data and focus on the consumer’s choice and behaviour (Pallathadka et al., 2021). This information allows the AI-powered software to predict the consumer’s behaviour, provide them with suggestions on a product to assist them effectively through their shopping or selection process (Gururaj, 2021; Pallathadka et al., 2021) and prevent information overload (Pratibha & Xiaojing, 2012). Personalisation can affect consumer experience and satisfaction, having a positive effect on continuance intention (Kim et al., 2021).

Moreover, variables such as trust in technology, autonomy in decision-making and aversion to algorithms can influence consumers' perceptions and responses to several types of recommendations (with or without AI). According to Ginting et al. (2023), trust in technology increases customer satisfaction and loyalty, while the autonomy of technology in decision-making can have the reverse effect due to the preference for human judgments over algorithmic judgments, even if algorithms perform better (Judek, 2024). Algorithm aversion affects the way consumers perceive automated decisions, their satisfaction with those decisions and consequently their purchase intention (Van Doorn et al., 2017).

Although companies are investing more in this type of personalisation, there still exists a lack of empirical research on how personalisation significantly influences consumer experience (Tyrväinen et al., 2020). The fast integration of AI technologies in online retail necessitates a comprehensive understanding of their impact on consumer behaviour.

To bridge this knowledge gap, this thesis aims to answer the following question: “What is the impact of RA-assisted purchasing decision-making, compared to traditional decision-making on consumer responses.” Traditional decision-making refers to purchasing decisions made by the consumer without the use of AI.

To discuss the research question, the following three sub-questions will be covered: “Does the type of decision (with or without AI) impact consumer satisfaction with the choice made?”, “Does it impact purchase intentions?” and “How do variables such as trust in the technology and autonomy of the technology impact this behaviour?”. Together, these sub-questions offer an in-depth framework for comprehending the ramifications of applying recommendation algorithms to consumer decision-making and how they impact purchase intentions, consumer satisfaction, and the role of trust, autonomy technology and algorithm aversion in the decision-making process.

By better identifying how their personalised content generates responses, retailers can increase their value to customers. It is critical to comprehend how RAs affect consumer satisfaction and purchase intent since doing so not only highlights the revolutionary potential of AI in marketing but also offers useful information to companies looking to maximise their relationships with customers.

This research provides data to the small amount of existing knowledge about how AI-driven personalisation affects online retail customer experiences. Second, provides a thorough knowledge of the strategic implications of RAs for marketers navigating this technologically driven world by comparing the results of purchasing experiences with and without AI involvement.

2. LITERATURE REVIEW

This work uncovers valuable information regarding the prospective applications of AI and explains how it affects customer behaviour. Therefore, identifies the most representative literature works about various disciplines of research that highlight the importance of utilizing technology in the analysis of consumer behaviour.

2.1. THE IMPACT OF AI ON CONSUMER EXPERIENCE

Major changes in the world of digital marketing have been brought about by AI. The application of AI in this field has resulted in a change in basic assumptions that has profoundly changed how companies communicate with their clients, impact their decision-making, and develop and retain such ties (Ng & Wakenshaw, 2017). It has opened new possibilities, enabling marketers to better understand their target audiences and improve consumer experiences.

It is important to realize that AI is a tool, not a strategy in and of itself. It makes current marketing techniques better and more efficient by optimizing and enhancing them. Consequently, digital marketing has been altered by AI, becoming more user-centric, efficient, and personalised. It makes current marketing techniques better and more efficient by optimizing and enhancing them (Sheth, 2020).

In a crowded digital market, personalisation is essential for standing out (Tam & Oliveira, 2016). Moreover, large-scale personalisation is one of AI's most remarkable applications in digital marketing (Huang & Rust, 2018). The introduction of AI has proven revolutionary personalised experiences for all users, helping with customized information, tailored product recommendations, and tailored interactions. To deliver customized content, AI can examine a customer's previous purchases, browsing history, and customer interactions. This improves user experience and increases customer engagement (Volkmar et al., 2022). Hence, a high degree of personalisation encourages a positive user experience, which frequently results in a rise in lifetime value and customer loyalty (Kaperonis, 2018).

Predictive analysis, in which AI algorithms forecast future customer behaviour based on historical data, is an application of AI's capacity to evaluate massive datasets and aims to create more successful marketing plans. Moreover, customer service has been transformed by AI-powered chatbots and virtual assistants (Gkikas & Theodoridis, 2022). By providing full support, such as product details and question resolution, they improve user experience and free up human resources for more complex jobs.

Predictive analytics capabilities of AI are also essential for improving user experience. AI can predict future user behaviour by analyzing past data, which helps advertisers anticipate the wants and preferences of their target audience (Li & Karahanna, 2015). For instance, promotional materials for babies may be sent to a customer who regularly buys baby products before they even know they need them. Predictive user experiences like these dramatically increase consumer engagement and satisfaction (Kaperonis, 2024).

Because AI can automate tasks, the user experience has been significantly improved by making the user journey more efficient. AI shortens the user journey and reduces friction by automating tasks like customer service and product suggestions (Souiden et al., 2019). AI can save users time and effort by using data from past user encounters to automatically fill out forms. AI opens the door for a more efficient and easy user experience by streamlining these procedures, which improves the user experience in the end (Kaperonis, 2024).

2.2. RECOMMENDER AGENTS ASSISTED DECISION

2.2.1. RECOMMENDATION SYSTEMS

In retailing contexts, recommendation agents are a well-known application of predictive Information Technology (IT) and businesses have embraced this tool to enhance customer experiences and automate tasks (Rohden & Zeferino, 2023). These systems were born out of the need to navigate through large datasets and offer consumers customized recommendations based on their preferences among a wide range of services and products (Osman et al., 2019).

Recommendation engines concentrate on comprehending client preferences and behaviours when examining a customer's past data. They manage clicks, past transactions, shopping cart items, and search queries with ease (Gururaj, 2021). With stability, accuracy, disparity, and novelty considered, these systems strive to provide well-balanced recommendations (Osman et al., 2019).

Machine learning techniques are integrated into recommendation engines as a basic component. According to Rashidi et. al (2022), these algorithms are divided into groups according to how they filter data: content-based filtering suggests added items only based on the user's past behaviour; collaborative filtering suggests new purchases by considering the actions of other people who share similar interests and viewpoints; and hybrid filtering, which combines aspects of both techniques.

With the use of data, AI software can predict customer behaviour and offer helpful recommendations while making decisions or buying (Gururaj, 2021; Pallathadka et. al., 2021). Personalised recommendations resolve the issue of information overload by aiding users in their research and decision-making, which increases sales and improves customer satisfaction (Fernández-Tobías, 2016). By using predictive intelligence, RAs eliminate the need for human involvement to do jobs that would otherwise require human intervention, such as complex or time-consuming tasks. This optimization of the customer-shopping experience has a noticeable effect on customers' purchasing behaviour (Xiao and Benbasat, 2007).

To secure their long-term survival, most e-commerce businesses are attempting to implement tailored recommendation systems in response to the success stories of market leaders such as Netflix, Google, and Amazon (Das et al., 2007; Kim et al., 2010). As an illustration, Netflix has achieved prominence by deploying a personalised recommendation algorithm based on deep neural networks, solidifying its leadership in the realm of movies and dramas (Bennet & Lanning, 2007). Google integrates AI assistant services into its real-time news recommendations, tailoring them to users' interests and locations (Das et al.,2007), and Amazon recommends new products based on past purchases (Puntoni et al., 2021).

Jae et al. (2021) state that the notion of hyper-personalisation has surfaced as a development beyond conventional personalisation, signifying the growing significance of customer-satisfied services in the e-commerce domain. The integration of recommendation systems by various companies has proven instrumental in boosting sales and converting targeted suggestions into tangible purchases.

2.2.2. TYPE OF DECISION: RA VS. HUMAN

A growing number of fields are utilizing Automated Decision-Making (ADM), which has led to an increasing concern that intelligent robots will soon take the position of many humans in decision-making (Jarrahi, 2018). In AI-enabled systems, algorithms are free to choose factors based on patterns they find, while in systems without AI, humans choose which variables to consider when making decisions. Algorithms can take the place of human decision-makers entirely in certain situations, such as self-driving cars, and Amazon's purchase suggestions (Mahmud et al., 2022).

Algorithmic decision-making provides several advantages over human decision-making, including speed, ubiquity, and low consumption (Bonnefon et al., 2016). People like Elon Musk emphasize how disruptive AI is going to be and predict that it will replace humans in many jobs (Leetaru, 2016). In this direction, Kelly (2012) argues that AI and other smart technologies are perceived as drivers for the change of decision-making into a cognitive and information-centric process. According to a recent PWC poll from 2023, 73% of US companies have already incorporated AI into their operations (PWC, 2023).

Human decision-making usually differs from strict rationality, where people may not always maximize predicted benefits. Instead, biases and heuristics are extensively used to affect judgements (Kahneman, 2011).

Alternatively, Jarrahi & Kern et al. (2018, 2022) emphasize the complementary nature of AI and humans. Kern et al. (2022) found that people do not view the application of algorithms to guide decision-making as problematic. Consumers appreciate participating in the decision-making process. However, exclusively algorithmic decisions are less accepted.

Jarrahi (2018) looks at how each can contribute their unique strength to organizational decision-making processes that are often marked by equivocality, complexity, and uncertainty. While humans can still provide a more comprehensive, intuitive approach when handling uncertainty and ambiguity in organizational decision-making, AI with its increased computational information processing power and analytical approach, can enhance human cognition when addressing complexity. When it comes to assessing and facilitating decision outcomes, machines rely on people to provide subconscious decision heuristics. Algorithms typically assist humans in making decisions in the actual world (Acharya et al., 2018).

AI may support and enhance human decision-making, but it will not take its place. Rather than automating (or replacing) human capabilities, it makes more sense to think of AI as a tool for extending human capabilities (Jarrahi, 2018).

E-commerce providers use AI tools, such as recommendation engines, on their websites to direct customers to more interesting products based on their long-term preference profile or on the products they are currently interested in and provide immersive purchasing opportunities (Gururaj, 2021). Therefore, adapting the theoretical contributions to the field of Recommendation Systems applied to online commerce, users are not only receptive to automated recommendations but also show an inclination towards active involvement in the decision-making process. This perspective highlights that users value the convenience and efficiency provided by automated suggestions, while at the same time seeking a participatory role in shaping and refining recommendations, thus underlining the importance of finding a balance between automation and user involvement.

2.3. Consumer Responses to RA

Consumer behaviour refers to human cognitive patterns and behaviour-engaging notions, such as free will. Logic, self-control, and carefully constructed behaviour are all components of free will. Consumer behaviour examines the variables that influence customers' decision to buy the good or service that best meets their needs within the range of their free will (Baumeister et al., 2008).

In this new era, researchers and decision-makers look at ways to improve customer satisfaction. Massive amounts of individualized web data are continuously examined to uncover patterns in consumer behaviour that will help buyers and customers to have richer experiences (André et al., 2017).

The customer journey, behaviour, free will, decision-making, and customer experience are all intricately linked in marketing science. The customer journey functions as a guide for comprehending the needs of the customer. AI enables decision-makers to quickly understand the demands of customers, enabling focused marketing efforts across a variety of platforms, including social media, websites, e-commerce sites, online portals, and applications. The information gathered from user interactions on these platforms helps to categorize, evaluate, and target the actions and intentions of users (Baumeister et al., 2008).

AI monitors customers during distinct phases of their decision-making process. As a result, AI can gather information and develop predictions. AI tools assist in defining needs and making recommendations for solutions that the audience interprets as tailored suggestions that address their immediate needs (Kietzmann, 2018).

During the customer decision-making process, there is the assessment phase in which AI technologies examine data in real-time to produce content that persuades users that a specific option is right for them. In the final stage of the customer decision process, customer responses to the decision process are evaluated, namely consumer satisfaction with the purchase process, satisfaction with the product, the possibility of making another purchase and the ability to influence others (Kietzmann, 2018).

2.3.1. Customer Satisfaction

Within the field of marketing, customer satisfaction corresponds to how a customer feels that a product or service effectively meets their requirements and expectations, considering the context in which it is used (Cengiz, 2010). Customer satisfaction is what keeps people using a product over time, staying loyal to it, and recommending it to others (Ginting et al.,2023).

Maintaining customer satisfaction is essential in the e-commerce industry to stay ahead of the competition (Calvo-Porral & Lévy-Mangin, 2015). When customers are satisfied with the recommendations they receive from an online shopping platform, they are more likely to make repeat purchases and recommend the platform to their friends and family (Jae et al., 2021).

The algorithms used in recommender systems were designed with the belief that as the system becomes more accurate, customer satisfaction also increases. Many studies have supported this idea, indicating that higher accuracy in recommendations leads to greater customer satisfaction (Zhou et al., 2010). To put it simply, if a recommender system provides precise suggestions, users are more likely to be satisfied. This satisfaction stems from the increased likelihood of customers finding items that align with their preferences.

Therefore, reflecting the relationship between the recommender system and customer satisfaction, the following hypothesis is presented:

H1: The use of Recommender Agents in the purchasing process positively influences consumer satisfaction with the decision.

2.3.2. Purchase Intention

Behaviour has intention as its direct antecedent (Ajzen, 2002). Purchase intention is the tendency of a customer to purchase at a particular moment or circumstance (Lu et al., 2016).

According to Pu et al. (2011), consumers nowadays prefer to employ recommender system technology while making decisions on what to buy. The possibility that a client will buy the products that are recommended to them can rise dramatically if recommendation technology is adopted by users (Pursel et al., 2016). The technology used in RAs might encourage users to purchase what is recommended. Furthermore, repeat purchases may happen because of their overall pleasure, which will raise the possibility that they will visit the website again and refer their friends to it (Pu et al., 2011; Roudposhti et al.,2018).

However, Bhagat et al. (2022) studied distinct aspects influencing consumers' purchasing intentions, in the context of online commerce, using a technology-cantered model. According to the results, customers are more likely to make a purchase when artificial intelligence is incorporated into the process. Hence, the following hypothesis is proposed:

H2: The use of Recommender agents in the purchasing process positively influences purchase intention.

2.4. MEDIATORS

2.4.1. TRUST IN THE TECHNOLOGY

Shin (2020) argues that trust is a necessary component of human perception, behaviour, and technological evaluation, allowing people to engage with AI in a variety of ways. However, to address the role of trust in consumer buying behaviour, it is relevant to understand the role of trust in e-commerce environments.

Mcknight et al. (2002) have chosen to characterize trust as a person's subjective belief, subjective probability, willingness to be vulnerable, and reliance on parties other than oneself. According to Yeon et al. (2019), trust is defined as a party's (trustor) confidence in another party (trustee or a trusted third party). Because face-to-face interaction cannot deepen understanding in virtual networks, trust plays a significant role in Internet-based consumer behaviour (Wang et al., 2022).

A lot of trust-promoting variables have been studied and examined, as well as how they affect consumer behaviour intentions, including vendor reputation, brand recognition and security concerns. Teo and Liu (2007) investigated e-commerce vendors' characteristics, discovering that system assurance and e-commerce vendor reputation have an impact on e-commerce customer trust. According to Oliveira et al. (2017), brand reputation also has a significant impact on consumer trust, because a consumer who trusts a well-known brand will buy a product from that brand. Customers are also concerned about the security and privacy of their data (Falahat et al.,2019). Consequently, a guarantee of online security may improve customer trust by lowering perceptions of transactional risk. This analysis shows that trust cultivates an attitude that is advantageous to purchase intention and reduces perceived risk (Oliveira et al.,2017).

When it comes to online decision aids, trust aspects in the technology are complex because consumers are worried about an agent's ability to meet their demands, as well as its integrity and benevolence to work in their best interests rather than that of a manufacturer or online retailer (Benbasat & Wang,2005). Therefore, Benbasat & Wang (2005) define trust in RAs as a person's expectation of an agent's competence, benevolence, and integrity.

According to Araujo (2018), people experience positive feelings when they see humanity. Users' perceptions of these systems' humanity determine if they are accepted. As a result, the author states that higher levels of perceived humanity are correlated with higher levels of emotion and trust.

Wang and Benbasat (2008) identified the factors influencing users' trust in decision-support technologies. Their findings indicate that four reasons influence users' trust in RAs (i.e., calculative, interactive, knowledge-based, and dispositional) and three of them —calculative, interactive, and knowledge-based—are influenced by the user's technological experience. In the context of RAs, calculative reasons refer to the evaluation of benefits and costs that users make when interacting with the RAs, interactive reasons refer to the users' expectations of the RAs behaviour and performance, and knowledge-based refers to the explanations and information about the RA, that can be provided as stand-alone services or from interacting with the recommendation systems.

Concerning consumer responses, Wiwiek (2020) states that the influence of customer trust on customer satisfaction is insignificant. However, in contrast to this result, research conducted by Ginting et al. (2023), explains that customer satisfaction is positively and significantly influenced by customer trust in the technology, implying that consumers who are satisfied with a product or company are far more likely to trust in it. Customers are more likely to visit again and make additional purchases from an e-commerce website when they gain trust in it and have a valuable experience. In the e-commerce industry, establishing a strong customer base requires fostering trust and satisfaction (Eid, 2011).

As a result, the following hypothesis is proposed:

H3a: Trust positively mediates the effect of the type of decision on consumer satisfaction.

Trust is one of the key factors affecting the intention to make an online transaction (Zhao et al.,2019). In determining online purchase intention, Zhao et al. (2019) looked at the connection between buyers' continuous purchase intents and their level of trust in e-vendors and showed that trust plays a critical role and can increase customers' intents to shop online and encourage additional shopping behaviours. The biggest obstacle to consumers making purchases online is a lack of trust because buyers will not purchase online if they do not trust the vendors (Urban et al., 2009).

Furthermore, purchase intention is positively correlated with members' trust (Farivar et al., 2017). Therefore, based on the theoretical explanation and extending this background to the RA context, the following hypothesis can be presented:

H3b: Trust positively mediates the effect of the type of decision on purchase intention.

2.4.2. AUTONOMY OF TECHNOLOGY

Retail technologies are growing more autonomous, enabling them to perform tasks and make decisions on behalf of customers. Retailers, however, are missing empirical data regarding consumer reluctance to use autonomous systems (Bellis & Venkataramani, 2020; Sohn, 2024).

Fan & Liu (2022) conducted an empirical study to verify how consumers react to different degrees of algorithmic decision autonomy. They verified that reduced algorithmic decision autonomy has a negative impact on the choices made by consumers.

Along the same line, when high algorithmic decision autonomy exists, there is a downside effect on consumer purchasing decisions as well. Self-determination theory (SDT) defends that when algorithms take the lead in human-algorithm partnerships as autonomous decision-makers, human autonomy declines and generates a risk of algorithmic overdependence, which would reduce human happiness and exacerbate systemic biases against AI algorithms (Banker & Khetani, 2019). This relationship between humans and algorithms may cause people to become less internally motivated as they believe AI algorithms are controlling their behaviour. This will have a detrimental effect on their freedom and autonomy to make decisions, which may cause resistance (André et al., 2018). Therefore, high algorithmic decision autonomy consequence in a negative impact on purchase decisions (Fan & Liu, 2022).

People may become apprehensive when computer programs decide for themselves because they might experience discomfort and fear. People's perceptions about these automated decision-making programs may vary due to this emotional shift. It could make them question whether relying on these algorithms is an innovative idea and impact how satisfied they are with the decisions made by the algorithms (Van Doorn et al., 2017).

On the other hand, when there is an intermediate level of autonomy and algorithmic decision-making functions as a collaborative assistant, algorithmic decision autonomy has the most impact on customer purchase decisions, which indicates the most comfortable agent relationship (Fan & Liu, 2022). When the autonomy of technology is at the middle level exists the potential to increase decision-making efficiency (Yin and Qiu, 2021), and preserve their right to make their own decisions (Fan & Liu, 2022).

Considering these considerations, the following hypotheses are proposed:

H4a: Perceived decision autonomy positively mediates the effect of the type of decision on consumer satisfaction.

H4b: Perceived decision autonomy positively mediates the effect of the type of decision on purchase intention.

2.5. MODERATOR EFFECT OF ALGORITHM AVERSION

Decision-making by algorithms is growing increasingly effective and frequently exceeds human performance. When algorithms display superior performance, people show reluctance to depend on them and a phenomenon known as algorithm aversion occurs (Mahmud et al., 2022).

Mahmud et al. (2022) describe algorithm aversion as the conscious or unconscious preference for making one's own or other people's decisions over automated decisions. The authors suggest that people either "consciously or unconsciously" devalue algorithmic conclusions because they see that some people discount them out of habit without considering how well the decisions work, while others reject them after carefully weighing their performance. It is possible to perceive this logical behaviour as a behavioural anomaly, which could lower the predicted utility for human subjects (Dietvorst et al., 2014).

Human responses to algorithms are complex and frequently impacted by several variables (Berger et al., 2021; Dietvorst et al., 2014; Kawaguchi, 2020). According to Judek (2024), human judgment is preferred over algorithms, even when algorithms perform better overall. This has consequences for algorithmic systems' adoption and deployment. Even in cases where the decisions made by people and algorithms are equally accurate, algorithm aversion is still present (Berger et al., 2021)

Additionally, people exhibit aversion not just when comparing the decisions of algorithmic systems to those of human experts, but also when comparing their own decisions to those of algorithmic systems. Researchers have also found that certain individuals have an innate dislike of algorithms because they fundamentally mistrust them, regardless of how well they work (Kawaguchi, 2020).

This understanding can be extended to the context of engaging with RA, which suggests that algorithm aversion manifests decreased trust in the RA, people will be less likely to let the technology operate independently, a decreased level of satisfaction with the RA; 's recommendations, and a decreased intention to make purchases based on those recommendations when interacting with a RA. Given this, the following hypothesis is proposed:

H5: Algorithm aversion will negatively moderate the relationship between type of decision and customer satisfaction (a) and intention to purchase (b).

2.6. CONCEPTUAL FRAMEWORK

A conceptual framework has been constructed which represents the dependent and independent variables. The type of decision (decision-making with RA vs. Human) is the independent variable. Customer satisfaction with the recommendations and the intention to buy the recommendation made by RA are the dependent variables. In addition, trust in technology and autonomy of technology are the mediators of the relationship between the independent variable and the dependent variables. Finally, algorithm aversion is the moderating variable of this relationship.

Based on the hypotheses formulated, the theoretical model was constructed, which can be seen in Figure 1.

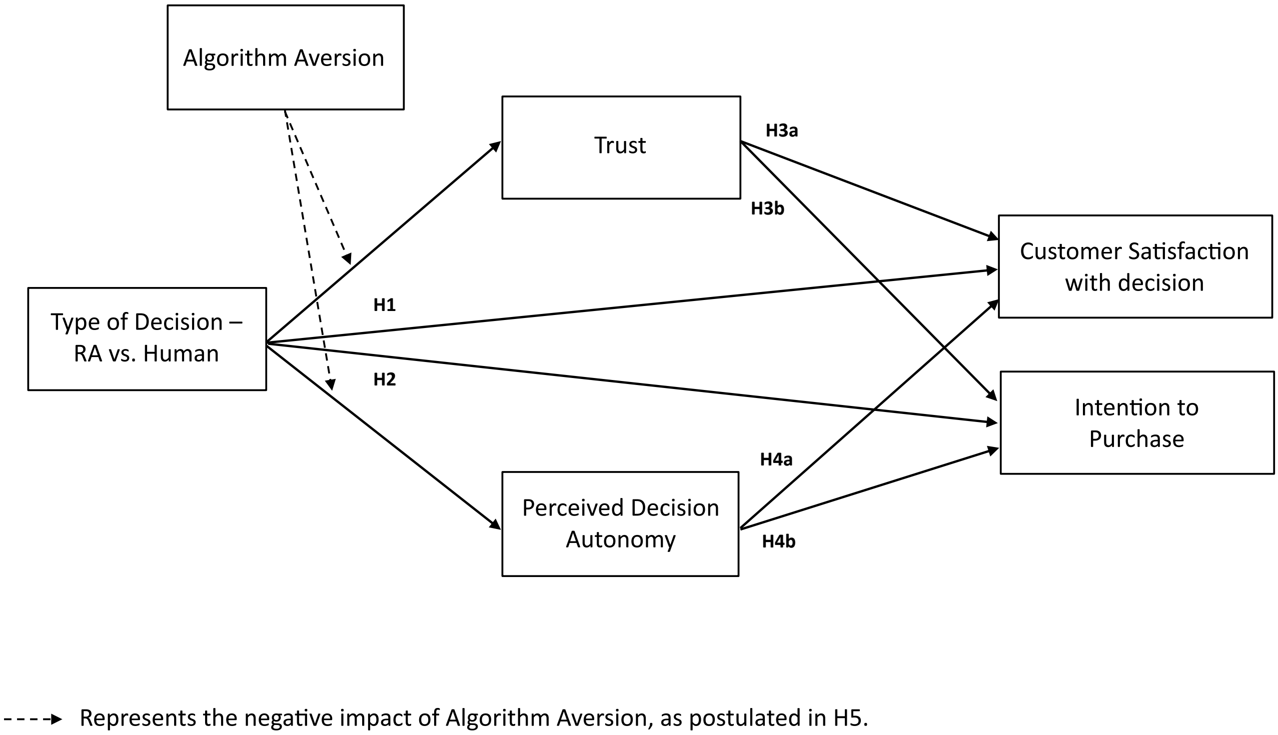


Figure 1 – Conceptual Model. Source: Author

3. METHODOLOGY

3.1. RESEARCH DESIGN

The next chapter focuses on the current study's methodological approaches after going over the main concepts and theories discussed in the literature review. To provide accurate and trustworthy data, primary data will be gathered through quantitative research.

Quantitative research is a method to assess objective theories by looking at the relationship between variables. These variables can be measured, allowing statistical processes to be applied to the numerical data for analysis. The reason behind selecting the quantitative research approach is its aim to broadly discover the factors influencing a specific outcome (Creswell, 2014).

To validate the conceptual model, this study used experimental design as a data collection technique. Experiments are a type of quantitative research approach that measures and quantifies relationships between variables and then tests a hypothesis and statistical relationships (Koschate-Fischer and Schandelmeier, 2014). "A true experiment is the best method for determining whether one thing truly causes another," as Aronson et al. (1990, p. 9) emphasise. The capacity of experiments to guarantee stimulus similarity in experimental circumstances and to answer causal questions is one important benefit (Wilson et al., 2010).

This data collection technique aligns with the research question posed in this study: “What is the impact of RA-assisted purchasing decision-making, compared to traditional decision-making on consumer´s responses.” Naturally, this study entails examining the causal connections between consumer responses and the use of recommendation systems. Using an experimental design, this study can control the degree to which RA support is provided during the decision-making process and track the direct effects of that intervention on other relevant variables, such as consumer satisfaction and purchase intention.

To accurately capture causality, the independent variable that was manipulated in this single-factor experiment was the type of decision (Human vs. Recommender Agents). A targeted investigation of how the presence or absence of recommendation agents affects customer behaviour, satisfaction levels, and purchase intents is made possible by modifying the type of decision-making process chosen. The research is possible to determine the precise impacts of RA support on customer decision-making dynamics in online retail settings by methodically altering this independent variable.

Considering it was a between-subjects experiment, participants were split into two equal groups and only exposed to one of the two circumstances at random, to be generalized to a broader group and enhance the study's external validity. There will be less chance of bias in the outcomes because participants will be subjected to the same standardized processes and stimuli (Viglia et al., 2021).

3.2. MEASUREMENT

All the components' measuring scales are based on previously published research and modified for use with recommender agents. Every metric is derived from a five-point Likert scale, where 1 represents "strongly agree" and 5 represents "strongly disagree". The coding was done in reverse, where lower scores indicate higher levels of agreement. Table 1 displays the measurement scales, their corresponding sources, and descriptions of the measures.

Table 1 - Description and Measurement of Variables. Source: Author

Variable	Items	Source
Decision Autonomy	How much control do you feel you have over the choices you get to see? How much control do you feel you have over the purchase decision?	Adapted from: Hussairi and Rossi (2024)
Decision Satisfaction	I would find the process of deciding which product to buy interesting. I would be content with the process of deciding which product to buy. I would be satisfied with my experience of deciding which product option to choose.	Adapted from: Heitmann et al. (2007)
Trust in AI	To what extent do you trust that technologies such as artificial intelligence know your preference and could assist you with purchase choices?	Adapted from: Kim et al. (2021)
Trust	I felt like the website has my best interest at heart. I believe this website provides accurate information. I felt I could rely on this store's suggestion of products.	Adapted from: Fernandes e Oliveira, (2021)
Purchase Intention	I would consider purchasing the product. I would contemplate the option of buying the product. It is likely that I am going to purchase the product.	Adapted from: Belanche et al. (2021)
Algorithm Aversion	How much would you trust a very well-qualified person to decide which sports shoes to purchase? How much would you trust an algorithm to decide which sports shoes to purchase?	Adapted from: Castelo et al. (2019)
Choice Confidence	I am convinced that the recommended items are suitable for me.	Adapted from: Ganguly et al. (2010)

	I am confident I will like the items recommended to me.

3.3. DATA COLLECTION

The data collection procedure utilized in the study, which aimed to identify how decision type (with or without RA assistance) affects customer satisfaction and purchase intention, is presented in the next chapter. Using the Qualtrics platform, a Portuguese-language questionnaire was constructed as the data-gathering tool. The questionnaire underwent 2 rounds of pre-testing to make sure it was clear and effective before it was distributed.

To guarantee comprehensive data collection, the questionnaire is then divided into four different sections. The survey starts with a brief introduction that covers the purpose of the study, the author's background, data confidentiality and informed consent. A selection and exclusion question is asked at the start of the survey to make sure that only individuals who purchase online participate. The behaviour of users concerning online shopping is covered in the second part. The third segment consists of questions designed to assess the conceptual model's variables. The last section is related to general questions about the interviewees, such as demographic data, including gender, age group, professional status, and location of residency in Portugal.

For this study, the responses were gathered using a convenience sample. Participants were chosen based on their willingness to participate in the survey and accessibility. Convenience sampling can introduce biases and it is important to note that the results might not apply to the full population. The survey was shared on my personal social media accounts, particularly on Facebook and Instagram.

4. EMPIRICAL STUDY

4.1. PRETEST 1

Pretesting the survey questionnaire was a crucial part of this experimental research study to optimize and improve it. This stage's objectives were to find and fix any questionnaire problems, guarantee that the best possible answers were obtained for the main research study that followed, and check that the audience had a clear understanding of the questions and their context.

The respondents were shown a scenario in which they were purchasing sports shoes from an online retailer, with a display offering twelve possibilities, in both conditions, as is shown in the following figure:

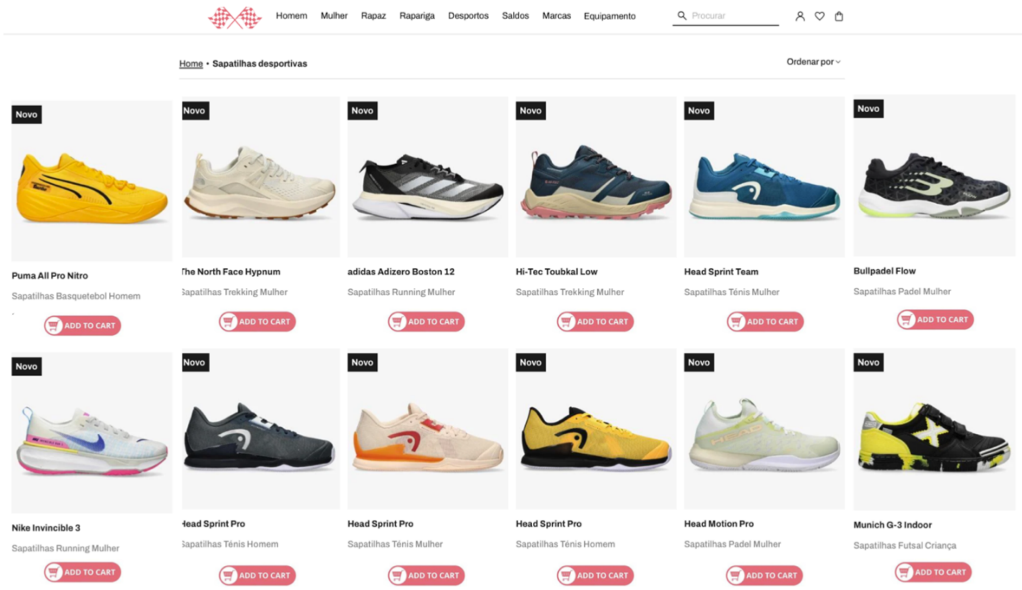


Figure 2 – Manipulation scenario. Source: Author

The people who did not have access to technology scenario were told to think about their shopping experience while choosing items from the list of options, without the help of a salesperson or technology. They read the following: “Answer the following questions taking into account your shopping experience with the products you would select from this list, without the help of technology or a salesperson.”

Those with access to the technology condition read the following: “This website features an artificial intelligence (AI)-based recommendation system. In simpler terms, the AI will assess your past purchasing patterns and suggest three distinct types of sports shoes that align with your preferences, saving you the time and effort of having to evaluate every single item. Answer the following questions considering your shopping experience with the products you would select from this list, suggested by the AI.”

The results were analyzed using SPSS. The first pre-test involved 27 valid participants, 17 of which saw the AI-assisted scenario and 18 who saw the control scenario, without AI. An ANOVA showed that the manipulation didn't work as expected as there was no difference in the measures of the manipulation check ($F= 0.287$, $p = 0.596$), with respondents who saw the condition without technology perceiving the decision as influenced by AI ($M = 2.94$, $SD = 1.70$), and respondents in the recommendation agent condition perceiving the decision as also influenced by AI ($M = 2.65$, $SD = 1.58$). The second manipulation check also showed no significant difference ($F= 0.53$, $p=0.471$) with individuals in the technology condition perceiving it as such ($M= 2.53$, $SD= 1.28$) if compared to individuals with no technology scenario ($M= 2.89$, $SD= 1.61$).

To make the questions more accessible for the participants, it was imperative to complete the first stage.

4.2. PRETEST 2

In response to an inadequacy observed in the manipulation check during the first pretest, several modifications were made to the experiment. The adjustments were motivated by the participants' difficulty in understanding the scenario with RA assistance and the corresponding questions.

To increase clarity, specific adjustments were made to the description of the RA assistance scenario. In the first pre-test, the scenario with RA assistance was formulated as "This website includes a recommendation system based on Artificial Intelligence (AI). The AI will evaluate your previous buying patterns and suggest three diverse types of sports shoes that align with your preferences, saving you the time and effort of having to evaluate each item". In the second pre-test, this scenario was revised to "Imagine that instead of having this list of products, the AI would show you a personalised list with 3 products for you to decide which product to buy, based on your previous purchases. Evaluate how your experience would be with these 3 products in the following questions".

Similarly, the answer options for the manipulation check questions were also adjusted. In the first manipulation check, the answer options were changed from "In my analysis of the product" and "In the analysis of the product aided by Artificial Intelligence", to "In my analysis of the same list of products that other customers have access to" and to "In the analysis of a personalised list of products suggested by artificial intelligence". The second manipulation check was changed from "By my opinion" and "By the opinion of Artificial Intelligence", to "Decided without the help of technology" and "Decided with the help of an artificial intelligence tool".

Finally, a question was also added to find out how complex respondents think the decision to buy a pair of sports shoes is. The manipulated image was the same as pretest 1.

The results were analyzed using SPSS. The second pre-test involved 27 valid participants, of which 18 saw the AI-assisted scenario and 9 saw the control scenario, without AI. An ANOVA showed that the manipulation worked as expected (F= 434.67, p = 0.001), with respondents who saw the condition without technology perceiving the decision as influenced by humans (M = 1.11, SD = 0.33), and respondents in the recommendation agent condition perceiving the decision as influenced by AI (M = 4.72, SD = 0.46). The second manipulation check also worked as expected (F= 605.00, p=0.01) with individuals in the technology condition perceiving it as such (M= 4.89, SD= 0.32) if compared to individuals with no technology scenario (M= 1.22, SD= 0.44).

Following the pre-test, no more modifications were made to the survey or the manipulation of conditions.

4.3. STUDY 1

For study 1 a convenience sample was chosen based on the researcher's contacts. The Qualtrics platform was used to assist with primary data gathering and social media channels were used to disseminate the questionnaire link. The study employed identical text and image manipulation to those used in pre-test 2, guaranteeing methodological coherence and interoperability of the findings across the various stages of the investigation. Results analysis was performed with SPSS assistance.

4.3.1. DESCRIPTIVE ANALYSIS

Regarding the question "Have you ever purchased from an online store?", which served as a filter for the various cases of analysis, it was found that, out of a sample of 190, only 162 respondents have already made purchases online. Within this sample, 12 people did not complete the survey and were not considered.

Therefore, the study sample consisted of 150 valid responses, with respondents ranging from 18 and 79 (M = 34, SD = 13.53). 65% of the respondents were female and 35% male. As for their current situation, the majority live in the Lisbon district (80%) and are students (28%), student-workers (11%), self-employed (13%) and employees (49%). The socio-demographic information of the study sample is summarised in Table 2.

Table 2 - Socio-demographic characteristics of the sample. Source: Author

Sample	Options	%	N
Gender	Female	65	97
	Male	35	53
	Non-binary	0	0
	Prefer not to say	0	0
Age	<25	43	65
	26 - 41	21	32

	42 - 57	32	48
	58 - 67	2	3
	> 68	1	2
Professional Situation	Student	21	31
	Working student	11	16
	Employee	49	74
	Freelancer	13	19
	Unemployed	4	6
	Retired	3	4

We explored the online purchasing habits of the respondents to have a deeper understanding of the study sample. 74% of respondents buy online moderately, often and frequently (30%, 21% and 23%, respectively). This suggests that there is considerable interest in online shopping, which can provide a good basis for analyzing the impact of recommendation agents on consumer behaviour in this context.

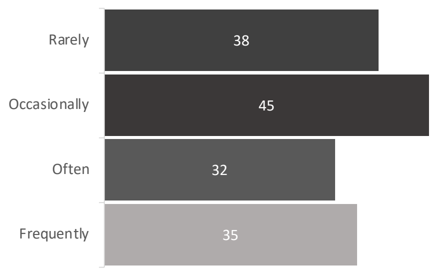


Chart 1 - Frequency of Online Purchase. Source: Author

Regarding their purchase behaviours, the results indicate that there is a variety of behaviours about the time dedicated to choosing products. While the majority of participants devote a maximum of 1 hour (51.4%), a significant proportion invest more time (48.6%), which suggests careful consideration when making a purchasing decision.

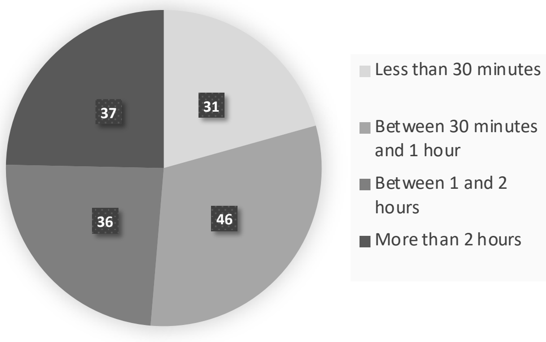


Chart 2 - Time dedicated to choosing a product in an Online Purchase. Source: Author

82% of the respondents indicate that they are satisfied or very satisfied (59% and 23%, respectively) with their online shopping experience, which is positive in general terms. However, there is still a small proportion of participants (18%) who expressed neutrality or dissatisfaction, which may indicate areas of improvement for online retailers. These perceptions of satisfaction may influence consumers' receptiveness to recommendation agents and their effectiveness in personalizing the shopping experience.

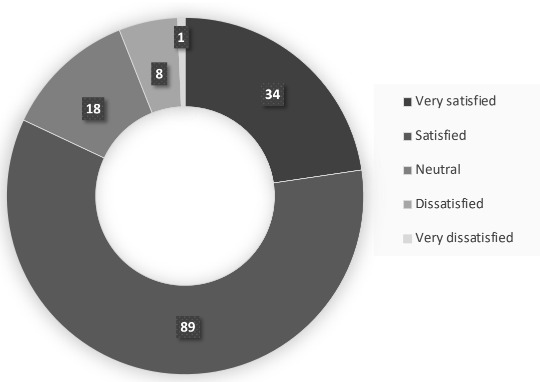


Chart 3 - Overall satisfaction with Online Purchases. Source: Author

Respondents reported being familiar with product recommendations based on previous online purchases (M=3.93, SD=1.31), and they indicate that the presence of AI to assist in the decision to buy sports shoes reduces their perceived complexity (M=2.25, SD=1.24), making the shopping experience potentially easier and less demanding. This highlights the potential positive impact of AI in simplifying the purchasing process for consumers.

4.3.2. SCALE RELIABILITY AND MANIPULATIONS

The questionnaire's reliability was examined to calculate Cronbach's alpha, a coefficient with a range of 0 to 1. When measuring, a Cronbach’s alpha value > 0.60 is considered trustworthy and consistent (Malhotra & Birks, 2023). Table 3 shows that all survey variables have alpha values over 0.60, indicating strong internal consistency and reliability.

Table 3 - Summary of reliability and internal consistency analysis. Source: Author

Variables	Cronbach’s Alpha
Customer Satisfaction	0.944
Perceived Decision Autonomy	0.898
Trust	0.938
Intention to Purchase	0.954

The manipulation worked as expected (F= 54.989, p= 0.001), with respondents who saw the condition without technology perceiving the decision as influenced by humans (M= 1.90, SD= 1.30), and respondents in the recommendation agent condition perceiving the decision as influenced by AI (M= 3.52, SD= 1.39). F= 52.263, p= 0.01 with individuals in the technology condition perceiving it as such (M=3.41, SD=1.54) if compared to individuals with no technology scenario (M= 1.84, SD= 1.11).

4.3.3. Analysis of Variance

For hypothesis testing, we used Analysis of Variance (ANOVA). Individuals who saw the condition of purchase with the assistance of AI reported higher levels of decision satisfaction (M= 1.87, SD= 0.93), than respondents who purchased without AI aid (M= 3.05, SD= 1.45). The ANOVA results were significant (F= 34.47, p = 0.001), therefore Hypothesis 1 was supported.

Individuals who saw the condition of purchase with the assistance of AI reported higher levels of intention to purchase (M=2.10, SD= 1.07), than respondents who purchased without AI aid (M= 3.20, SD= 1.24). The ANOVA results were significant (F= 33.40, p = 0.001), therefore Hypothesis 2 was supported.

4.3.4. Mediation analysis

For mediation analysis, we used model 4 of PROCESS by Andrew F. Hayes. Regarding the mediator trust on customer satisfaction, Path A from the type of decision to trust was significant (t = 7.11, p= 0.001), which means decisions made with the help of a RA significantly impact customer trust. Path B which tested the impact of trust on customer satisfaction was also significant (t = 13.87, p= 0.001). The total path from type of decision to customer satisfaction was significant (t=5.87, p= 0.001). The direct path was not significant (t = 0.68, p= 0.497) when we consider trust in the model. However, the indirect effect of the mediator was significant (LLCI = 0.568, ULCI= 1.043).

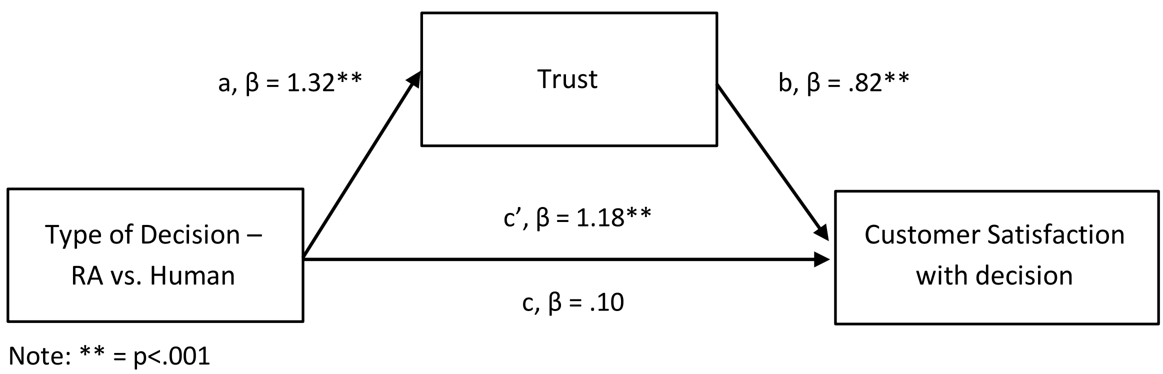
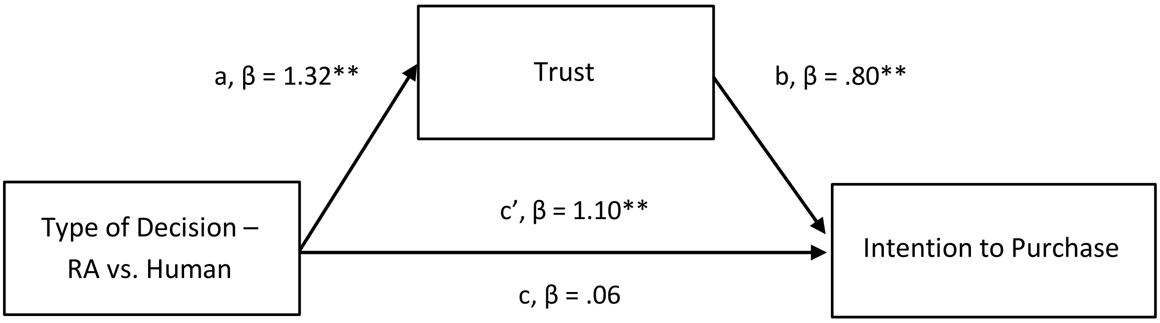


Figure 3 - Mediation of trust on customer satisfaction. ***p* < 0.001. Source: Author

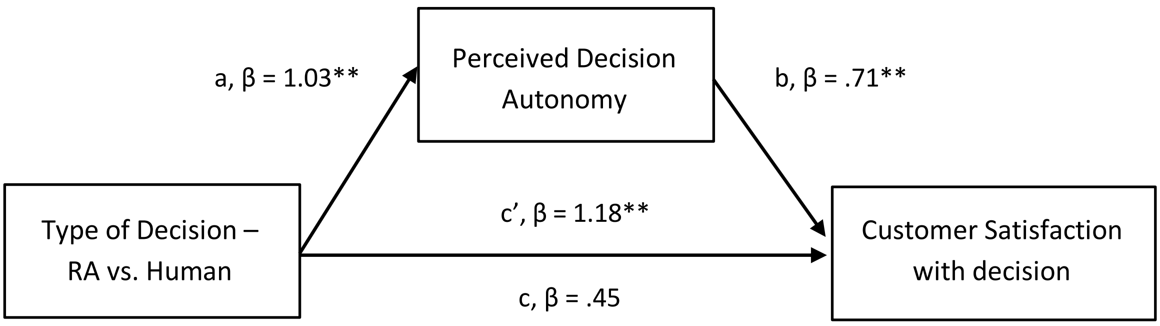
Regarding the purchase intention dependent variable, Path A from the type of decision to trust was significant (t = 7.11, p= 0.001). Path B which tested the impact of trust on purchase intention was also significant (t = 14.69, p= 0.001). The total path from the type of decision to purchase intention was significant (t=5.78, p= 0.001). However, the direct path was not significant (t = 0.40, p= 0.687) when we consider trust in the model. The indirect effect of the mediator was significant (LLCI = 0.590, ULCI= 1.047).



Note: ** = p<.001

Figure 4 - Mediation of trust on intention to purchase. $^{**}p < 0.001$. Source: Author

When it comes to the mediation analysis of autonomy, Path A from the type of decision to perceived decision autonomy was significant (t = 5.00, p= 0.001) meaning that decisions made with the help of RAs significantly impact perceived decision autonomy. Path B which tested the impact of perceived decision autonomy on customer satisfaction was also significant (t = 12.67, p= 0.001). The total path from the type of decision to customer satisfaction was significant (t=5.87, p= 0.001). However, the direct path was not significant (t = 3.01, p= 0.003) when we consider perceived decision autonomy in the model. The indirect effect of the mediator was significant (LLCI = 0.411, ULCI= 1.064).



Note: ** = p<.001

Figure 5 - Mediation of perceived decision autonomy on customer satisfaction. $^{**}p < 0.001$. Source: Author

Regarding the purchase intention dependent variable, Path A from the type of decision to perceived decision autonomy was significant (t = 5.00, p= 0.001). Path B which tested the impact of perceived decision autonomy on purchase intention was also significant (t = 9.71, p= 0.001). The total path from the type of decision to purchase intention was significant (t=5.78, p= 0.001), however, the direct path was not significant (t = 3.13, p= 0.002) when we consider perceived decision autonomy in the model. The indirect effect of the mediator was significant (LLCI = 0.337, ULCI= 0.883).

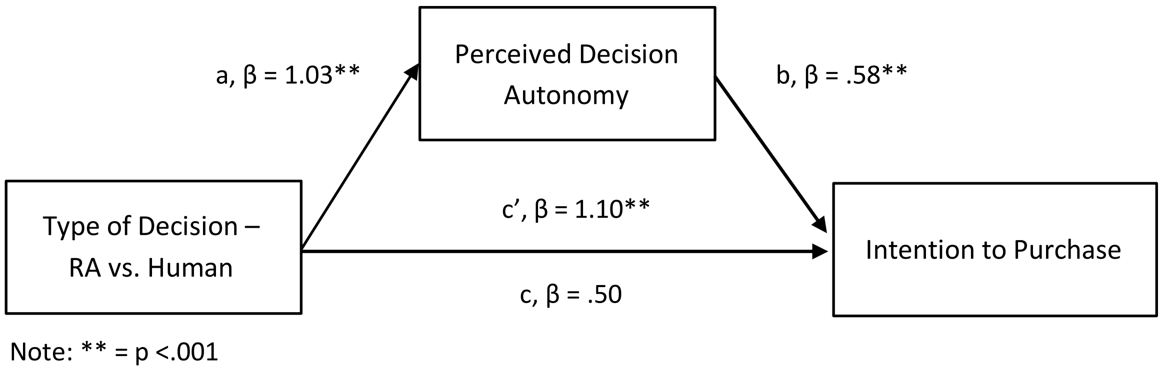


Figure 6 - Mediation of perceived decision autonomy on intention to purchase. ***p* < 0.001. Source: Author

4.3.4.1. MODERATION ANALYSIS

For moderation analysis, we used model 1 of PROCESS by Andrew F. Hayes. We tested the moderation of algorithm aversion considering the type of decision as the independent variable and satisfaction as the dependent variable. The interaction was significant and positive (t= -3.66, p= 0.0004). The moderation is not significant for individuals who reported lower levels of algorithm aversion (t= 1.77, p= 0.079). However, the conditional effects were significant for mid-levels of aversion (t= 6.70, p= 0.000) and higher levels of aversion (t= 7.11, p= 0.000). For high levels of algorithm aversion, the level of satisfaction is lower (M= 1.40, SD= 0.90) than the satisfaction reported by people with medium levels of aversion (M= 2.61, SD= 1.31) and lower levels (M= 3.67, SD= 1.59). In other words, the greater the aversion to the algorithm, the lowest the customer satisfaction.

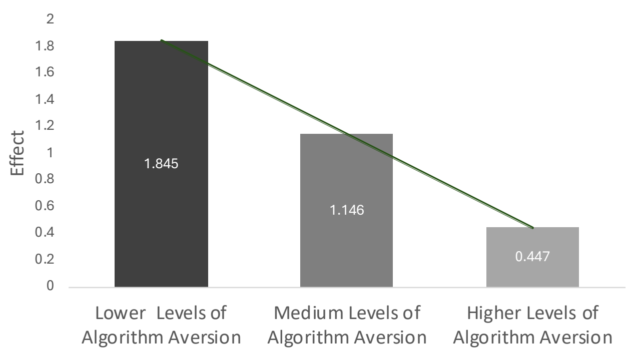


Chart 4 - Moderation Effect of Algorithm Aversion on Customer Satisfaction. Source: Author

Additionally, we tested the moderation of algorithm aversion by considering the type of purchase as the independent variable and purchase intention as the dependent variable. The interaction was significant and positive (t= -2.76, p= 0.007). Additionally, we tested the moderation of algorithm aversion by considering the type of purchase as the independent variable and purchase intention as the dependent variable. The interaction was significant and positive (t= -2.76, p= 0.007). The conditional effects were also significant for mid-levels of aversion (t= 5.93, p= 0.000) and higher levels of algorithm aversion (t= 5.94, p= 0.000). However, moderation is not significant for individuals who reported lower levels of algorithm aversion (t= 1.93, p= 0.056). For high levels of aversion to the algorithm, the level of purchase intention is lower (M= 1.46, SD= 1.16) than the intention reported by people with medium levels of aversion (M=3.18, SD= 0.86) and lower levels (M= 4.19, SD= 1.18). In other words, the greater the aversion to the algorithm, the lower the intention to buy.

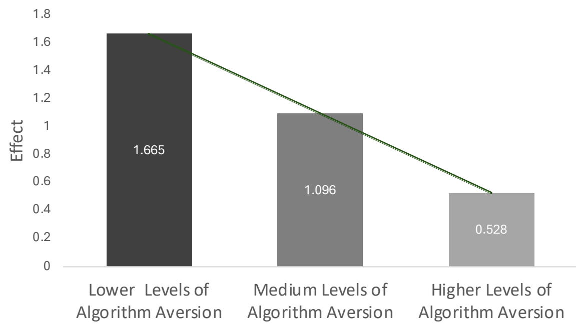


Chart 5 - Moderation Effect of Algorithm Aversion on Intention to Purchase. Source: Author

5. RESULTS AND DISCUSSION

This section summarizes the study's findings and makes a comparison between them and the current literature. The main goal is to determine the impact that RA-assisted purchasing decision-making, in contrast to conventional decision-making, has on consumers' responses, in online and retailing contexts.

The overarching objective is to investigate how the kind of decision-making impacted by RA affects the complex dynamics of trust, autonomy, and algorithm aversion in the decision-making process, as well as consumer satisfaction and purchase intents.

Verification of the hypotheses explored in this study is achievable following analysis of the findings. Using Table 4, the study performed earlier with SPSS allows for the following conclusions to be made:

Table 4 - Hypothesis Verification. Source: Author

Hypothesis	Verification
H1. The use of Recommender Agents in the purchasing process positively influences consumer satisfaction with the decision	Confirmed
H2. The use of Recommender agents in the purchasing process positively influences purchase intention	Confirmed
H3a. Trust positively mediates the effect of the type of decision on consumer satisfaction	Confirmed
H3b. Trust positively mediates the effect of type of decision on purchase intention	Confirmed
H4a. Perceived decision autonomy positively mediates the effect of the type of decision on consumer satisfaction	Confirmed
H4b. Perceived decision autonomy positively mediates the effect of the type of decision on purchase intention	Confirmed
H5. Algorithm aversion will negatively moderate the relationship between type of decision and customer satisfaction (a) and purchase intention (b)	Confirmed

As we can analyze, every hypothesis was verified. These results highlight how important recommender agents (RAs) are for raising customer satisfaction and purchase intent in retail and online settings. Trust and perceived choice autonomy have positive mediation effects that highlight the key components that influence these results. Furthermore, the negative moderation caused by algorithm aversion implies that although RAs can be very successful, their success depends on the scepticism of automated decision-making systems being overcome.

6. CONCLUSIONS

6.1. THEORETICAL CONTRIBUTIONS

This study provides several relevant contributions that could benefit researchers. The present study contributes theoretically by developing a conceptual framework. It synthesized previous works by summarizing key contributions of extant literature.

First, in line with previous research, the study verifies that using RAs increases customers' satisfaction and purchase tendencies. This research validates the hypothesis that AI-driven personalisation can enhance consumer decision-making and overall experience by offering empirical data (Davenport et al., 2020; Kim et al., 2021). This contributes to the increasing amount of evidence showing that in online retail contexts, favourable consumer responses are significantly influenced by personalised recommendations.

Second, by studying trust and perceived decision autonomy in interactions with AI technology, our research adds to our knowledge of these concepts. The study contributes to the theoretical frameworks about perceived decision autonomy and trust in technology by examining how these variables influence the relationship between the use of RAs and consumer responses. The results support and extend the hypotheses put forth by earlier studies (Pratibha & Xiaojing, 2012; Nilashi et al., 2016) by showing that consumer happiness and purchase intentions are positively impacted by more trust in AI and a sense of autonomy while using RAs.

Furthermore, the study emphasizes the revolutionary potential of AI-driven personalisation in influencing customer behaviour by comparing AI-assisted and traditional decision-making processes. The empirical research validates the literature's consensus that AI technologies have the potential to dramatically improve customer experiences and accelerate company success (Evans, 2019; Gururaj, 2021).

Finally, by demonstrating that algorithm aversion has moderating effects on the relationship between the use of RA and customer responses, the study contributes to the current literature and knowledge on the subject. This finding is significant because it aids in the application of AI technology and indicates that optimising the use of AI technologies for online shopping would require overcoming algorithm aversion.

6.2. MANAGERIAL CONTRIBUTIONS

The research findings bring benefits to companies and marketers, especially those involved in online retail, helping them to use RAs more effectively to improve the customer experience. Companies can adjust their strategy to improve customer engagement, knowing how personalised recommendations affect consumer satisfaction and purchase intentions.

One specific suggestion for companies is to implement real-time recommendation systems that update product suggestions based on the most recent customer interactions. For example, if a customer frequently views sports equipment, the system should prioritize and highlight the latest sports equipment promotions on the homepage. This immediate relevance can increase engagement and sales.

In addition, the study offers recommendations for the strategic use of AI technologies. To reduce consumer resistance and enhance satisfaction, companies should ensure transparency in AI operations. This can be achieved by adding a feature that explains why certain products are recommended. For instance, a note saying "Recommended because you viewed similar items" can increase trust in the technology, making customers feel more comfortable in the AI's capabilities and less aversion to the algorithm.

The study highlights the potential influence of RAs on customer behaviour and provides actionable advice on using these technologies to increase marketing effectiveness. For example, companies should integrate AI-driven chatbots into their websites to help customers in real-time by offering personalised product suggestions and answering questions promptly. This not only improves customer service but also encourages purchases.

Finally, another specific recommendation is to create a rewards program in which customers earn points for interacting with personalised recommendations and making purchases. These points can be exchanged for discounts or special offers, promoting loyalty and repeat business.

6.3. LIMITATIONS AND RECOMMENDATIONS FOR FUTURE WORK

This study has several limitations that should be addressed. First off, there is a lack of research in this domain comparing traditional versus AI-assisted decision-making, which presents substantial obstacles. Moreover, the fast-changing field of AI makes matters more complicated because it is challenging to keep the research as current as feasible due to the frequent appearance of recent studies and technological developments, which calls for ongoing revisions to the thesis.

The study's scope, which was limited to a single category of product—sport sneakers—is another limitation. The results cannot be applied to other kinds of consumer purchases because of this restricted emphasis. In future studies, it would be useful to investigate purchases with greater involvement, such as vacation trips. Contrary to the current study's result that consumers prefer AI support when buying sports sneakers, these kinds of purchases may indicate a larger impact of human sales assistance over AI.

Because the study used a non-random and, hence, non-probabilistic sample, its findings cannot be applied to the entire population. Moreover, valid gender comparisons are restricted by the sample's female composition.

This study assessed several variables, including algorithm aversion, perceived decision autonomy, and trust. To provide a more thorough knowledge of consumer behaviour in the context of AI-assisted decision-making, future studies may consider more variables. Perceived usefulness, for instance, looks at how customers view recommender agents' utility in contrast to a human salesperson, and perceived ease of use compares how simple users find using AI-based recommender systems to working with a human sales assistant. Future research can provide more detailed insights into the complex ways that AI recommender agents affect consumer satisfaction and purchase intention, as well as how these impacts differ from those of conventional decision-making techniques, by including these extra variables.

Moreover, it is suggested that further research look at ways to lessen algorithm aversion as well as the long-term impacts of RA use on customer autonomy and trust in a variety of settings.

Finally, it is suggested that the conceptual model be replicated with another AI technology, like chatbots, to see if any comparable patterns or insights show up. Furthermore, it would be exciting to connect this research to a real-world scenario.

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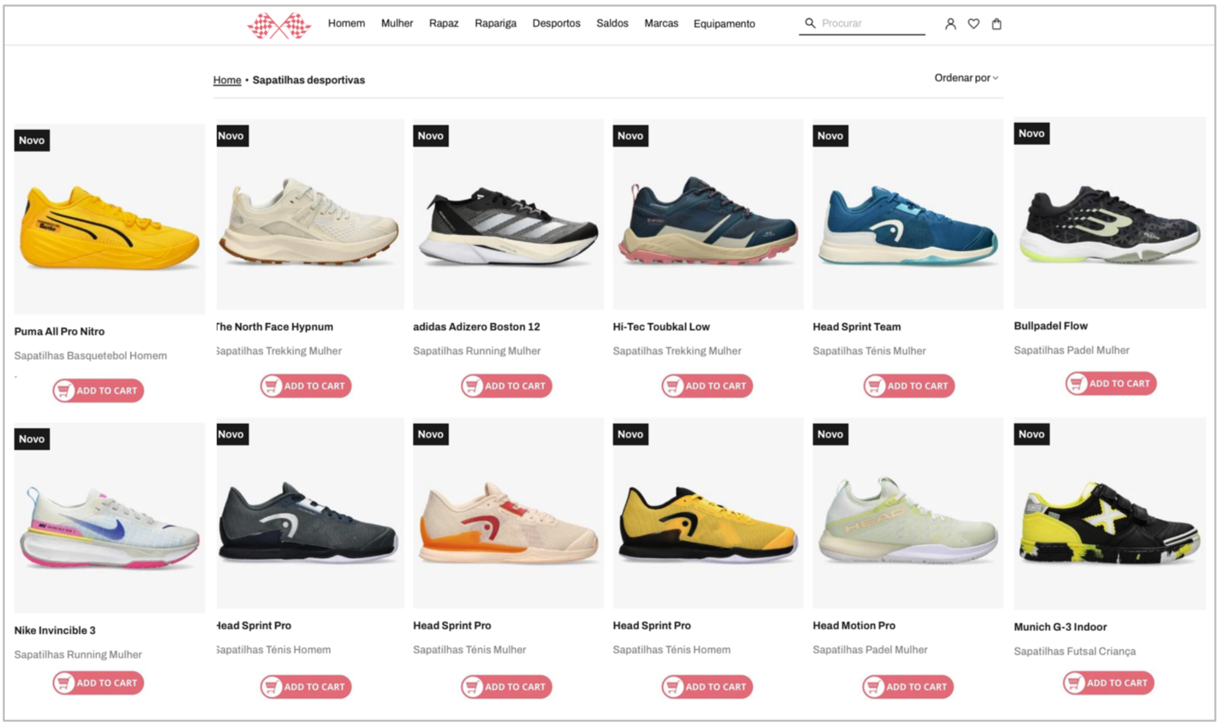
APPENDIX A: MANIPULATION OF THE KIND OF PURCHASE DECISION

All scenarios

Imagine you are considering buying some sports shoes from an online store. The store's website provides you with a selection of diverse options and brands of sneakers, from which you can choose the product you want. Here is an illustration:



For each option, you will have information about the characteristics of the sneakers, among other details.

With RA assistance

However, this website includes a recommendation system based on Artificial Intelligence (AI). Simply put, the AI will evaluate your previous buying patterns and suggest three distinct types of sports shoes that align with your preferences, saving you the time and effort of having to evaluate each item.

Answer the following questions considering your shopping experience with the products you would select from this list, suggested by the AI.

Without RA assistance

Please answer the following questions considering your shopping experience with the products you would select from this list, without technology or a salesperson.

APPENDIX B: SURVEY IN PORTUGUESE

Introdução

Caro participante, o presente questionário é realizado no âmbito de uma dissertação de mestrado em Data-Driven Marketing, com especialização em Digital Marketing and Analytics, pela Universidade Nova IMS. Esta investigação pretende avaliar o **impacto da Inteligência Artificial (IA) na satisfação do consumidor e intenção de compra**. Deverá ter uma duração aproximada de 5 minutos.

Pede-se que responda de forma honesta a todas as questões. A sua participação é inteiramente voluntária e pode abandonar o questionário a qualquer minuto. O inquérito é anónimo e os dados recolhidos são estritamente confidenciais e só serão utilizados para efeitos de investigação. A sua resposta é relevante para o estudo.

Se tiver alguma dúvida ou sugestão, por favor contacte: 20221110@novaims.unl.pt.

Agradeço a sua disponibilidade e colaboração!

Consentimento

Declaro que tenho 18 anos ou mais e concordo com a participação nesta pesquisa. Declaro que fui informado que a minha participação neste estudo é voluntária e que posso abandonar este inquérito a qualquer momento sem qualquer penalização, sendo que todos os dados são confidenciais. Compreendo que este estudo não oferece riscos graves. Eu li e comprendi o formulário de consentimento acima apresentado e desejo de livre e espontânea vontade participar neste estudo.

- ○ Sim
- ○ Não

Bloco 2

Alguma vez realizou uma compra numa loja online?

- ○ Sim
- ○ Não

Com que frequência realiza compras online?

- ○ Frequentemente
- ○ Muitas vezes
- ○ Moderadamente
- ○ Raramente

Quanto tempo costuma dedicar à escolha de produtos antes de efetuar uma compra?

- ◯ Menos de 30 minutos
- ◯ Entre 30 minutos e 1 hora
- ◯ Entre 1 e 2 horas
- ◯ Mais de 2 horas

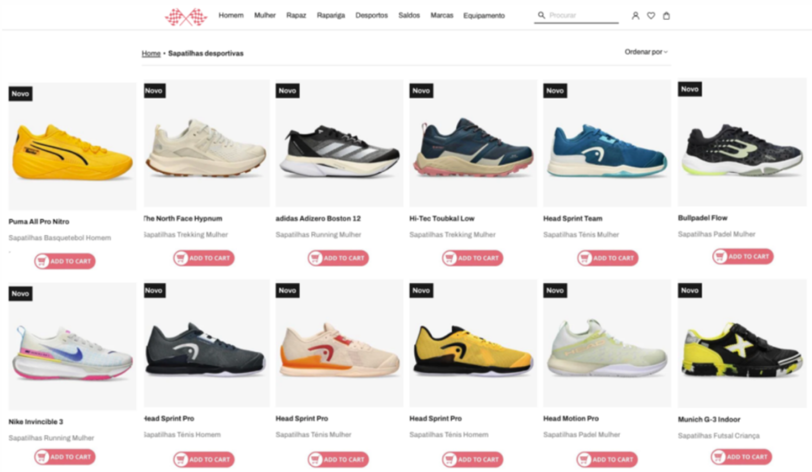
Considerando a sua experiência de compra online, quão satisfeito está?

- ◯ Muito satisfeito
- ◯ Satisfeito
- ◯ Neutro
- ◯ Insatisfeito
- ◯ Muito insatisfeito

Manipulação_IA

Preste atenção ao seguinte cenário apresentado.

Imagine que considera comprar umas sapatilhas de desporto numa loja online. O website da loja fornece-lhe uma seleção de várias opções e marcas, a partir das quais pode escolher o produto desejado. Aqui está uma ilustração:

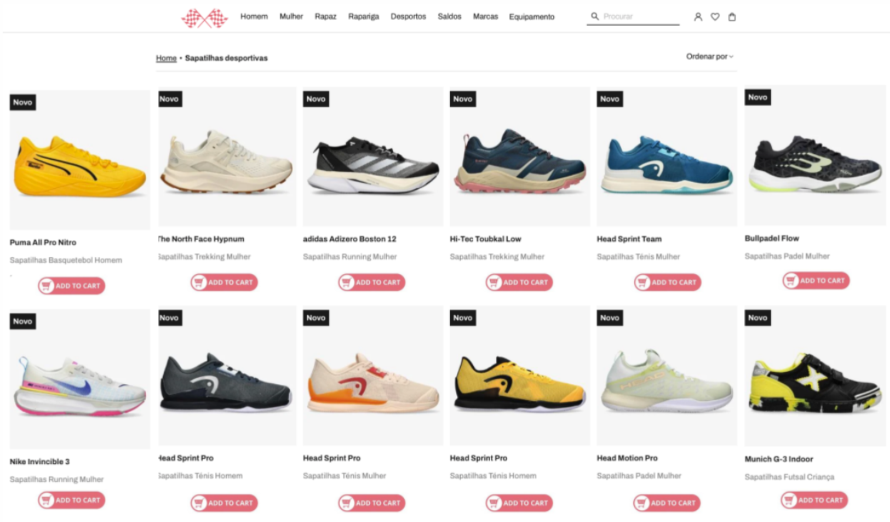


Este website inclui um sistema de recomendação baseado em Inteligência Artificial (IA). **Imagine que ao invés de ter esta lista de produtos, a IA mostraria-lhe uma lista de 3 produtos personalizada para que você decida qual produto comprar, com base nas suas compras anteriores.** Nas seguintes questões avalie como seria a sua experiência com a lista de produtos personalizada.

Manipulação_sem_IA

Preste atenção ao seguinte cenário apresentado.

Imagine que considera comprar umas sapatilhas de desporto numa loja online. O website da loja fornece-lhe uma seleção de várias opções e marcas, a partir das quais pode escolher o produto desejado. Aqui está uma ilustração:



Tendo em conta que todos os clientes têm acesso a essa mesma lista de produtos, e que você vai decidir qual produto comprar sem ajuda de tecnologias ou vendedores, avalie como seria a sua experiência nas questões a seguir.

Perguntas de Manipulação

Relativamente à situação que acabou de ler, a escolha das sapatilhas de desporto seria baseada...

	1.	2.	3.	4.	5,	
Na minha análise da lista de produtos que os demais clientes têm acesso	○	○	○	○	○	Na análise de uma lista personalizada de produtos sugeridos pela Inteligência Artificial

Na sua percepção, a escolha das sapatilhas de desporto seria...

	1.	2.	3.	4.	5.	
Decidida sem a ajuda de tecnologia	○	○	○	○	○	Decidida com a ajuda de uma ferramenta de Inteligência Artificial

Variáveis

Por favor responda à seguinte questão com base na situação que acabou de ver (1 = Concordo totalmente | 5 = Discordo totalmente)

	1.	2.	3.	4.	5.
Sinto que tenho controlo sobre os produtos que estou a ver neste website.	○	○	○	○	○
Sinto que tenho controlo sobre a decisão de compra das sapatilhas de desporto.	○	○	○	○	○
Sinto que tenho autonomia na decisão de compra.	○	○	○	○	○

Por favor responda à seguinte questão com base na situação que acabou de ver (1 = Concordo totalmente | 5 = Discordo totalmente)

	1.	2.	3.	4.	5.
Consideraria interessante o processo de decisão sobre as sapatilhas de desporto a comprar.	○	○	○	○	○
Ficaria satisfeita/o com o processo de decisão sobre as sapatilhas de desporto a comprar.	○	○	○	○	○
Ficaria satisfeita/o com a experiência de decidir qual a opção de sapatilhas de desporto a escolher.	○	○	○	○	○

Por favor responda à seguinte questão com base na situação que acabou de ver (1 = Concordo totalmente | 5 = Discordo totalmente)

	1.	2.	3.	4.	5.
Senti que o website tem em conta os meus interesses.	○	○	○	○	○
Acredito que este website fornece informações exactas.	○	○	○	○	○
Senti que podia confiar na sugestão de produtos deste website	○	○	○	○	○

Por favor responda à seguinte questão com base na situação

Por favor responda à seguinte questão com base na situação que acabou de ver (1 = Concordo totalmente | 5 = Discordo totalmente)

	1.	2.	3.	4.	5.
Estou convencida/o de que os artigos recomendados são adequados para mim.	○	○	○	○	○
Estou confiante de que vou gostar dos artigos que me foram recomendados.	○	○	○	○	○

Recomendação pelo website

Quão complexa considera ser a decisão de compra de umas sapatilhas de desporto? (1 = Nada complexa | 5 = Muito complexa)

	1.	2.	3.	4.	5.	
Nada complexa	○	○	○	○	○	Muito complexa

Quando faço compras online, os websites recomendam-me frequentemente produtos com base no meu comportamento ou em compras anteriores

	1.	2.	3.	4.	5.	
Discordo totalmente	○	○	○	○	○	Concordo totalmente

Dados demográficos

Idade (coloque apenas um número. Exemplo: 30)

Género

- ◯ Feminino
- ◯ Masculino
- ◯ Não-Binário
- ◯ Prefiro não dizer

Formação Académica

- ◯ Ensino básico (até ao 9º ano)
- ◯ Ensino secundário (até ao 12ºano)
- ◯ Licenciatura
- ◯ Mestrado
- ◯ Doutoramento
- ◯ Outro

Situação Profissional

- ◯ Estudante
- ◯ Trabalhador-estudante
- ◯ Trabalhador por conta própria
- ◯ Trabalhador por conta de outrém
- ◯ Desempregado
- ◯ Reformado
- ◯ Outro

Distrito de Residência

- ◯ Aveiro
- ◯ Beja
- ◯ Braga
- ◯ Bragança
- ◯ Castelo Branco
- ◯ Coimbra
- ◯ Évora
- ◯ Faro
- ◯ Guarda
- ◯ Leiria
- ◯ Lisboa
- ◯ Portalegre
- ◯ Porto
- ◯ Região Autónoma dos Açores
- ◯ Região Autónoma da Madeira
- ◯ Santarém
- ◯ Setúbal
- ◯ Viana do Castelo
- ◯ Vila Real

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