Artificial Intelligence vs. Human Recommendations: How Trust and Transparency affect Purchase Intent in the Online Fashion Industry

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Abstract

Title: Artificial Intelligence vs. Human Recommendations: How Trust and Transparency affect Purchase Intent in the Online Fashion Industry

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This dissertation examines the impact of trust and transparency on purchase intent in the context of artificial intelligence (AI) and human recommendations, focusing on the online fashion industry. To do so, three primary research questions were addressed: (1) How do AI recommendations affect the willingness to buy of customers? (2) How does trust differ between humans and AI, and how does this affect purchase intent? (3) How does recommendation transparency affect trust and willingness to buy? To address these questions, a quantitative experimental study with a 2x2 design was conducted, manipulating the recommendation source and transparency levels. The results revealed no significant differences in participant's trust or purchase intent between AI and human recommenders. However, when perceived transparency was considered, AI recommenders were trusted less than human ones. In both cases, higher levels of trust were linked to a higher willingness to buy. While actual transparency was not found to moderate trust, perceived transparency did have significant effects here. In addition, the results of the study showed that the more familiar participants were with AI, the greater their trust and willingness to buy. This dissertation has practical importance since it provides valuable insights into recommendations and AI in the online fashion industry.

Keywords: Artificial Intelligence, AI Recommendations, AI Transparency, Decision-Making Processes, Online Fashion Industry, Trust

Sumário

Título: Inteligência Artificial vs. Recomendações Humanas: Como a Confiança e a Transparência Afetam a Intenção de Compra na Indústria da Moda Online

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Esta dissertação tem como objetivo analisar o impacto da confiança e da transparência na intenção de compra na indústria da moda online, num contexto de recomendações feitas por inteligência artificial (IA) e por humanos. Foram abordadas três questões principais de investigação: (1) Como as recomendações da IA afetam a disposição de compra dos clientes? (2) Como a confiança em recomendações feitas por IA difere da confiança em recomendações feitas por humanos, e de que forma essa diferença influencia a intenção de compra? (3) De que forma a transparência das recomendações afeta a confiança e a disposição de compra? Para abordar estas questões, foi realizado um estudo experimental quantitativo com um design 2x2, manipulando a fonte da recomendação e os níveis de transparência. Os resultados não revelaram diferenças significativas na confiança ou intenção de compra dos participantes entre recomendações provenientes de IA e recomendações provenientes de humanos. No entanto, quando se considerou a transparência percetiva, as recomendações provenientes da IA revelaram-se menos confiáveis. Em ambos os casos, níveis mais elevados de confiança foram associados a uma maior predisposição de compra. Embora o critério da transparência real não tenha tido impacto da confiança, o critério da transparência percetiva teve um impacto bastante significativo. Além disso, uma maior familiaridade com a IA revelou uma maior confiança e um aumento na disposição para efetuar compras com base em recomendações provenientes da IA. Esta pesquisa tem um significado prático, pois oferece insights valiosos para empresas na indústria da moda online.

Palavras-chave: Confiança, Indústria da Moda Online, Inteligência Artificial, Processos de Tomada de Decisão, Recomendações de IA, Transparência da IA

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List of Abbreviations

&	and
α	Cronbach's Alpha
AI	Artificial Intelligence
AC	Attention Check
b	Regression Coefficient
BootLLCI	Bootstrapped Lower Limit Confidence Interval
BootSE	Bootstrapped Standard Error
BootULCI	Bootstrapped Upper Limit Confidence Interval
CC	Comprehension Check
CI	Confidence Interval
df	Degrees of Freedom
DV	Dependent Variable
F	F-statistic
GDPR	General Data Protection Regulation
H1	Hypothesis 1 (2-3 respectively)
HLEG	High-Level Expert Group
IV	Independent Variable
M	Sample Mean
MC	Manipulation Check
ML	Machine Learning
n	Sample Size
NLP	Natural Language Processing
p	p-value
R^2	Coefficient of Determination
RQ	Research Question
SD	Standard Deviation
SE	Standard Error
t	t-statistic
VIF	Variance Inflation Factor
WOM	Word-of-Mouth
WTB	Willingness to buy

Abbreviations for Hayes PROCESS macro

M	Mediator
W	Moderator
X	Independent Variable
Y	Dependent Variable

1. Introduction

1.1 Topic Presentation

"Is artificial intelligence less than our intelligence?"

- Spike Jonze

This question, asked by the American film director Spike Jonze, has been quoted quite often in the last couple of years. It makes you think. Are we, humans, still superior to AI? Are we more intelligent? Is our judgement better than that of AI? If not, is AI going to replace us?

The interesting thing is, there is no definitive answer to all these questions. Although AI has been around for quite some time, its advancements in the last couple of years has been tremendous. If you had asked someone three years ago how AI impacts their daily life, the answer of most respondents would likely have been "not at all" or maybe "slightly". This does not mean that AI was not present three years ago, it rather symbolizes the shift in its active, recognized use. Programs like ChatGPT, an innovative AI chatbot which was made public in November 2022, have become part of everyday life for many people, in private, academic, and even professional settings (Anderson et al., 2023; Taecharungroj, 2023). To put numbers to it: as of April 2024, ChatGPT generated around 1.6 billion visits per month, and even its corporate version has already gained over 600,000 users (Davalos, 2024; Duarte, 2024). With numbers like these, it is no surprise that prior research has found AI to have large-scale impacts on society as a whole, on organizations, and us humans in particular (Makridakis, 2017). Individuals' behaviour and their decision-making processes can get shifted through AI, making it a hot topic across various industries (e.g., Bao, Gong, & Yang, 2023; Minton, Kaplan, & Cabano, 2022; Yazdani & Darbani, 2023). One such industry is the online fashion industry. With rapid growth and an estimate to reach a market value of over 1.2 trillion U.S. dollars worldwide by 2027, AI's impact here could be tremendous (Cellan-Jones, 2024).

1.2. Problem Statement & Research Objective

But is the incorporation of AI into the online fashion industry even that beneficial? The answer to that is "Yes". One significant problem in this industry is the overwhelming amount of big data available, which humans cannot fully leverage; however, AI can be used to generate and better process this big amount of data which in turn helps to generate better customer insights, content creation, and overall increased customer engagement (Solis, 2017; Wien & Peluso, 2021). Additional research, as the one from Lee (2021), found that AI can improve

personalization, co-designing, and manufacturing planning. Facilitating the decision-making process with AI has also been identified as an improvement in that industry (Giri et al., 2019). While there is no doubt that AI recommender systems can be beneficial from the businesses perspective (Jankovic & Curovic, 2023; Jia et al., 2022), there is still not much known about how customers value these systems in the online fashion industry. Does it increase or decrease their willingness to buy? When looking at past research, no clear answer can be found. One study by Longoni and Cian (2020) found the acceptance of AI recommender systems to be actually tied to the respective context, while differing between hedonic and utilitarian situations. Since the fashion industry can encompass both (Choo et al., 2012), the following study tries to solve that exact problem and fill the research gap.

To do that, the following research question was compiled:

RQ1: *How does knowing that a recommendation is proposed by AI impact consumers' willingness to buy?*

Furthermore, in the existing body of literature, trust has frequently been identified as having a mediating effect on customer experience (e.g. Ameen et al., 2021; Rose et al. 2012). Building on this, this study also investigates the mediating role of trust on the relationship between recommendation source and willingness to buy. Furthermore, it will examine whether there is a difference in trust between human- and AI-generated recommendations. Thus, the following research question emerges:

RQ2: *Do the trust individuals have in recommendations generated by AI differ from the trust individuals have in recommendations made by humans, and how does this trust influence their anticipated willingness to buy?*

Finally, since this study intends to deliver results that can be acted upon in the real-life, it will also investigate the role of transparency – specifically, whether it is beneficial for marketeers to explain the recommendation process to the customers. Prior research, like Lee and See (2004) and Shin and collaborators (2020) found transparency of algorithms to increase trust. Additionally, the General Data Protection Regulation (GDPR), a relatively new law that regulates data collection and processing of personal information for European organizations, includes a "principle of transparency" (General Data Protection Regulation, 2016). Therefore, the following third research question was formulated:

RQ 3: *How does transparency about the recommendation process impact trust in the recommendation source, and how does it impact consumers' anticipated willingness to buy?*

With these three research questions, this thesis aims to explore the impact of AI on decision-making with a focus on product recommendations.

In order to do this, the following paper presents an experimental study, in which the type of recommender (AI vs. human) is varied. To see if there are significant differences in the way individuals take recommendations generated by AI or humans, the anticipated willingness to buy after receiving the recommendations was measured. To deepen this understanding, the study also explored whether transparency had a moderating role in this context. Finally, trust was measured as a proposed mediating variable.

1.3. Managerial & Academic Relevance

In broader terms, this thesis explores the effect of AI on consumer behaviour, focusing on the interrelations of AI, transparency, consumer trust, and willingness to buy (WTB). The findings will be relevant for managers as well as academics in the following ways.

Managerial relevance

The following study especially aims at providing businesses, managers, and marketing units valuable insights that they are able to act upon. The findings of this study offer direct managerial implications for the online fashion industry. Firstly, if marketing recommendation messages should contain the information of AI involvement. And secondly, if the way recommendations are generated should be communicated transparently. This allows managers to have a better understanding of what consumers want in online marketing. Subsequently they can better tailor their strategies to align with customer preferences, which in turn has a positive impact on profits (Anderson et al., 2018).

Academic relevance

In the academic context of this thesis, the conducted study adds to the body of academic research in the area of human decision-making. As indicated in section 1.2, there is still a significant gap in the understanding of the impact of AI on human decision-making processes, particularly focused on transparency and the online fashion industry. The novelty of this study is not just the inclusion of the role that transparency plays in consumer trust in AI and its subsequent impact on anticipated WTB, but also the investigation of the differences between

actual and perceived transparency in that context. This approach broadens the scope of research, shifting the focus from merely looking at the impact of AI on decision-making to examining the underlying factors.

1.4. Structure

Following the presented introduction, which has already covered the general topic in 1.1, the research questions in 1.2 and the academic relevance in 1.3, this thesis further shines light on the proposed research questions in Chapter 2. Here a literature review dives deep into the concepts of decision-making, source credibility, and AI to make informed hypotheses regarding the research questions. Subsequently, Chapter 3 outlines the methodology of this experimental study, followed by Chapter 4 which presents this study's results. Chapter 5 discusses these findings from a critical perspective and concludes, while proposing limitations and possible areas of future research.

2. Literature Review

The following section provides an overview of human decision-making with particular focus on the role of recommendations and the impact of AI on decision-making processes. Based on this, hypotheses for this study get derived and a conceptual model will be presented.

2.1 Human Decision-Making

2.1.1 Decision-Making Processes

Having to make decisions is something humans face every day (Morelli et al., 2021). It may be a trivial decision on what to have for lunch or an important one, like the decision to take a job offer. No matter how insignificant the decision seems to be, it is still subject to the human decision-making process. This particular process can be subdivided into the following three stages: 1) the formation of preferences among options, 2) the selection and execution of an action, and 3) the experience or evaluation of an outcome (Ernst & Paulus, 2005).

While researchers have been studying this process for many years, there is still no complete agreement on how exactly decisions are made by humans.

One theory proposed, as early as in the 18th century, is the "*Rational Choice Theory*" by Adam Smith. This theory states that individuals make decisions rationally by weighing the potential benefits and costs of their actions (Bezar, Noreen, & Ali, 2021). Later on, "*behavioural economics*" started to extend Adam Smith's approach in a way, that also considers the fact that

humans are not perfectly rational agents: they are also prone to cognitive biases, heuristics, and bounded rationality (Lieder et al., 2018; Kahneman, 2003; Kenrick et al., 2009).

To better understand the role of recommendations in decision-making processes, as will be explored in section 2.2, it is important to first understand behavioural economics, since cognitive biases, heuristics, and bounded rationality play an important role here by serving the purpose of making decision-making easier and less effortful (Crumlish & Kelly, 2009; Gigerenzer & Gaissmaier, 2011).

To further clarify, cognitive biases are systematic behavioural patterns that lead humans to deviate from rationality, leading to inaccurate judgements and decisions (Hansen, 2020). Heuristics on the other hand refer to shortcuts or "rule-of-thumbs" humans use to make decisions (Hansen, 2020).

Getting back to decision-making theories, the fact that humans are not perfectly rational agents is a key consideration of *'Dual Process Theories'*. According to those, humans have two distinct systems: system 1, which is fast, intuitive, and emotional, and system 2, which is slow, more thoughtful, and logical (Kahneman, 2011). These two systems provide the basis for human decision-making. However, always using system 2 can be draining for humans which results in a more frequent use of system 1, making decisions therefore prone to faults and biases (Kahneman, 2011).

So, as seen in the previous section, human decision-making processes are quite complex. But next to biases, heuristics and irrational thinking patterns, other important factors can have a significant impact on decisions as well, which will get explored in the following.

2.2 The Role of Recommendations in Decision-Making Processes

2.2.1 Underlying Factors

When making decisions, humans often rely not only on their own judgement but also on the input of others. This highlights the significant role of social influence in shaping decision-making processes. A study by Fershtman and Segal (2018) found that social influence shapes individuals' behavioural preferences in a way that they differ from their core preferences. In other words, social influence affects individuals' equilibrium behaviour (Fershtman & Segal, 2018).

One form of social influence that plays an important role in decision.-making is the so-called word-of-mouth (WOM). In fact, WOM has been found to be the most important source of information when individuals are making purchase decisions (Litvin et al., 2008). It can be described as the exchange of marketing-related information between consumers that shape their behaviours and perceptions of products and services significantly (Katz & Lazarsfeld, 1966). Recommendations are in fact a way individuals spread this WOM (Huete-Alcocer, 2017).

But why and how do recommendations influence decision-making processes? One theory, the *Social Proof Theory* by Cialdini (1993), suggests that individuals refer to the behaviour of others when making decisions, particularly when they are faced with uncertainty. In this context, receiving a recommendation by a peer serves as social proof, significantly influencing the decision of the individual (Talib & Saat, 2017).

In addition, recommendations serve as cognitive shortcuts: having recommendations in place facilitates individuals' decision-making (Smith, Menon, & Sivakumar, 2005). A study conducted by Lawrence and collaborators found that recommending new products tailored to the individual customer provided decision aid and therefore boosted supermarket revenues (2004). This goes hand-in-hand with the reduction of cognitive overload recommendations offer, since providing recommendations narrows down choices and, therefore, helps individuals to focus on the relevant information and decisions (Jacoby, 1984).

Oftentimes these recommendations are in line with prior beliefs or perceptions individuals hold beforehand. This exact phenomenon was coined by Plous in 1993 as *confirmation bias*, which is the tendency to select, understand, and remember information in a manner that reinforces one's existing beliefs or perceptions.

2.2.2 The Importance of the Recommendation Source

Even though recommendations have a significant impact on decision-making processes, the extent to which they influence these processes can vary widely depending on the recommendation source. Research categorizes these sources as having either authority influence or emotional influence.

Authority influence: Schöbel and collaborators conducted a study in 2016 examining the effect authority has on individuals' decision-making. Findings suggested that recommendations by authority figures have a much higher impact on individuals than recommendations from their

peers (Schöbel et al., 2016). This can be attributed to the fact that authorities seem to be more knowledgeable, trustworthy, and credible than others (Schöbel et al., 2016).

Emotional influence: Emotional influence stems on the other hand from emotional connections to the recommender (Cialdini & Goldstein, 2004). Recommendations provided by individuals one trusts, e.g., friends or family, carry emotional weight and are therefore more impactful than recommendations from individuals one has no emotional connection to (Deng et al., 2017).

As illustrated above, the source of recommendation is crucial for the weight it has on decisions. Underlying factors include recommender credibility (trust, expertise, attractiveness) and transparency, which will be examined in the next section (Castelfranchi & Falcone, 2010; Ohanian, 1990).

2.2.3 The Role of Credibility in Recommendations

Factors influencing source credibility have been studied for years. The "*Source-Credibility Model*" was first developed by Hovland and collaborators (1953), highlighting expertise and reliability as the main factors for source-credibility. Over the years, additional research was conducted, and Ohanian (1990) reshaped this model, finding three factors responsible for source credibility: attractiveness, expertise, and trustworthiness. According to his findings, individuals that are more physically attractive were seen as more credible (Ohanian, 1990). Furthermore, a higher perceived expertise, such as through experience, knowledge, skill, and qualification of the source, made individuals appear more credible as well. And lastly, individuals seen as trustworthy (dependent, honest, reliable, and sincere) were found to display a higher source credibility (Ohanian, 1990).

Since this following study uses trust in the recommendation source as a mediator, the next section delves deeper into this particular dimension of credibility.

Trust: According to Mayer and collaborators (1995) trust can be defined as "the willingness of a party to be vulnerable to the actions of another party based on the expectations that the other will perform a particular action important to the trustor, irrespective of the ability to monitor or control that other party" (p. 712).

Past research, like Gino and Schweitzer (2008), found individuals to be more influenced by advice when they trust their advisors than when they do not have a trustful relationship with them. This is because using another's advice involves making oneself vulnerable (Mayer, Davis, & Schoorman, 1995). Still, findings suggest the scope of the impact of trust to be task

dependent: a study conducted by Swol and Lyn (2011) found trust in the advisor and shared values to be significant predictors of the acceptance of advice for tasks without a correct answer. On the other hand, advice acceptance of tasks with a correct answer was found to be more shaped by the advisor's confidence (Swol & Lyn, 2011). Nevertheless, even then trust played a significant role in advice acceptance, making later oftentimes used as a behavioural measure of trust (Mayer, Davis, & Schoorman, 1995)**.**

Therefore, the building of trust is crucial for enhancing the credibility of a recommendation. In order to achieve trust, Abrams and collaborators (2003) found the following behaviours as being of particular importance: discretion, consistency, collaboration, and ensuring transparency. This goes hand in hand with Djafarova and Trofimenko's (2018) findings that found transparency, among other dimensions, to be an important factor for trustworthiness in the realm of online source credibility. With transparency being a moderating factor in the following study, a detailed examination of this aspect will be presented in section 2.3.4.

2.3 The Impact of AI on Decision-Making Processes

2.3.1 An Overview on Artificial Intelligence (AI)

In recent years, the term Artificial Intelligence, or AI, has become a part of our every-day language, even though it has already been around since the 1950s. It was first introduced at a seminal workshop in 1956 at Dartmouth College (Hutson, 2017). Back then the term was taken to mean "making a machine behave in ways that would be called intelligent if seen in a human" (Hutson, 2017, p. 19). Since then, researchers often tried to enrich the definition of AI, as Russell and Norvig did in 2016. According to their modern approach, AI can be seen as systems that replicate human cognitive functions like learning, speech, and problem solving (Russell & Norvig, 2016). This "human replication" is one of the factors that makes people have mixed feelings towards AI, since it increases AI's capability to do tasks that are generally performed by humans (Dwivedi, 2019). While some might perceive AI as a threat, like Stephen Hawking that once said, "AI could spell the end of the human race", some view its potential more optimistically (Cellan-Jones, 2014).

While the merging of physical and virtual worlds was possible before, AI enables this to be done more effectively, resulting in processes that better address modern challenges, such as increased customization and reduced time for products to enter the market (Zheng, 2018). Even though this can be especially relevant for the manufacturing industry, AI has been seen to hold

the potential to shape and disrupt other industries like finance, manufacturing, retail, supply chain, utilities, logistics, and especially healthcare (Dwivedi, 2019).

One of the reasons why AI is so impactful in these industries is the fact that it speeds up, facilitates, and supports the decision-making processes, which was prior conducted by humans (Vincent, 2021). For instance, in finance, AI it can be used as an investment decision analysis tool (Zdravković, 2021). In healthcare, AI has been found to have the potential to significantly improve the early detection, decision on diagnosis and treatment, as well as the outcome of various diseases (Jiang et al., 2017).

But not only industries are transformed through the rise of AI, its impact on society as a whole and on individuals in particular has been heavily studied in recent years as well (e.g., Floridi et al., 2018; Vinuesa et al., 2020). One area of research, which is particularly interesting for businesses' marketing strategies, is aimed at understanding how AI impacts the consumer and its decision-making processes, which will be discussed in the next section.

2.3.2 The Impact of AI on Consumers' Decision-Making Processes

To further dive into the impact of AI on the decision-making processes of consumers, it is crucial to get an overview of AI's applications in the consumer market first. A notable example of this was LEGO's use of Watson Ads Omni during Black Friday 2018, leveraging AI's advertising capabilities by using Watson Ads Omni to display AI-powered interactive ads (Sweeney, 2018). These specific ads were tailored to every consumer based on their unique interests and needs and were furthermore capable of answering questions about LEGO products directly within the ad (Campbell et al., 2020). Using this kind of AI can significantly shape consumers' decision-making through meaningful, one-on-one conversations (Campbell et al., 2020). The relevant AI technologies for this purpose include the following:

Machine learning: One important AI technology in marketing is the so-called *machine learning* (ML), which can be defined as "a form of artificial intelligence that uses computer algorithms to identify patterns in large data sets" (Waljee, & Higgins, 2010, p. 1224). Having a more accurate way of understanding and analysing individual customer patterns makes it easier to provide more personalized marketing which, in turn, improves customer relationships (Dellaert et al., 2020). These personalized marketing strategies can take the form of recommendations, which adapt to the customer respectively.

Natural language processing: Another technology relevant in the consumer market is *natural language processing* (NLP), which is designed to analyse and represent human language and also interact with the user (Khurana et al., 2017; Lauriola et al., 2021). Areas of application include email spam detection, information extraction, or the answering of questions (Khurana et al., 2017). Especially the latter has been greatly used in the context of customer decision support in recent years: so-called "*chatbot*s" offer customers unique, convenient, and personal assistance when questions arise and therefore have been found to actually improve customer satisfaction in retail contexts (Chung et al., 2020; Rese et al., 2020).

Computer vision: Next to ML and NLP, *computer vision* techniques are used to improve the customer decision-making process. Through virtual try-ons, users are able to try on various outfits virtually and therefore do not have the effort to change clothes in real life (Hauswiesner, 2013).

All these applications are transforming the way consumers engage in their decision-making processes.

2.3.3 Challenges of AI

Algorithm aversion: But with every advancement, challenges and concerns occur. That is no different when it comes to AI technologies. These concerns lead individuals to inherit a so-called *algorithm aversion*, which makes individuals lose confidence in algorithmic forecasters more quickly than in human ones (Dietvorst et al., 2014). Underlying reasons for that have been identified as ethical, social, or legal concerns (Choi & Moon, 2023). Sharma on the other hand classified the concerns associated with the adoption of AI into the following three overreaching dimensions: ethical concerns, disruption concerns, and trust concerns (2024).

While ethical concerns include concerns about job displacements, unfairness, and human skill loss, disruption concerns deal with concerns about power shifts, changes in institutional structures and demand for different skillsets (Sharma, 2024).

Trust concerns include concerns about data privacy, data misuse, and transparency (Sharma, 2024). These concerns are valid, as some researchers, like Ryan (2020), have found AI to be untrustworthy due to a lack of emotive states, accountability, and interpersonal relationships.

Other voices on the other hand, like the European Commission's High-level Expert Group on AI (HLEG) are advocates of the establishment of trusted relationships with AI (HLEG AI, 2019). To promote these relationships, the HLEG came up with the so-called "7 Principles of

trustworthy AI", which should be met throughout a system's entire life cycle and read as follows: (1) human agency and oversight, (2) technical robustness and safety, (3) privacy and data governance, (4) transparency, (5) diversity, non-discrimination and fairness, (6) societal and environmental wellbeing, and (7) accountability (HLEG AI, 2019). In line with these principles, this study will dive deeper into the principle of (4) transparency, shining light on the effect increased AI transparency has on consumers.

2.3.4 Consumer Responses to AI Recommendations

This last section focuses on the way consumers react to AI recommendations and delves deeper into their anticipated willingness to buy, also considering the dimensions of trust and transparency.

Anticipated willingness to buy

In the last couple of years, research has also shed light on the impact AI recommendations have on the willingness to buy or purchase intent of customers. Generally, past research found customers to rather listen to human product recommendations than to those from AI (Wien & Peluso, 2021). Humans seem to be relevant, accurate, and trustworthy sources of product information (Simonson & Rosen, 2014). AI recommenders, on the other hand, can be oftentimes perceived as biased (Chen et al., 2023). In addition, humans tend to feel more psychologically distant when interacting with AI recommenders, making it harder for AI to persuade them (Ahn et al., 2021b). Nevertheless, research also showed the effectiveness of AI advice to be dependent on the context, domain or product type: While AI recommenders are preferred to human recommenders in more objective situations (Castelo et al., 2019) or situations when AI is known to outperform the human (Pezzo & Beckstead, 2020), human recommenders are preferred for example for medical and financial risk management decisions or employee selection (Diab et al., 2011; Larkin et al., 2021). Moreover, a study by Li and collaborators (2020) revealed that, in the specific context of online clothing recommendations, the initial acceptance of human recommendations was in fact higher than that of AI recommendations.

Furthermore, research also found human recommenders to be more effective than AI recommenders in influencing consumer reactions for the category of hedonic products (Wien & Peluso, 2021). In 2022, Longoni and Cian conducted a very extensive series of studies regarding this discrepancy and found AI recommenders to be more competent in utilitarian contexts and humans more in hedonic ones.

The following study will focus on the impact of AI recommendations in the context of e-commerce, specifically clothing. Due to the fact that clothing can have hedonic but also utilitarian motivations, Longoni and Cian's (2022) approach is not applicable in this context (e.g., Kang & Park-Poaps, 2010; Kim & Hong, 2011).

Still, the reviewed research allows to derive the following hypothesis:

H1: *The anticipated willingness to buy will be higher for individuals that received a human-generated recommendation than those who received an AI-generated recommendation.*

Trust

As already seen in section 2.3.3, trust is a huge area of concern in AI generally and in AI recommendations in particular. A study conducted by Li and collaborators (2020) specifically focused on "Who Should Provide Clothing Recommendation Services: Artificial Intelligence or Human Experts?" found human expert recommendations to be perceived as more trustworthy than AI recommendations. These findings are in line with prior research findings, like the ones by Senecal and Nantel (2004), which found human experts to be perceived as equally trustworthy as other consumers but more trustworthy than AI in online shopping.

For studies not specifically focusing on online shopping, findings are more diverse: For instance, Diab and collaborators (2011), whose study concerned how people perceive human versus mechanic evaluation for employee selection, found participants from the US to trust the human evaluation more while non-US participants slightly preferred mechanical integration for test scores. Logg and collaborators (2019) conducted a series of experiments concluding that people generally show algorithm appreciation but there are specific conditions and domains where this preference varies. Keeping that in mind while integrating the findings of Li and collaborators (2020) and Senecal and Natell (2004), the following hypothesis is derived:

H2a: *Having AI as the recommender will lead to lower trust in the recommendation source than having a human recommender.*

Trust in recommender systems is consequential for willingness to buy. Hsiao and collaborators (2010) conducted a study assessing how trust in recommendations influenced consumers' willingness to purchase products from the website. Results showed that higher trust in the product recommender positively influences consumers' purchase intentions (Hsiao et al., 2010). Factors like integrity, competence, and kindness collectively shape this trust in the

recommender, which then influences the purchase intent (Lăzăroiu et al., 2020), leading to the following hypothesis:

H2b: *Higher trust in the recommendation source will be positively associated with greater anticipated willingness to buy.*

Transparency

According to Siaua and Wang, a limited ability for humans to understand the respective AI technology has a negative impact on trust in it (2018). This is also something Sharma found prevailing in past research studies in this domain (2024). Transparency, indeed, seems to be one of the main factors influencing AI trustworthiness (Li et al., 2021). Therefore, it is also part of the "7 Principles of Trustworthy AI" (see section 2.3.3).

In a study from 2022, Yu and Li investigated how AI decision-making transparency affects employees' trust in AI. In fact, their findings were in line with prior research, just like Canal and collaborators (2020) or Panganiban and collaborators (2019) who found perceived transparency to positively influence trust in AI (Yu & Li, 2022). Having the participants understand AI's decision-making process better made them perceive AI as more reliable and effective which in turn lead them to have higher trust (Yu & Li, 2022). Nilashi and collaborators (2016) furthermore underlined that the transparency of the recommendation process is equally important to consumers for building trust as the recommendation quality.

Therefore, the following hypothesis is derived:

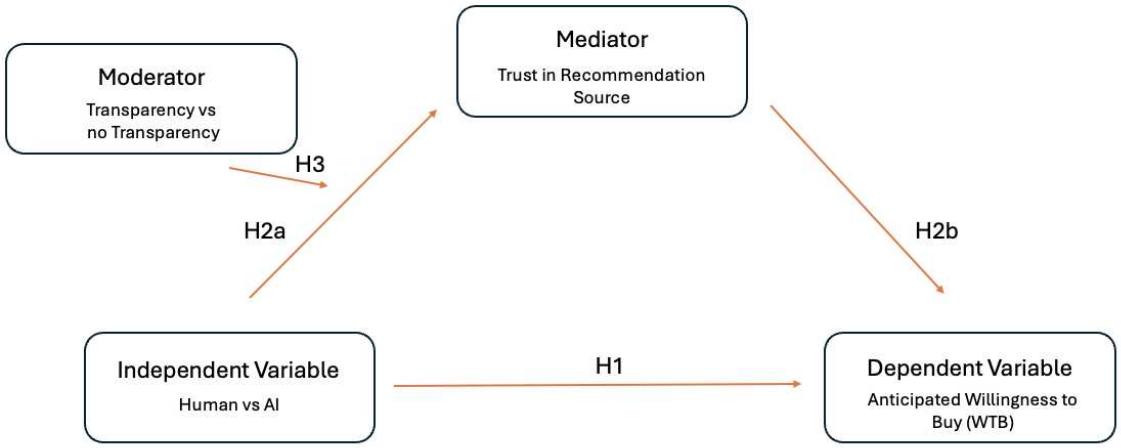
H3: *Algorithm transparency moderates the relationship between the recommendation source (Human vs. AI) and trust in the recommendation source, such that higher transparency about the recommendation source will positively impact trust in the recommendation source.*

2.4 Conceptual Model

The study's conceptual model can be seen in Figure 1.

Figure 1:

Conceptual Model



3. Methodology

The following methodology section provides an overview over this study's research design, sampling method, procedure, and the measurement of the variables used.

3.1 Research Design

The aim of this research is to understand how the source of recommendation (human or AI) influences consumers' willingness to buy. To accomplish that, this study takes a quantitative approach to facilitate the discovery of quantifiable information (Carr, 1994), specifically it consists of an experiment, since experimental studies have been found to be an adequate way to test for causality (Malhotra et al., 2017).

Therefore, a survey was created via the online survey software Qualtrics. The reason for that is that online surveys inherit, in comparison to offline surveys, lower costs, a quicker collection of data, as well as more diverse and higher participation rates (Teo, 2013).

Furthermore, this study has aimed to understand the moderating role of transparency and the mediating role of trust in this context (moderated mediation model), since prior research already

identified these as important factors in the context of AI and recommendations (e.g., Chen and Teng, 2013; Li et al., 2021; Yu & Li, 2022).

To include the testing of this moderating role of transparency in the study, a 2 x 2 between-subjects-design was applied, manipulating the independent variable (AI vs human) and the moderator (transparency; see Figure 2) while building on previous research (e.g. Kim & Lee, 2018; Longoni & Cian, 2020). Therefore, participants were randomly assigned to one of four different E-Mail marketing messages and answered to the same set of survey questions – dependent and mediator variables – to keep the results comparable. All variables were measured using pre-existing methods and scales from related research, with most of them adapted accordingly.

Figure 2:

Cross-Sectional Design Matrix

	AI	Human
No Transparency		
Transparency		

Regarding the moderator variable transparency, this study used two distinct variables: actual transparency and perceived transparency. Actual transparency was manipulated by giving or retaining the participants an explanation on how the recommendation got provided to them. Perceived transparency, on the other hand, was measured based on participants' subjective perception of transparency, which was captured through Likert scale questions. By including both manipulated actual transparency and measured perceived transparency, this study was able to provide a more comprehensive understanding of the concept of transparency in the context of recommendations.

3.2 Sampling Method

To gather participants for the survey, the online research platform Prolific was used. In Prolific, participants fill out surveys and get monetary compensation in return (Palan & Schitter, 2018).

Since participants have been tied to their availability and willingness to participate, Prolific has generally offered convenience sampling rather than random sampling (Etikan, 2016).

Nevertheless, the platform has been found to be suitable for recruiting subjects for experiments (Palan & Schitter, 2017). Moreover, research found Prolific's data quality to be superior to the data provided by similar platforms, like MTurk or CloudResearch (Peer et al., 2021).

For this study, I aimed to collect 300 responses, since the literature suggests aiming for 65 participants per condition for these kinds of experimental designs (Durlak, 2009). Since I conducted a 2 x 2 design study, I tried to receive at least 260 valid responses.

To increase response quality, I placed two comprehension check (CC) questions after the email exposure and one attention check (AC) question in the middle of the survey. Since Prolific allows for the replacement of participants that fail the AC, a higher rate of valid responses was expected. In addition, the pre-screen criteria were added so that only Prolific users with an approval rate of at least 95% in prior studies were allowed to take part.

Besides the condition that only English-speaking users and users over 18 could participate, I deliberately did not put any additional pre-screen criteria in place to increase external validity.

3.3 Method

Procedure

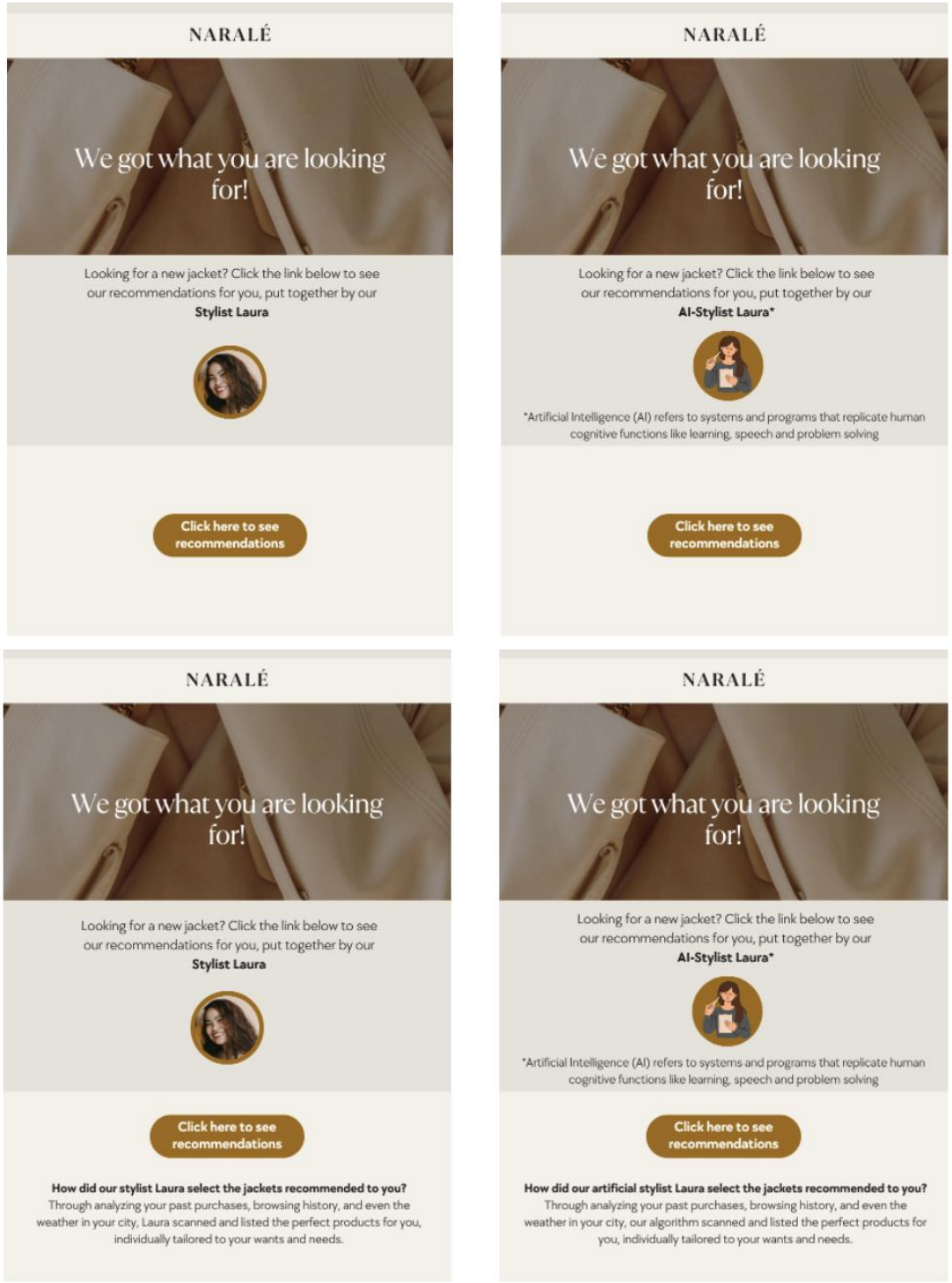
The survey started out with a consent form, including a short overview of what the participants awaited, an approximate completion time, possible side effects, and information on confidentiality. After that, participants were asked to agree to participate in the study by clicking "I agree".

The first part of the study contained one question for each of the two covariates: "How familiar are you with Online Shopping?" and "How familiar are you with AI and other advanced technologies?". Since participants with low familiarity in online shopping as well as AI and other advanced technologies were still able to give important insights, those questions were not framed as screening questions. Next, participants were exposed to one of the four different E-Mail marketing messages by the fictional clothing brand "NARALÉ" (Figure 3). The decision to use a fictional brand name instead of an existing one, like H&M or Zara, was based on the effort to distinguish any pre-held attitudes towards the brand, which could have distorted the findings while keeping the scenario as realistic as possible (Thakor & Lavack, 2003; Yorkston & Menon, 2004).

Furthermore, the marketing message was complemented by one uniform text asking participants to imagine themselves in the following situation: “You are currently in the need of a new jacket. Therefore, you have been browsing the internet for the last couple of days. Today you checked your E-Mail Inbox and stumbled across the following Marketing E-Mail by the fashion brand “NARALÉ””.

Figure 3

Marketing-Message Modifications



As seen in Figure 3, the marketing message invited the recipients to click on a button to see jackets recommended to them. The decision on the product category was driven by the aim to make the scenario as realistic and tangible as possible for the participants: fashion is the number one product category worldwide in retail e-commerce sales (Cellan-Jones, 2024). In addition, prior findings, like Longoni and Cian (2020), underlined the varying acceptance of AI recommendations for utilitarian versus hedonic products. Therefore, this study used jackets as the product since jackets can be perceived as both hedonic and utilitarian (Oh & Jasper, 2006). The text below the markeing message allowed to verify the participants' comprehension by asking "Who provided you with the recommendation?" and "Were you provided information on how the recommendation process works?".

Then it asked participants to imagine that they would click on the link in the email and the following page would show them a selection of 15 different jackets. The choice on the number "15" was made after I conducted a torough analysis of recommendation practices across four leading online fashion retailers: H&M, ASOS, Zara, and Zalando. In detail, I examined how many product recommendations each shop typically provided on related product category pages. The results ranged from 10 to 20. Taking the mean, I concluded 15 product recommendations to be an adequate number that followed industry norms while not overloading the user.

For the messages that involved AI, a short description was given, based on the definiton by Russell and Norvig (2016).

To keep participants from just skimming the text, a timer was set so participants had to remain on the page for a certain amount of time before continuing. For the marketing messages without the explanation, the timer was set to 15 seconds, with explanation to 20 seconds.

Then, participants were asked about their willingness to buy, recommendation process transparency, and their trust in the recommmendation source. Following the ceteris paribus principle, the questions asked remained the same for all participants, no matter the marketing message they received.

After that, ease of participation was assessed by asking participants how easy it was to imagine themselves in the previously described scenario. Finally, participants were asked to answer the demographic block of questions, which asked for gender, age, origin, education level, and employment status. This part also gave the participant the possibility to share any comments or

remarks in an open-ended question. Lastly, participants were thanked for participating and the aim of the study was explained in more detail.

Participants were unable to go back to questions or skip any questions. Please refer to Appendix 1 to see the full survey.

Participants

372 surveys were completed between the 21st and 22nd of August 2024 on the survey platform Prolific. Out of the total uncleaned sample, 13 participants (3.5% of total sample) failed the attention check question and were therefore eliminated from further analyses (see Appendix 2). Out of the remaining 359 surveys, 87 participants (24.2% of the remaining sample) answered at least one comprehension check question wrongly, with the number of passing participants for the AI x No Explaination-Condition being comparably low with $n = 48$ (13.4% of the remaining sample) (see Appendix 2). While the 43 participants (12% of the remaining sample) that failed the CC in the three remaining conditions were eliminated from further analyses, there was reason to believe that some participants of the AI x No Explaination-Condition might have misunderstood the CC question, thinking that the provided explanation of AI refers to the explanation of the recommendation process. To test that, the results of the AI x No Explaination-Condition with the failed CC on recommendation transparency ($n= 38$; 86.4% of the total AI x No Explaination-Condition failures) were compared to the participants of the AI x No Explaination-Condition that did not fail the CC. The results suggested a statistically significant difference between participants who passed and those who failed the comprehension check (see Appendix 3). Therefore, all participants that failed one or both CCs were eliminated from further analyses. The resulting sample-size comprised 272 participants (75.8% of the remaining sample).

Lastly, 8 participants (2.9% of 272 participants) were furthermore not included in the final sample since their z-scores' absolute value exceeded 3.5, so they were detected as univariate outliers (Berendrecht et al., 2022).

Therefore, the final sample encompassed a total of 264 participants, 45.8% (n=121) males, 53.4% (n=141) females, and 0.8% (n=2) preferred not to indicate their gender. The participants' age ranged from 18 to 73 years, with a mean age of $M = 33.54, SD = 11.53$. Furthermore, one third of the participants were from South Africa (n= 88; 33.3%), around one third were from the UK and Northern Ireland (n= 87; 33%) and the remaining 33.7% (n=89)

were from all over the world. The majority were employed (n=171; 64.8%) and held a bachelor's degree (48.1%). For detailed demographics see Appendix 4.

Also, the majority of participants (56.8%) indicated to be extremely familiar with online shopping. When asked about their familiarity with AI, most participants indicated to be very familiar with it (43.6%; see Appendix 4).

The total of the uncleaned sample (372 participants) were equally and randomly divided across four groups, but since 108 participants (29%) were excluded from the initial sample, the final sample did not show perfectly equal sample sizes (see Appendix 2).

Nevertheless, literature suggests at least 260 valid responses for a 2x2 design, which got accomplished (Durlak, 2009). Even though the target size of 65 participants per group was not reached for all groups (Durlak, 2009), the final number was close and the minimum sample size of 30 participants per cell for a comparison of groups suggested by Van Voorhis and Morgan (2007) was exceeded.

3.4 Measurement of variables

3.4.1 Covariates

Familiarity with Online Shopping: An extensive body of past literature, like Park and Stoel (2005), Weisberg and collaborators (2011), or Yoh and collaborators (2003), identified familiarity and past experience with online shopping and the internet as having an impact on purchase intent/ willingness to buy of consumers. While these research papers assessed this familiarity with a dichotomous (Yes/No) question, I figured that using a 5-point-Likert scale would result in greater insights (1= *Not familiar at all; 5= Extremely familiar)*.

Familiarity/Understanding with AI and other advanced technologies: Also, past research found the level of AI understanding to be a significant determinant of trust in AI-related technologies (Kang & Lou, 2022). To include this in the survey while ensuring consistency, a 5-point-Likert scale was also used to assess the participants understanding of AI (1= *Not familiar at all; 5= Extremely familiar).*

To avoid the possibility of a systematic bias resulting from the condition one has been assigned to, I purposely placed these two covariate questions at the beginning of the survey before exposure to the marketing message.

3.4.2 Main Variables

Independent Variable - *Source of recommendation:* In this study, the source of recommendation (either AI or Human) displays the independent variable. In the survey, this variable was manipulated by exposing the participant to a marketing message including recommendations either by AI-stylist Laura or the human stylist Laura. To keep conditions comparable, the text of this message stayed the same.

Moderator - *Algorithm transparency:* As seen in previous literature, process transparency can have an influence on individuals trust (e.g., Canal et al., 2020; Li et al., 2020). To explore the moderating effect of actual algorithm transparency in this study, the moderator was manipulated by exposing the participants to two different versions of the marketing message, one with an explanation about how the recommendations were put together and one without. To measure the participants' perceived transparency, adapted items from Yang and Battocchio's (2020) study on the effects of transparent brand communication on perceived brand authenticity and consumer responses were used. These items were framed as statements participants had to indicate their agreement with (e.g., "*The brand NARALÉ is transparent in its recommendation process disclosure";* 1 = *Strongly disagree*; 7 = *Strongly agree*).

Dependent Variable - *Willingness to buy:* After the exposure of the marketing message, measuring the impact on the dependent variables was of high interest. Past research identified the source of recommendation as well as trust in the recommender as a factor that influences individuals' willingness to buy (e.g., Castelo et al., 2019; Larkin et al., 2021; Li et al. 2020). To measure this impact in this study the questions on willingness to buy by Barber et al. (2012) were used while slightly adapted accordingly. Participants were shown statements, like "*I would consider purchasing one of the jackets*" where they were asked to indicate their agreement on a 7-point Likert scale (1 = *Strongly disagree*; 7 = *Strongly agree*).

Mediator - *Trust in source*: Lastly, the mediator, trust in source, which has been identified as a key factor influencing willingness to buy before (e.g., Chen & Teng; 2013), was measured following the 7-point bipolar scales of Ohanian (1990). For instance, participants were asked to indicate their feelings of honesty (*Dishonest – Honest*).

4. Data Analysis and Results

The following section describes how the study's data were analysed and the proposed hypotheses tested. Furthermore, it also presents the results.

4.1 Scale Reliability

As described in the previous section, the final sample after cleaning encompassed 264 participants. Even though the scales used to measure anticipated willingness to buy, transparency, and trust were used and validated in literature before (Barber et al., 2012; Ohanian, 1990; Yang & Battocchio, 2020), scale reliability tests were conducted to verify reliability in this analysis.

To measure if the items of each scale were related and therefore reliable, Cronbach's alpha was calculated for each of the three scales. The calculation for the anticipated WTB scale showed a value of $\alpha = .91$, for the transparency scale $\alpha = .94$, and for the trust scale $\alpha = .93$ (see Appendix 5). Therefore, all three scales presented excellent internal consistency (George & Mallery, 2003). For the upcoming analyses, the items within each of the three scales were combined by calculating the mean for that specific scale.

4.2 Manipulation Checks

To check if the manipulation worked as intended, three tests were conducted regarding the full sample (*n=372)*. First a Chi-square test regarding the actual source (AI vs human) and the self-reported source revealed significant test results ($p < .001$). With just a few participants getting the source wrong (*n=19*, 5.1% of the total sample), the results showed the manipulation of the recommendation source to be successful. Regarding the manipulation of transparency, another Chi-square test was conducted. Results showed this manipulation to be successful as well ($p < .001$). However, the number of participants that wrongly recognized transparency was especially high for the "no transparency" condition (*n=73*, 19.6% of the total sample). Lastly, to check if the manipulation also worked for perceived transparency, an independent samples t-test got conducted. Results showed a significant difference in means between the "no transparency" and "transparency" condition ($p = .017$), indicating that the manipulation worked here as well. For more details, please refer to Appendix 6.

Even though, as stated in the methodology section, participants that did not successfully identify the recommendation source and/or the recommendation explanation were eliminated from the

dataset during the data cleaning process, the results of these tests suggested that all in all, this study's manipulation worked.

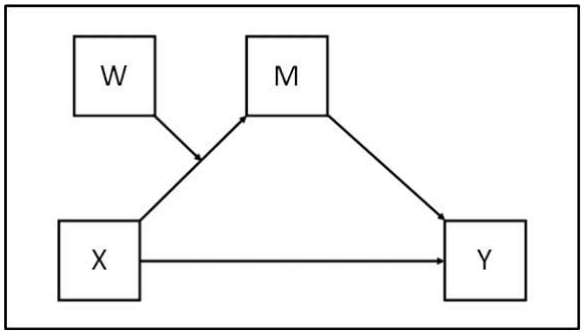
4.3 Hypotheses Testing

4.3.1 Actual Transparency Variable

To test for the four hypotheses, Hayes' *PROCESS* macro for SPSS was used to statistically analyse the conceptual model. By using a bootstrapping approach, the *PROCESS* macro employs regression-path analysis to uncover moderated mediation effects by estimating regression coefficients (Hayes, 2018). Since this study is aimed at investigating the moderated mediation effect, whether the mediation effect of an independent variable (X) on a dependent variable (Y) through a mediator (M) is influenced by a moderator (W*), PROCESS* Model 7 was the appropriate model for this analysis (see Figure 4).

Figure 4

PROCESS Model 7 (Hayes, 2018)



Since this model is fundamentally based on regression analysis, it was crucial to ensure that the regression assumptions, which include linearity, homoscedasticity, independence of errors, normality of errors, and no multicollinearity, were met before running the process macro.

To test for linearity and homoscedasticity, a visual inspection of scatterplots and residual plots was conducted. Results showed the linearity and homoscedasticity to be met (see Appendix 7). To check for independence of errors, a Durbin-Watson test was conducted. Results also showed this assumption to be fulfilled by yielding a value close to 2, which suggested that the residuals were independent and there was no significant autocorrelation issue in the model (see Appendix 7). Lastly, the no multicollinearity assumption was tested by examining the Variance Inflation

Factor (VIF) and tolerance values. Results showed them to be within acceptable limits, indicating multicollinearity to not be a concern in this model (see Appendix 7).

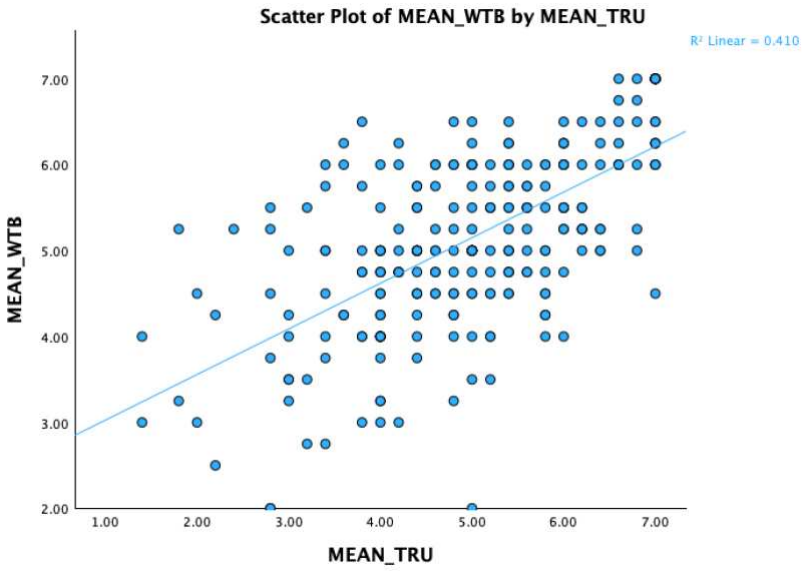
Since all necessary regression assumptions were met, hypotheses testing using the PROCESS Model 7 was conducted. While applying the macro a 5%-significance-level was chosen. In addition, the number of bootstrap samples yielded 5,000.

When testing for H1, the analysis revealed that the direct effect of the recommendation source on anticipated willingness to buy was negative but not statistically significant ($t(259) = -0.48$, $b = -0.05$, $p = .629$), even though the model explained 45.35% of the variance in willingness to buy ($R^2 = .4535$, $F(4, 259) = 53.74$, $p < .001$). This indicates that the type of recommendation source (human vs AI) did not lead to a significant difference in the participants' anticipated willingness to buy. Therefore, H1 was not supported by the data. When testing for H2a, the data also did not support this hypothesis: although the effect of the recommendation source on trust was negative, this effect was not statistically significant ($t(258) = -1.62$, $b = -0.29$, $p = .106$). Therefore, there was no significant proof that a recommendation generated by AI reduced trust compared to a recommendation provided by a human. H2a was therefore not supported.

H2b, which hypothesized that higher trust in the recommendation source would be positively associated with greater willingness to buy, was confirmed by the findings: trust in the recommendation source was positively and significantly associated with anticipated willingness to buy ($t(259) = 12.04$, $b = 0.48$, $p < .001$). In addition, the model explained 45.35% of the variance in anticipated willingness to buy ($R^2 = 0.4535$, $F(4, 259) = 53.7366$, $p < .001$), demonstrating that higher levels of trust in the source significantly increased participants' anticipated willingness to buy (see Figure 5).

Figure 5

Relationship between Trust (TRU) and Willingness to Buy (WTB)



Moving on to H3, it was hypothesized that algorithm transparency would moderate the relationship between the recommendation source (human vs. AI) and trust in the recommendation source, such that more transparency about the recommendation process would positively impact trust. In fact, this hypothesis was not supported by the findings: the interaction between recommendation source and transparency on trust was not statistically significant ($t(258) = 0.54$, $b = 0.16$, $p = .591$). Therefore, transparency did not significantly moderate the relationship between the recommendation source and trust.

When examining whether the indirect effect of the recommendation source on anticipated willingness to buy through trust was moderated by transparency, the analysis revealed the effects to be not significant at any level of transparency (transparency = 0; 95% CI [-.30, .01] and transparency = 1; 95% CI [-.32, .17]). The index of moderated mediation was also not significant ($b = 0.08$, BootSE = 0.15, BootLLCI = -0.22, BootULCI = 0.37). Therefore, the findings suggested that transparency did not significantly influence the relationship between the recommendation source and trust, nor did it alter the impact of trust on anticipated willingness to buy.

Lastly, when looking at the covariates, familiarity with AI had a significant positive effect on both trust and anticipated willingness to buy. Specifically, a higher familiarity with AI was associated with greater trust in the source of recommendation ($t(258) = 4.27$, $b = 0.35$, $p < .001$)

and increased anticipated willingness to buy ($t(259) = 4.53$, $b = 0.27$, $p < .001$). When furthermore investigating the difference between AI and human recommendations in terms of how trust was affected by AI familiarity, no significant interaction effect was found ($t(258) = 0.54$, $b = 0.16$, $p = .591$). Therefore, there was no statistically significant difference between those two.

Also, familiarity with online shopping did not have significant effects on either trust ($t(258) = 1.11$, $b = 0.15$, $p = .268$) or anticipated willingness to buy ($t(259) = -1.68$, $b = -0.16$, $p = .094$).

4.3.2 Perceived Transparency Variable

In terms of H3, it was necessary to investigate if the results of the perceived transparency vary significantly from the results of a categorical manipulation of transparency. To test that, the same procedure reported previously was applied: first, linearity, homoscedasticity, independence of errors, normality of errors, and no multicollinearity were assured to be met. Since multicollinearity issues in the initial regression model for perceived transparency were identified, the transparency variable was centred by subtracting its mean from each observed value. The interaction term (centred transparency * recommendation source) was redone, and the regression analysis was then rerun, yielding a resolution of the multicollinearity issue (for details, see Appendix 9).

Then the process macro got executed again. The results also showed no significant interaction between recommendation source and transparency on trust ($t(258) = -1.4284$, $b = -0.1601$, $p = 0.1544$). Therefore, the hypothesis that algorithm transparency would moderate the relationship between the recommendation source (human vs. AI) and trust in the recommendation source was not supported again.

When investigating whether the indirect effect of the recommendation source on anticipated willingness to buy through trust was moderated by transparency, findings showed the effects only to be significant at medium (CMEA_TRA = 0.27; 95% CI [-.27, -.03]) and high levels of transparency (CMEA_TRA = 1.27; 95% CI [-.42, -.02]). However, the index of moderated mediation was not significant ($b = -0.08$, BootSE = 0.06, BootLLCI = -0.2, BootULCI = 0.05). Therefore, the findings suggested that while transparency did influence the indirect effect at certain levels, it did not significantly moderate the overall relationship between the recommendation source and trust, nor did it alter the impact of trust on anticipated willingness to buy.

Additionally, investigating the other hypotheses (H1, H2a, and H2b) and covariates, results showed the same outcome for H1 (not corroborated), H2b (corroborated), and the covariates, but not for H2a. In fact, the analysis showed that the recommendation source had a significant effect on trust, with AI recommendations leading to lower trust levels than human recommendations ($t(258) = -2.14$, $b = -0.26$, $p = 0.033$). For greater detail, refer to Appendices 7 and 9.

A more thorough investigation of these differences and the results in general will be provided in the following section.

5. Discussion

This section interprets this study's findings and investigates how they relate to existing literature. Furthermore, this section explores the implications of these results and identifies limitations and areas for future research.

5.1 Research Findings

This study focused on examining the impact of the recommendation source (human vs. AI) on the anticipated willingness to buy, the mediating role of trust, and the moderating influence of transparency in recommendations. In this realm, four different hypotheses were set.

H1 hypothesized that the anticipated willingness to buy would be higher for individuals receiving a human-generated recommendation than for those receiving an AI-generated recommendation, but it was not supported. The recommendation source was therefore not seen to have significant influence on anticipated willingness to buy. This finding diverges from much of the existing literature since past research, like Wien and Peluso (2021), generally found customers to rather listen to human product recommendations than to those from AI, which was also found in the specific context of online clothing recommendations (Li et al., 2020). The divergence from this study's results could therefore stem from the specific context of this study, since jackets were used in the experiment which can be of hedonic or utilitarian nature (Kim & Hong, 2011; Longoni & Cian, 2022). Perhaps, it is because the distinction may not be as clear-cut, that no significant difference between AI and human recommendations could have been found here. Therefore, this finding highlights the importance of context in that realm. Furthermore, this study found that the more familiar the participants were with AI the higher their anticipated willingness to purchase was. This could indicate that with nowadays high

levels of familiarity with AI, as most participants indicated to be very familiar with AI (43.6%), might be narrowing the gap between the effectiveness of human and AI recommenders.

H2a addressed the varying levels of trust based on the recommendation source, proposing that AI recommenders would lead to lower trust in the recommendation source compared to human recommenders. The results did also not support the hypothesis. These findings also differ from most of the existing literature in an online shopping context, since past studies found that human experts were generally perceived as more trustworthy than AI systems (Li et al., 2020; Senecal & Nantel, 2004). However, when examining perceived transparency, this study's results align with past research and support the hypothesis H2a.

This finding highlights the importance of understanding the difference between perceived transparency and actual transparency, since the way transparency got manipulated in this study did not directly result in perceived transparency. Therefore, when looking at past research that measured transparency and found it to positively influence trust in AI (e.g., Canal et al., 2020; Li et al., 2021), this study's results suggest that research like this needs to be carefully assessed, as it may not be transparency itself but rather perceived transparency yielding these results. Studies that found perceived transparency to positively influence trust, like Panganiban and collaborators (2019) and Yu and Li (2022), therefore are in line with the results of this study, also underlining the importance of understanding that how transparency is communicated may matter more than the transparency itself. This is not a phenomenon tied to the concept of transparency alone, in consumer behavior perception often drives decisions more than objective facts (Jelena & Kristina, 2011).

Next, H2b was supported by the study's findings: higher trust in the recommendation source was positively associated with greater anticipated willingness to buy. This also supports previous findings by researchers like Hsiao and collaborators (2010) and furthermore highlights the critical role of trust in consumer decision-making: higher trust in the recommendation source, regardless if it comes from AI or humans, leads to a greater willingness to buy. This means that building trust with consumers is crucial for influencing their purchasing behavior. Therefore, this insight adds to the existing literature on trust in marketing and consumer behavior, particularly in the context of digital and AI-driven environments.

Regarding H3, actual algorithm transparency was not found to significantly moderate the relationship between the recommendation source (human vs. AI) and trust in the recommendation source. No support was found for the idea that more actual transparency about

the recommendation process positively impacts trust in the recommendation source. This is in contrast to previous literature on that topic: Canal and collaborators (2020), Li and collaborators (2021) or Panganiban and collaborators (2019) all found transparency to positively influence trust in AI. This divergence could be explained by different ways of how transparency was communicated or different levels of transparency used by the studies. Also, participants could not have fully understood the algorithm explanation. Interestingly, when analysing the study using perceived transparency, significant indirect effects at medium and high levels of perceived transparency were identified. This indicates, in line with past research, that transparency is of significant value in that context. Additionally, it once again highlights the importance of acknowledging the difference between perceived transparency and actual transparency, adding to the body of existing literature on transparency and trust in the context of digital and AI-driven environments.

Additional findings showed that the more familiar the participants were with AI the higher their trust in the recommendation source was. These results are consistent with the results found by Berger and collaborators (2020), which suggested that increasing familiarity with AI can counteract algorithm aversion, allowing users to trust AI systems more than familiar human advisors. Likewise, Oksanen and collaborators (2020) found that technology exposure and technology education reinforce trust in AI, supporting this study's results.
In contrast, for familiarity with online shopping no significant interaction was found. This diverges from past researches' findings, such as Chen and Barnes (2007) and Stouthuysen and collaborators (2018), who found that familiarity with online shopping actually fosters initial trust in online recommendations.

5.2 Academic Implications

The goal of this study is to add to the body of academic research in the area of human decision-making, in particular the impact of AI on human decision-making processes, focused on transparency and the online fashion industry. The results suggest four prevalent academic implications:

The first academic implication deals with the contextual influence on AI and human recommendations. Even though some research already acknowledges the impact of context in recommendation effectiveness (e.g., Longoni & Cian, 2022), this study further highlights its critical role in AI recommendation effectiveness. Hereby, the study challenges the generalized

assumptions of previous studies that customers would rather listen to human product recommendations than to those from AI.

The second academic implication deals with the impact of AI familiarity on consumer behavior. As this study's findings suggest, increased familiarity with AI correlates with higher trust and anticipated willingness to buy. This highlights the importance of AI familiarity in the existing and future body of literature in the context of AI and purchase decisions, shifting the focus from more well-known influencing factors like trust (e.g., Li et al., 2020) to less researched factors like prior held attitudes. Given the ongoing change in familiarity with AI, particularly nowadays, future research should generally prioritise the incorporation of AI familiarity as an important influencing factor on consumer behaviour, particularly considering that this factor is constantly evolving.

Another academic implication of this study deals with the importance of a distinction between perceived versus actual transparency. Even though this is not the main focus of this study, the present results highlight the need for a distinction between perceived and actual transparency and should be acknowledged in the academic realm since they lead to different insights. For instance, Cruijsen and Eijffinger (2010) investigated the discrepancy between perceived and actual transparency in the context of the European Central Bank, finding this discrepancy not just stem from poor transparency knowledge but also from individual and psychological characteristics. Similarly, Licht (2014) examined the difference of public perceptions of decision-making transparency and actual transparency in the political context. This study's findings suggested perceived transparency to have a more significant impact on decision acceptance than actual transparency. So as demonstrated, research acknowledging the difference between actual and perceived transparency has been conducted in other contexts. However, research of this nature in the field of AI recommendations has yet to be conducted.

Lastly, the findings of this study underline the importance of continuing to focus on trust as a mediator in decision-making processes, in the sphere of AI as well as human recommendations. Past research in that area already acknowledged this importance by including trust into their research (e.g., Hsiao et al., 2010), but this study furthermore highlights the foundational quality of trust in the area of purchase intent and recommendations.

5.3 Managerial Implications

The findings of this study have four managerial implications, which provide information on the practical application of this knowledge.

First, managers need to understand the importance of tailoring recommendations specifically to the context of the products they advertise. The effectiveness of AI recommendations varies from context to context and displays no uniformity. Especially in the context of online clothing, like this study, the decision to use AI or human recommendations is not as straightforward, which might be due to the fact that clothing holds hedonic but also utilitarian attributes (Choo et al., 2012). Managers must therefore carefully consider if they want to apply AI, humans, or a combination of both in marketing, considering the good they are marketing carefully.

Next, managers should prioritize increasing customer familiarity with AI, since this study found that a higher AI familiarity leads to more trust and a higher anticipated willingness to buy. Companies could do that by fostering hands-on experience with AI for customers. For the online fashion industry in particular, this could be implemented by providing services like virtual stylists or chatbots (Horowitz et al., 2023). Practices like this foster AI familiarity, leading over time to trust in the recommendation source and a higher willingness to buy.

In addition, managers should focus on communicating transparency effectively, due to the fact that this study's findings suggest there to be a difference between actual and perceived transparency. Since medium and high levels of perceived transparency increase trust in AI and therefore increase willingness to buy, managers should make sure that consumers are not just exposed to transparency but moreover understand and perceive it. To do that, managers could for instance make use of visual aids or interactive features (Gatto et al., 2022). This way, perceived transparency increases, which in turn increases trust levels which then increases consumers' willingness to buy.

Finally, managers should prioritize building trust with their customers. When customers trust the recommendation source, this positively influences their anticipated willingness to buy. To do so, managers must ensure to provide customers relevant recommendations adjusted to their wants and needs, especially in the online clothing industry (Panniello et al., 2016). Furthermore, they should ensure data security and additionally act upon customer feedback (Bao et al., 2016; Martin et al., 2017). This way, companies can build trusting relationships with their customers, positively influencing purchase intent.

5.4 Limitations and Future Research

The previous parts of this paper provide several insights. Still, those are subject to limitations that must be acknowledged in this context.

Starting with limitations arising from this study's sample representativeness and generalizability, participants were recruited via the online survey platform Prolific, which may have introduced bias, as these participants are likely to be more tech-savvy than the general population. Furthermore, most participants were either from the UK or from South Africa, also limiting the generalizability geographically. In terms of sample size, the unequal distribution of participants across experimental groups could have also influenced the robustness of this study's findings. Therefore, future studies should try to improve the external validity of these findings by using a more generalizable sample and furthermore applying more balanced group sizes.

Also, the setting of the experiment was artificial, meaning that in real-world situations much more factors influence customers' decision-making than in this study. For example, brand loyalty, the general context the customer is in, or the personal connection a customer has to a specific brand could impact customer trust or willingness to buy. Interestingly, a majority of participants found it somewhat easy (48.5%) or extremely easy (41.3%) to imagine themselves in the scenario (see Appendix 4). However, some participants might have answered differently if they had seen actual jackets instead of just imagining them being presented by the recommendation source. For instance, one participant commented, "*It's hard to know If I would/wouldn't purchase a jacket based on the recommendations without actually seeing the suggestions!"* (see Appendix 11 g). Therefore, future research should try to conduct studies that replicate naturalistic settings even better or even conduct studies that observe consumers' actual behavior.

Furthermore, the scope of this study was quite limited to the online fashion industry, and jackets in particular. Since the study only focused on one experimental setting, its findings are therefore not suitable to apply to other contexts. Therefore, future studies should focus on exploring AI's recommendation impact for other product categories and other contexts.

All these suggestions aim at improving the understanding of the role of AI in consumer decision-making within the online fashion industry and beyond.

6. Conclusion

Investigating ways to influence consumers' decision processes has been relevant to research for quite some time now. In the last couple of years, the focus on AI in that particular context gained more and more relevance, especially in the online fashion industry. The findings of this study reveal that there is no one-fits-all approach to shaping customers' purchase decisions. Context likely plays a crucial role, as well as the differentiation between actual and perceived transparency, leaving much room for future research diving deeper into this topic.

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Appendix

Appendix 1: Survey

Start of Block: Consent Form

Q1 Welcome and thank you for considering participating in this experiment. I, Freya Tilly am conducting this experiment as part of my Master Thesis at Católica Lisbon School of Business and Economics, under the supervision of Filipa de Almeida.

The study consists of answering multiple questions related to a marketing E-mail you will get exposed to. And it will take about 4 minutes to complete. The purpose is to gain insight into the way individuals perceive advice in different scenarios. Potential side effects are similar to those applicable to looking at a computer screen for circa 4 minutes, for instance, fatigue. In the end, you will learn more about scientific research.

Please answer as honestly as possible.

Data will be treated according to the RGPD, all responses will be kept strictly confidentially and are anonymous. This means that it will not be possible to link your responses to your identity. The data collected will be used for research purposes only and may be presented in my thesis or disseminated in academic journals, always in an aggregated form, never about any individual response.

We ask you to take the study in one go, without interruptions.

There are no expected side effects of participating in this study beyond those associated with looking at a computer screen for circa 4 minutes.

You may change your mind and drop out at any point of the study during its completion.

If you have any questions about this study, please email me, Freya Tilly (s-ftilly@ucp.pt). You may also contact filipadealmeida@ucp.pt.

Please click "I agree", if you consent to participate in this study.

Thank you!

- ○ I agree (1)
- ○ I don't agree (2)

End of Block: Consent Form

Start of Block: Prolific ID

Q3 What is your Prolific ID?
Please note that this response should auto-fill with the correct ID

_____

End of Block: Prolific ID

Start of Block: Covariate Questions

Q6 How familiar are you with Online Shopping?

- Not familiar at all (1)
- Slightly familiar (2)
- Moderately familiar (3)
- Very familiar (4)
- Extremely familiar (5)

Q7 How familiar are you with AI and other advanced technologies?

- Not familiar at all (1)
- Slightly familiar (2)
- Moderately familiar (3)
- Very familiar (4)
- Extremely familiar (5)

End of Block: Covariate Questions

Start of Block: E-Mail Exposure

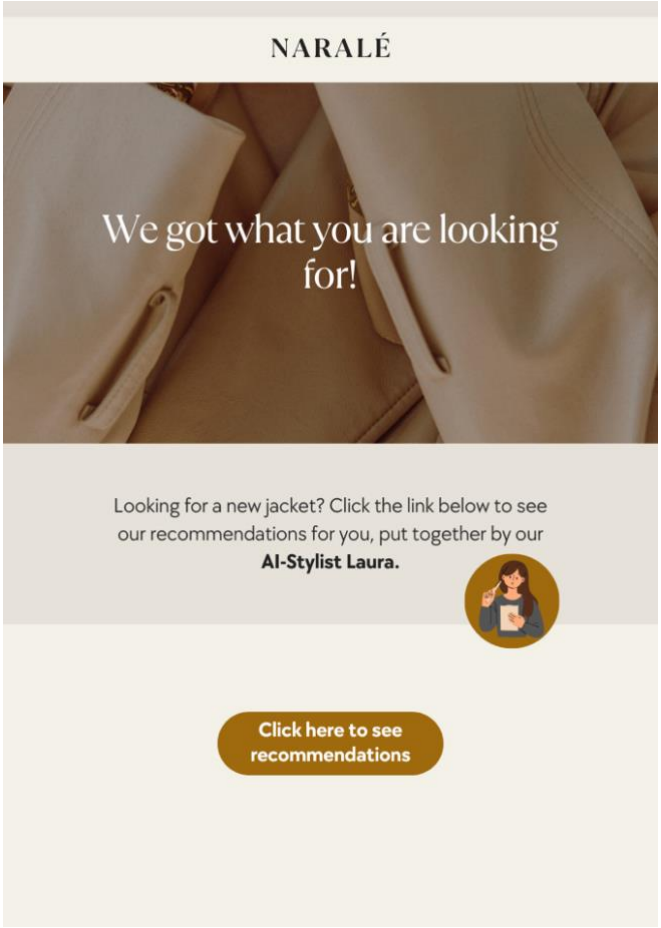
Q8 In this part, you will be presented with a scenario and subsequently will get asked multiple questions about your perceptions and opinions on that.
Please click “>” when you are ready.

End of Block: E-Mail Exposure

Start of Block: AI x No Explanation

Q9 Imagine yourself in the following situation: You are currently in the need of a new jacket. Therefore, you have been browsing the internet for the last couple of days.

Today you checked your E-Mail Inbox and stumbled across the following marketing E-Mail by the fashion brand “NARALÉ”:



Q44 To make sure, you understood the marketing message correctly, please indicate who provided you with the recommendation.

- ○ A human (depicted by a photograph of a woman) (1)
- ○ An AI (depicted by a cartoon drawing) (2)

Q45 To make sure, you understood the marketing message correctly, please indicate if you received an explanation on how the jackets were selected.
*This is **not** equal to a simple explanation of AI.*

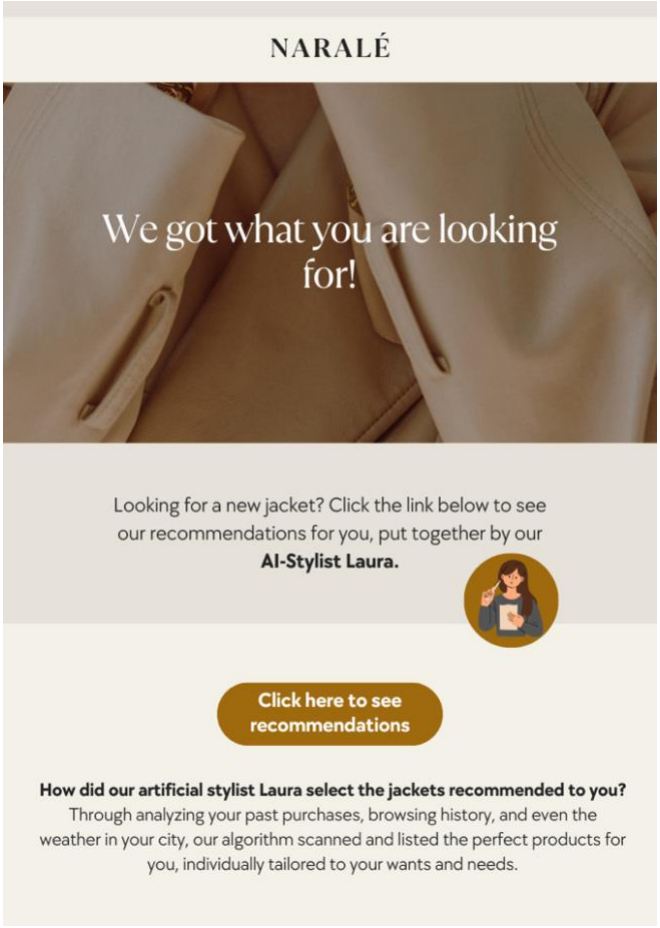
- ○ Yes, I received an explanation of the selection process. (1)
- ○ No, I did not receive an explanation of the selection process. (2)

End of Block: AI x No Explanation

Start of Block: AI x Explanation

Q11 Imagine yourself in the following situation: You are currently in the need of a new jacket. Therefore, you have been browsing the internet for the last couple of days.

Today you checked your E-Mail Inbox and stumbled across the following Marketing E-Mail by the fashion brand “NARALÉ”:



Q46 To make sure, you understood the marketing message correctly, please indicate who provided you with the recommendation.

- ○ A human (depicted by a photograph of a woman) (1)
- ○ An AI (depicted by a cartoon drawing) (2)

Q47 To make sure, you understood the marketing message correctly, please indicate if you received an explanation on how the jackets were selected.
*This is **not** equal to a simple explanation of AI.*

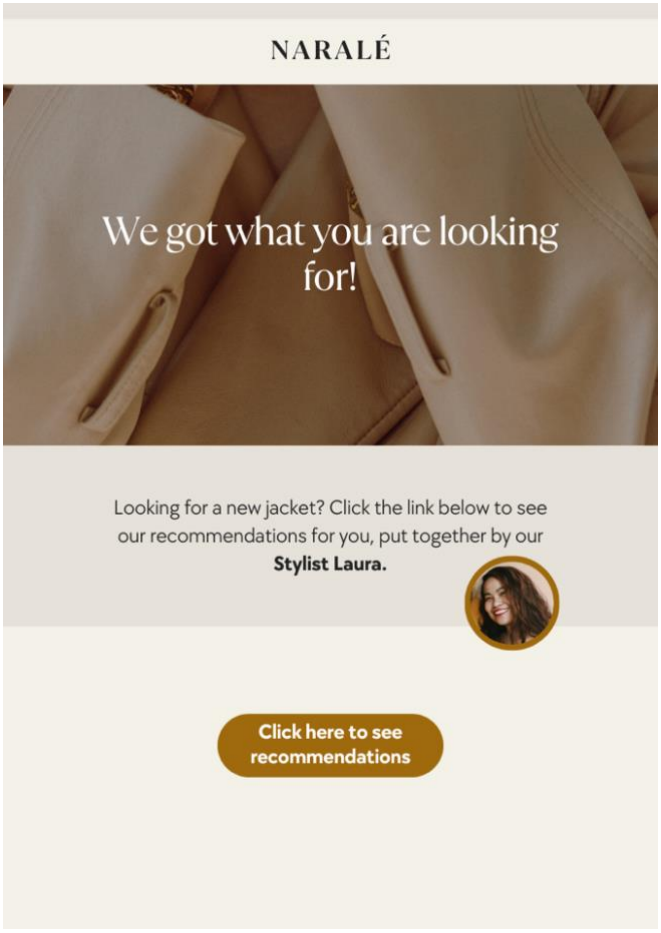
- ○ Yes, I received an explanation of the selection process. (1)
- ○ No, I did not receive an explanation of the selection process. (2)

End of Block: AI x Explanation

Start of Block: Human x No Explanation

Q12 Imagine yourself in the following situation: You are currently in the need of a new jacket. Therefore, you have been browsing the internet for the last couple of days.

Today you checked your E-Mail Inbox and stumbled across the following Marketing E-Mail by the fashion brand “NARALÉ”:



Q48 To make sure, you understood the marketing message correctly, please indicate who provided you with the recommendation.

- ○ A human (depicted by a photograph of a woman) (1)
- ○ An AI (depicted by a cartoon drawing) (2)

Q49 To make sure, you understood the marketing message correctly, please indicate if you received an explanation on how the jackets were selected.
*This is **not** equal to a simple explanation of AI.*

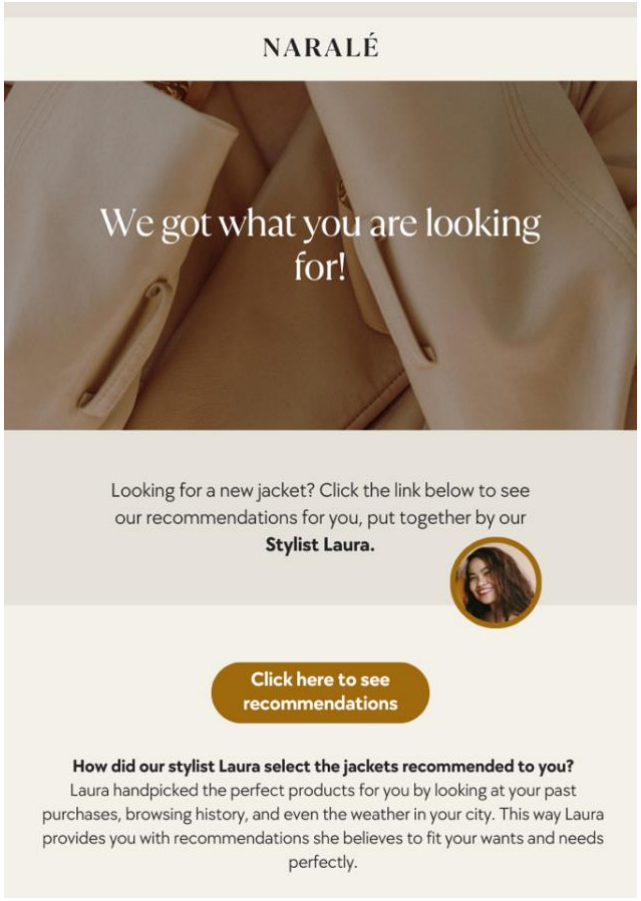
- ○ Yes, I received an explanation of the selection process. (1)
- ○ No, I did not receive an explanation of the selection process. (2)

End of Block: Human x No Explanation

Start of Block: Human x Explanation

Q13 Imagine yourself in the following situation: You are currently in the need of a new jacket. Therefore, you have been browsing the internet for the last couple of days.

Today you checked your E-Mail Inbox and stumbled across the following Marketing E-Mail by the fashion brand “NARALÉ”:



Q50 To make sure, you understood the marketing message correctly, please indicate who provided you with the recommendation.

- ○ A human (depicted by a photograph of a woman) (1)
- ○ An AI (depicted by a cartoon drawing) (2)

Q51 To make sure, you understood the marketing message correctly, please indicate if you received an explanation on how the jackets were selected.
*This is **not** equal to a simple explanation of AI.*

- ○ Yes, I received an explanation of the selection process. (1)
- ○ No, I did not receive an explanation of the selection process. (2)

End of Block: Human x Explanation

Start of Block: Instructions

Q43 Now that you have seen the previous marketing message, please imagine that you would click on the "Click here to see recommendations" button. The following page would show you a selection of 15 different jackets. With that in mind, please answer the following questions.

End of Block: Instructions

Start of Block: Anticipated Willingness to Buy

Q21 Please indicate how much you think you would agree/ disagree with the following statements once you have seen the recommended jackets.

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
“I would consider purchasing one of the jackets” (1)	○	○	○	○	○	○	○
“I would intend to try one of the jackets” (2)	○	○	○	○	○	○	○
"I would plan on buying one of the jackets” (3)	○	○	○	○	○	○	○
“I would be interested in wearing one of the jackets” (4)	○	○	○	○	○	○	○

End of Block: Anticipated Willingness to Buy

Start of Block: Algorithm Explanation/ Transparency

Q25 Please indicate how much you think you would agree/ disagree with the following statements.

	Strongly Disagree (1)	Somewhat disagree (2)	Neither agree nor disagree (3)	Somewhat agree (4)	Strongly agree (5)
"The brand NARALÉ is transparent in its recommendation process disclosure" (1)	○	○	○	○	○
“The brand NARALÉ is candid in delivering information about its recommendation process” (2)	○	○	○	○	○
“The brand NARALÉ provides clear information about its recommendation process” (3)	○	○	○	○	○
“The brand NARALÉ is open in communicating its recommendation process” (4)	○	○	○	○	○
"Overall, the brand NARALÉ provides relevant information to ensure transparency of its recommendation process” (5)	○	○	○	○	○
To see if you are still paying attention, please check “Strongly Agree” (6)	○	○	○	○	○

End of Block: Algorithm Explanation/ Transparency

Start of Block: Trust in Source

Q26 On a scale of 1 to 7, please check the box that best reflects your feelings towards Laura's trustworthiness.

	1 (1)	2 (2)	3 (3)	4 (4)	5 (5)	6 (6)	7 (7)	
Undependable	○	○	○	○	○	○	○	Dependable
Dishonest	○	○	○	○	○	○	○	Honest
Unreliable	○	○	○	○	○	○	○	Reliable
Insincere	○	○	○	○	○	○	○	Sincere
Untrustworthy	○	○	○	○	○	○	○	Trustworthy

End of Block: Trust in Source

Start of Block: Ease of Imagination

Q29 Please indicate how easy it was for you to imagine yourself in the previous described scenario.

- ○ Extremely difficult (1)
- ○ Somewhat difficult (2)
- ○ Neither easy nor difficult (3)
- ○ Somewhat easy (4)
- ○ Extremely easy (5)

End of Block: Manipulation Check

Start of Block: Demographics

Q30 What is your gender?

- ○ Male (1)
- ○ Female (2)
- ○ Non-binary / third gender (3)
- ○ Prefer not to say (4)

Q31 How old are you?

_____

Country What country are you from?

▼ Drop down menu from Qualtrics

Q36 What is you highest level of education?

- ○ Less than Secondary education (1)
- ○ Secondary Education (2)
- ○ Bachelor's degree (3)
- ○ Master's degree (4)
- ○ Doctoral degree (5)
- ○ Other (Please specify) (6)

_____

Q37 What is your current employment status?

- ○ Employed (1)
- ○ Unemployed (2)
- ○ Self-employed (3)
- ○ Student (4)
- ○ Working Student (5)
- ○ Retired (6)
- ○ Other (Please Specify) (7)

_____

Q38 Do you have any comments or remarks you would like to share?
If no, leave blank.

_____

End of Block: Demographics

Start of Block: End of Survey Message

Q5 Thank you for your participation in this study. In this study I want to study how the source of recommendation (AI vs human) affects individuals' anticipated willingness to buy. In addition, I research the role of an explanation on how the recommendation got made here. For that, participants were randomly assigned to one of four different E-Mail messages. I did not disclose the full goal of the tasks you were exposed to as doing so would render the results of the current study not informative.

Please click the button below to be redirected back to Prolific and register your submission.

End of Block: End of Survey Message

Appendix 2: Sample Cleaning

Attention Check

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Pass	359	96.5	96.5	96.5
	Fail	13	3.5	3.5	100.0
	Total	372	100.0	100.0	

Comprehension Check

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Pass	272	75.8	75.8	75.8
	Fail	87	24.2	24.2	100.0
Total		359	100.0	100.0	

Experimental Group Sizes

		AixNoExplanation	AIxExplanation	Humanx NoExplanation	Humanx Explanation
N	Valid	92	89	88	90
	Missing	267	270	271	269

Experimental Group Sizes after Comprehension Check

	Cases					
	Valid		Missing		Total	
	N	Percent	N	Percent	N	Percent
AIxNoExplanation * CC Pass or Fail	48	13.4%	311	86.6%	359	100.0%
AIxExplanation * CC Pass or Fail	87	24.2%	272	75.8%	359	100.0%
HumanxNoExplanation * CC Pass or Fail	56	15.6%	303	84.4%	359	100.0%
HumanxExplanation * CC Pass or Fail	81	22.6%	278	77.4%	359	100.0%

Appendix 3: Independent Samples t-test: AI x No Explanation (passed vs failed CC)

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means							
						Significance				95% Confidence Interval of the Difference	
		F	Sig.	t	df	One-Sided p	Two-Sided p	Mean Difference	Std. Error Difference	Lower	Upper
MEAN_WTB	Equal variances assumed	1.617	.207	-2.004	84	.024	.048	-.54249	.27069	-1.08079	-.00419
	Equal variances not assumed			-1.940	67.060	.028	.057	-.54249	.27963	-1.10062	.01564

Descriptives

CC Pass or Fail				Statistic	Std. Error
MEAN_WTB	Pass	Mean		4.6615	.15569
		95% Confidence Interval for Mean	Lower Bound	4.3482	
			Upper Bound	4.9747	
		5% Trimmed Mean		4.6597	
		Median		4.7500	
		Variance		1.164	
		Std. Deviation		1.07867	
		Minimum		2.00	
		Maximum		7.00	
		Range		5.00	
		Interquartile Range		1.25	
		Skewness		-.137	.343
		Kurtosis		.030	.674
	Fail	Mean		5.2039	.23228
		95% Confidence Interval for Mean	Lower Bound	4.7333	
			Upper Bound	5.6746	
		5% Trimmed Mean		5.3114	
		Median		5.5000	
		Variance		2.050	
		Std. Deviation		1.43185	
		Minimum		1.00	
		Maximum		7.00	
		Range		6.00	
		Interquartile Range		1.75	
		Skewness		-1.286	.383
		Kurtosis		1.447	.750

Comment: The tables above suggest a significant difference between the "Pass" and the "Fail" group, in terms of their WTB (t(84) = -2.00, p = .048, 95% CI [-1.08, -0.00]). With the mean of the "Fail" group (M = 5.20, SD = 1.43) being higher than the mean of the "Pass" group (M = 4.66, SD = 1.079).

Appendix 4: Sample Statistics

Gender

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Male	121	45.8	45.8	45.8
	Female	141	53.4	53.4	99.2
	Prefer not to say	2	.8	.8	100.0
	Total	264	100.0	100.0	

Age

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	18	3	1.1	1.1	1.1
	19	5	1.9	1.9	3.0
	20	7	2.7	2.7	5.7
	21	7	2.7	2.7	8.3
	22	11	4.2	4.2	12.5
	23	18	6.8	6.8	19.3
	24	10	3.8	3.8	23.1
	25	10	3.8	3.8	26.9
	26	10	3.8	3.8	30.7
	27	14	5.3	5.3	36.0
	28	9	3.4	3.4	39.4
	29	9	3.4	3.4	42.8
	30	12	4.5	4.5	47.3
	31	9	3.4	3.4	50.8
	32	12	4.5	4.5	55.3
	33	16	6.1	6.1	61.4
	34	7	2.7	2.7	64.0
	35	12	4.5	4.5	68.6
	36	5	1.9	1.9	70.5
	37	7	2.7	2.7	73.1
	38	3	1.1	1.1	74.2
	39	9	3.4	3.4	77.7
	40	8	3.0	3.0	80.7
	41	3	1.1	1.1	81.8
	42	4	1.5	1.5	83.3
	43	4	1.5	1.5	84.8
	44	2	.8	.8	85.6
	45	1	.4	.4	86.0
	46	2	.8	.8	86.7
	47	4	1.5	1.5	88.3
	48	2	.8	.8	89.0
	49	2	.8	.8	89.8
	51	2	.8	.8	90.5
	52	2	.8	.8	91.3
	54	2	.8	.8	92.0
	55	3	1.1	1.1	93.2
	57	2	.8	.8	93.9
	58	2	.8	.8	94.7
	59	1	.4	.4	95.1
	60	1	.4	.4	95.5
	61	1	.4	.4	95.8
	62	1	.4	.4	96.2
	63	4	1.5	1.5	97.7
	66	1	.4	.4	98.1
	67	1	.4	.4	98.5
	68	1	.4	.4	98.9
	70	1	.4	.4	99.2

Descriptive Statistics Age

	N	Minimum	Maximum	Mean	Std. Deviation
Age	264	18	73	33.54	11.528
Valid N (listwise)	264				

Country

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Australia	1	.4	.4	.4
	Austria	1	.4	.4	.8
	Brazil	1	.4	.4	1.1
	Canada	10	3.8	3.8	4.9
	Chile	1	.4	.4	5.3
	China	2	.8	.8	6.1
	Czech Republic	1	.4	.4	6.4
	Germany	2	.8	.8	7.2
	Greece	5	1.9	1.9	9.1
	Hungary	4	1.5	1.5	10.6
	India	2	.8	.8	11.4
	Ireland	3	1.1	1.1	12.5
	Israel	1	.4	.4	12.9
	Italy	1	.4	.4	13.3
	Japan	1	.4	.4	13.6
	Kenya	5	1.9	1.9	15.5
	Latvia	1	.4	.4	15.9
	Mexico	1	.4	.4	16.3
	Netherlands	1	.4	.4	16.7
	Nigeria	4	1.5	1.5	18.2
	Philippines	3	1.1	1.1	19.3
	Poland	8	3.0	3.0	22.3
	Portugal	8	3.0	3.0	25.4
	Slovenia	1	.4	.4	25.8
	South Africa	88	33.3	33.3	59.1
	Spain	3	1.1	1.1	60.2
	Sweden	1	.4	.4	60.6
	Switzerland	1	.4	.4	61.0
	United Kingdom of Great Britain and Northern Ireland	87	33.0	33.0	93.9
	United States of America	13	4.9	4.9	98.9
	Zimbabwe	3	1.1	1.1	100.0
	Total	264	100.0	100.0	

Employment Status

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Employed	171	64.8	64.8	64.8
	Unemployed	25	9.5	9.5	74.2
	Self-employed	28	10.6	10.6	84.8
	Student	17	6.4	6.4	91.3
	Working Student	11	4.2	4.2	95.5
	Retired	8	3.0	3.0	98.5
	Other (Please Specify)	4	1.5	1.5	100.0
	Total	264	100.0	100.0	

Employment Status - Text

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid		260	98.5	98.5	98.5
	Disabled	1	.4	.4	98.9
	Housewife	1	.4	.4	99.2
	Part-Time	1	.4	.4	99.6
	self employed	1	.4	.4	100.0
	Total	264	100.0	100.0	

Highest Level of Education

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Secondary Education	72	27.3	27.3	27.3
	Bachelor’s degree	127	48.1	48.1	75.4
	Master’s degree	48	18.2	18.2	93.6
	Doctoral degree	6	2.3	2.3	95.8
	Other (Please specify)	11	4.2	4.2	100.0
	Total	264	100.0	100.0	

Highest Level of Education - Text

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid		253	95.8	95.8	95.8
	Associates of Applied Science	1	.4	.4	96.2
	College	1	.4	.4	96.6
	College A Levels	1	.4	.4	97.0

	College certificate	1	.4	.4	97.3
	college certification	1	.4	.4	97.7
	Diploma	1	.4	.4	98.1
	High School diploma	1	.4	.4	98.5
	Higher Certificate	1	.4	.4	98.9
	PHD	1	.4	.4	99.2
	Post graduate	1	.4	.4	99.6
	some post-secondary	1	.4	.4	100.0
	Total	264	100.0	100.0	

Descriptive Statistics: Familiarity Online Shopping & AI

	N	Minimum	Maximum	Mean	Std. Deviation
Familiar Online Shopping	264	3	5	4.54	.557
Familiar AI	264	1	5	3.66	.914
Valid N (listwise)	264				

Familiarity Online Shopping

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Moderately familiar	8	3.0	3.0	3.0
	Very familiar	106	40.2	40.2	43.2
	Extremely familiar	150	56.8	56.8	100.0
	Total	264	100.0	100.0	

Familiarity AI

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Not familiar at all	3	1.1	1.1	1.1
	Slightly familiar	26	9.8	9.8	11.0
	Moderately familiar	75	28.4	28.4	39.4
	Very familiar	115	43.6	43.6	83.0
	Extremely familiar	45	17.0	17.0	100.0
	Total	264	100.0	100.0	

Ease to imagine Scenario

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Somewhat difficult	9	3.4	3.4	3.4
	Neither easy nor difficult	18	6.8	6.8	10.2
	Somewhat easy	128	48.5	48.5	58.7
	Extremely easy	109	41.3	41.3	100.0

Total	264	100.0	100.0	

Appendix 5: Scale Reliability

Anticipated WTB

Reliability Statistics

Cronbach's Alpha	N of Items
.912	4

Transparency

Reliability Statistics

Cronbach's Alpha	N of Items
.938	5

Trust

Reliability Statistics

Cronbach's Alpha	N of Items
.930	5

Comment: All three values for Cronbach's Alpha are above .9 which indicates an excellent reliability of the scales.

Appendix 6: Manipulation Check

REC_SOURCE * SR_SOURCE Crosstabulation

Count

		SR_SOURCE		
		Human	AI	Total
REC_SOURCE	Human	172	12	184
	AI	7	181	188
Total		179	193	372

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	300.071[a]	1	<.001		
Continuity Correction[b]	296.487	1	<.001		
Likelihood Ratio	366.650	1	<.001		
Fisher's Exact Test				<.001	<.001

Linear-by-Linear Association	299.264	1	<.001		
N of Valid Cases	372				

a. 0 cells (0.0%) have expected count less than 5. The minimum expected count is 88.54.
b. Computed only for a 2x2 table

REC_TRANSPARENCY * SR_TRANSPARENCY Crosstabulation

Count

		SR_TRANSPARENCY		
		Explanation	No Explanation	Total
REC_TRANSPARENCY	Explanation	180	5	185
	No Explanation	73	114	187
Total		253	119	372

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	145.087[a]	1	<.001		
Continuity Correction[b]	142.421	1	<.001		
Likelihood Ratio	170.183	1	<.001		
Fisher's Exact Test				<.001	<.001
Linear-by-Linear Association	144.697	1	<.001		
N of Valid Cases	372				

a. 0 cells (0.0%) have expected count less than 5. The minimum expected count is 59.18.
b. Computed only for a 2x2 table

Group Statistics

	REC_TRANSPARENCY	N	Mean	Std. Deviation	Std. Error Mean
PERC_TRANSPARENCY	Explanation	185	5.2011	1.25447	.09223
	No Explanation	187	4.8791	1.33961	.09796

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means							
						Significance		Mean	Std. Error	95% Confidence Interval of the Difference	
		F	Sig.	t	df	One-Sided p	Two-Sided p	Difference	Difference	Lower	Upper
PERC_TRANSPARENCY	Equal variances assumed	.781	.377	2.392	370	.009	.017	.32194	.13460	.05727	.58660
	Equal variances not assumed			2.393	368.892	.009	.017	.32194	.13455	.05736	.58651

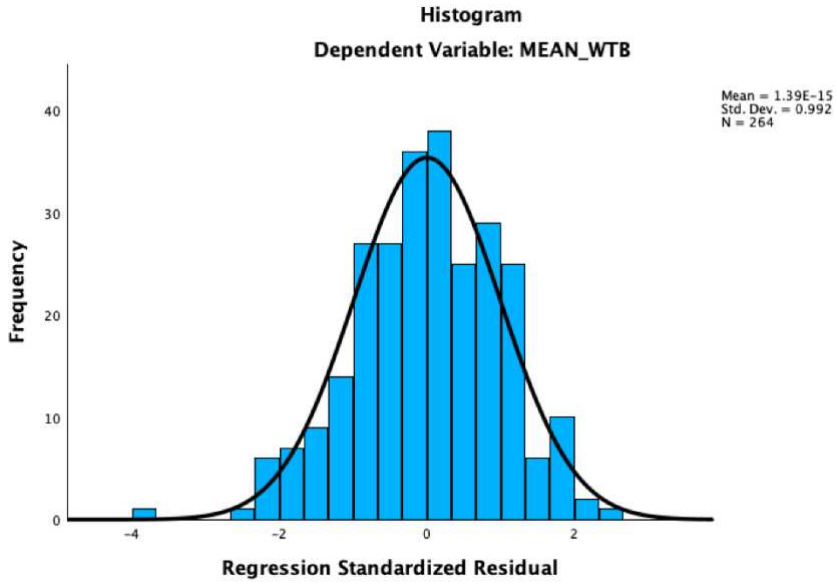
Independent Samples Effect Sizes

		Standardizer[a]	Point Estimate	95% Confidence Interval Lower	Upper
PERC_TRANSPARENCY	Cohen's d	1.29797	.248	.044	.452
	Hedges' correction	1.30061	.248	.044	.451
	Glass's delta	1.33961	.240	.035	.445

a. The denominator used in estimating the effect sizes.
Cohen's d uses the pooled standard deviation.
Hedges' correction uses the pooled standard deviation, plus a correction factor.
Glass's delta uses the sample standard deviation of the control (i.e., the second) group.

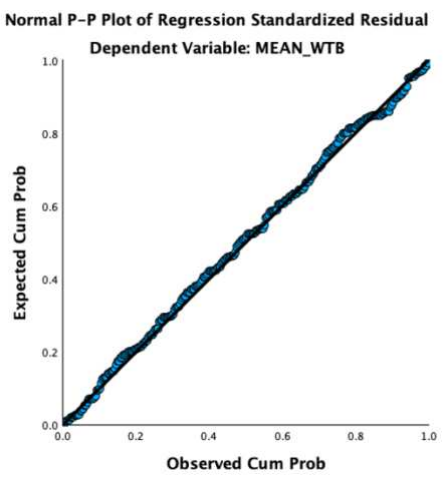
Appendix 7: Assumptions Check: Actual Transparency

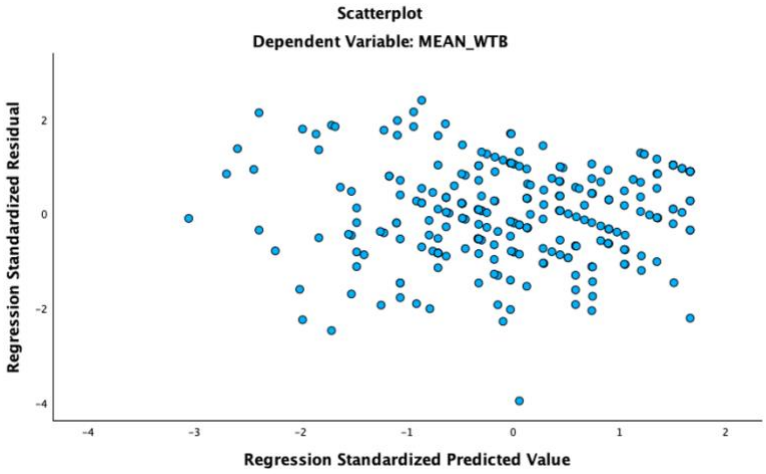
Normality of Errors



Comment: The histogram displays a bell-shaped curve that follows the overlaid black curve. In addition, the distribution is symmetric around the mean, which is very close to zero (M=1.39E-15). This suggests that the residuals are close to being normally distributed. The Normality of Errors Assumption gets therefore supported.

Linearity & Homoscedasticity





Comment: The P-P plot shows a roughly diagonal line of the different dots, indicating the residuals to be approximately normally distributed and linearly related to the predicted values. The assumption of linearity gets therefore satisfied. In addition, since the residuals fall closely along the diagonal line without significant deviations, homoscedasticity gets supported.

Comment: The scatterplot supports homoscedasticity as well, since it shows a fairly random distribution of residuals around the horizontal axis.

Independence of Errors

Durbin-Watson Statistic

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate		Durbin-Watson
1	.648[a]	.419	.410	.80408		1.862

a. Predictors: (Constant), INT_SRC_TRANS, MEAN_TRUST, Dummy Recommendation Source, Dummy Recommendation Transparency
b. Dependent Variable: MEAN_WTB

Comment: The value of the Durbin-Watson statistic is very close to 2 which suggests that there is likely no significant autocorrelation in the residuals. This supports the assumption of independence of errors.

No Multicollinearity

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	2.541	.249		10.219	<.001		
	MEAN_TRUST	.519	.042	.626	12.365	<.001	.875	1.143
	Dummy Recommendation Source	.109	.126	.052	.862	.389	.615	1.625
	Dummy Recommendation Transparency	.057	.149	.026	.381	.704	.471	2.125
	INT_SRC_TRANS	-.350	.205	-.127	-1.706	.089	.405	2.472

a. Dependent Variable: MEAN_WTB

Comment: The table displays tolerance values above 0.1 and VIF values below 10. This suggests multicollinearity to be of no concern in this model.

Appendix 8: Hayes PROCESS Macro Output: Actual Transparency

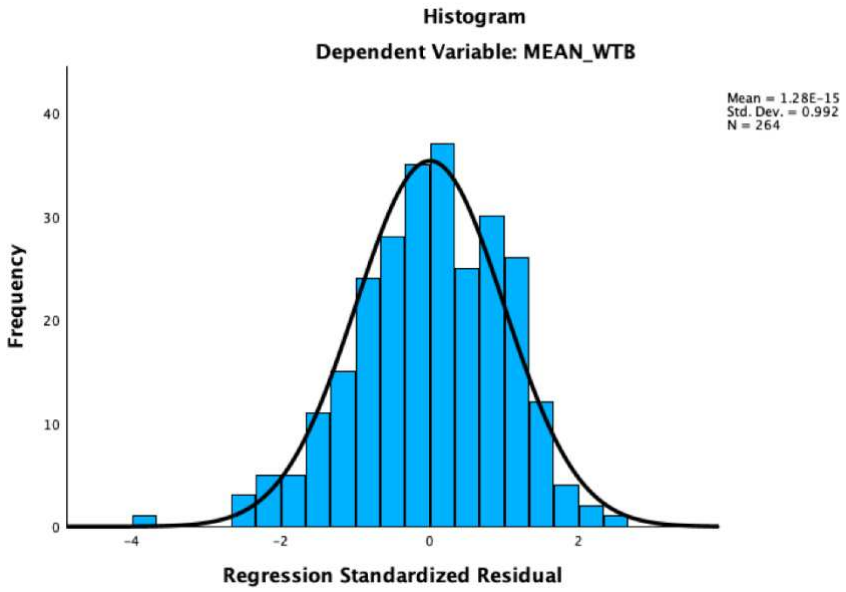
```
Run MATRIX procedure:

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

          Written by Andrew F. Hayes, Ph.D.
www.afhayes.com
    Documentation available in Hayes (2022).
www.guilford.com/p/hayes3

**************************************************************************
************
Model  : 7
    Y  : MEAN_WTB
    X  : DU_REC_S
    M  : MEAN_TRU
    W  : DU_REC_T

Covariates:
 FAMIl_OS FAMIL_AI

Sample
Size:  264
```

```
**************************************************************
************
OUTCOME VARIABLE:
 MEAN_TRU

Model Summary
          R       R-sq        MSE          F        df1
df2          p
      .4564      .2083     1.2880    13.5782     5.0000
258.0000      .0000

Model
              coeff         se          t          p
LLCI       ULCI
constant     3.4801      .6121     5.6856      .0000
2.2748     4.6854
DU_REC_S     -.2912      .1794    -1.6237      .1057     -
.6444      .0620
DU_REC_T     -.9194      .2027    -4.5347      .0000    -
1.3186     -.5201
Int_1         .1565      .2908      .5384      .5908     -
.4160      .7291
FAMIl_OS      .1528      .1377     1.1094      .2683     -
.1184      .4239
FAMIL_AI      .3549      .0830     4.2744      .0000
.1914      .5184

Product terms key:
 Int_1    :        DU_REC_S x        DU_REC_T

Test(s) of highest order unconditional interaction(s):
       R2-chng          F        df1        df2          p
X*W      .0009      .2898     1.0000   258.0000      .5908

**************************************************************
************
OUTCOME VARIABLE:
 MEAN_WTB

Model Summary
          R       R-sq        MSE          F        df1
df2          p
      .6734      .4535      .6085    53.7366     4.0000
259.0000      .0000

Model
              coeff         se          t          p
LLCI       ULCI
constant     2.4973      .4252     5.8733      .0000
1.6600     3.3345
```

```
DU_REC_S      -.0470      .0972     -.4837      .6290     -
.2384      .1444
MEAN_TRU       .4842      .0402    12.0412      .0000
.4050      .5634
FAMIl_OS      -.1587      .0945    -1.6802      .0941     -
.3448      .0273
FAMIL_AI       .2671      .0590     4.5271      .0000
.1509      .3833


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

Direct effect of X on Y
     Effect         se          t          p       LLCI
ULCI
     -.0470      .0972     -.4837      .6290     -.2384
.1444

Conditional indirect effects of X on Y:

INDIRECT EFFECT:
 DU_REC_S    ->    MEAN_TRU    ->    MEAN_WTB

   DU_REC_T     Effect     BootSE   BootLLCI   BootULCI
      .0000     -.1410      .0794     -.2982      .0120
     1.0000     -.0652      .1276     -.3221      .1711

Index of moderated mediation (difference between conditional
indirect effects):
              Index     BootSE   BootLLCI   BootULCI
DU_REC_T      .0758      .1507     -.2150      .3652

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

Level of confidence for all confidence intervals in output:
  95.0000

Number of bootstrap samples for percentile bootstrap
confidence intervals:
  5000

------ END MATRIX -----
```

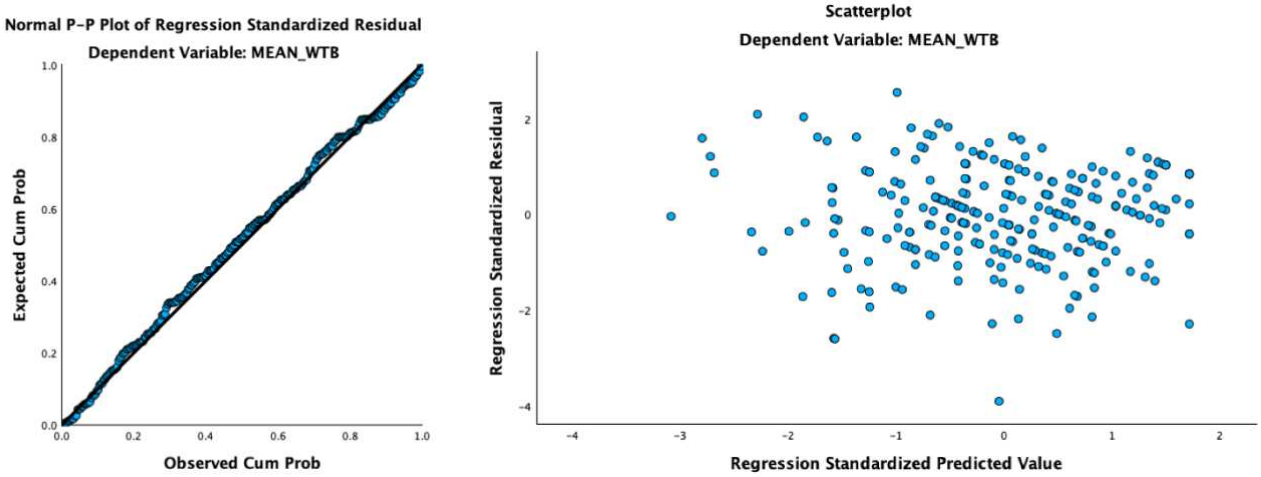
Appendix 9: Assumptions Check: Perceived Transparency

Normality of Errors



Comment: The histogram displays a bell-shaped curve that follows the overlaid black curve. In addition, the distribution is symmetric around the mean, which is very close to zero (μ=1.28E-15). This suggests that the residuals are close to being normally distributed. The Normality of Errors Assumption gets therefore supported.

Linearity & Homoscedasticity



Comment: The P-P plot shows a roughly diagonal line of the different dots, indicating the residuals to be approximately normally distributed and linearly related to the predicted values.

The assumption of linearity gets therefore satisfied. In addition, since the residuals fall closely along the diagonal line without significant deviations, homoscedasticity gets supported.

Comment: The scatterplot supports homoscedasticity as well, since it shows a fairly random distribution of residuals around the horizontal axis.

Independence of Errors
Durbin-Watson Statistic

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.655[a]	.429	.420	.79720	1.807

a. Predictors: (Constant), Continous Interaction term source x transparency, MEAN_TRU, MEAN_TRA, Dummy Recommendation Source
b. Dependent Variable: MEAN_WTB

Comment: The value of the Durbin-Watson statistic is very close to 2 which suggests that there is likely no significant autocorrelation in the residuals. This supports the assumption of independence of errors.

No Multicollinearity

1) Initial Transparency Variable

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients			Collinearity Statistics	
		B	Std. Error	Beta	t	Sig.	Tolerance	VIF
1	(Constant)	2.595	.263		9.861	<.001		
	MEAN_TRU	.468	.049	.565	9.564	<.001	.632	1.582
	Dummy Recommendation Source	-.590	.353	-.282	-1.672	.096	.077	12.955
	MEAN_TRA	.062	.073	.064	.847	.398	.381	2.623
	Continous Interaction term source x transparency	.148	.091	.287	1.624	.106	.070	14.206

a. Dependent Variable: MEAN_WTB

Comment: The table displays tolerance values below 0.1 and VIF values above 10. This suggests potential multicollinearity issues.

2) Centered Transparency Variable

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	2.826	.261		10.822	<.001		
	MEAN_TRU	.468	.049	.565	9.564	<.001	.632	1.582
	Dummy Recommendation Source	-.038	.099	-.018	-.383	.702	.982	1.019
	MEAN_TRA_CENTERED	.062	.073	.064	.847	.398	.381	2.623
	CINT_SRC_TRANS	.148	.091	.106	1.624	.106	.521	1.918

a. Dependent Variable: MEAN_WTB

Comment: Multicollinearity Resolved - Now the table displays all tolerance values above 0.1 and VIF values below 10. This suggests that multicollinearity issues are no longer a problem after centering the variables and creating the interaction term.

Appendix 10: Hayes PROCESS Macro Output: Perceived Transparency

```
Run MATRIX procedure:

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

          Written by Andrew F. Hayes, Ph.D.
www.afhayes.com
    Documentation available in Hayes (2022).
www.guilford.com/p/hayes3

**************************************************************************
************
Model  : 7
    Y  : MEAN_WTB
    X  : DU_REC_S
    M  : MEAN_TRU
    W  : CMEA_TRA
```

```
Covariates:
 FAMIl_OS FAMIL_AI

Sample
Size:  264

************************************************************
************
OUTCOME VARIABLE:
 MEAN_TRU

Model Summary
          R       R-sq        MSE          F        df1
df2          p
      .6418      .4120      .9567    36.1496     5.0000
258.0000      .0000

Model
              coeff         se          t          p
LLCI       ULCI
constant     4.0232      .5235     7.6856      .0000
2.9924     5.0540
DU_REC_S     -.2608      .1217    -2.1438      .0330     -
.5004     -.0212
CMEA_TRA      .7295      .0782     9.3239      .0000
.5754      .8835
Int_1        -.1601      .1121    -1.4284      .1544     -
.3808      .0606
FAMIl_OS      .0114      .1193      .0954      .9241     -
.2235      .2463
FAMIL_AI      .2918      .0719     4.0575      .0001
.1502      .4334

Product terms key:
 Int_1    :        DU_REC_S x        CMEA_TRA

Test(s) of highest order unconditional interaction(s):
       R2-chng           F        df1        df2           p
X*W      .0047     2.0404     1.0000   258.0000      .1544

************************************************************
************
OUTCOME VARIABLE:
 MEAN_WTB

Model Summary
          R       R-sq        MSE          F        df1
df2          p
      .6734      .4535      .6085    53.7366     4.0000
259.0000      .0000
```

```
Model
              coeff         se          t          p
LLCI       ULCI
constant     2.4973      .4252     5.8733      .0000
1.6600     3.3345
DU_REC_S     -.0470      .0972     -.4837      .6290     -
.2384      .1444
MEAN_TRU      .4842      .0402    12.0412      .0000
.4050      .5634
FAMIl_OS     -.1587      .0945    -1.6802      .0941     -
.3448      .0273
FAMIL_AI      .2671      .0590     4.5271      .0000
.1509      .3833


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

Direct effect of X on Y
     Effect         se          t          p       LLCI
ULCI
     -.0470      .0972     -.4837      .6290     -.2384
.1444

Conditional indirect effects of X on Y:

INDIRECT EFFECT:
 DU_REC_S    ->    MEAN_TRU    ->    MEAN_WTB

   CMEA_TRA     Effect     BootSE   BootLLCI   BootULCI
    -1.3311     -.0231      .1011     -.2268      .1686
      .2689     -.1471      .0628     -.2744     -.0289
     1.2689     -.2246      .0999     -.4252     -.0240

      Index of moderated mediation:
              Index     BootSE   BootLLCI   BootULCI
CMEA_TRA     -.0775      .0619     -.1996      .0446

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

Level of confidence for all confidence intervals in output:
  95.0000

Number of bootstrap samples for percentile bootstrap
confidence intervals:
  5000

W values in conditional tables are the 16th, 50th, and 84th
percentiles.
------ END MATRIX -----
```

Appendix 11: Comments (Extract)

a) *AI works better than humans I.must say. We dont get to deal with angry people its just a machince giving you exactly what you need no feelings attached.*

b) *I would not totally trust AI recommendations.*

c) *I would like to point out that it would make a significant difference in the outcome to know if the recommendations were based on previous items that I had seen (in this or other webpage) or whether the AI was simply doing a generic recommendation. I say this because I would trust more the AI's choices knowing that they had been tailored subjectively to my profile and that of similar people to me (in preferences).*

d) *Most people feel safer if there is a person behind a message rather than an AI.*

e) *I think i would presume the "stylist" was AI.*

f) *AI is without doubt starting to become very relevant in all walks of life and as an older person i am finding it very interesting and from what i have seen of it so far i am finding it very useful and reliable and it will be very interesting to see where it goes in the future.*

g) *It's hard do know If I would/wouldn't purchase a jacket based on the recommendations without actually seeing the suggestions!*