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The Impact of Recommendations Agents in consumers' purchasing decisions and satisfaction

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Master Thesis

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

NOVA Information Management School
Instituto Superior de Estatística e Gestão de Informação
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The Impact of Recommendations Agents in consumers' purchasing decisions and satisfaction

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 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

This work explores the impact of recommendation agents on consumer purchasing decisions and satisfaction. With the rise of Artificial Intelligence (AI), recommendation agents have become a significant part of consumers' daily lives, offering product suggestions based on analysis of customers' online behaviors. These agents simplify decision-making by reducing information overload and personalizing the shopping experience. The research tries to understand how RA helps consumers deal with choice overload and how it conditions the purchase decision and satisfaction of online consumers. The main results of the research show that, although we did not obtain significant results between the RA and the purchase intention and satisfaction variables, we were able to verify that the participants who had AI assistance had a lower choice overload, and a higher purchase intention and satisfaction compared to the participants who did not have AI assistance. Furthermore, the research considers the differences between maximizers and satisficers to try to understand how each group reacts to personalized recommendations and a control variable, privacy concerns, to understand if users with AI are more subject to online attacks than those without AI. The results of this study contribute to the understanding of the strategic implications of RA in online retail and offer insights for future research on this topic and on how companies can optimize their recommendation strategies to better meet consumers' needs. To obtain this insight, this thesis was developed through quantitative analytic research via an online questionnaire with 130 responses.

KEYWORDS

Artificial Intelligence; Recommendation Agents; Consumer Behavior; Online Shopping; Purchase Intention; Satisfaction

Sustainable Development Goals (SDG):

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LIST OF ABBREVIATIONS AND ACRONYMS

AI	Artificial Intelligence
RA	Recommendation Agents

1. INTRODUCTION

Recommendation agents (RA), or recommendation systems, frequently use Artificial intelligence (AI) software in marketing strategies to assist clients in making purchasing decisions. These recommendation agents offer suggestions for products based on an analysis of the customers' online movements and behaviors. (Hostler et al., 2011). RA has become a significant part of customers' daily lives since they are frequently approached by them wherever (and whenever) the customer may be considering the decision to purchase (Zhao et al., 2023). Following this line of thought, they allow the personalization of the shopping journey and simplify decision-making (Rohden & Espartel, 2024). This is supported by the fact that RA not only simplifies decision-making by making search, comparison, and selection less complicated, but they also reduce the sense of information overload and personalize the buying experience (Rohden & Zeferino, 2023). Due to the fact that consumers are faced with a wide range of product variety, RA is an effective tool that helps the consumer to choose the product that better suits their needs by sparing time on the analysis of all the given options, reducing the choice overload. This phenomenon, "Choice overload", is a term used to describe a variety of unfavorable effects that result from having too many options. These consequences include a greater chance of delaying decisions, changing options, or feeling regret, as well as a decline in confidence and satisfaction with the choices made.

It is undeniable that with the growth of Artificial Intelligence, the consumer experience online has changed and grown a lot, and more importantly, it has shaped and paved the way to a new type of online shopping. It is estimated that online consumption represents 23% of global sales, a figure that is expected to grow over the years (Wang et al., 2023). As a result, online shoppers are at risk of experiencing information overload. (Wang et al., 2023). On the contrary, even with a large online product offering, there are consumers who still prefer to buy, see, or even try things physically, not falling into the temptation of being deceived by the illusion of purchasing an item without seeing it firsthand, guaranteeing complete control over the purchase (Pantano et al., 2023).

When AI, particularly recommendation agents, act in these consumer purchase decisions, uncertainties may arise with the purchase made (Rohden & Espartel, 2024), that is why it is important to acknowledge that there are two types of consumers: maximizers and satisficers. On one hand, maximizers try to assess all options and make the best possible choice given the circumstances; on the other hand, satisficers have a more subtle behavior, as they evaluate options until they find one that exceeds the acceptability threshold (Rohden & Espartel, 2024). These types of consumers represent two important contrasts for the research, as one seeks the "best possible" option and the other the "good enough" option. (Shin & Yoon, 2023), displaying two distinct consumer types who search for their items online with different levels of effort.

Following this, the research question is: How do AI-powered recommendation agents influence consumer willingness to delegate the decision and satisfaction with the choice made in online retail environments?

This research addresses these gaps since there is still a lot to be unveiled on how RA influences consumer behavior, given the amount of information and options provided by them, and, consequently, whether they are, in fact, satisfied with AI-supported decisions or not. Hence, the study will consider the differences between Maximizers and Satisficers, focusing on these two references to obtain a better understanding of what type of people are considered when using Recommendations Agents. Therefore, this research is relevant because it is in line with what consumers face on a daily basis with the constant presence of RA, which leads to an important point: By comprehending what consumers expect from AI, we can act more strategically and effectively. Moreover, it explores a thorough comprehension of how AI influences consumer choice and consumer behavior by providing a detailed and in-depth understanding of the interaction between the customer and the recommendations agents and how they can truly save time and meet their demands, which is the ultimate goal.

Additionally, it provides a clear perspective on how RA influences consumers on their purchase intentions and whether they are indeed satisfied with the AI's aid, while not omitting the possibility of the consumer getting overwhelmed with the realm of choices they get offered. Putting it into other words, is RA truly beneficial to the consumer's purchase, or does it only puzzle them?

2. LITERATURE REVIEW

2.1 Recommendation Agents

With the growth of e-commerce and web applications, Recommendation Agents have become an important part of the consumer's daily life, providing quick and easy product suggestions based on the consumer's preferences, personalizing their shopping experience (Zhao et al., 2023). They are tools based on algorithms that help consumers have an improved and more effective experience by facilitating access to products. These systems aim to filter, organize, and prioritize information, suggesting personalized options based on the user's interests and behaviors (Fayyaz et al., 2020).

In this way, to effectively personalize recommendations to consumers with different preferences, RA are divided into several categories: collaborative filtering, content-based, utility-based, demographic-based, knowledge-based, and hybrid approaches (Alfaifi, 2024). Among these, collaborative filtering, content-based, and hybrid methods are the most common due to their great effectiveness and versatility (Rashidi et al., 2022).

Collaborative filtering predicts consumer preferences based on historical evaluations, mapping an active consumer's preferences to a database to identify target consumers or similar items and produce recommendations (Herlocker et al., 2004), being divided into user-based filtering and item-based filtering (Sarwar et al., 2001).

Content-based filtering, unlike collaborative filtering, acts independently, recommending new products without the need for their ratings (Fayyaz et al., 2020), using other knowledge such as demographic data and item descriptions to improve the efficiency of the recommendation (Vasile et al., 2016).

Hybrid recommendation systems, as many studies mention, combine different recommendation techniques to increase their precision and reduce common problems (Alfaifi, 2024). In contrast, according to Burke, the most common technique is to combine collaborative filtering with another technique, such as content-based filtering (Burke, 2002). For example, it can use collaborative filtering to find customers with the same characteristics and content-based filtering to recommend items that these consumers have liked or shown interest in. While we know how RA works and how it attacks the market with its purchase personalizations, it is important to understand how RA influences consumer behavior and how consumers' perceptions change when a purchase decision is made with the assistance of an RA rather than making the choice alone (Rohden & Espartel, 2024).

On one hand**,** RA facilitates the purchasing journey by simplifying choices; on the other hand, they can generate discomfort and uncertainty associated with perceptions (Lalicic & Weismayer, 2021). This negative impact can reduce the probability of consumers trusting the technology and negatively influence both purchase intention and satisfaction with the choices made (Rohden & Espartel, 2024). According to the study carried out by Rohden and Espartel, it has been proven that RA-assisted decisions create more uncertainty than unassisted decisions since they reduce perceived control over choices. This greater uncertainty results in lower satisfaction with the decision, as well as a negative effect on purchase intention (Rohden & Espartel, 2024)

H1: Decisions assisted by RAs result in more satisfaction with the choices made compared to decisions made independently.

2.2 Purchase Intention

Purchase intention is described as the willingness of consumers to use online services to buy products (Close & Kukar-Kinney, 2010), raising interest and discussion in the e-commerce literature to understand this willingness of consumers to engage in online transactions (Sudibyo et al.,2020). In e-commerce, due to the amount of information, consumers can end up being influenced when they are buying a product online (Mangold & Faulds, 2009), with purchasing intention being one of the factors that affect the behavior of online consumers (Ajzen, 1991) . Lohse believes that if online retailers want consumers to buy more products, they need to identify the factors that influence their shopping intention (Lohse et al., 2000).

According to a previous study by Ajzen, intention is directly affected by attitude toward the behavior, subjective norms, and perceived behavior control (Ajzen, 1991).

The first one is the attitude towards the behavior and refers to the level in which a person has a favorable or unfavorable evaluation of the behavior (Ajzen, 1991). In other words, it is the consumer's feelings desirable, or undesirable based on the use of the internet to buy products from retail websites (Ha et al., 2021).

The second is called subjective norm, which refers to the perceived social pressure to perform or not perform the purchase behavior (Ajzen, 1991). The online sphere means whether the consumer makes a purchase according to the most recent attitudes surrounding that product or not (Lin, 2007).

The third antecedent of intention is the level of perceived behavioral control, which refers to the perceived ease or difficulty of carrying out the behavior (Ajzen, 1991). For better understanding, perceived behavior control describes consumers' perception of the availability of necessary resources, knowledge, and opportunities to go online shopping (Lin, 2007).

Therefore, studies like Lin, 2007; Ajzen, 1991; Ha, 2021, defend that online shopping has a positive impact on consumer purchase intention. Thus, if a consumer has a positive attitude towards an e-commerce shop, they are more likely to shop there.

From a contrasting perspective, there have been previous studies that shows that risk is a factor that has a huge impact on the consumer's intention to shop online, since consumers use the Internet to make purchases and contact their retailers. Therefore, consumers are exposed to economic risks, which can result in loss of money, risk from sellers, risk of privacy (personal information can be illegally revealed) and risk of security (information of credit cards may be stolen) (Pavlou, 2003).

H2: Decisions assisted by RAs result in higher purchase intentions, compared to decisions made independently.

2.3 Choice Overload

Today's e-commerce websites present consumers with an array of products with a variety of information, requiring them to process large amounts of information at the same time (C. H. Wu et al., 2023). Previous studies in consumer behavior have shown that when there is a large number of options for consumers (or more than the sellers' own resources), the choice becomes confusing and difficult, resulting in a disadvantage for the seller and the consumer themselves. This phenomenon has been named choice overload and refers to the accumulation of products presented to the consumer (Misuraca et al., 2024).

Different studies have claimed that various factors influence consumers' purchasing decisions, such as the purchase intention, the number of options, the popularity of those options (Wang et al., 2023) , choice set complexity, decision task difficulty preference uncertainty, and decision goal (Chernev et al., 2012). Wang argues that with the accumulation of purchase options, consumers may experience choice fatigue (Wang et al., 2023), as they may find it time-consuming to analyze and often compare purchase options to find the best products in order to be satisfied. (Chen et al., 2009).

Therefore, Recommendation Agents, supported by AI, have come to alleviate choice overload, preventing consumers from having to process data (J. Wu et al., 2022), by providing products that match their personal preferences, considering their previous behaviors or past purchases (Bollen et al., 2010). In parallel, although recommendation systems can reduce information overload, it does not mean that consumers will find it easier to make purchasing decisions, since the number of products and information is so high that Recommendation Agents can become overwhelmed when evaluating all potential options, causing choice overload to consumers and reduce their satisfaction (Iyengar & Lepper, 2000).

According to previous studies, having a long list of options assigned by RA has different consequences for consumer satisfaction and purchase intention, making it more likely that consumers will find the product they are looking for, increasing satisfaction consequently. (Chernev et al., 2012). Opposingly (Bollen et al., 2013), affirms that larger groups of items do not necessarily result in greater choice satisfaction compared to smaller groups.

H3a: Choice overload mediates the impact of the use of recommendation agents on satisfaction with the choices.

H3b: Choice overload mediates the impact of the use of recommendation agents on purchase intention.

2.4 MAXIMIZERS VS SATISFICERS

The paradox of maximization is one of the most important and significant terms in the decision-making of consumers, also known as Maximizers, who invest excessive time and resources in looking for the 'best' products while still being dissatisfied with their decisions (Dar-Nimrod et al., 2009). This paradox defines maximisers as consumers who invest more time in making decisions, exploring more options and making more comparisons between choices, but feel more negatively about what they have chosen (Chowdhury et al., 2009)

This study along with previous ones, follow the work done by Simon, who introduced the difference between maximizing and satisficing as choice making strategies (Simon, 1955).

While maximizers spend more time evaluating all the products to make the best possible choice, satisficers have a more subtle behavior, in which they evaluate the products they want to buy until they find one that meets their needs, or in simpler terms, the one that is "good enough" (Luan & Li, 2017). For instance, Shiner showed that maximizers are less satisfied than satisficers after making irreversible decisions, but in fact, they are actually more satisfied than satisficers after making reversible decisions, at least in the short term.

Maximizers attribute a lot of importance to choosing the perfect product, no matter what context they are in (a large set or a small set), which can reduce the effectiveness of Recommendation Agents' in suggesting the ideal products for the respective consumer (Luan et al., 2022). Generally, people who are determined by high levels of maximization find it harder to deal with various choices (choice overload), take longer to make their choices and become dissatisfied, as tend to keep looking for a better option even after they have found the one that could potentially satisfy their standards (i.e. the maximization goal) (Shin & Yoon, 2023). Alternatively, since satisficers don't put any effort into choosing the products they want to buy, Recommendation Agents are more likely to be able to help satisficers find what they desire (Luan et al., 2022), considering satisfiers tend to stop looking when they find options that meet their needs (Shin & Yoon, 2023). As a result, maximizers, with their presence and desire to choose the product that has all the features they want, may show higher levels of anxiety and stress, as well as regret and dissatisfaction with their purchase (Iyengar et al., 2006). On the contrary, from the satisficers perspective, they are less likely to suffer from decision fatigue or choice overload due to their ability to accept a viable solution that fulfils their expectations (Diab et al., 2008). For instance, Shiner showed that maximizers are less satisfied than satisficers after making irreversible decisions, but as a matter of fact, they are actually more satisfied than satisficers after making reversible decisions, at least in the short run (Shiner, 2015).

Overall, studies have shown that maximizers are less happy and less optimistic than satisficers.

H4: Maximizers are more likely to experience choice overload and dissatisfaction when using AI-based recommendation systems due to the number of options presented and their constant search for the perfect choice, while Satisficers experience less choice fatigue and are more satisfied with the options that are suggested.

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

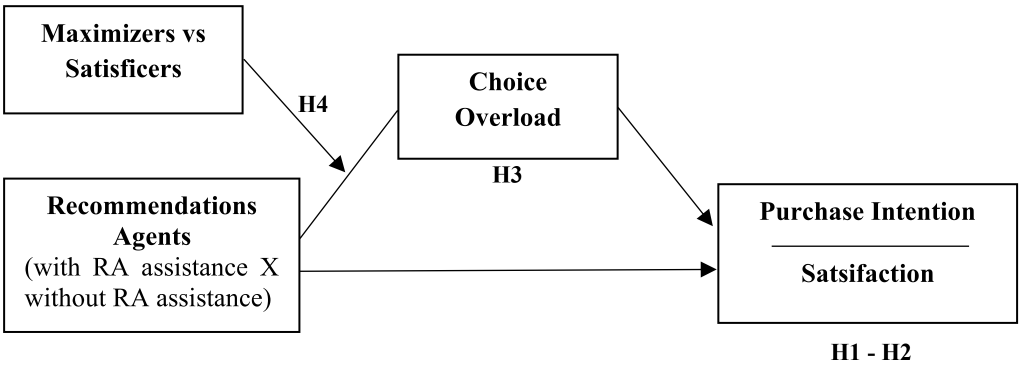


Figure 1 – Conceptual Model

3. METHODOLOGY

3.1 Research Design

This study used experimental design to investigate consumer responses when confronted with the help of recommendation agents versus without their help. The research makes it possible to identify the impact of RA support on customer decision-making in online retail contexts by manipulating the independent variable. As a result, the experiment was divided into two different samples, being a randomized single factor between-subjects experiment. Both samples viewed the same website page, but with one difference: while one sample was subject to the help of recommendation systems, the other did not have access to this functionality. After interacting with the scenario, the participants answered a set of specific questions designed to capture the perceptions and decisions made in each situation.

There were different ways of examining and explaining a study and presenting its conclusions. So, for this study, we followed quantitative research, which is a method of employing numerical values derived from observations to explain and describe the phenomena that the observations reflected on them (Sukamolson, 2007). There were different approaches to this method, ours was experimentation, which helped us test our hypotheses, answer questions, and discover new facts (Taherdoost, 2022).

Following this technique, we analyzed our research question, “How do AI-powered recommendation agents influence the consumer's willingness to delegate the decision and satisfaction with the choice made in online retail environments?” and understood the impact RA had in helping consumers choose their products.

3.2 Measure

All the components' measuring scales are based on previously published research and have been modified for use with recommender agents. Every metric is derived from a 7-point Likert scale, where 1 represents "totally disagree" and 7 represents "totally agree". In order to respond to the conceptual model, we present in Table 1 the measurement scales and corresponding sources, where all variables have 3 items, except for maximizers vs satisficers, which have 4 items. A control variable was added, privacy concerns with 3 3-item measure. This control variable was chosen in order to understand whether the information retained from consumers by RA has an impact on consumers' decision to consume online, given that one of the aspects of the privacy concern are the perception of how risky it is to purchase in an online environment, and the concern that some people have about the use of their data (Miyazaki & Krishnamurthy, 2002).

Table 1 – Description an Measurement of Variables

Variable	Items	Source
Purchase Intention	I would plan to use this website for online shopping again. I would intend to shop online from this website in the future. I would strongly recommend this website to others.	(Lin, 2007)
Satisfaction	I believe I would feel satisfied with my purchase choice	(Iyengar & Lepper, 2000)
Choice Overload	I would enjoy making a purchase choice in this situation I would find it difficult to make a purchase decision in this situation I would feel frustrated about making a purchase choice in this situation I believe I would feel satisfied with my purchase choice	(Iyengar & Lepper, 2000)
Maximizers vs Satisficers	I will wait for the best option, no matter how long it takes. I don't like having to settle for "good enough". When shopping, I have a hard time finding the product that I really love. Once I make a decision, I don't lookback.	(Schwartz et al., 2002)

Privacy Concerns	I believe my personal data (e.g. name, personal number, address, telephone number or payment details) have been monitored, searched, recorded, or stored at least once without my permission. I have had bad experiences with regards to the privacy of my personal data when using services online. I have been a victim of privacy invasion at least once in the past as a result of using services online	(Mwesiumo et al., 2021)

3.3 DATA COLLECTION

For the following study, convenience sampling was used for gathering data, which is a non-probability technique that selects participants from a set population based on ease of access (Golzar & Tajik, 2022). In this way, the questionnaire was shared via the college's institutional email, shared via WhatsApp, Instagram, LinkedIn and in a corporate world, thus opening the possibilities of differentiation where we had access to participants who usually buy online and participants who prefer to buy in a physical store. Participants were included in the sample based on criteria such as being over 18 years old and consenting to participate in the study. Before data collection began, the study was submitted for approval by the ethics committee.

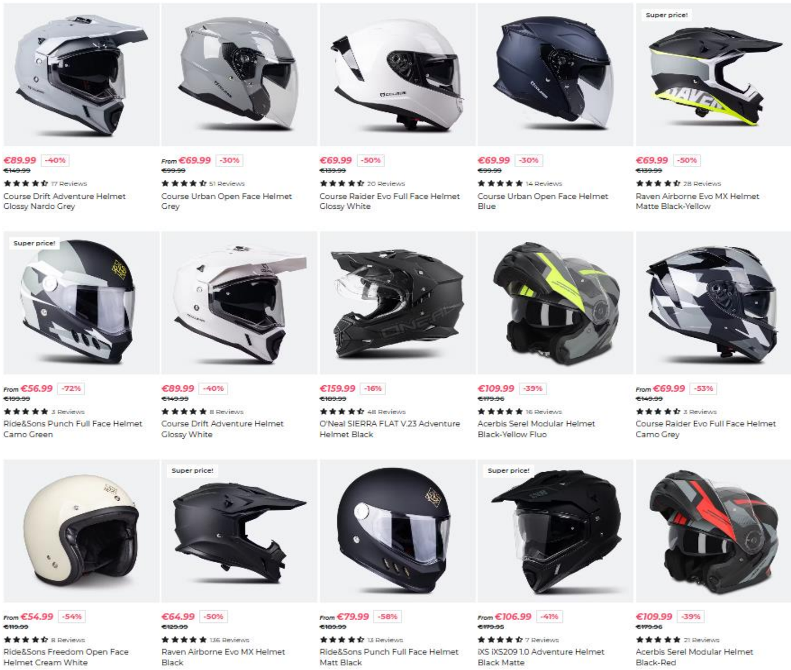
4. EMPIRICAL STUDY

4.1. PRE-TEST

A Pretest was performed to check whether the respondents understand the manipulation check of the questionnaire so that we could proceed to the main study without any issues.

Respondents were presented with a scenario in which they perceived themselves as frequent buyers of motorcycle material and their intention was to buy a motorcycle helmet through a website.

Below is an image of the website.



One of the scenarios involved participants who did not have access to a AI system who were asked to consider their experience of buying items from the given list of options, without the help of a salesperson or technology. They read the following: "Answer the following questions, considering that your purchase intention will be without the assistance of Artificial Intelligence or a salesperson."

The other scenario involved participants that were presented with an AI system on the website to help choose the products. They read the following: "This website has a recommendation system based on Artificial Intelligence (AI), which will analyze your previous behavior and recommend three products that match your buying habits so that you can choose from a set of helmets instead of analyzing all the products.

Once the collection was complete, all the data from the questionnaire was exported to Excel, where the analysis was treated by removing the columns that were not relevant to the analysis. After that, the analysis was done in SPPS, where we found that the questionnaire had 28 participants, in which 14 saw the scenario without AI and the remaining 14 saw it without AI. The sample was 68% female and 32% male with an average age of 28 (SD = 8.42).

We can see that the Manipulation Checks worked (t = - 3.227, p = .003) with the participants who saw the scenario without AI (M = 5.71, SD = 1.81), and the participants in the AI condition perceived the decision as influenced by AI (M = 3.21, SD = 0.604).

Regarding the scenario with participants who saw the scenario with AI, it was also significant (t = 5.908, p = .001) with individuals in the condition with AI perceiving it as such (M = 5.71, SD = 0.286) compared to the scenario without AI (M = 2.43, SD = 0.477).

We also ran a linear regression to verify the main effect where we include the control variable, privacy concerns and where has a significant impact on Purchase Intention (F= 4.403, p = .04, ETA= .265).

4.2. Study 1

For study 1 we kept the pre-test questionnaire without making any changes, but now we collected a larger sample of 130 people who hadn't answered the pre-test. We used the Prolific website to collect responses, with an “Online Shopping Frequency” as screening criteria. The study used the same design and between subject’s design as the pre-test. Results analysis was performed with SPSS assistance.

4.2.1. Descriptive analysis

The first manipulation check worked as expected (t = -4.71, p = .001) with participants who saw the scenario without AI perceiving that the purchase intention will be made without the help of AI or a salesperson (M = 5.65, SD = 1.81) compared to individuals who saw the scenario with AI perceiving that the purchase intention will be made with the help of AI (M = 4.06, SD = 2.02). In the case of the second manipulation, it was also significant (t = 4.82, p = .001), with participants without AI reporting (M = 3, SD = 2.22) and participants with the help of AI reporting (M = 4.77, SD = 1.93). At the end of the questionnaire, the question “Do you own or usually ride a motorcycle?” was asked, with 64.6% answering “No” and 35.4% “Yes”, which was not significant for the study after a T-test, reporting (t = -1.601, p = 0.112).

There were 130 valid responses in this study, 52% female and 48% male, with participants ranging in age from 20 to 68 (M = 34, SD = 10.72). Table 2 summarizes the demographic characteristics of the sample.

Table 2 - Socio-demographic characteristics of the sample

Sample	Options	%	N
Gender	Female	52	67
	Male	48	61
	Non-binary	0	0
	Prefer not to say	0	0
Age	<25	22	28
	26 - 41	59	76
	42 - 57	15	20
	58 - 67	3	5
	>68	1	1

4.2.2. SCALE RELIABILITY AND MANIPULATIONS

The reliability of the questionnaire was examined to calculate Cronbach's alpha, a coefficient that varies between 0 and 1. When measuring Cronbach's alpha value > 0.60 is considered reliable and consistent. Table 3 shows that all variables have alpha values greater than 0.60, except for the Maximizers vs. Satisficers variable.

Table 3 - Cronbach´s Alpha values (reliability and internal consistency)

Variables	Cronbach´s Alpha
Purchase Intention	0.936
Choice Overload	0.812
Maximizers x Satisficers	0.227
Privacy Concerns	0.786

4.2.3. ANALYSIS OF VARIANCE

To test the hypothesis, we used the Independent Samples T Test. The participants who had the help of AI in purchasing the products, although there was little difference, showed greater satisfaction with their choice (M = 5.5, SD = 1.33) than the participants who did not have the help of AI in purchasing the products (M = 5.4, SD = 1.34). The results were not statistically significant (t = 0.37, p = 0.848), meaning that hypothesis H1 was not supported.

The analysis shows that the Purchase Intention variable was not significant (t = 0.73, SD = 0.466), showing that the participants with AI had a slightly higher purchase intention (M = 5.52, SD = 1.26) as opposed to those without AI (M = 5.3, SD = 1.41). H2 was, therefore not significant.

Despite the average results of the Choice Overload variable being slightly lower in the group that used AI (M = 2.67, SD = 1.24), we can say that based on the questions that were asked, it was in line with what was expected about the impact it has on satisfaction and purchase intention, compared to the group without AI (M = 2.82, SD = 1.30). However, this difference was not statistically significant (t = -6.91, p = 0.491).

A T-test was also carried out for the study's control variables. In the case of the privcy concerns variable, participants with AI help reported that on average they were more subject to online attacks (M = 4.04, SD = 1.824) as opposed to those without AI help (M = 3.78, SD = 1.563), indicating that participants subject to AI are more subject to attacks on their data than those without AI help. The relationship between the two groups was not statistically significant (t = 0.853, p = 0.395).

4.2.4. Mediation Analysis

For the mediation analysis, model 4 of PROCESS by Adrew F. Hayes v4.2 was used. Two tests were carried out, in which the group with AI and without AI were the independent variables, purchase intention and satisfaction were the dependent variable and the mediator was choice overload.

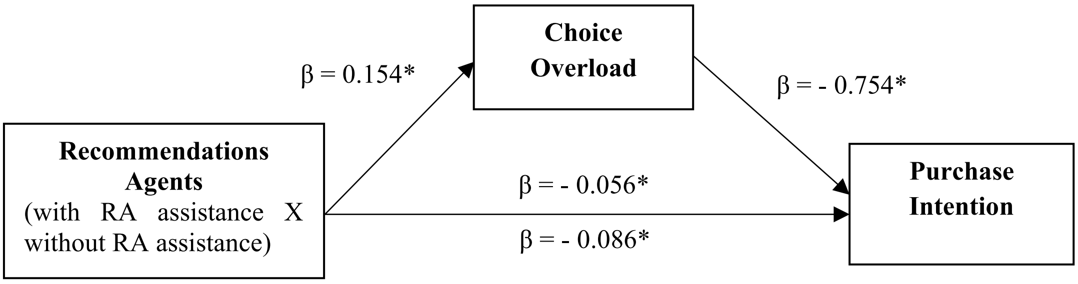


Figure 2 - Mediation of Choice Overload on Purchase Intention

The results showed that Path A was not significant, with choice overload not being influenced in both scenarios (b = 0.154, t = 0.691, p = 0.4908). Path B from choice overload to purchase intention showed a significant relationship (b = -0.754, t = -11.485, p = 0.001), meaning that the number of options influences consumers' purchase intentions. There was no statistically significant direct effect between IV and DV (b = -0.056, t = -0.338, p = 0.7358). The results of the indirect effect showed a non-significant relationship between IV and Purchase Intention (b = - 0.086, LLCI = - 0.331, ULCI = 0.148).

Once the analysis has been carried out, we can conclude that there was no mediation, since only Path B was statistically significant, while Path A was not significant, indicating that Choice Overload did not act as a significant mediator between IV and Purchase Intention.

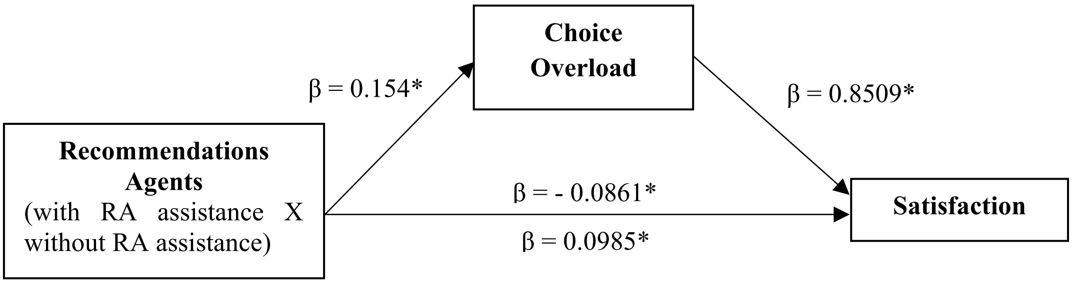


Figure 3 - Mediation of Choice Overload on Satisfaction

The results showed that Path A was not significant, with choice overload not being influenced in both scenarios (b = 0.154, t = 0.691, p = 0.4908). Path B from choice overload to satisfaction showed a significant relationship (b = 0.8509, t = 15.540, p = 0.001), meaning that the number of options influences consumers' satisfaction. There was no statistically significant direct effect between IV and Satisfaction (b = -0.0861, t = -0.6221, p = 0.5350). The results of the indirect effect showed a non-significant relationship between IV and Satisfaction (b = 0.0985, LLCI = - 1.856, ULCI = 0.3698).

Once the analysis has been carried out, we can conclude that there was no mediation, since only Path B was statistically significant, while Path A was not significant, indicating that Choice Overload did not act as a significant mediator between IV and Satisfaction.

4.2.4. Moderation Analysis

For the last analysis, we tested moderation with the model 1 of PROCESS by Andrew F. Hayes v4.2, including the moderator of our study, Maximizers vs Satisficers.

The overall results of the model with purchase intention as the DV indicate that the variance is relatively low ($R^2 = 0.0607$), and was not statistically significant (F = 0.4774, p = 0.0477). Looking at the individual analysis, we notice that IV had no significant effect on purchase intention (t = -0.4230, p = 0.6730). Following on with the analysis, we found that the moderator was not statistically significant (t = -0.9028, p = 0.3683), suggesting that the two groups do not show substantial differences in purchase intention. The relationship between the moderator and the IV was not confirmed, showing that there is no moderation between the two variables (t = 0.0362, p = 0.9712).

For the analysis with Satisfaction as DV, the results of the model indicate that the variance is also relatively low ($R^2 = 0.0224$), and was not statistically significant (F = 0.9625, p = 0.4127). Looking at the individual analysis, we notice that IV had no significant effect on satisfaction (t = 0.0947, p = 0.9247). Following on with the analysis, we found that the moderator was not statistically significant (t = 0.5756, p = 0.5659), suggesting that the two groups do not show substantial differences in satisfaction. The relationship between the moderator and the IV was not confirmed, showing that there is no moderation between the two variables (t = -0.0455, p = 0.9637).

5. RESULTS AND DISCUSSION

This section presents the conclusions of the research and discusses the possible reasons for rejecting each hypothesis based on the existing literature. The goal of this study is to determine what the impact of recommendation agents are to delegate the decision and satisfaction with the choice made in online retail environments. The results of this study indicate that the scenario manipulation worked, but none of the four proposed hypotheses were confirmed, suggesting that, in the specific context analyzed, the manipulated variables had no significant impact on consumer satisfaction and purchase intention.

After analyzing the results, it is possible to verify the hypotheses tested in this research. It is possible to draw the following conclusions through Table 4 from the analysis carried out earlier using SPSS:

Table 4 - Hypothesis Verification

Hypothesis	Verification
H1. Decisions assisted by RAs result in more satisfaction with the choices made, compared to decisions made independently.	Rejected
H2. Decisions assisted by RAs result in higher purchase intentions, compared to decisions made independently.	Rejected
H3a. Choice overload mediates the impact of the use of recommendation agents on satisfaction with the choices	Rejected
H3b. Choice overload mediates the impact of the use of recommendation agents on purchase intention.	Rejected
H4. Maximizers are more likely to experience choice overload and dissatisfaction when using AI-based recommendation systems due to the number of options presented and their constant search for the perfect choice, while Satisficers experience less choice fatigue and are more satisfied with the options suggested.	Rejected

As it can be analyzed, none of the four hypotheses were confirmed. In the case of hypothesis 1, although Recommendation Agents are seen as an AI tool that helps the consumer make a purchase decision, they may have not had such an impact on the scenario presented, not reflecting the increase in consumer satisfaction, since they may not have realized that it was a determining factor in increasing satisfaction. The literature suggests that although RA can reduce cognitive overload (Iyengar & Lepper, 2000), it can also generate discomfort and uncertainty if consumers feel that the technology is limiting their options or excessively controlling their choices (Rohden & Espartel, 2024). In our study, this may have occurred, and the lack of significant effect may reflect that consumers did not perceive a substantial improvement in their satisfaction when using RA. Furthermore, according to (Häubl & Trifts, 2000), transparency about recommendation criteria and adaptation to user preferences are essential for consumers to see value in RA. If the participants did not understand or value the RA suggestions, this may have neutralized their expected positive effects on satisfaction with the choice (Lalicic & Weismayer, 2021)

Regarding hypothesis 2, the fact that it was not confirmed may be related to the complexity of online shopping behavior. Although the literature suggests that personalizing recommendations can increase purchase intention (Fayyaz et al., 2020). The context in which consumers shop may be more complex, where we know that purchase intention is directly affected by attitude towards behavior, subjective norms and perceived behavioral control (Ajzen, 1991). For example, factors such as perceived online risk (Pavlou, 2003) and privacy and security concerns (Lalicic & Weismayer, 2021), can negatively affect purchase intention, especially when RA are not perceived as trustworthy or if consumers feel they are being targeted when they don't need to be. Analyzing our control variable, privacy concerns, we see that those who use AI are more likely to suffer an online attack. In addition, the lack of a significant difference may reflect that, even with the personalization offered by RA, other external factors, such as the consumer's prior knowledge of the products presented with the brand or their confidence in making decisions without the help of AI, may have had a greater weight in the purchase decision.

Hypothesis 3 was not confirmed, meaning choice overload does not play a central role in mediating the relationship between RA use and consumer satisfaction and purchase intention. Since RA aims to reduce cognitive overload by filtering out options (J. Wu et al., 2022), consumers may not have experienced choice overload in a significant way, or they may have considered the options presented to be sufficiently satisfactory. The lack of perceptions of choice overload could be related to the kind of product displayed. Perhaps if only people who buy helmets were included in the data collection, the results would have been different. Past studies have stated that when there is choice overload, there can be disadvantages for both sellers and consumers, as the choice of products can become confusing and difficult (Misuraca et al., 2024). This was not the case in our study, which could mean that the participants did not feel that choice overload interfered with the relationship between RA and the two DV.

Finally, Hypothesis 4 was also not confirmed, and the literature states that maximizers tend to seek the best possible option, while satisficers opt for an alternative that is satisfactory. (Schwartz et al., 2002). However, the results suggest that this difference in decision-making style may not have significantly influenced the perception or impact of RA. Although maximisers tend to be more demanding and dissatisfied with their choices (Dar-Nimrod et al., 2009), we were unable to distinguish the behavior of the two types of consumers to understand the impact of RA on purchasing decisions. Furthermore, following the analysis, satisficers, who tend to be more unworried with their choices, may have experienced less choice overload, but this did not translate into a significant difference in satisfaction or purchase intention. This suggests that, in the context of the presented study, the characteristics of maximisers and satisficers did not substantially affect consumer behavior outcomes related to the use of RA.

6. CONCLUSIONS AND FUTURE RESEARCH

6.1 Theorical Contributions

Theoretically, this study advances our knowledge of RA and how they affect customer behavior in online retail settings. This study explores the current understanding of AI on purchase intent, and customer satisfaction by incorporating findings from previous research.

These results cast doubt on the belief that AI recommendations inevitably improve customer experiences and according to Lalicic and Weismayer there are elements that can mediate their effectiveness, such as perceived control, trust in AI and decision-making autonomy (Lalicic & Weismayer, 2021). Therefore, for future research, these variables could play an important role in consumer behavior.

The topic of choice overload was also explored in depth in this study, where we aimed to confirm whether RA helped combat choice overload in purchase intention and increased satisfaction. The literature suggests that AI-driven recommendations can mitigate decision fatigue by filtering out options (J. Wu et al., 2022), but according to the results of our research, the presence of RA does not always significantly reduce choice overload. The results obtained are in line with the argument that the sheer volume of recommended options can still overwhelm consumers, particularly those seeking the best possible decision (Schwartz et al., 2002). Future research should therefore explore how personalization algorithms can be refined to balance variety of choice and cognitive ease (Misuraca et al., 2024).

Moreover, this work advances knowledge of consumer typologies in AI-assisted decision-making, particularly Maximizers and Satisficers. According to earlier research, individuals who maximize their options are more likely to be unhappy with their choices than to regret them (Shin & Yoon, 2023). Our findings show that recommendation systems could not be effectively suited to various customer profiles because the existence of AI recommendations has no apparent effect on Maximizers' or Satisficers' satisfaction levels. According to (Chernev et al., 2012), this conclusion necessitates more research into how AI may modify recommendation tactics in response to user behavior and decision-making preferences.

Finally, this research contributes to the growing discourse on AI adherence and consumer scepticism towards AI recommendations. Some consumers remain reluctant to trust AI for decision-making, perceiving automated suggestions as less reliable than human judgement (Rohden & Zeferino, 2023). The results suggest that addressing algorithm aversion through explainable AI models and hybrid recommendation approaches could increase the acceptance and effectiveness of RA in online retail (Luan et al., 2022).

In summary, this study provides helpful details about the complex nature of AI recommendation systems and how they affect customer behavior. It contributes to the larger conversation on AI personalization, trust, choice autonomy, and customer pleasure in online retail environments by improving theoretical models and suggesting directions for further research.

6.2 Managerial Contributions

This study offers some valuable insights for businesses, marketing professionals, and electronic commerce platforms that aim to improve customer experience through RA driven by AI. The findings provide strategic implications for the implementation of personalized recommendation systems and the management of consumers' interactions with AI in the digital marketplace.

Since the results challenge the assumption that RA automatically increase consumer satisfaction and purchase intent, brands should focus on improving the transparency and explainability of AI-driven recommendations. Previous research suggests that when consumers realize they have control over their choices, their willingness to interact with AI recommendations increases (Lalicic & Weismayer, 2021). Companies should invest in AI models that allow consumers to understand why certain products are being recommended, promoting trust in the system and improving the overall shopping experience.

As choice overload remains a challenge in AI-assisted decision-making, companies must take into consideration that RA balances variety with simplicity. The results of this study indicate that AI recommendations did not significantly reduce choice overload, suggesting that the volume and presentation of options in the study did not play a crucial role in consumer decision-making.

According to the literature, presenting too many options can overwhelm consumers, while too few can reduce engagement (Iyengar & Lepper, 2000; Misuraca et al., 2024). Companies can improve the overall effectiveness of RA and enhance consumer satisfaction if they incorporate more advanced filtering techniques that refine recommendations based on individual browsing behavior, thus minimizing decision fatigue and improving the overall effectiveness of RA.

In addition, it is necessary to understand the type of consumer in order to better personalise AI-driven recommendations. Maximisers, who seek the best possible option, may require detailed product comparisons and expert insights, while Satisficers, who settle for satisfactory options, may benefit from simplified recommendations with fewer alternatives (Schwartz et al., 2002; Shin & Yoon, 2023). Implementing segmented AI strategies based on these preferences can help companies increase consumer satisfaction and purchase intent.

As we have understood from our results, consumers who use AI have already been subjected to at least one online attack, which is in line with the literature that states consumers with high privacy concerns may be reluctant to engage with AI systems, fearing data misuse (Mwesiumo et al., 2021; Pavlou, 2003). Companies should, establish guidelines to ensure that AI-based recommendation systems are transparent, ethical, and secure.

6.3 LIMITATIONS AND RECOMMENDATIONS FOR FUTURE WORK

This study has several limitations that should be recognized. Although this study provides insights into the role of RA in consumer decision-making, the results show that the expected benefits of AI recommendations don't always materialize as expected. The lack of a significant effect on consumer satisfaction and purchase intent highlights the complexity of AI adoption in online shopping environments and suggests that additional factors may play a more influential role.

Furthermore, this study did not examine the potential influence of variables such as perceived control, trust in AI and autonomy in decision-making, which have been identified by Lalicic & Weismayer as mediating factors in the effectiveness of AI recommendations. Future studies should incorporate these variables that may play a significant role in consumer behavior.

A limitation found was the specific context of the research, which focused on a controlled experimental environment. While this allowed for accurate measurement of the effects of AI on consumer decision-making, it did not fully capture the complexity of online shopping experiences. Future research could benefit from studying AI recommendations in naturalistic environments, such as live e-commerce platforms, to validate and expand on these findings.

Choice overload also raises a limitation as it remains a challenge in AI-assisted decision-making. Although RA aims to simplify consumer choices, the results show that there was no significant impact and that they don't always reduce decision fatigue, probably because participants didn't feel choice overload with the scenario presented. Future research should pay attention to how it exposes the scenario to participants and should explore alternative recommendation strategies, such as adaptive filtering and dynamic ranking systems, to better balance variety and simplicity in AI-generated suggestions.

One of the limitations of this study was the fact that not all the participants used the product chosen in the study, which may have meant that the participants didn't experience the purchase process in the way they expected, as they had no connection with the product, which may have had an impact on the results. In future studies, other products that the participants have already bought at least once should be considered, to guarantee the minimum relationship between the respondents and the product in the study.

Additionally, this study only used quantitative data analysis, which is useful for identifying overall patterns but may overlook the true intentions and attitudes of customers toward AI recommendations. Qualitative techniques like focus groups and in-depth interviews could be used in future studies to better understand how customers feel about AI-based decision-making.

By addressing these limitations future research should offer a more thorough knowledge of how AI suggestions affect customer behavior and how businesses might optimize these systems for increased efficiency and consumer trust by addressing these constraints and broadening the study.

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APPENDIX 1 (MEASUREMENTS AND SCALES)

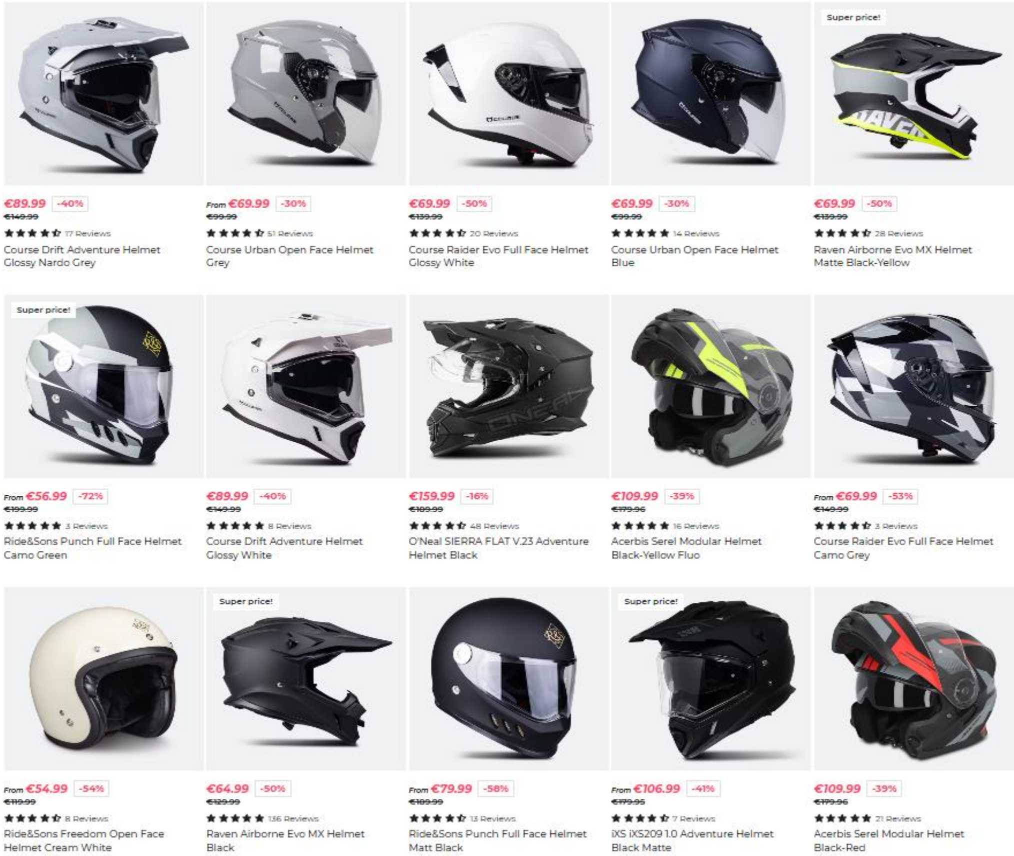
Variable	Items	Source
Purchase Intention	I would plan to use this website for online shopping again. I would intend to shop online from this website in the future. I would strongly recommend this website to others.	(Lin, 2007)
Satisfaction	I believe I would feel satisfied with my purchase choice.	(Iyengar & Lepper, 2000)
Choice Overload	I would enjoy making a purchase choice in this situation. I would find it difficult to make a purchase decision in this situation. I would feel frustrated about making a purchase choice in this situation. I believe I would feel satisfied with my purchase choice.	(Iyengar & Lepper, 2000)
Maximizers vs Satisficers	I will wait for the best option, no matter how long it takes. I don't like having to settle for "good enough". When shopping, I have a hard time finding the product that I really love. Once I make a decision, I don't look back.	(Schwartz et al., 2002)

Privacy Concerns	I believe my personal data (e.g. name, personal number, address, telephone number or payment details) have been monitored, searched, recorded, or stored at least once without my permission. I have had bad experiences with regards to the privacy of my personal data when using services online. I have been a victim of privacy invasion at least once in the past as a result of using services online.	(Mwesiumo et al., 2021)

APPENDIX 2 (MANIPULATION OF THE KIND OF PURCHASE DECISION)

All Scenarios

Consider that you are a frequent buyer of motorcycle products and are using an online platform to decide which helmet to buy. The website presents you with a list of various helmet options so that you can choose the product you want. This is an example of the type of merchandise on offer.



Each product will have various information such as price, description of the helmet, size, weight and other fundamental characteristics for correct product information.

With RA assistance

This website has a recommendation system based on Artificial Intelligence (AI), where it will analyze your previous behavior and recommend a set of 3 products that match your buying habits, so that you can choose from a set of 3 helmets instead of analyzing all the products. Answer the following questions, considering that your shopping experience with the products will be recommended by this artificial intelligence.

Without RA assistance

Answer the following questions, considering that your shopping experience with the products will be without the assistance of technology or a salesperson.

APPENDIX 3 (ETHICS COMMITTEE)

This is to certify that
Project No.: **DDMKT2025-1-205249**
Project Title: **The impact of recommendation agents in consumers' purchasing decisions**
Principal Researcher: **Vasco Diniz**

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 1/20/2025.

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, 1/20/2025

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