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Impact of AI Recommendations' transparency in E-Commerce

Understanding the impact of covert and overt personalization

Bernardo Pereira Guerreiro

Master Thesis

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

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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

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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.

Lisbon, July 2025

Bernardo Pereira Guerreiro

ABSTRACT

With the increasing usage of Artificial Intelligence in marketing and e-commerce, techniques such as product recommendations have been enhanced through usage of consumers' behavior and preferences to optimize their efficiency. While this has many benefits, it also raises concerns over data privacy and usage. This study addresses a gap in the current literature by examining how the transparency of AI recommendations - defined as overt and covert - affects perceived benefits and privacy concerns, and how these effects may vary depending on the customer journey stage that the recommendation is made. The research was based on a 2x2 between-subjects experimental design with transparency (overt vs covert) and customer journey stage (pre-purchase vs post-purchase) as the two manipulated factors. The results indicate that transparency alone does not have a significant impact on perceived benefits or privacy concerns, refuting some assumptions in previous research. However, higher perceived benefits were associated with lower privacy concerns. Additionally, the impact of transparency on perceived benefits was significant in the pre-purchase phase, but not in the post-purchase phase. These findings offer a new look that connects transparency and timing in the context of recommendations in e-commerce, while expanding the existing literature to the realm of AI-generated recommendations.

KEYWORDS

Personalization; Recommendation; Artificial Intelligence; Privacy Concerns; Perceived Benefits

Sustainable Development Goals (SDG):

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF ABBREVIATIONS AND ACRONYMS

AI	Artificial Intelligence

1. INTRODUCTION

In 2019, personalization was expected to be the prime driver of marketing success within five years (Boudet, 2019). Six years have passed, and personalization became, indeed, one of the most prominent and discussed topics in marketing and companies strive more than ever to incorporate personalization into their interactions with their customers. However, while new technologies, such as Artificial Intelligence (AI), are providing new innovative and groundbreaking ways for personalization (De Keyser et al., 2011, cf. Weidig et al., 2024), affecting marketing techniques such as recommender systems or image generation (Puntoni, 2024), concerns regarding privacy continue to emerge. As a result, customers are increasingly weighting the benefits of technology against the costs of sharing personal information (Schweidel, 2022).

While these new advances in technologies, such as AI, maximize the potential of personalization tools such as recommendation systems, it also brings challenges. On one hand, AI can help e-commerce organizations enhance the accuracy of the recommendations in a faster pace (Longoni and Clan, 2022), on the other hand, a high accuracy may have a contrary effect and increase privacy concerns (Bleier & Eisenbeiss, 2015). A considerable number of studies have focused their efforts on understanding these privacy concerns and indicate that more privacy controls can be effective (Martin et al., 2017), as well as consumers having high perception of benefits can also contribute to reduce concerns (Li & Unger, 2012).

As AI helps reshaping personalization in e-commerce, the attention to privacy concerns felt by consumers gains even more importance and, transparency plays a bigger role to help companies manage this paradox – whether by adopting an overt approach based on transparent communication about how and why the recommendation is done (Aguirre et al., 2015) or by adopting a covert approach which consists on recommending while not showcasing or being open about the process that led to it. While overt strategies can improve trust among consumers, it can also paradoxically increase privacy concerns (Sundar & Marathe, 2010), highlighting what is often called the 'personalization-privacy paradox' (Karwatzki et al., 2017).

The stages of the customer journey significantly influence how people perceive the benefits and privacy concerns of recommendations. At different points in their journey, customers have different needs and expectations towards a particular brand, shaping their response to them. For instance, privacy concerns may be higher in early stages as customers are unfamiliar with the brand (Weidig et al., 2024). Considering this, it is relevant to consider the timing of the recommendation.

While some of the past research regarding personalization have taken into consideration the transparency involved and the customer journey stages (e.g. Weidig et al., 2024) and some other regarding recommendation systems have taken into consideration the benefits and privacy concerns associated (e.g. Sun et al., 2023), there is a gap in the literature in which these factors are taken into consideration in an integrated manner.

With all this being considered, the present study aimed to take a different approach and measure the impact of the transparency regarding AI Recommendations in the perceived benefits and privacy concerns while understanding how it is affected by the customer journey stage in which the recommendation is done. Therefore, the research question that this study aimed to answer was: "How does the transparency of AI-driven recommendations (overt vs. covert) influence consumers' perceived benefits and privacy concerns across different stages of the customer journey?". To answer this research question, a quantitative experimental study was conducted and whose results were analysed to extract conclusions that help us deepen our understanding of the impact of transparency in AI recommendations in e-commerce and how they are influenced by the customer journey stage. Before that, and right in the next chapter, a literature review over the most important concepts of this research was presented.

2. LITERATURE REVIEW

2.1. PERSONALIZATION IN AI RECOMMENDATIONS

Although personalization as a concept is vital and very connected to the discipline of marketing, it is a multidisciplinary topic, intersecting many fields such as business management, decision science, information system and psychology (Chandra et al., 2022). It is also not just a question of being multidisciplinary, but as well as being a concept with a broad range of interpretations, for example, as Fan and Poole (2009) state, for architects, personalization means creating functional and pleasant personal spaces, while, for an information scientist, personalization is described as "delivering to a group of individuals relevant information that is retrieved, transformed, and/or deduced from information sources".

Despite the variations in interpretations, a common understanding keeps emerging: personalization involves the creation or delivery of something individually tailored to meet the specific needs of a group or individual.

When applied to the field of marketing, the pattern remains consistent. Riemer and Totz (2003) claim that personalization focuses on fostering customer loyalty through a "meaningful one-to-one relationship", understanding the unique needs of each individual and through supporting them in achieving a "goal that addresses them in a specific context". Arora et al. (2008) mentions the importance of having customer data to achieve personalization, by stating that personalization is the firm's decision on making marketing mix variables tailored to the individual based on "previously collected customer data". Around six years later, Dawn (2014) adds another very relevant variable to describe personalization, technology, by saying that personalization is the usage of both technology and customer information to tailor the firm's product to the individual and specific needs of the customers.

As new technologies, such as AI, continue to break through, new ways of personalization also emerge. One significant example in the digital era is the increasing usage of recommendation systems, which have become used by many e-commerce companies (Fayyaz et al., 2020). Recommendation systems is a tool used by e-commerce sites to make product suggestions to their users, usually influenced by data collection such as demographics or previous purchasing/consumption behaviour (Schaffer et al., 1999).

These recommendation systems can be classified into three different types based on their data source and inputs (Zhang et al., 2022): collaborative-based filtering, content-based filtering and mixed/hybrid filtering. The first type, collaborative-based filtering, focuses on operating on the assumption that customers are inclined toward products similar to those they have previously liked, as well as items appreciated by other customers with comparable preferences, examples of types of information that can be used to achieve this filtering are user ratings, actions and correlation between users (Javed et al., 2021). This method is particularly valuable when detailed information about a product is unavailable or minimal. However, given the extensive range of products offered by online retailers, there is often limited data on customer preferences for many items (Chinchanachokchai et al., 2021) which may lead to biased recommendations favouring items with a high volume of reviews or popular ones. On the other hand, content-based filtering is characterized by putting a focus on the preferences of a customer for the attributes of a specific product to then recommend items with similar characteristics to another customer (Cami et al., 2017). Through the identification of those features that appeal to customers, it suggests products that also have those attributes. This approach operates on the assumption that a customer's tastes and interests are represented by the attributes of the items they have searched for or bought, leading to recommendations of other products with comparable qualities (Marchand & Marx, 2020). On the contrary to collaborative-based filtering, this technique tends to favour niche products (Jozani et al., 2023). Finally, the hybrid filtering uses both of the previous methods, the proportion of each depending from system to system.

Recommendation systems, as a personalization tool, also can differ in terms of transparency - being either covert or overt (Mehmood et al., 2023). Overt aims to personalize the interaction with the customer while being open about the process and the data collection (Aguirre et al., 2015), while covert personalization involves not revealing directly to the customer and trying to create a more subtle and seamless experience. In the case of recommendation systems, an overt recommendation would explain the recommendation itself, why happened and/or how it was done, while a covert recommendation would recommend the products to the user while not explicitly mentioning the data collection or the process as a whole.

2.2. PERCEIVED BENEFITS

Recommendation systems are tools that e-commerce companies can leverage in order to deliver a better customer experience. It is widely studied that customers express themselves through the products and services that they consume and that they, ultimately, tend to opt for and be loyal to brands whose values are in line with the consumers' self (Kressmann et al., 2006; Tuškej et al., 2013).

When a company successfully recommends a product to a customer, it not only reinforces the customers' self but also reduces search efforts, churn and increases loyalty (Yan et al., 2016). Even beyond that, it increases the possibilities of up-selling and cross-selling, boosting the revenue and profitability (Oestreicher-Singer & Sundararajan, 2012). According to recent research, recommendation systems are a key driver for profitability and growth (Lee & Hosanagar, 2019) with examples such as Netflix having 80% of his stream hours influenced by their recommendation system and estimations of 1 billion dollars saved per year through personalization and recommendation (Gomez-Uribe & Hunt, 2015) and Amazon, having an estimated 30% of their website page views been generated from recommendations (Sharma et al., 2015).

Although it is not essentially tied to the concept of technology or AI, recommendation systems highly benefited from the breakthroughs in both technology and AI by dealing with the problem of information overload and, therefore, producing relevant and faster user recommendations (Konstan and Riedl, 2012; Longoni and Clan, 2022). AI increasing usage in recommendation systems is also aiming to reduce the AI classification failures - when a recommendation made through AI classification is perceived by the customer as inaccurate, provoking frustration due to being misunderstood (Gonçalves et al., 2024). In order to make the recommendation, AI systems classify users according to their past consumption and their personal characteristics (Rai, 2020) and it is this classification that can either generate the AI classification failures or generate satisfaction (Puntoni et al., 2021).

Regarding covert and overt personalization, the research is not extensive on the perceived benefits, although some authors reported more liking and confidence towards the overt recommendation (Sinha & Swearingen, 2002) and, in the same direction, better acceptance and understanding of the recommendation were connected those transparent recommendations (Cramer et al., 2008). On the other hand, the literature is richer in terms of connection between perceived benefits and privacy concerns, with previous research highlighting that when the benefits perceived are higher, privacy concerns tend to lower (Li & Unger, 2012). Finally, in terms of data collection, some authors conducted research that connect overt data collection techniques to more favourable customer responses and bigger purchase intentions (e.g. Grigorios et al., 2022).

Boosted by the lack of conclusion in the benefits of overt vs covert personalization and lack of literature in terms of this application in recommendation systems, this study will focus on how the transparency in AI recommendations can impact the perceived benefits of the recommendation itself. This being said, the following hypothesis will be studied:

H1 - Overt AI recommendations (vs. covert) impact positively in the perceived benefits

2.3. Privacy Concerns

While modern technologies and more data collection tools have increased the possibilities of personalization, the misuse of both creates privacy concerns (Cloarec, 2020). Previous research highlights that privacy concerns can bring such negative effects that can even reverse the advantages of personalization (Aguirre et al., 2015).

Many previous studies have studied this balance between personalization and privacy concerns which has become widely known as the “personalization-privacy paradox” (e.g. Karwatzki et al., 2017; Wang et al., 2024). Personalization and, in particular, recommendation systems, leverage data, such as personal characteristics and past consumption leading to a dilemma in which companies try to maximize the potential of the tools while minimizing the privacy concerns that arise among customers, which is not easy due to a very high level accuracy being associated to customers feeling watched (Bleier & Eisenbeiss, 2015). Thus, creating a balance between the potentiation of those tools and the privacy concerns that they generate is a challenge that firms face.

In order to leverage data, organizations use data collection to personalize user experiences which can be either explicit or implicit. (Taylor et al., 2009). In explicit data collection, the organization asks the customers in a direct way for information about their preferences and interests (Li & Karahanna, 2015), while implicit data collection involves gathering customer data through past interactions, for example, through browser cookies (Yang & Yue, 2020). The data collection operated by organizations is being potentialized by AI - which helps ultimately to deal with larger amounts of data and increase the efficiency of recommendations and other ways of personalization - can have a perverse effect and increase privacy concerns among consumers (Bleier & Eisenbeiss, 2015).

However, research continues trying to explore ways to understand privacy concerns. Some studies indicate that customers have bigger control over their personal information are associated with more receptiveness towards marketing practices such as personalization (Martin et al., 2017) and even receptiveness on providing sensible information (Brandimarte et al., 2013). Still in the realm of transparency, different conclusions can be found with some authors such as Lambillotte et al. (2022) indicating that a bigger transparency (overt personalization) reduces overall privacy concerns, while others in early research such as Sundar and Marathe (2010) indicated that it actually increases privacy concerns. Moreover, personalization when too visible is considered to increase privacy concerns among customers (Goldfarb & Tucker, 2011).

Regarding recommendation systems, there is a relevant variable to consider: they contain a very large amount of information about their users - information and behaviour - which makes them an attractive target for cyberattacks (Jeckmans et al., 2013). For example, information being reconstructed (Sun et al., 2023) which happens when, even though sensitive user information is anonymous, attackers can cross other information used in recommendations and discover the protected sensitive information.

Having outlined these privacy concerns and research that indicates how they might be reduced, this study will analyse how the transparency in communicating AI recommendations can affect privacy concerns and how the interplay exactly works between the perceived benefits and the privacy concerns. Therefore, the studied hypothesis will be:

H2 - Overt AI recommendations (vs. covert) reduce privacy concerns

H3 - Perceived benefits negatively impact users' privacy concerns

2.4. CUSTOMER JOURNEY STAGES

Previous research has considered many different stages to be part of the customer journey since it is a widely used term within the marketing field, making clear that there is a lack of common understanding about it (Kuehnl et al., 2019). As a concept, customer journey, although frequently used in different contexts, has been defined as “the process a customer goes through, across all stages and touch points, that makes up the customer experience” (Lemon & Verhoef, 2016). This journey typically encompasses multiple phases each of which involves various touchpoints such as online or physical interactions. Understanding the customer journey has proven to be strategically crucial for organizations as it allows them to better understand their customers and enhance and personalize the touchpoints with which they interact with them. Furthermore, the customer journey is not linear, it is influenced by a complex combination of factors, including social interactions and emotional triggers, making its mapping, optimization and categorization a constant challenge for organisations and their marketing professionals.

Due to this high complexity and low linearity, the different stages considered constantly differ from study to study. For example, Schamp et al. (2019) used consideration and choice as the two customer journey phases. Others, such as Farah et al. (2019), consider a higher number of stages, namely awareness, consideration, engagement, purchase and loyalty. While these and other stages are considered by some authors, this study will from now on consider the customer journey stages as the three considered by authors such as Lemon & Verhoef (2016): pre-purchase, purchase and post-purchase.

The authors define those stages as being the touchpoints the moments before, during and after the purchase. Firstly, the pre-purchase stage, being the touchpoints that the customer interacts with before the purchase, includes behaviours such as need, recognition, search and consideration and only ends up in the moment of the purchase by satisfying the need. Second, the purchase stage, being the interactions that the customer has with the brand during the purchase, includes behaviours like choice, ordering and payment. Finally, the post-purchase stage consists of the interactions between the customer and the brand following the purchase, with behaviours such as usage, consumption, post purchase engagement and service requests being included. According to the research, the product itself becomes a touchpoint with great importance, being its consumption the act that generates touchpoints, for example, as repurchase or returns.

Considering these stages definitions, this study will evaluate whether the stage where the AI recommendation is made impacts or not the results of H1 and H2 and therefore the following hypothesis will be studied:

H4 - The customer journey stage moderates the relationship between transparency in AI recommendations and (a) perceived benefits and (b) privacy concerns.

Taking into consideration the four presented variables and hypothesis, the conceptual framework for this research is the following:

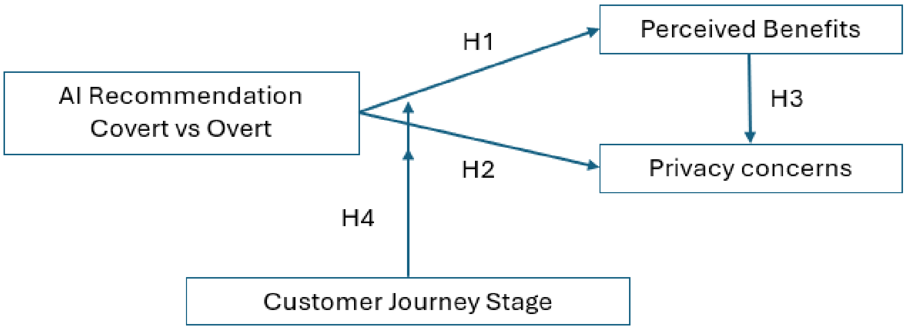

Figure 1 - Conceptual Model

3. METHODOLOGY

The data presented followed a quantitative research and was gathered through an online survey that followed a 2x2 between-subjects experimental design (based on the model presented on figure 1). When talking about experimental methods, the between-subjects consists in exposing different individuals to different treatments, randomizing their group assignment and analysing results by comparing the behaviour from those in one assigned group to the behaviour of those assigned to the other group (Charness et al., 2012). This allows to compare how the responses from respondents differ from one to scenario to another and, therefore, compare the difference of impact that overt and covert had, as well as both responses in different customer journey phases – pre- and post-purchase.

The questionnaire was developed on Qualtrics (displayed in Appendix A), was available both in English and Portuguese and was distributed between March and April to respondents via email and social media to an aimed audience of 150 participants. Participants were previously informed about the purpose of the study and asked for consent before participation.

After accepting to proceed, participants were presented one of two scenarios equally distributed both happening in a pre-purchase phase in which an initial context about the phase is given "Imagine that you're navigating in a website from which you haven't made a purchase and you're presented with the following situation". Half of the audience was led to an overt scenario with information about how the recommendation was done and other half to a covert scenario with zero information besides the recommendation itself.

Figure 2 - Overt scenario in pre-purchase

Figure 3 - Covert scenario in pre-purchase

After reading the presented scenario, two manipulation questions were also presented to confirm the participants acknowledged that it is a personalized recommendation and whether it is an overt or covert situation. Subsequently, the perceived benefits and privacy concerns were evaluated with several questions adapted from Aiolfi et al. (2021) evaluating the level of agreement in a Likert Scale from 1 (Strongly Disagree) to 5 (Strongly Agree). The same logic was repeated for a post-purchase phase.

Figure 4 - Overt scenario in post-purchase

Figure 5 - Covert scenario in post-purchase

In the end of the questionnaire, it was measured the participants' frequency of online shopping, degree of privacy concerns and familiarization with product recommendations, as well as demographic questions such as age, gender, education level and employment status.

The statistical analysis was performed through Statistical Package for the Social Sciences (SPSS), processing and interpreting the collected data through various analysis such as measurement of the Cronbach's alpha coefficient, T-test for the manipulation check, MANOVA for the measurement of the transparency effects, a linear regression to measure the relationship between perceived benefits and privacy concerns and, lastly, PROCESS Model 1 to conduct the moderation analysis regarding to the customer journey stage.

Tabel 1 - Measurement of Variables

Constructs	**Number of items**	**Scale**	**Questions**
Perceived Benefits (Aiolfi et al., 2021)	4	Likert Scale	• These recommendations help me achieve my purchase goals faster • These recommendations improve my shopping journey • These recommendations increase the effectiveness of my shopping journey • These recommendations make it easier to achieve my purchase goals
Privacy concern (Aiolfi et al., 2021)	5	Likert Scale	• I am concerned that this company is able to track information about my online activity • I am concerned that this company has so much information about me • I am concerned that this company is able to access information about me • I am concerned that my information can be used in ways I can't predict • I am concerned about what others might do with the history of my online activity

4. EMPIRICAL STUDY

4.1. SAMPLE

A total of 277 responses were collected for the survey. After excluding 3 responses due to lack of consent and 111 incomplete submissions, the final sample comprised 163 participants. The sample consisted predominantly of young individuals, with an average age of 29,98 years. In terms of gender, the majority identified as female (65%), followed by male (33,7%), with one respondent identifying as non-binary and one preferring not to disclose their gender. Regarding educational background, 38% held a bachelor's degree, 31,9% had completed a master's or postgraduate degree, 1,2% held a PhD, 11% reported technical or professional education, 16,6% had completed high school, and 1,2% had not completed high school. Employment status was also diverse: 65% of participants were employed full-time, 16% were students, 7,4% worked part-time, 4,9% were unemployed, 2,5% were retired, and 4,3% selected other categories.

Tabel 2 - Sample Characteristics

Variable	Answer	%	N
Gender	Female	65,0	106
	Male	33,7	55
	Non-binary	0,6	1
	Prefer not to say	0,6	1
Education	Less than high school	1,2	2
	High School	16,6	27
	Technical/Professional course	11,0	18
	Bachelor degree	38,0	62
	Masters/Post-graduation degree	31,9	52
	PhD	1,2	2
Employment	Student	16,0	26
	Unemployed and looking for work	4,9	8
	Working part-time	7,4	12
	Working full-time	65,0	106
	Retired	2,5	4
	Other	4,3	7

Respondents were also asked questions regarding the important concepts of this study, namely their online shopping habits, their familiarization with personalized recommendations and their concern about data privacy. Regarding their online shopping habits, the majority (52,1%) affirmed to do it sometimes (a few times a year), while only 11,7% do it rarely (once per year or less). In terms of privacy concerns, only 2,5% said to not be concerned and 13,5% to be neutral to it. The rest (84%) revealed any degree of concern, although concentrated in the lower scales: moderately concerned (35%), somewhat concerned (16%) and slightly concerned (12,9%). Finally, regarding to the familiarization to personalized recommendations, only 4,9% responded to not be familiarized and only 9,8% responded to be neutral. The rest, just as the previous situation, revealed any degree of familiarization, also concentrated in the lower scales: moderately familiarized (35%) and somewhat familiarized (22,7%).

Tabel 3 - Descriptive Statistics

Variable	Answer	%	N
Shopping Habits	Rarely (once a year or less)	11,7	19
	Sometimes (a few times a year)	52,1	85
	Often (every month)	31,9	52
	Very often (every week or less)	4,3	7
Privacy Concerns	Not concerned at all	2,5	4
	Slightly concerned	12,9	21
	Somewhat concerned	16,0	26
	Neutral	13,5	22
	Moderately concerned	35,0	57
	Highly concerned	13,5	22
	Very concerned	6,7	11
Personalization	Not familiarized at all	4,9	8
	Slightly familiarized	7,4	12
	Somewhat familiarized	22,7	37
	Neutral	9,8	16
	Moderately familiarized	35,0	57
	Highly familiarized	12,3	20
	Very familiarized	8,0	13

4.2. Manipulation Check

The manipulation was successfully done. It consisted out of two questions, one confirming the participants perceived the scenarios as personalized recommendations and the other confirming if the users perceived the absence or presence of an explanation (covert and overt). In the first manipulation, both the overt ($M = 3,74$) and covert ($M = 3,50$) had positive responses with no significant difference between them, $t(324) = 1,91$, $p = 0,057$, $d = 0,21$. In terms of the perceived explanation, participants in the overt scenarios ($M = 3,72$) perceived significantly more the existence of the explanation than the ones in the covert scenarios ($M = 2,64$), $t(324,27) = 7,73$, $p < 0,001$, $d = 0,86$. This outcome confirms that the participants perceived a clear difference between overt and covert recommendations.

4.3. Measurement

To assess the internal consistency of the measurement scales, Cronbach’s alpha was calculated for both Perceived Benefits and Privacy Concerns. The Perceived Benefits scale yielded a Cronbach’s alpha of 0,942, while the Privacy Concerns scale produced a value of 0,946. These values indicate excellent internal reliability (α > 0,9), suggesting that the items within each scale consistently measure their respective constructs. The high reliability supports the validity of subsequent analyses based on these scales.

Tabel 4 - Cronbach's Alpha

	Cronbach's Alpha
Perceived Benefits	0,942
Privacy Concerns	0,946

Proceeding to descriptive statistics comparing the transparency scenarios, participants reported higher benefits in overt scenarios (M = 3,33, SD = 0,93) than in covert scenarios (M = 3,18, SD = 0,99), but they also reported higher privacy concerns in those overt scenarios (M = 3,92, SD = 0,98) compared to covert scenarios (M = 3,84, SD = 0,95), which points in the same direction as Sundar and Marathe (2010) study that suggested this effect.

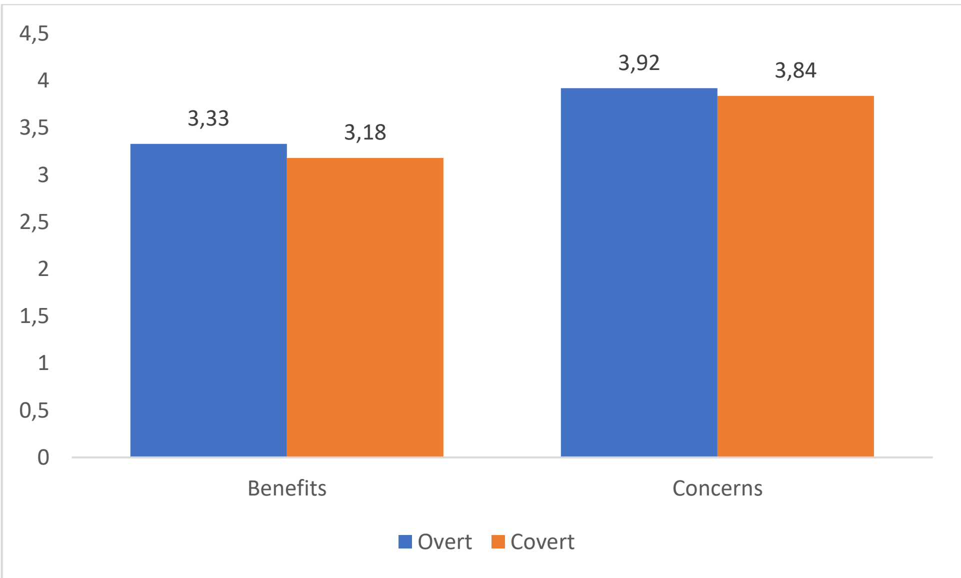

Figure 6 - Descriptive Statistics of Transparency

Regarding the customer journey phase, participants reported higher benefits in the post-purchase scenarios (M = 3,29, SD = 0,95) than in the pre-purchase scenarios (M = 3,21, SD = 0,93). Along with that, they also reported lower privacy concerns (M = 3,84, SD = 0,97) compared to the pre-purchase (M = 4,02, SD = 0,92).

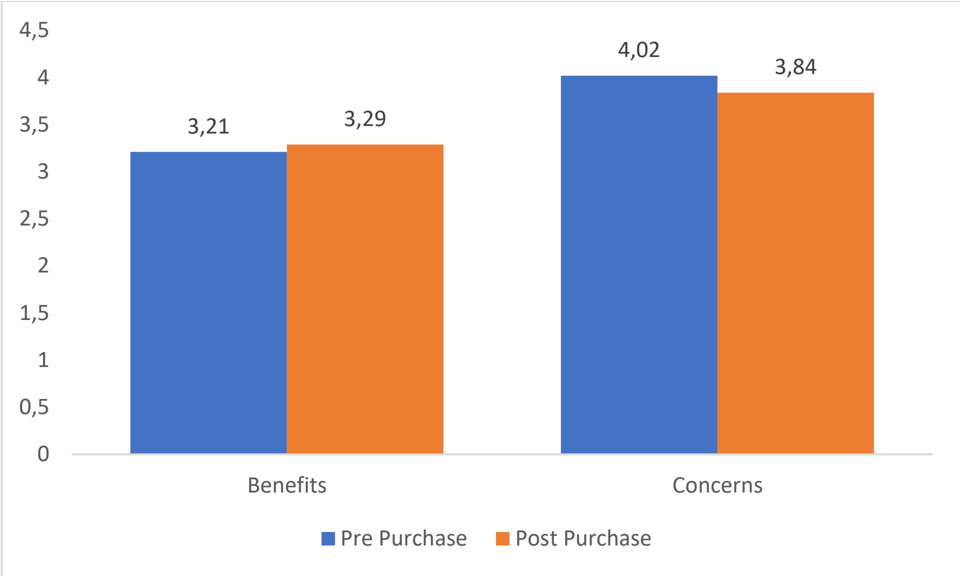

Figure 7 - Descriptive Statistics of Customer Journey Phase

To evaluate whether the level of transparency (overt vs covert) in an e-commerce recommendation influenced significantly participants' privacy concerns and perceived benefits, a Multivariate Analysis of Variance (MANOVA) was conducted. Transparency condition was used as the independent variable and the two dependent variables were privacy concerns and perceived benefits.

In the MANOVA results, Levene's Test indicated homogeneity of variances for both dependent variables, with all significance values above the 0,05 threshold (privacy concerns: $p = 0{,}354$; perceived benefits: $p = 0{,}871$). This suggests that error variances were approximately equal across groups. Meanwhile, the multivariate test revealed that transparency did not have a statistically significant effect on the combined dependent variables (Wilks' Lambda = 0.985, $p = 0{,}305$, partial $\eta^2 = 0{,}015$). This indicates that the overall model, considering both privacy concerns and perceived benefits, was not significantly influenced by the transparency of the recommendation. Lastly, the univariate results confirmed this scenario, showing that transparency had no significant effect on both dependent variables (privacy concerns: $p = 0{,}694$, partial $\eta^2 = 0{,}000$, and perceived benefits: $p = 0{,}226$, partial $\eta^2 = 0{,}005$). These results indicate that transparency condition did not significantly impact participants' privacy concerns or their perception of benefits in the context of the recommendation.

Next, we proceeded to run a linear regression analysis to figure out the hypothesis 3 – whether perceived benefits negatively impact users' privacy concerns or not. The results showed that higher perceived benefits were connected to lower privacy concerns ($\beta = -0{,}166$) with a statistical significance ($p = 0{,}003$), even though the explained variance was small ($R^2 = 0{,}027$).

Finally, to examine whether the stage of the customer journey significantly affected the effect of the transparency on consumers' response, two moderation analysis were conducted using PROCESS model 1 with 5000 samples (Hayes, 2022). The independent variable in both models was transparency (overt or covert), the moderator was the customer journey phase (pre or post purchase) and the dependent variables were perceived benefits in the first model and privacy concerns in the second. This approach allowed us to examine not only the direct effects of transparency and journey phase, but also whether the stage of the customer journey moderates the impact of transparency on consumer perceptions.

Perceived Benefits

The moderation model predicting perceived benefits was statistically meaningful ($p = 0,061$, $R^2 = 0,023$) and while not very explanatory (2,3% of variance explained), several specific values were significant. Customer journey phase (coded as 1 = pre purchase, 2 = post purchase) had a significant effect ($b = -0,7600$, $SE = 0,3342$, $t = -2,27$, $p = 0,0236$), showing that perceived benefits were lower in the post-purchase phase. Also, the interaction between transparency and customer journey phase was statistically significant ($b = 0,4922$, $SE = 0,2114$, $t = 2,33$, $p = 0,0205$), confirming that the impact of transparency on perception of benefits is influenced by the customer journey stage.

Digging deeper into this relation, the analysis concluded that in the pre-purchase phase transparency had a significant negative effect ($b = -0,3936$, $SE = 0,1490$, $t = -2,64$, $p = 0,0087$), which confirms that covert transparency significantly reduced perceived benefits in the pre-purchase phase, and, consequently, overt transparency increases perceived benefits, while in the post-purchase phase, this effect was not significant ($b = 0,0986$, $SE = 0,1499$, $p = 0,5115$).

Privacy Concerns

In contrast, the moderation model predicting privacy concerns yielded no significant effects. The overall model was not statistically significant ($p = 0,1601$, $R^2 = 0,016$), indicating that only 1.6% of the variance in privacy concerns was explained. The main effect of transparency was non-significant ($b = -0,0540$, $SE = 0,3364$, $t = -0,16$, $p = 0,8726$), the main effect of customer journey phase was also non-significant ($b = -0,2106$, $p = 0,5325$) and the interaction (transparency with customer journey phase) was highly non-significant: $b = -0,0142$, $t = -0,0666$, $p = 0,9469$.

These results suggest that privacy concerns remained relatively stable across both transparency conditions and customer journey stages. In other words, neither the format of the scenario (overt vs. covert) nor the timing of the interaction (pre-purchase vs post-purchase) significantly influenced how participants felt about their privacy.

5. RESULTS AND DISCUSSION

Considering the preceding analysis, we aim now to investigate if the previously defined hypothesis were supported and also define what are the practical and theoretical implications that this study leaves behind.

Tabel 5 - Hypothesis Verification

H	Decision
H1 - Overt AI recommendations (vs. covert) impact positively in the perceived benefits	Not supported
H2 - Overt AI recommendations (vs. covert) reduce privacy concerns	Not supported
H3 - Perceived benefits negatively impact users' privacy concerns	Supported
H4 - The customer journey stage moderates the relationship between transparency in AI recommendations and (a) perceived benefits and (b) privacy concerns.	Partially supported

Confirming the lack of conclusiveness stated in the literature, the hypothesis H1, which suggested that overt AI recommendations positively impact perceived benefits compared to covert recommendations, was not supported by the initial MANOVA and univariate analyses. Transparency had no statistical significance on perceived benefits, indicating that users did not perceive overt recommendations as more beneficial than covert ones. This conclusion was similar to the one observed in H2, which suggested that overt AI recommendations reduce privacy concerns compared to covert recommendations. Just like the first hypothesis, this second hypothesis also has no statistical significance, concluding that the transparency does not significantly influence privacy concerns, which does not confirm the literature that stated that transparency (overt recommendations) could lead to reduced privacy concerns.

On the other hand, the third hypothesis H3 which stated that perceived benefits could negatively impact users' privacy concerns was, indeed, supported, which also confirmed the statement in the literature.

Lastly, the hypothesis H4, which stated that the customer journey stage moderated the studied hypothesis H1 and H2, was partially supported. Ultimately, in this hypothesis was investigated whether the customer journey phase being in the pre-purchase or the post purchase influenced the impact that transparency (covert or overt) has in the perceived benefits and the privacy concerns. As for perceived benefits, the PROCESS 1 analysis indicated that perceived benefits were in fact positively impacted in the pre-purchase by overt AI recommendations, while in the post-purchase this effect was not significant. As for privacy concerns, the overall effect in both phases was also not significant.

5.1. THEORETICAL IMPLICATIONS

The findings from this study conclude that the transparency of AI recommendations does not significantly influence the perceptions of benefits which does not confirm either Lambillotte et al. (2022) study nor Sundar and Marathe (2010) study. Further, the study also concluded that transparency also did not significantly influence privacy concerns which does not confirm the conclusions suggested by authors such as Goldfarb & Tucker (2011). Both conclusions suggest that transparency alone may not be sufficient to change consumer perceptions unless by additional elements that might add trust to the consumers such as perceived control, just like suggested in the literature by Martin et al. (2017).

On the contrary, when talking about the third hypothesis, this study brings confirmation to the existing literature, suggesting that just like Li & Unger (2012) stated, when the benefits perceived are higher, it tends to lower privacy concerns, which also extends this confirmation to the context of AI recommendations.

Lastly, this study creates space for investigation in a very lacking literature which is the moderation role between customer journey phase and the impact of transparency in perceived benefits and privacy concerns. This study empirically demonstrates that the effect in perceived benefits – not in privacy concerns - is affected depending on the customer journey phase – if it significant in the pre-purchase stage but not in the post-purchase.

Overall, this study helps extend existing research to the context of AI recommendations, while also bringing insights into the connection between the timing of the recommendation and the transparency of the recommendation itself.

5.2. PRACTICAL IMPLICATIONS

This study provides valuable insights for businesses and professionals in the fields of digital marketing and e-commerce. While most of the literature focused their studies on exploring the impacts of transparency in recommendations, this study goes further and expands the literature to the realm of AI recommendations while adding the customer journey phase to the equation.

One of the main key insights is that transparency alone is not sufficient to reduce privacy concerns. This challenges previous research that, although indicating different effects, claim that transparency by itself is enough to cause a significant effect on privacy concerns and perceived benefits. This may indicate that companies and marketing professionals could add trust elements such as control over the data as support transparency in order to cause a more significant effect on both reducing privacy concerns and increasing perceived benefits.

Additionally, by extending the research to AI recommendations, this study was able to confirm that also in this type of recommendations privacy concerns reduce as perceived benefits increase, meaning that marketing professionals, in AI-generated recommendations, should keep communicating the relevance, convenience and other possible benefits of the recommendation. By doing this, companies and marketing professionals can assure that they are doing what is possible to reduce privacy concerns among customers.

Lastly, and considering the dimension of the timing introduced in this research, companies and marketing professionals should consider the timing of the recommendation when doing so. This study has indicated that in the pre-purchase stage overt transparency can increase perceived benefits and, therefore, it is possible to conclude that one-size does not fit all. Instead, businesses should consider what consumers expect and are comfortable with in each stage of the customer journey and, ultimately, look to emphasize transparency more in the early stages of the consumer journey, potentially where consumers are less familiar with the brand and more likely to take into consideration the trustworthiness of the recommendation.

6. CONCLUSIONS AND FUTURE RESEARCH

The ultimate objective of this study was to answer the research question "How does the transparency of AI-driven recommendations (overt vs. covert) influence consumers' perceived benefits and privacy concerns across different stages of the customer journey?". In order to achieve that, the study analysed the way consumers respond to different levels of transparency while interacting with AI-generated recommendations, more specifically, the benefits that they perceive and the privacy concerns that they feel. The research also added the variable of the timing of the recommendation and analysed if the customer journey stage influenced the impact of the transparency in the perceived benefits and privacy concerns.

The findings indicated that transparency alone does not have a significant impact on privacy concerns and perceived benefits, despite some assumptions in the existing literature. Some limitations about these results may be the not so large sample - 163 respondents – and, therefore, a larger sample could help extracting more conclusive results. Furthermore, the presented scenarios were generic and with made up products and brands which could have made the situation personally irrelevant or unimportant. Future research can also dig deeper into the effect of transparency by adding trust or user control to the equation.

In the opposite direction, this study was able to confirm that higher perceived benefits lead to lower privacy concerns. By adding the trust or user control to the equation in future studies, researchers can explore whether it also amplifies this relationship and, therefore, reduce even more privacy concerns by maximizing perceived benefits.

Lastly, in the last hypothesis, where this research sought to conclude whether the first two hypothesis were influenced by the customer journey stage in which the AI-generated recommendation was done, the conclusion was that the influence was only significant when talking about perceived benefits and only in the pre-purchase phase. Possible limitations to further conclusions can include the absence of more customer journey phases, for example, a three-stage model where purchase is also included or an even broader model with other types of customer journey stages. Another possible limitation can be the lack of difference between the scenarios in the pre-purchase and post-purchase phase, which were differentiated through an initial copy that indicated whether the respondent made a purchase or not before in that exact website which possibly led to similar answers to both scenarios. Future research can improve and deepen the results regarding the effects per customer journey phase through specifically focusing on this effect, creating a deeper differentiation between scenarios or even adopting different customer journey models.

Overall, this research allowed a deeper understanding of recommendations in an e-commerce context, not only by expanding previous studied questions to the realm of AI-generated recommendations, but also by considering the timing of the recommendation. This study allowed the extraction of some insights, but more important than that, it provided ways to be continued by future researchers.

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APPENDIX A

Thesis survey

Dear participant,

This study is conducted as part of an academic research project at the NOVA Information Management School in Lisbon, Portugal, which is called "Impact of AI Recommendations' transparency in E-Commerce: Understanding the impact of overt and covert personalization".

You will be presented with two distinct scenarios. After each scenario, you'll be asked to answer a few questions about your experience considering that particular scenario.

Carefully read the provided scenarios and answer the following questions. Remember that your participation in this survey is voluntary, which means that you are free to participate or not, as well as give up at any time, but keep in mind that your responses are very important for the completion of this project. All your answers are completely anonymous, will be used only for academic purposes and do not involve any risk.

This survey will take approximately between 5 to 7 minutes.

Anything related with this project, you can contact me through the following e-mail: 20230163@novaims.unl.pt

My sincere thanks to every one that will spend a portion of their day to help me completing this project.

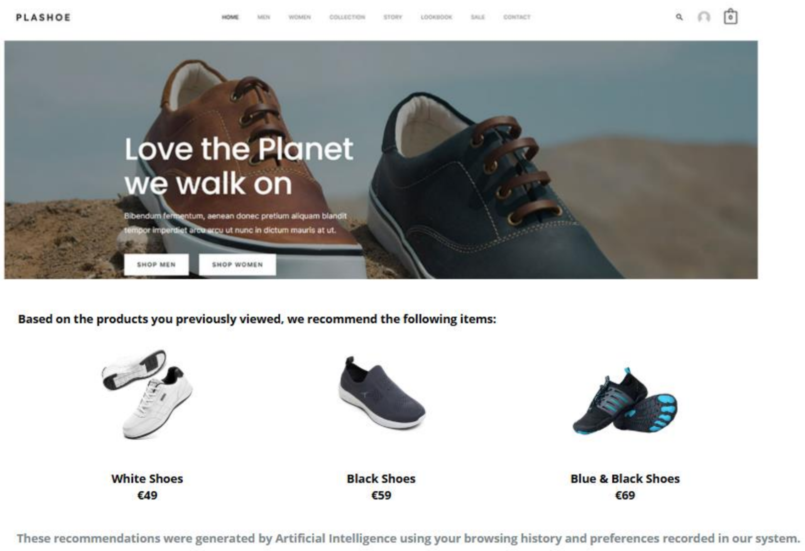
Informed Consent Form I declare that I am 18 or over and agree to participate in this research. I declare that I was informed that my participation in this study is voluntary and that I can leave this survey at any time without penalty, and all data is confidential. I understand that I will evaluate responses and that this study does not offer serious risks.

○ I agree to participate.

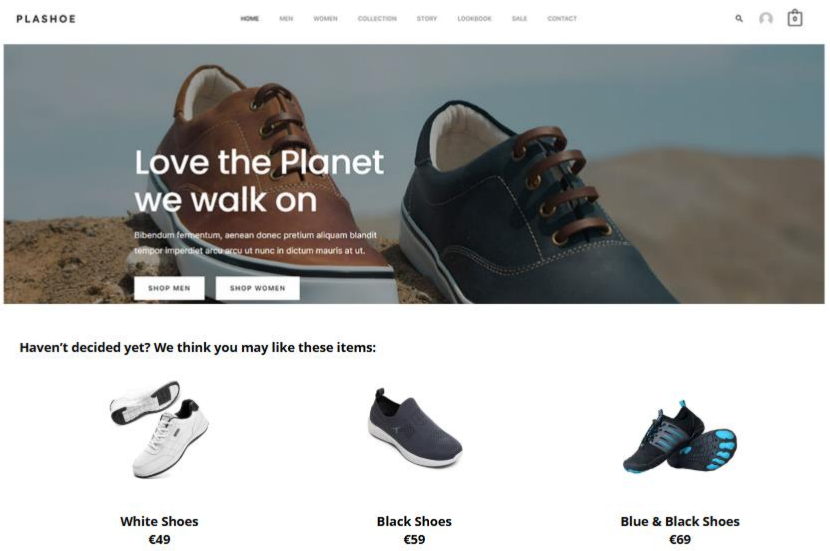
○ I do not agree to participate.

Imagine that you're navigating in a website from which you **haven't made a purchase before** and you're presented with the following situation:

Scenario 1:



Scenario 2:



Please indicate your level of agreement/disagreement with the following statements regarding the read scenario using the scale below:

	1. Strongly disagree	2. Disagree	3. Neither agree nor disagree	4. Agree	5. Strongly Agree
This scenario presents to me a personalized recommendation	○	○	○	○	○
This scenario contained a transparent recommendation about the way it was done	○	○	○	○	○

Please indicate your level of agreement/disagreement with the following statements regarding the read scenario using the scale below:

	1. Strongly disagree	2. Disagree	3. Neither agree nor disagree	4. Agree	5. Strongly Agree
These recommendations help me achieve my purchase goals faster	○	○	○	○	○
These recommendations improve my shopping journey	○	○	○	○	○
These recommendations increase the	○	○	○	○	○

effectiveness of my shopping journey					
These recommendations make it easier to achieve my purchase goals	○	○	○	○	○

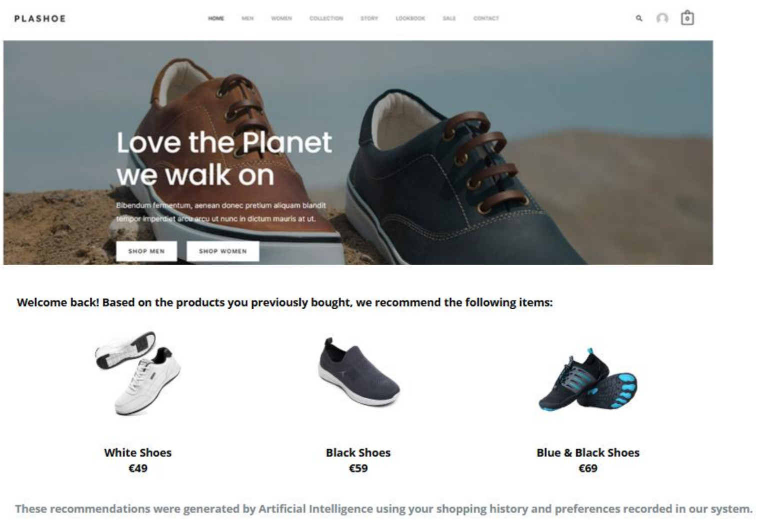
Please indicate your level of agreement/disagreement with the following statements regarding the read scenario using the scale below:

	1. Strongly disagree	2. Disagree	3. Neither agree nor disagree	4. Agree	5. Strongly Agree
I am concerned that my personal data collected by this website could be misused	○	○	○	○	○
I am concerned about the privacy of the data collected about me in this website	○	○	○	○	○
I am concerned that my personal data collected could be used in a	○	○	○	○	○

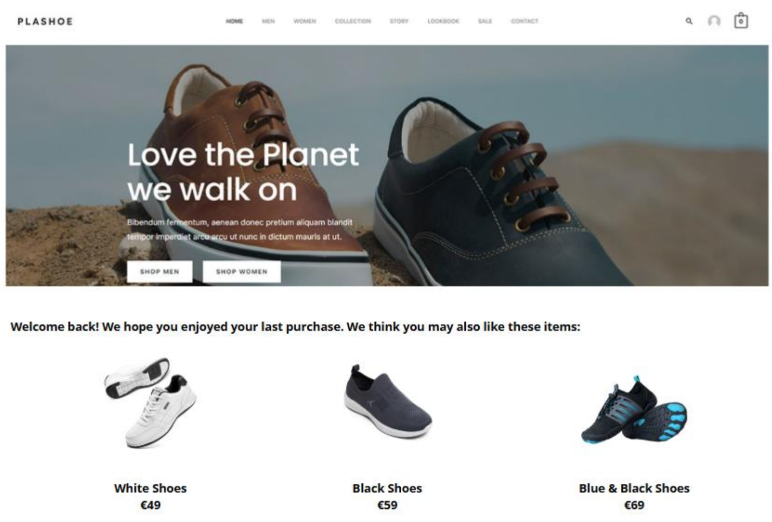
way I did not foresee					
I am concerned that this website might know/track the sites I visited	○	○	○	○	○
I am concerned that this website shares my personal information with other parties	○	○	○	○	○

Imagine that you're navigating in a website **from which you already ordered items before** and you're presented with the following situation:

Scenario 1:



Scenario 2:



Please indicate your level of agreement/disagreement with the following statements regarding the read scenario using the scale below:

	1. Strongly disagree	2. Disagree	3. Neither agree nor disagree	4. Agree	5. Strongly Agree
This scenario presents to me a personalized recommendation	◯	◯	◯	◯	◯
This scenario contained a transparent recommendation about the way it was done	◯	◯	◯	◯	◯

Please indicate your level of agreement/disagreement with the following statements regarding the read scenario using the scale below:

	1. Strongly disagree	2. Disagree	3. Neither agree nor disagree	4. Agree	5. Strongly Agree
These recommendations help me achieve	◯	◯	◯	◯	◯

my purchase goals faster					
Attention check (Select 4. Agree)	○	○	○	○	○
These recommendations improve my shopping journey	○	○	○	○	○
These recommendations increase the effectiveness of my shopping journey	○	○	○	○	○
These recommendations make it easier to achieve my purchase goals	○	○	○	○	○

Please indicate your level of agreement/disagreement with the following statements regarding the read scenario using the scale below:

	1. Strongly disagree	2. Disagree	3. Neither agree nor disagree	4. Agree	5. Strongly Agree
I am concerned that my personal data collected by this website could be misused	○	○	○	○	○
I am concerned about the privacy of	○	○	○	○	○

the data collected about me in this website					
I am concerned that my personal data collected could be used in a way I did not foresee					
I am concerned that this website might know/track the sites I visited					
I am concerned that this website shares my personal information with other parties					

How frequently do you shop online?

- Never
- Rarely (once a year or less)
- Sometimes (a few times a year)

○ Often (every month)

○ Very often (every week or less)

Please tell us:

	Not concerned at all	Slightly concerned	Somewhat concerned	Neutral	Moderately concerned	Highly concerned	Very concerned
What is your level of concern about data privacy when shopping online?	○	○	○	○	○	○	○

Please tell us:

	Not familiarized at all	Slightly familiarized	Somewhat familiarized	Neutral	Moderately familiarized	Highly familiarized	Very familiarized
What is your familiarization with personalization in e-commerce (for example: product recommendations)?	○	○	○	○	○	○	○

What is your age? Please use numbers.

____

How do you describe yourself?

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

What is the highest level of education you have completed?

- ◯ Less than high school
- ◯ High School
- ◯ Technical/professional course
- ◯ Bachelor degree
- ◯ Masters/post-graduation degree
- ◯ PhD

What is your employment status?

- ◯ Working full-time
- ◯ Working part-time

- Unemployed and looking for work
- Student
- Retired
- Other

APPENDIX B

NOVA IMS Information Management School

This is to certify that
Project No.: **DDMKT2025-5-247136**
Project Title: **Impact of AI Recommendations' transparency in E-Commerce**
Principal Researcher: **Bernardo Pereira Guerreiro**

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 5/24/2025.

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, 5/24/2025

NOVA IMS Ethics Committee
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