The impact of analytical and intuitive appeals on the persuasiveness of e-commerce recommendations and the moderating roles of product type, involvement, and thinking styles

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Abstract

Title: The impact of analytical and intuitive appeals on the persuasiveness of e-commerce recommendations and the moderating roles of product type, involvement, and thinking styles

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Technological advancements have changed many aspects of our daily lives, with one of them being our shopping behavior, as more and more consumers are starting to rely on online retail. This move created a few new challenges to businesses, mainly in how they could adapt and still support the consumer through this different channel. To try to mitigate this issue, retailers introduced chatbots that not only can respond to any queries the consumer may have but are also able to push personalized recommendations. This dissertation intends to study how different types of appeals embedded in a recommendation message, describing the product's features in either an intuitive or analytic manner, affect the persuasiveness of the recommendation. Moreover, I try to understand the moderating role that product type, level of involvement and consumers' tendencies to rely more on an intuitive or analytic way of processing information, may play in this effect. The results of the experiment did not show support to the hypothesis that the type of appeal affects the persuasive power of the recommendation message, nor that product type or level of involvement play a moderating role. However, they did show a partial effect of matching the type of appeal with participant's thinking style, meaning that messages with intuitive appeals were more persuasive for individuals that tended to rely on an intuitive way of processing information. Chatbot recommendation design should take these findings into account, although future studies should seek to clarify the existence of these results in a practical setting.

Keywords: Chatbot; Recommendation; Appeal type; Thinking style; Involvement; Product type; Persuasion

Sumário

Título: O impacto de apelos analíticos e intuitivos na persuasão das recomendações no comércio online e o papel moderador do tipo de produto, envolvimento e estilos de pensamento

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Os avanços tecnológicos mudaram muitos aspetos das nossas vidas, sendo um deles o nosso comportamento de compra, com cada vez mais consumidores a fazerem compras online. Esta mudança trouxe novos desafios para os retalhistas, principalmente na forma de prestar apoio ao cliente sem poderem interagir diretamente com ele. Para tentar mitigar este problema, muitas organizações implementaram chatbots que não só conseguem responder a qualquer dúvida que o consumidor possa ter, como também permitem o envio de recomendações personalizadas. Esta dissertação pretende estudar como diferentes tipos de apelos incorporados na mensagem de recomendação, descrevendo as características do produto de forma intuitiva ou analítica, afetam o poder persuasivo da recomendação. Além disso, procuro analisar o papel moderador que o tipo de produto, o nível de envolvimento e a tendência dos consumidores em processar informação de forma mais intuitiva ou analítica, podem representar nesse efeito. Os resultados do estudo não suportam a hipótese de que o tipo de apelo afeta o poder persuasivo da mensagem, nem que o tipo de produto ou nível de envolvimento moderam esta relação. No entanto, os resultados mostraram um efeito parcial em combinar o tipo de apelo com o estilo de pensamento do participante, o que significa que a mensagem com apelos intuitivos foi mais persuasiva para indivíduos que mostraram ter uma tendência em processar informação de uma forma mais intuitiva. O design e implementação dos chatbots deverá ter estes resultados em consideração, embora seja necessário que futuros estudos procurem esclarecer a existência destas conclusões num cenário prático.

Palavras-chave: Chatbot; Recomendação; Tipo de apelo; Modo de processar informação; Envolvimento; Tipo de producto; Persuasão

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Glossary

α	Cronbach's index of reliability
β	Standardized coefficient
b	Unstandardized coefficient
&	And
AI	Artificial Intelligence
ANCOVA	Analysis of covariance
df	Degrees of Freedom
F	F distribution, fishers F ratio
FI	Faith in intuition
M	Mean
N	Total number of cases
p	P value
NFC	Need for cognition
RQ	Research Question
SD	Standard Deviation
SE	Standard Error

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1. Introduction

We are living in times of unprecedented changes. The technological advancements of the past few decades introduced numerous implications to the way we live, work, and interact with the world. The fourth industrial revolution, or industry 4.0, as many describe it, brought innovation with no historic match in terms of speed, scope, and impact, through the integration of many different emerging technologies, such as robotics, Artificial Intelligence (AI), the internet of things, and others. These innovations were reflected in, for example, how easy it became to connect with people across the globe, or the improvements in information processing power, storage capacities, and knowledge access. The combination of all these developments led to the disruption of several industries as well as the emergence of a number of new business models (Schwab & Davis, 2018).

One of the industries that was most affected by such a disruption was retail. The digital revolution created a data-driven environment, causing an increasing number of firms to enter the online space. For these retailers, one of the most appealing aspects of the online channel was the unique opportunity to collect, gather, and analyze consumer information that became much more accessible and could be used to better understand consumers and more effectively develop products to satisfy their ever-evolving needs (Rindfleisch et al., 2017). As such, the competition in the online commerce space increased, and so did the need for players to be innovative and do everything they could to maintain and acquire new customers. Among some of the most significant innovations was the integrated use of robotics and artificial intelligence, particularly in the form of chatbots. These can be described as "a computer program, which simulates human language with the aid of a text-based dialogue system" (Zumstein & Hundertmark, 2017, p.98), and are one of the most meaningful examples of intelligent human-computer interaction. Chatbots started getting a lot more traction in the past 5 years, at the same time as artificial intelligence improved, and digital marketing became more essential (Chung et al., 2020).

Personalization has been shown to be one of the most important elements to improve customer relationships in electronic commerce (Fan & Poole, 2006). Because of that, retailers always strive to offer the best and most personal shopping experience to their consumers, which may be one reasons that helps explain why e-commerce was one of the main sectors in which chatbots had such a wide diffusion. In fact, their use is already incredibly common, even across very distinct categories of retail and consumer assistance, ranging from Coca-Cola and

Domino's in the food sector, Gucci and Louis Vuitton in the luxury brands department, to more e-service oriented platforms like Amazon or eBay (Luo et al., 2019; Chung et al., 2020). By using chatbots, businesses are now capable of communicating with their consumers 24/7 and help solve their issues with effectiveness (Ashfaq et al., 2020). Moreover, these automated programs are not limited in the types of tasks they can perform, as they "serve a range of roles, from personal assistant, to intelligent virtual agent, to companion" (Radziwill & Benton, 2017). Because of its functional diversity, ease of accessibility and low costs, around 80% of businesses either already use chatbots or are planning to incorporate them soon (Press, 2019). In e-commerce, chatbots are typically positioned as personal assistants that are used to give advice and information to the customer. However, besides delivering on general information that is requested by the customer, these agents can also be used to provide recommendations for specific products (Rhee & Choi, 2020).

Research on product recommendations has been an important area of study, and it goes beyond just focusing on the algorithmic mechanisms that are used to generate them. In fact, many authors have tried to understand the psychological aspects that may help explain the persuasive effects that recommendation can have (Chen & Lee, 2008). Previous studies (Epstein, 1994; Stanovich, 2009) have shown that individuals vary in the way in which they make decisions and process information. While some tend to rely more on their intuition, others will tend to make decisions in a more analytic manner. Therefore, it is very unlikely that two individuals that have this difference in thinking styles will react in the same way to a one-size-fits-all recommendation message. Actually, to have persuasive recommendations, one of the most effective methods is to personalize the message to the audience that it is targeting (Teeny et al., 2021). Today, the combination of technological advancements in tools like chatbots and the widespread of consumer information made the implementation of this personalization technique to be easier than ever as, by leveraging on this combination, retailers can better support each customer and be adaptable to their individual differences and preferences (Teeny et al., 2021).

Still, there are other factors that may influence consumers' responses to recommendation messages, even if personalized to their characteristics. One of the major limitations of e-commerce is consumers' inability to physically assess and experience the characteristics of products, especially experience goods, which are those that are "dominated by attributes that are inherently subjective" (Gao et al., 2012, p.772), such as accessories, clothing, or cosmetic products. In fact, previous research has shown that the type of product in consideration can

affect consumers' search and learning behaviors in technologic settings (P. Huang et al., 2009). Along with product type, consumers' engagement with a given product, or in other words, their level of involvement, can also impact the cognitive strategy that consumers will rely on to form their attitudes (Petty et al., 1983). Therefore, it is very important that both these factors are considered when assessing the potential persuasive effects of a recommendation message.

In this paper, I intend to explore how a product recommendation provided by a chatbot may take advantage of consumers' individual differences in thinking styles, by integrating different types of appeals in the recommendation message. As such, the following questions arise: How can chatbots affect the consumers' purchase decision-making process, and more concretely, their purchase intention? What role do the individual differences that characterize consumers play in this interaction? And which combinations between appeal and product type result in the best persuasiveness and acceptance of the recommendation? Finding answers to these questions is the aim of this dissertation.

1.1. Relevance of the topic & problem statement

The digital revolution brought an increasing number of consumers and organizations to engage in online retailing interactions. To be more effective in managing these interactions, many companies implemented chatbots that can, in an automated manner, assist users throughout their decision-making journey.

To better understand how this interaction plays out, researchers have been mainly focusing on the design (Araujo, 2018), implementation (Ciechanowski et al., 2019; Przegalinska et al., 2019), and adoption (Rese et al., 2020) of chatbots, and the impact that these factors have on the satisfaction users get from interacting with them. However, the role played by the type of communication used by the chatbot while interacting with a consumer is an area that is left to be explored. Specifically, there is still much to be discovered about how different types of linguistic appeals can be incorporated in the content of a product recommendation message to incentivize consumers' purchase intentions. Thus, the aim of this dissertation is to conduct research that can help answer the following question: "What influences do chatbots recommendations have on customers' purchase intention: the role of product and appeal type". As a result, the following research questions have been elaborated and will be answered throughout this paper:

RQ1: Are intuitive appeals more effective than analytical appeals in general?

RQ2: Does higher involvement lead to higher persuasiveness of analytical appeals vs. intuitive appeals?

RQ3: Is matching of consumer thinking style and persuasion appeal type important for persuasion effectiveness?

RQ4: Is matching of product type and appeal type important for persuasion effectiveness?

1.2. Structure

To achieve the objective of this dissertation, I will be conducting an experimental study through a questionnaire. Regarding the organization of the paper, after this introduction there will be a literature review of the following topics: artificial intelligence, chatbots, e-commerce, persuasion and personalization, dual systems of thought, the role of intuition, and the elaboration likelihood model. Then, a description of the methodology used will be given, detailing the research design and strategy, the overall characteristics of the participants, and the procedure. Next, there will be a presentation, analysis and discussion of the results obtained through the experiment. Finally, I will share the main conclusions that derive from the results, as well as their implications. The dissertation ends with the identification of limitations and the proposition of possible future research avenues that can be explored.

2. Literature review

2.1. Artificial intelligence

The term "Artificial Intelligence" was first used back in 1956, when "John McCarthy (Dartmouth College), Marvin L. Minsky (MIT), Nathaniel Rochester (IBM), and Claude Shannon (Bell Laboratories) conducted the Dartmouth Summer Research Project on Artificial Intelligence" (commemorative plaque reproduced in Moor, 2006). At that time, they thought of it from the following perspective: For every aspect of learning or feature of intelligence that can be accurately and precisely described, it is possible to command a machine to simulate it (Moor, 2006).

From this starting point, the initial years of investigation and developments in AI were successful, even if in a limited way, considering computers still had very primitive processing capabilities and there was a lack of programming tools at that time (Russell & Norvig, 2010).

Nonetheless, the early results left researchers confident on the promising developments that could arise from their studies. However, these expectations did not materialize in the period that followed. In fact, the evolution in the area was slower than anticipated, comprised of cycles of success as well as periods of excessive optimism that caused retractions both in terms of enthusiasm and, most importantly, funding. It was mainly through the introduction of new creative approaches and the refinement of the most promising advances that progress was achieved (Russell & Norvig, 2010). In the past decade, digitalization led to the generation of unprecedented volumes of information, which created the necessity to develop technologies capable of handling these large datasets and take advantage of the insights that could be derived from them. As such, the investment and research focusing on this field increased, and it led to improvements in computational processing power and the development of more advanced methods to analyze information, such as complex algorithms that could be used in AI applications (Bughin et al., 2017; Brynjolfsson & McAfee, 2017).

The developments in computational power and technological tools created an opportunity for disruption in the digital space. Netflix, Amazon, or Google are some of the most well-known organizations that grew exponentially during this digitalized era, and they did so by being highly agile, data-driven companies that could take advantage of the new opportunities to deliver their business value at scale (Davenport, 2018). That created a sense of urgency among more traditional companies for the need to adopt AI technologies and leverage their data assets to maintain and build on their previous successes and not be left behind by such a significant industry transformation (Bean, 2019). Therefore, many organizations across the world started adopting and implementing AI into their operations, as these intelligent systems offered a set of capabilities that helped generate operational improvements in terms of innovation, speed, flexibility, and decision-making (Wilson & Daugherty, 2018), contributing towards value creation.

To be considered an intelligent system there are four components that must always be present. The first is natural language processing features, which allows it to communicate information to humans in a natural form. The second is knowledge representation, which acts as the system's memory and stores complex information. The third is automated reasoning, which makes possible the use of the stored information to answer questions and infer new facts based on that information. And, finally, machine learning to detect new patterns and adapt to new circumstances (Russell & Norvig, 2010). By incorporating all four elements, AI systems will be able to mimic human-like intelligence and, because of that, represent a source of added

value to business processes. This can happen by creating the opportunity for the development of new products or services, introducing new forms of customer-company interaction, or by automating tasks, even those that require cognitive resources (Davenport, 2018; Ransbotham et al., 2018).

Technological innovations that derive from improvements in artificial intelligence have more recently been the subject of extensive research both in academia and in the practical world (Tran et al., 2021). The application of such innovations can vary, with some noteworthy examples being the development of autonomous operated vehicles or, more relevant to the scope of this study, the improvement in chatbot functionality.

2.2. Chatbots

Chatbots are "an example of a virtual conversational service robot" (Chung et al., 2020, p. 588), that incorporates aspects of both AI and robotics. They are artificial intelligent robots that can provide human-computer interaction, and by doing so, allow organizations the opportunity to add a new layer of customer engagement and support to their operations by guaranteeing that, whatever the time or place, a personalized service is available to satisfy their consumers' needs (Rese et al., 2020).

Many consider that the idea of chatbots emerged in 1950, when Alan Turing decided to test the extent to which a machine would be able to exhibit intelligent behavior that would resemble that of a human to the point where the interlocutor would be unable to realize that they were interacting with a machine. This is now known as the Turing Test, but it was originally called the Imitation Game (Turing, 1950). The first creation of a chatbot occurred in 1966, with the ELIZA program, which was designed to allow a natural language conversation with a computer (Weizenbaum, 1983). ELIZA was still very limited in its ability to communicate and in the topics that it could cover, as was to be expected given the time of its creation. Nonetheless, it set the stage for subsequent developments of new chatbots (Klopfenstein et al., 2017). From this initial attempt to the goal of having fully developed intelligent agents capable of having conversations using natural language, a long path was crossed, and a very significant step in this journey was the introduction of AI. In practice, advancements in linguistic processing, speech recognition, and other artificial intelligence tools eliminated the restrictions of previous iterations of chatbots, like only being able to match predefined scripts to specific keywords,

which were narrowing the scenarios where these intelligent robots could be used (Abu Shawar & Atwell, 2007).

In the last decade, the development of chatbots gained a big momentum with numerous organizations getting involved in their implementation. Nowadays, this tool is used in a wide range of sectors like health care, education, entertainment, marketing, and, more relevant to this study, retail and customer service (Kerly et al., 2007; Palanica et al., 2019; Brandtzaeg & Følstad, 2017; Van den Broeck et al., 2019). Due to the impossibility of experiencing products before purchasing or physically interacting with human assistants, it was in the online retail channel that chatbots added the most benefits to both consumers and retailers.

2.3. E-commerce

E-commerce, as defined by the Organization for Economic Co-operation and Development (OECD, 2011), stands for the transactions of goods or services through computer networks with methods specifically designed with the objective of placing or receiving orders. Despite the online nature of the transaction, the payment method and delivery of the product or service can be done offline without excluding it from being considered part of electronic commerce.

In the beginning of the 90s, the introduction of the world wide web marked the start of e-commerce. The diffusion of web sites and the development of search engines meant that the internet had become an effective channel for organizations to reach their consumers. Still, at this time, it was mainly a one-sided interaction, as businesses could only react to requests and send out information regarding their products. The continuous development of websites as well as the introduction of new technologies, like cookies, allowed for a more integrative online environment, characterized by more interaction between buyers and sellers as well as further customization and personalization (Chu et al., 2007). Among the earliest and most successful adopters of this retailing channel were Amazon, which completed its first sale in 1995, and eBay, launched in that same year. The growth and development of these businesses, complemented by the increased security in online payments that platforms like PayPal introduced (1998), set the stage for other businesses to enter and expand the sector which is, nowadays, the fastest growing segment within retail. These great advancements were the steppingstone for what we see today, which is numerous online transactions being completed daily, occurring mainly through the two more common types of e-commerce: business-to-business and business-to-consumers (Tian & Stewart, 2006).

In this paper, the focus will be placed on the transactions that have the consumer as the end user and businesses as the vendor. Both parties benefited greatly from the developments in online retailing. For consumers, e-commerce drastically increased the convenience with which purchases could be made, in terms of the speed, flexibility and overall transparency of the purchase process, as they gained access to more information than ever before (Huseynov & Özkan Yıldırım, 2019). For businesses, it helped them expand their marketplace, both nationally and internationally, reaching more consumers in a faster and cost-efficient manner (Vijayasarathy, 2004). However, this different sales channel has its own advantages and disadvantages, and its specificities imply that products that typically perform well in more traditional channels may not do so in online commerce (Rosa & Malter, 2003).

2.3.1. E-commerce and product types

A major limitation of e-commerce when compared with the more traditional offline retail channels is the lack of physical interaction that consumers have with the product. Nonetheless, this constraint does not have the same impact across all types of products.

There are a few different classifications of products, with all of them holding their own relevancy. One that has proven to be particularly significant is the differentiation between search and experience products (Rosa & Malter, 2003). Still, even within this discrimination, there is some division on what exactly sets the separation between the two. Some older studies (Nelson, 1974) define that search goods are the ones that can be experienced by the shopper prior to the purchase. This is, however, a definition that would imply that all products that are sold online would be classified as experience products, given that there is no way for consumers to experience them before buying. So, a definition that was less channel dependent was needed (Weathers et al., 2007). Aligned with this latest perspective, Weathers et al., (2015) conceptualize the distinction between search and experience products "as the extent to which shoppers feel the need to directly experience goods to evaluate their quality" (p. 14) . Generally speaking, every product contains both search and experience attributes (Sheffet, 1983). Nonetheless, the greater the need that consumers feel to directly experience the product to evaluate its quality, the more experience traits it has. Because of that, (Weathers et al., 2007) look at a good as the aggregation of its different attributes, and so, they consider the classification at the product level. In previous research that uses this differentiation, laptops and digital cameras have been typically identified as examples of search products, and cosmetics and accessories as experience ones.

In e-commerce, it is very important that retailers are clearly aware of the distinction between search and experience goods, as consumers may be more hesitant to purchase experience products due to having more uncertainties in assessing their quality (Weathers et al., 2015). An alternative typically used by consumers to try to reduce this uncertainty is relying on external sources of information, such as product reviews. The perceived validity of these reviews is, however, also dependent on the type of product they are describing. As demonstrated by Weathers et al. (2015), the different levels of uncertainty associated with search and experience products also translates into the information we look for in their reviews, and the content and depth of the message tends to affect its perceived helpfulness. Nonetheless, these online reviews are often generated by other consumers and typically beyond the control of the retailer. So, they must find other ways to actively engage with consumers, while also considering this need for differentiation when trying to mitigate their uncertainties and hesitancies as well as incentivizing purchases.

2.3.2. E-commerce challenges and opportunities

Electronic commerce brought numerous advantages to consumers and retailers. However, such benefits attracted the attention of more and more businesses towards this retailing channel, and with the increased number of players came a rise in competitiveness (Jiang et al., 2015). This, in turn, resulted in several practical implications for both retailers and consumers. The latter started facing an overwhelming amount of information to be considered when evaluating all the different purchase alternatives, which undoubtably began to affect their shopping process (Ben Mimoun et al., 2017). In addition to this challenge, many e-consumers end up failing to complete their purchase (Kukar-Kinney & Close, 2010) due to experiencing difficulties in settling on one option among such variety in offerings (Chen et al., 2009), the inability to physically interact with the product (Citrin et al., 2003), or the unavailability of someone there to assist them (Punj & Moore, 2009).

The responsibility to overcome these hurdles rests on the retailers that are forced to try to be innovative in ways that not only distinguish them among peers, but also improve the customer's purchase experience.

2.3.3. Chatbots in e-commerce

Electronic retailers have been adopting new technologies and systems to try to suppress some of the challenges that affect e-commerce. Their goal is to introduce tools that help bridge the gap between consumers' expectations and the actual shopping experience that retailers have to offer, while simultaneously increasing operational efficiency and contributing towards value creation (Chung et al., 2020).

One innovation that has gained significant traction over the past few years is the use of chatbots or, from a broader perspective, e-service agents. These are assistants that are consistently available and, among other functionalities, can help maintain and improve customer relationships, give detailed information regarding products' characteristics, and allow customers to make a more efficient utilization of their time (Lee & Choi, 2017). Going one step forward, in addition to aiding the consumer with any queries throughout their purchase decision-making process, these agents can also assume a more active role by trying to incentivize purchases, with the use of personalized product recommendation messages.

2.3.4. Chatbots and product recommendations

Traditional recommendation agents are personalized computer agents that can be implemented in e-commerce websites to guide consumers through their product selection. They take into account consumers' actions, and try to match their needs, interests, and preferences with the recommendations that are provided (Papagelis & Plexousakis, 2005), typically with the aid of an algorithmic mechanism. The utilization of this type of agent has been increasing over the years, as electronic retailers try to explore new ways to make consumers' decision to select a product an easier process and seek to entice their purchases (Nikolaeva & Sriram, 2006). However, for these agents to be effective, it is key that they are perceived as trustworthy by consumers (Benbasat & Wang, 2005), which is one of the main challenges for these traditional agents.

Chatbots added a new wrinkle to the relationship between consumers and the agent by allowing for a natural two-way interaction. Previous studies (Bickmore & Cassell, 2001) have shown that, by being able to engage in a back-and-forth conversation, consumers can establish long-term rapport and trust in these systems, therefore mitigating what is one of the main weaknesses of the recommendation agents. Furthermore, chatbots allow for a level of personalization that is not only limited to the product selection that is recommended but can

also be seen in the communication style that is used to deliver the message. Personalization in the product that is recommended has been proved to help reduce consumers' information overload and result in higher satisfaction (Komiak & Benbasat, 2006; Liang et al., 2006). However, the effect of using a personalized communication style that is tailored to consumers' individual differences is an avenue that is still somewhat unexplored.

2.3.5. Persuasion and personalization in e-commerce

One of the main objectives of every retailer, be it in an online or offline channel, is to be effective in their efforts to incentivize customers to buy a specific product or service. To do so, several different tactics and strategies have been utilized and studied, with particular emphasis on the role of pricing as a persuasive tactic to entice consumers (Kachersky, 2011). However, persuasive strategies can involve many other variables that go beyond just the role of price in and of itself.

When consumers face a persuasive claim, they can rely on various aspects of the message to help form their opinion. Specifically, an individual can look for the expertise or gender of the message source, the content or length of the information that is provided, or even the linguistic cues that are present in the message itself. Therefore, it is very important that retailers not only consider what they are communicating to others, but also how the message is being communicated (Ng & Bradac, 1993). In this sense, linguistic cues can play a key role on the effectiveness of a persuasive message.

Thus, a question arises: How should linguistic cues be utilized to maximize the potential effectiveness of the persuasive message? Previous studies (Sparks & Areni, 2002) have shown that combining the style of the message and its content can increase the difficulty in being able to identify the difference in effect between the two. This shows that the perceptions of the linguistic cues and the message content are evaluated and processed simultaneously, which increases the chances of a persuasive appeal directly impacting consumers' perceptions of the information conveyed in the message. Still, it is very unlikely that the same persuasive appeal will hold the same impact across all the different consumers that are targeted by the message. In fact, it has been pointed out that individual traits, such as someone's personality, can influence their shopping behavior (Anaza, 2014). This points to the need of personalization in persuasive efforts, which is a hypothesis also supported by Berkovsky et al. (2012). These authors suggest that personalization and persuasion affect one another and is their combined

utilization that enhances its potential effects on changing behaviors, and not their application in isolation.

2.4. Two systems of thought

To be effective in the personalization efforts, it is necessary to understand and identify the type of consumer that the online retailers, via the chatbot, are addressing. In terms of their decision-making style, there are a few different theories that try to categorize consumers. One that gained significant traction was developed by Nobel laureate Daniel Kahneman. In his book *Thinking, Fast and Slow* (2011), he proposes a dual system through which people make decisions, with system 1 representing a more emotional, automatic reaction to information, and system 2 representing a more tempered, controlled evaluation process.

Besides Kahneman's system 1 and system 2 perspective of human decision-making processes, other theories that adopt a similar dualist view have been developed. To name a few, Epstein (1994) developed a dualist theory with experiential and rational systems, Stanovich (2009) with type 1 and type 2 processes, and Hammond (1996) with intuitive and analytic judgments. These popular theories have their foundation on the assumption that information processing is accomplished via two different but complementary manners. The first, intuitive, typically requires less elaboration and processing effort, and happens at a much faster speed. The other, analytic, is typically more demanding, requires thorough deliberation and therefore, takes longer to process (Evans, 2008). Although these theories are not all equivalent, in this dissertation I will use the term system 1 to refer to thinking processes that are typically unconscious and automatic, and the term system 2 to refer to thinking processes that are typically conscious and deliberate.

In a few of the studies that focus on this duality (Kahneman, 2003; Stanovich, 2009), it is argued that both systems will often work together. This way, there will be times when the initial, immediate response that is a result of the first system will be correct and accepted, but others when this response will bias reasoning. When this happens, it is required that the second system has the capacity of generating a more elaborated response that is perceived by the individual as a better solution to the situation. Hence, in these occasions, system 2 can override the belief-based decision that is provided by system 1 (Stanovich & West, 2000).

However, there are some contradictory views in the literature regarding this conflict monitoring component that occurs during the decision-making process (De Neys & Glumicic,

2008). While some argue that both systems run in parallel and compete to determine behavior (Evans, 2007), others (Kahneman & Frederick, 2002) argue that, by default, people will be more likely to rely on their system 1 without actively engaging their system 2, as most of the time they are simply not aware that their initial response may not be the optimal one. In his book *The Happiness Hypothesis*, Jonathan Haidt describes this situation with a beautiful metaphor. He puts it in terms of an elephant and its rider. The former is responsible for all automatic and implicit processes, while the latter is responsible for the conscious and voluntary reasoning. Although the relatively smaller rider may lead the elephant, if the elephant wants to choose another path, it will do so no matter what the intention of the rider is. He may think that he is in control and making the decisions, but more often than not, his job is to serve the elephant. One of the main takeaways from this view on processing differences is that, for a persuasion attempt to be successful, an individual may first need to want to agree with the message implicitly (at the elephant level), and only after will the rational processes start to find reasons to support that agreement (at the rider level; Haidt, 2006).

In the research that focuses on understanding individual differences in the processing of information, there are two main dimensions of cognitive styles (Akinci & Sadler-Smith, 2013), with one that is intuitive and the other that is analytic. This implies that some individuals will have a tendency to make decisions in a more intuitive manner, whereas others will tend to rely more heavily on their analytical analysis. One commonly used instrument to measure these individual differences is the Rational-Experiential Inventory (REI; Epstein et al., 1996). This instrument contains items that have been adapted from both the Faith in Intuition (Pacini & Epstein, 1999) and Need for Cognition (Cacioppo & Petty, 1982) scales and assesses the tendency for individuals to engage in intuitive-experiential and analytical-rational thinking styles. Still, while it is mostly clear for everyone what is an analytical and a rational way of processing information, understanding and defining what is intuition is something that may vary for different individuals. And, "without understanding intuition, is it impossible to develop any meaningful conceptualization of cognition" (Dörfler & Ackermann, 2012, p.546).

2.4.1. Role of intuition

Research on intuition has gained a lot of traction in the last couple of decades. This is true both in management literature, with a particular focus on its role in decision-making (Pratt & Dane, 2007), and in the academic world more generally (Lieberman et al., 2004). Perhaps due to this wide range of disciplines interested in the study of intuition, a definition that is

agreed upon and used by all can be difficult to find. Nonetheless, in their research, Pratt and Dane (2007) identified four key similarities among all the different definitions that are attributed to intuition. They characterize the process of intuition as nonconscious, fast, involving making holistic associations, and resulting in affectively charged judgments. Similarly, although in an older study, Westcott (1961) described this intuitive process as an inference-making mode of thought that uses limited information to make judgements and arrive at conclusions, that will tend to be perceived as correct. This process bridges the gap between the available evidence and the intuitive conclusion.

As discussed previously in this dissertation, one of the major limitations of e-commerce is the information asymmetry that exists between retailers and consumers. Consumers often have to make decisions with only partial information, as they are not able to experience the product before completing the purchase. In fact, this inability to inspect the product, leads to consumers' tendency to rely more on other sources of information, like consumer reviews, or product recommendations (Senecal & Nantel, 2004). Still, it remains mostly true that uncertainty and risk are factors that are associated with the act of purchasing products online.

A study by Inbar et al. (2010) found that intuitive judgements become quite prevalent when individuals are facing risk and ambiguity. This finding has support even in the e-commerce context, where the experimental results from Roghanizad and Neufeld (2015) show that online consumers tend to employ intuitive processes when presented with situations involving ambiguity and risk. Therefore, I hypothesize that an intuition appeal in a product recommendation message (as a cognitive heuristic that will act as a prime and activate the intuitive processing), will result in higher perceived attribute and product quality, as well as purchase intention.

H1: *Intuitive appeals will result in higher message persuasiveness for both experience and search products, in comparison to analytic appeals.*

2.4.2. Elaboration likelihood model

Dualist theories have not been limited to the research on types of information processing. In fact, they have been proposed in many fields that study human behavior, among which is consumer psychology. In this field, Samson and Voyer (2012) identified three main

areas associated with dual process models, which are: persuasion and attitude change, judgement and decision-making, and consumption behavior.

To maximize the persuasive effects that recommendations may have on consumers, it is critical to understand the mechanisms that are behind the attempts to promote attitude changes. Numerous researchers have focused on trying to describe and model these underlying processes, and much of their findings were the foundation to what is one of the most well-known and influential theories in the study of persuasion (Petty & Briñol, 2012; Maio et al., 2019), the Elaboration Likelihood Model (ELM; Petty & Cacioppo, 1986).

The ELM is, in essence, a dual process theory that aims at explaining the thinking processes that may occur when an attempt is made to change someone's attitudes through communication. It states that there are individual differences in how much effort is put into thinking about a message and its content. This level of effort, or as it is described in the model, elaboration, can vary from high to low along an elaboration likelihood continuum, that is also composed with the central and peripheral routes of persuasion at each respective end. When an individual's motivation to think about a given persuasive message is low, they will be more likely to utilize peripheral cues, such as the source, style, or context of the message to process the information contained within it and, ultimately, determine their attitudes (Teeny et al., 2017). In the completely opposite scenario, when the motivation and effort that are used to process the message are high, individuals will be more likely to evaluate the merits of the message based on the coherence and strength of its arguments. This means that any given persuasive variable, such as an intuition or analytic appeal, can have effects on attitudes through different processes depending on the point of the continuum in which an individual is situated (Petty et al., 2000). For example, consider a persuasive variable like intuition/analytical appeal that is embedded in the description of product features. In practice, in low elaboration conditions, a persuasive variable could be seen as a simple peripheral cue for product quality because it matches with the consumer's tendency to rely on intuition. In contrast, in high elaboration conditions, this same variable can be perceived as an actual strong argument in favor of the product's quality (Teeny et al., 2021).

Previous studies (Petty et al., 1983) have shown that there are ways in which it is possible to influence an individual's motivation to think about a specific product. By doing so, researchers can constraint the effect of the persuasive variable in either a high or low (depending on what best suits their studies) elaboration level of the continuum. However, that is not the

intention in this dissertation. Still, as discussed, the level of involvement (i.e., the motivation to elaborate) that an individual has for a particular product affects the influence that a message can have in changing attitudes. Because of that, I expect that individual involvement with the target product will act as a moderator for the relationship between the message appeal and consumers' purchase intentions.

H2: *Involvement plays a moderator role in the effectiveness of the recommendation appeal. Low involvement will result in higher message persuasiveness for intuitive appeals and high involvement will result in higher message persuasiveness for analytic appeals.*

2.4.3. Matching individual characteristics and type of appeal

"One of the most reliable and impactful methods for enhancing a persuasive appeal is to match an aspect of the proposal (i.e., its content, source, or the setting in which it is delivered) to an aspect of the consumer receiving it" (Teeny et al., 2021, p. 382). There are several different aspects of the recipient's characteristics that can be used to achieve this matching effect, such as the ways in which they think, feel, or behave, that is, their individual differences (Teeny et al., 2021).

According to Akinci and Sadler-Smith (2013), individuals are mainly divided between those that rely more on their intuition, and those that rely more on analytical thinking. It would be expected that, by matching these two dimensions of human cognition with the type of appeal that can be embedded in a persuasive message, one would achieve the most significant effect. Research by Haddock and Maio (2008) contributed to the literature of this field by suggesting that to maximize persuasive impacts, individual differences should be aligned with the type of message that is used to adress them. These authors showed that matching individuals high in need for affect with affective messages and individuals high in need for cognition with cognition-based messages resulted in the most positive attitudes towards the message.

In this study, I hypothesize that an effective appeal, that is, one that results in higher perceived recommendation usefulness, credibility, and product purchase intention, will result from matching the type of appeal that is embedded in the recommendation message with consumers' individual characteristics.

H3: *There is a significant and positive matching effect between individuals' characteristics (REI scores) and their attitudes towards recommendation's appeals.*

H3.1: *Those that are more reliant on an intuitive-experiential thinking style (high scores in faith in intuition) will respond more favorably to intuitive appeals.*

H3.2: *Those that are more reliant on an analytical-rational thinking style (high scores in need for cognition) will respond more favorably to analytic appeals.*

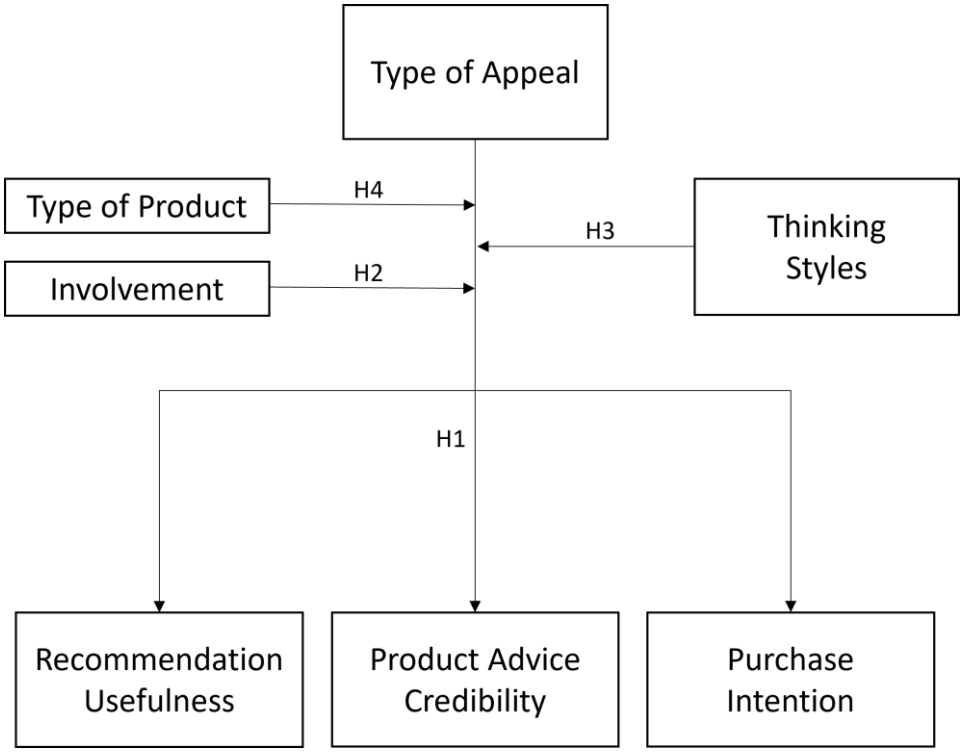
Besides matching persuasive appeals with consumer's profiles to optimize its effectiveness, researchers have also been advocating matching the type of appeal with the type of product (Kronrod & Danziger, 2013). Although this proposal was made from a perspective that focuses on the hedonic versus utilitarian differentiation of products, it still emphasizes the need to adapt the type of persuasive appeal to a specific product. Still, it remains unclear what should be the criteria used to achieve this matching effect. Franke et al. (2004) point out that consumers will use ample information when shopping for search products, but the same is not applicable to experience products, for which the required information levels are much lower. These findings lead me to believe that consumers are more likely to engage in active reasoning when shopping for search products and rely more on their unconscious thought for experience products. Additionally, prior research shows that when it comes to experience product purchasing, consumers can achieve higher levels of satisfaction by relying on their unconscious thought rather than their conscious thought (Gao et al., 2012). Considering these factors, I hypothesize that consumers will tend to rely more on their analytic reasoning when assessing search products and because of that, analytic appeals will be more persuasive. In contrast, for experience goods, consumers will tend to rely more on unconscious thought and because of that, intuitive appeals will be more persuasive.

H4.1: *Intuitive appeals will result in higher message persuasiveness for experience products.*

H4.2: *Analytic appeals will result in higher message persuasiveness for search products.*

2.5. Conceptual model

Figure 1 - *Conceptual Model*



3. Methodology

3.1. Research design

The aim of this dissertation was to test the effect that different types of appeals embedded in product recommendation messages being given by an AI chatbot can have on consumers' purchase intentions. Moreover, I intended to study whether the product type and consumers' individual differences in involvement and thinking styles may play a moderator role in this relationship. To do so, the experimental design consisted of an online questionnaire created through Qualtrics, an online survey platform. A 2 (product type: search vs. experience) x2 (recommendation appeal type: intuition vs. analytic) between-subjects factorial design was employed, resulting in a total of 4 conditions. The participants were randomly allocated to each condition because, by doing so, potential sources of biases are controlled for as all groups will tend towards having identical compositions. By having each participant responding to only one scenario it was possible to ensure that participants did not transport knowledge from one condition to another and that the observed differences are a result of the different scenarios and not other, unmeasured differences.

3.2. Participants

The study's questionnaire was distributed through several online channels, which included websites that focus on gathering research participants, as well as through my personal network. Additionally, it is important to note that all the participants involved in this study were volunteers.

A total of 159 responses were collected, and 144 were complete and considered valid to be considered in the study. Of the relevant sample size, 41% were males, the average age of all participants was 26.4 years (*SD* = 6.679), and almost half of them (48.6%) had a minimum education level of a bachelor's degree in college. Because the survey was distributed in a few different channels, 38 different nationalities were recorded, with Portuguese accounting for the highest percentage of the total (22.2%), followed by American with 11.1%. For more demographic information please consult Appendix A.

3.3. Procedure

Participants started by reading an introductory page where the general description of the survey was provided and it stated that, by continuing to the next page, they were consenting to be a participant in this research. The first block was composed of basic demographic questions, followed by a set of independent measures. These included the 10-item Rational-Experiential Inventory scale, a product involvement scale, and control scales for chatbot familiarity, online shopping experience, and product knowledge. Then, participants were randomly assigned to one of the four conditions of the study: search product with intuitive appeals embedded in the recommendation message, search product with analytic appeals embedded in the recommendation message, experience product with intuitive appeals embedded in the recommendation message, or experience product with analytic appeals embedded in the recommendation message. The final block was comprised of measurements for the dependent variables, which were the recommendation usefulness, the product advice credibility, and the purchase intention. The survey ended with a message of appreciation for the participant's collaboration, as well as my contact information in case they wanted to gather any further information on the study. For the full detailed version of the questionnaire, please refer to Appendix B.

3.4. Variable measurement

3.4.1. Control variables

Online Shopping Experience: Prior research found that online shopping experience has one of the strongest associations with online purchase intent (Ranganathan & Jha, 2007). Therefore, I decided to include this variable as a control in the experiment. To do so, I used a 3-item scale retrieved from Khalifa and Liu (2017). The items (e.g., "I have shopped online extensively"; "I have used the internet to shop for a long time") were rated in a 5-point Likert-scale format that ranged from "strongly disagree" to "strongly agree".

Product Knowledge: In the literature (Yoon et al., 2013; Xiao & Benbasat, 2007), consumer's product knowledge has been negatively associated with the influence of recommendation agents. Because of that, I decided to include this variable as a control in this study. It was measured with a 4-item scale (e.g., "My friends and family would refer to me as a cellphone expert."; "I put a lot of effort into understanding how to use my cellphone.") adapted from Nielsen et al. (2018). These items were rated in a 7-point Likert-scale format that ranged from "strongly disagree" to "strongly agree".

Chatbot Familiarity: Familiarity is a requisite for trust (Luhmann, 1988), and prior research has pointed out that initial trust in chatbots increases the intention to use them (Mostafa & Kasamani, 2021). Therefore, I also decided to control for chatbot familiarity in this study by measuring it with a simple and single item ("How familiar are you with chatbots/and or other conversational interfaces?") rated with a 5-point Likert-scale ranging from "not at all familiar" to "extremely familiar".

3.4.2. Independent variables

Product Type: In this experiment I used two different types of products, a search good and an experience good. As discussed in the literature review section of this paper, what separates them is the extent to which consumers feel they need to experience the product to assess its quality. To select the products that would represent each category I relied on previous research. Bei et al. (2004), L. Huang et al. (2013), and Luan et al. (2016) all support the decision of using a cellphone as a search product. Regarding the experience product, Mudambi and Schuff (2010) first used a videogame as a product belonging to this category, and subsequent studies supported this classification (Xu et al., 2015).

Type of Appeal: In this experimental design I adapted the methodology used by F. Loureiro (2021) by presenting the persuasive arguments included in the recommendation message as describing the product features in either an intuitive or analytic manner. To do so, and in line with the method used by F. Loureiro, the descriptions were held similar across the two conditions, with the only differentiating factor being the nature of the appeals, that emphasized either central aspects of intuition or analytics. This can be seen on the tables below (Table 1 and Table 2).

Table 1 - *Experience product features described intuitively and analytically in the recommendation message*

Videogame Features	Intuitive Description	Analytic Description
Menus/ Ease of Use	[…] navigate in a **fast and intuitive** manner, and have **effortless control** over all the features […]	[…] **thorough and detailed** navigation experience as well as an **in-depth control** over all the features […]
Graphics	[…] allow you to **extend your senses** and really **feel** like you are in the game […]	[…] show even the **most minute details** and allow you to **effectively observe and analyze** your environment […]
Gameplay Experience	[…] The other game characters, (..) were programmed to be able to **sense and predict** your inputs, (…) can **react quickly and automatically**, resulting in a **seamless** gameplay experience.	[…] The other game characters, (…) were programmed to be able to **collect and assess** your inputs, and **act based on this data**, resulting in a **logical** gameplay experience.

Table 2 - *Search product features described intuitively and analytically in the recommendation message*

Cellphone Features	Intuitive Description	Analytic Description
Screen/Menus	[…] provides **fast, intuitive** menus (…) allowing for **effortless control** over the full applications features […]	[…] provides **thorough, detailed** menus (…) allowing for an **in-depth control** over the full applications features […]
Camera (Night Mode)	[…] that **extends your senses** and helps you identify difficult to observe objects. […]	[…] that **collects the smallest detail** and helps you identify difficult to observe objects. […]
Battery	[…] able to **quickly sense** and **predict** your day-to-day usage to maximize battery life.	[…] able to **effectively observe** and **analyze** your day-to-day usage to maximize battery life.
Processing	[…] capable of **acting effortlessly and automatically** to deliver optimal performance, […]	[…] capable of **analyzing data and acting in accordance** to deliver optimal performance, […]

3.4.3. Moderator variables

Product Involvement: In order to assess participants involvement for either the experience or search product, depending on the condition they were randomly assigned to, I used a scale retrieved from Zaichkowsky (1994). Participants were instructed to complete a sentence, "To me, a [cellphone / videogame] is …" using ten items and a 7-point semantic differential scale (e.g., "important-unimportant"; "appealing-unappealing"; "worthless-valuable").

Rational-Experiential Inventory (REI): This scale was introduced to measure individual differences in tendencies to engage in a more experiential or rational processing. A rational style implies a tendency to make decisions based on logical and analytical reasoning, whereas an experiential style involves a predisposition to rely on immediate responses and intuition to make decisions. In this study I utilized the short-form version of this scale developed by Epstein et al. (1996), that contains five items to evaluate someone's Need for Cognition (NFC) and five more for their Faith in Intuition (FI). Each scale's items were chosen based on their total correlations and factor loadings from the first study of the same paper that uses a 31-item REI scale, and the short version replicated the findings of the original. The items were rated on a 5-point scale that ranged from "completely false" to "completely true".

3.4.4. Dependent variables

Product Advice Credibility: In order to measure participants perception of the credibility of the recommendation message provided by the chatbot I adapted a 3-item scale (e.g., "The information provided by the Virtual Service Agent is accurate."; "The information provided by the Virtual Service Agent is credible.") developed by Eastin (2001), that was also used in recent studies involving the utilization of chatbots (Beldad et al., 2016). The items were measured in a 5-point Likert-scale format that ranged from "strongly disagree" to "strongly agree".

Perceived Usefulness: To assess participants perceived usefulness of the recommendation provided by the virtual service agent, I used a scale adapted from Nysveen and Breivik (2005), and that has been utilized by other researchers (Hostler et al., 2011; Yoon et al., 2013), though with some different adaptations. The scale contained 4-items (e.g., "The product recommendation was relevant."; "I became interested in the product after it was recommended by the Virtual Service Agent.") that were measured in a 5-point Likert-scale format that ranged from "strongly disagree" to "strongly agree".

Purchase Intention: To measure participants intention to purchase the product that is recommended to them, I used an adaptation of the scale developed by Rodgers (2003). This scale included three items (e.g., "I'm likely to purchase this product."; "I'm interested in this product.") that were measured in a 5-point Likert-scale format that ranged from "strongly disagree" to "strongly agree".

4. Results

4.1. Data preparation

Some of the scales had items that were measured with reverse scoring, so I recoded them before combining the various items of each scale into their mean value, which was used to represent that variable. Additional variables were created as dummies for both the type of appeal and type of product, as well as their interaction factor with both the involvement scale and the need for cognition and faith in intuitions scales. No outliers were found from the variables under analysis and, because the dependent variables already resembled a normal distribution, no transformation of these variables was conducted.

4.2. Scale reliability

Although all scales in this experiment were retrieved from prior studies, because some items were adapted, I decided to test each scale's Cronbach alpha to determine their reliability, with the results being displayed in Table 3. The only scale that reported an alpha under .7 was the Need for Cognition scale, even though all the items in this scale were used exactly as in the original experiment conducted by Epstein et al. (1996), which found them to be "sufficiently reliable and independent" (p.399).

Table 3 - *Scale's reliability test results*

Scale	Number of items	Cronbach's alpha
NFC	5	.611
FI	5	.816
Online Shopping Experience	3	.885
Recommendation Usefulness	4	.851
Product Advice Credibility	3	.806
Purchase Intention	3	.749
Experience Product Knowledge	4	.933
Search Product Knowledge	4	.822
Experience Involvement	10	.950
Search Involvement	10	.823

4.3. Descriptive statistics

Table 4 exhibits the number of participants that were represented in each condition as well as its percentage of the total number of responses. Moreover, Table 5 displays the descriptive information of the scale variables that were present in this experiment.

Table 4 - *Absolute frequency per condition*

Condition	Absolute Frequency	%
Experience Product & Analytic Appeal	41	28.5
Experience Product & Intuitive Appeal	32	22.2
Search Product & Analytic Appeal	38	26.4
Search Product & Intuitive Appeal	33	22.9
Total	144	100

Table 5 - *Means and Standard Deviations (SD) of all the variables used*

Scale	*N*	*M*	*SD*
NFC	144	3.483	0.654
FI	142	3.558	0.731
Online Shopping Experience	144	3.671	1.041
Recommendation Usefulness	144	3.486	0.800
Product Advice Credibility	144	3.340	0.722
Purchase Intention	143	3.494	0.805
Product Involvement	144	4.690	1.322
Chatbot Familiarity	144	2.92	1.058
Product Knowledge	144	3.361	1.616

4.4. Hypothesis testing

4.4.1. The effect of type of appeal on recommendation persuasiveness, and the moderating role of product type.

The first hypothesis (H1) predicted that intuitive appeals would result in higher persuasiveness in comparison to analytic appeals. Further, in H4 I predicted that there would be a moderating effect played by the type of product, such that intuitive appeals would be more effective for experience products while analytic appeals would be more effective for analytic products. To test for these hypotheses, I conducted three two-way ANCOVA in which the independent variables were dummies for both the appeal type and the product type. The type of appeal was coded as -1 for analytic appeals and 1 for intuitive appeals and, similarly, product type was coded as -1 for search products and 1 for experience products. To measure the persuasiveness of the recommendation message, I used three dependent measures: perceived recommendation usefulness, product advice credibility, and purchase intention. Each one was used in its own model. Finally, chatbot familiarity, product knowledge, and online shopping experience were used as covariates. For more information, please refer to Appendix E.

Regarding H1, none of the three models presented results that supported the hypothesis. Although I predicted that intuitive appeals would generate higher message persuasiveness, the type of appeal did not have a significant effect for either of the three dependent variables, registering $p = .351$ for purchase intention, $p = .319$ for product advice credibility, and $p = .643$

for recommendation usefulness. Nonetheless, online shopping experience and product knowledge did have direct effects on purchase intention, with F (1,136) = 4.635, p = .033 and F (1,136) = 6.808, p = .010 respectively. Thus, as online shopping experience increased, purchase intention increased, and as product knowledge increased, purchase intention increased as well.

As for H4, predicting a moderator role of product type in the persuasiveness of the type of appeal, results showed only a very partial support to this proposal. By itself, product type did not have a significant effect in any of the three dependent variables, neither was it expected to. However, the interaction factor between product type and appeal type did have a significant effect on recommendation usefulness, F (1,137) = 5.337, p = .022, such that intuitive appeals in search products (M = 3.45, SD = 0.85) and analytical appeals in experience products (M = 3.27, SD = 0.81) led to a decrease in recommendation usefulness compared with intuitive appeals in experience products (M = 3.62, SD = 0.81) and analytical appeals in search products (M = 3.64, SD = 0.70). There was no moderation on purchase intention or product advice credibility, p = .130 and p = .338, respectively.

4.4.2. The moderating role of involvement on the persuasiveness of the recommendation message.

Hypothesis 2 stated that involvement would play a moderating role in the effectiveness of the type of appeal embedded on the recommendation message. Somewhat differently from the method used to test the first and fourth hypothesis, I used a linear regression to assess H3, because I wanted to investigate the interaction between a scale-type variable (involvement) and a categorical variable (type of appeal).

The dependent and control variables used were the same as in the models created to test the previous hypotheses. As for the independent variables, this model included the type of appeal, involvement, and an interaction term between the two.

There were no moderating effects found in the results, meaning that the interaction factor between involvement and appeal type was not significant for any of the three dependent variables tested, with all p values > .263. Nonetheless, it is important to note that involvement did play a significant direct effect on purchase intention, b = 0.169, SE = 0.056, β = 0.273, p = .003. Thus, in this model, as involvement increased, purchase intention increased as well. For more detailed information, see Appendix F.

4.4.3. Matching effects between type of appeal and thinking styles.

H3 proposed that by matching the type of appeal with participants' thinking styles, the most effective persuasive effects would be observed. This means that individuals that scored high in the Faith in Intuition (FI) scale should be matched with intuitive appeals, while individuals that scored high in the Need for Cognition (NFC) scale should be matched with recommendation messages that contain analytic appeals.

As in the analysis on involvement moderation, I also ran a regression model to test the interactions stated by this hypothesis. Again, recommendation usefulness, product advice credibility, and purchase intentions were the dependent variables used, and chatbot familiarity, online shopping experience, and product knowledge acted as controls. For the independent variables, I considered NFC, FI, type of appeal, and the interactions between the three (NFC * type of appeal, FI * type of appeal, NFC * FI).

Starting with the model that had purchase intention as its dependent variable, the results partially supported the hypothesis given that the interaction term between FI and type of appeal had a significant effect on purchase intentions, $b = 0.201$, $SE = 0.091$, $\beta = 0.909$, $p = .029$. Thus, a higher faith in intuition and an intuitive appeal and a lower faith in intuition and an analytical appeal resulted in higher purchase intentions. Still, all other effects from the independent variables were non-significant.

When recommendation usefulness was the dependent variable, the results did not support the hypothesis, as the interaction terms of both the NFC and FI with appeal type did not have significant effects, $p = .167$ and $p = .075$ respectfully. Nonetheless, the three independent variables had significant direct effects on participants' perceived usefulness of the recommendation message, NFC: $b = 1.190$, $SE = 0.486$, $\beta = 0.975$, $p = .016$; FI: $b = 1.344$, $SE = 0.457$, $\beta = 1.234$, $p = .004$; appeal type: $b = -1.055$, $SE = 0.497$, $\beta = -1.325$, $p = .036$, such that higher NFC, higher FI and an analytic appeal resulted in higher perceived usefulness.

Finally, the model with product advice credibility as the dependent variable found similar results to the first, as the interaction term between the type of appeal and FI also had a significant direct effect, $b = 0.208$, $SE = 0.085$, $\beta = 1.051$, $p = .016$. Additionally, the type of appeal by itself also registered a significant effect, $b = -1.113$, $SE = 0.469$, $\beta = -1.548$, $p = .019$. Hence, analytic appeals increased product advice credibility, and the same happened when a higher faith in intuition was matched with an intuitive appeal and a lower faith in intuition was matched with an analytical appeal.

In all, the results did not show any significant effects on any of the three dependent variables from matching participant's Need for Cognition scores with the type of appeal. However, for the interaction between participant's Faith in Intuition scores and the type of appeal used, results did show significant effects on both purchase intention and product advice credibility, and marginal effects on recommendation usefulness. Therefore, the hypothesis stating that matching thinking styles with the type of appeal embedded in the recommendation message was only partially supported. For more detailed information, please refer to Appendix F.

5. Discussion

5.1. Summary of results

The implementation of chatbots in the online retail channel has turned into a reality over the past decade. Besides responding to consumer queries, these intelligent robots can be used to give personalized recommendations that are adapted to each consumer's needs, preferences, and individual differences. An example of these differences is in how people process information, their thinking styles. In this dissertation, my aim was to understand how personalized recommendations provided by a chatbot may influence consumer's attitudes, and the role that their thinking styles, their level of involvement, and the type of product played in this effect.

An experiment with three different analyses was used to test the effects of the recommendation message on consumers' attitudes. The first analysis was used to evaluate the first and fourth hypotheses. The results did not support H1's prediction that intuitive appeals would be more persuasive that analytic appeals, regardless of the type of product under consideration. Additionally, in terms of H4, introducing an interaction of type of appeal with product type (search or experience) did not change the significance of the results, except for the case where recommendation usefulness was used as the dependent variable. Thus, using intuitive appeals for experience products and analytic appeals for search products proved to have a positive and significant effect on participants perceived usefulness of the recommendation message, although the same did not hold true for their purchase intention or perceived credibility of the recommendation. Similarly, the results did not find support for the H2, which predicted that involvement would play a moderating role for the effects of product recommendations on participant's attitudes, as the term that interacted involvement with type

of appeal was not significant for any of the three dependent variables. Finally, in H3, I predicted that the most effective persuasion would be obtained by matching intuitive appeals with individuals that have a higher tendency to rely on intuitive thinking, and analytic appeals with individuals that have a higher tendency to rely on their analytic thinking. The results only showed partial support to this prediction. They found significant effects of matching participants with high scores on the FI scale with intuitive appeals on purchase intention and product advice credibility, and marginal effects on recommendation usefulness. However, these results only covered one part of the hypothesis. The other, predicting that analytic appeals would be more effective for participants with high scores on the NFC scale, was not supported, as no significant effects were found for all three dependent variables.

5.2. Implications

The findings of this dissertation, although limited, do offer some contributions to the academic and managerial context. Research on the area of chatbots and product recommendations has focused mainly on the design of the tool and mechanisms behind the recommendation, such as the algorithms that define it. In this paper I intended to expand on these studies by concentrating on the human-chatbot interaction and investigating how individuals' cognitive differences may be used in the personalization of the message.

The results show that persuasion effectiveness increases when intuitive appeals embedded in the recommendation message are matched with individuals that are more reliant on intuitive thinking. This points towards the importance of understanding individual differences in thinking styles, and how personalization should not only focus on finding a product that matches consumers' wants and needs but also on delivering the message in a way that matches their specific characteristics. This finding supports previous research (Briñol & Petty, 2006) stressing that successful persuasive communication is also dependent on matching messages with individuals' thinking styles.

5.3. Limitations and future studies

This research has a set of limitations that need to be mentioned, as well as possible ways to correct them that can be used in future studies. One of the most obvious limitations relates to the relative short sample size that was obtained in this experiment and used to analyze its results. Not only that, but the participants that compose this sample were also not selected at random,

as for a big portion of them, they were directly chosen and asked to participate. It is possible to assume that a bigger and more representative sample could have changed the significance of the results obtained, and perhaps led to different findings.

Secondly, I used an experimental study to try to replicate what could happen in a real-life scenario, as this was the most effective solution to try to obtain hypothetical evidence. However, even though participants were asked to try to imagine that they were really experiencing the described scenario, this approach is still lacking on its attempt to duplicate reality. Despite not finding significant results to support all the hypothesis, it is possible to wonder how this may have differed if the experiment was implemented in a practical scenario. As many e-retailers already use chatbots, this experiment is something that might not be too difficult to implement, and results could be measured through the actual purchases of the recommended products and the feedback consumers can provide on the credibility and usefulness of the recommendation message.

Another limitation present in this study relates to the scales that were used to measure the different variables. Particularly the Rational-Experiential Inventory scale. Due to the constraint of having to rely on volunteer participants, it was important that the questionnaire was neither too long nor too complex to complete. This led to the necessity of having some tradeoffs in the construction of the survey, one of which being the REI scale that was selected. The most updated version of this scale, developed by (Pacini & Epstein, 1999) includes a total of 40 items, equally divided by rational and experiential scales, that also have subscales to measure ability and engagement in each mode. However, the one that was used in this study was comprised of only 10 items, five of which adapted from the NFC scale and the other five from the FI scale. By conducting a reliability analysis with the data from this experiment, it was found that the NFC scale was less reliable than the FI scale, $\alpha = .611$ and $\alpha = .816$ respectfully. This difference in reliability can account for some difference in the validity of each scale. In fact, “because low reliability attenuates correlations” (Pacini & Epstein, 1999, p. 973), it is plausible to assume that the significance of the relations of NFC scores with other variables could be underestimated. If this is the case, it could help explain why results support H3 in terms of the matching effects between FI scores and intuitive appeals, but the same is not true for NFC scores and analytic appeals. By using a different and more complete version of the REI scale, it is possible that future research may find support for this theory. Alternatively, researchers may choose to use the full versions of each scale, although differences in the way

they are constructed, such as the content and valence of their items, may again lead to differences in their reliability.

It is also possible that the lack of significant results found between NFC scores and type of appeal had less to do with the construct of the scale, even with its limited reliability, and more to do with the nature of the appeal itself. Although I tried to have both types of appeals as similar as possible, it may be the case that the analytic appeals were less powerful than the intuitive appeals. Future studies may tackle this limitation by conducting a manipulation check through a pretest whereby participants will be randomly assigned to either a group that will receive a message with an intuitive appeal, or one that will receive a message with an analytic appeal. Following the message, participants' perceived product quality should be measured as well as their REI scores. The goal should be to have an average perceived product quality relatively similar across both groups, so that we can try to ensure that the strength of each appeal type is as equal as possible. This, of course, while having the two groups of respondents holding similar characteristics in terms of their demographics and thinking style, so that the results can be comparable.

Similarly, I relied on findings from previous research to determine which products to use as search and experience and tried to choose them based on the intended demographic that would be targeted to participate in the questionnaire, mainly young adults. However, it is possible that these products might slightly differ in the level of familiarity, attitudes, and complexity participants feel towards them. Future studies should conduct a pretest similar to Weathers et al. (2015), to help identify a comparable set of search and experience product. First, a question should be introduced asking participants to sort various experience and search products into three groups depending on how easy they feel these products are to evaluate when shopping online ("best able to evaluate,", "moderately able to evaluate," and "least able to evaluate."). In a second task, respondents would be asked to indicate how important it is for them to physically interact with each product to evaluate its quality. Finally, the level of product familiarity and perceived complexity should be measured for each good. The products selected for the study should be the ones that record similar results of familiarity and complexity and are in similar and opposite ends of the search versus experience product dimension, as measured by the first two scales.

Finally, the structure and order by which participants responded to each question may have influenced the results obtained. Particularly for the REI scale, it is possible that by having

participants respond to it before reading the recommendation message could have acted as a prime to activate a specific style of thinking, which would bias the responses to the dependent measures that followed. Although it is also true that the appeals that participants are exposed to may change what people report on the REI scale, if the intention was to have it at the end. My decision of introducing this measure before the recommendation message was based on the methodology of previous studies, but to try to mitigate any possible unintended effects resulting from the order of the scale, future studies may want to randomize its placing on the survey, either before the recommendation messages, or right at the end. This way, on average, half of the individuals will report it before being exposed to the linguistic cues in the message, and the other half, after this exposure.

Regarding future avenues to expand on this study, researchers may choose to focus, for example, on the source of the recommendation message. Some studies (Beldad et al., 2016) have already investigated differences on how consumers perceive AI chatbots or humans as assistant agents in e-commerce, or even how different characteristics of the chatbot itself, like the presence of human qualities (Roy & Naidoo, 2021), influences consumers' attitudes. Combining these two streams of research, a future paper may seek to understand if there is a relationship between the type of appeal that is being used, and the source of the message that is offering such appeal. Perhaps consumers will respond more favorably to intuitive appeals if these come from a human assistant, as they will perceive them as more credible, while for analytic appeals, an AI chatbot may be more suitable to increase its effectiveness. Furthermore, alterations can be done to the measures that are used to evaluate matching effects between appeals and individuals' characteristics. While in this dissertation I use the NFC and FI scales to evaluate participants' tendencies to be more reliant on intuition or analysis, other measures can be used. As F. Loureiro (2021) applied in his doctoral dissertation, assessing someone's perceived validity of intuition or analysis can prove to be a very effective variable to use in measuring matching effects with the type of appeal implemented.

5.4. Conclusion

When trying to conceive personalized recommendations that can influence consumers' attitudes, it is important that retailers do not only consider what product is being advised, but also how the message is being communicated. Even if only through partial effects, this study showed that there is a benefit in matching the type of appeal embedded in the message with individuals' thinking styles. Due to the limitations in this research, it would be important that a

follow-up study is done to try to further test this effect and see if the results found for the roles of type of appeal, type of product, or involvement level either differ or support the ones found in this experiment.

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7. Appendix

A. Study demographic characteristics

Table 6 - *Sample demographic characteristics*

		Count	%
Gender	Male	59	41.0
	Female	83	57.6
	Non-binary / third gender	1	.7
	Prefer not to say	1	.7
Education Level	Less than high school degree	3	2.1
	High school graduate	12	8.3
	Some college but no degree	11	7.6
	Associate degree in college	8	5.6
	Bachelor's degree in college	70	48.6
	Master's degree	35	24.3
	Doctoral degree	3	2.1
	Professional degree	0	.0
	Other	2	1.4

Table 7 - *Mean age and SD recorded*

	N	Mean	Std. Deviation
Age	144	26.40	6.679

Table 8 - *Sample nationality distribution*

	Frequency	Percent
Australian	4	2.8
Belgian	4	2.8
Brazilian	2	1.4
Bulgarian	2	1.4
Canadian	6	4.2
English	10	6.9
French	3	2.1
German	11	7.6
Greek	3	2.1
Indian	6	4.2
Irish	3	2.1
Italian	4	2.8
Japanese	2	1.4
Lithuanian	3	2.1
Malaysian	2	1.4
Dutch	4	2.8
Norwegian	2	1.4
Portuguese	32	22.2
Romanian	2	1.4
Serbian	2	1.4
Taiwanese	2	1.4
British	4	2.8
American	16	11.1
Other	15	10.4

B. Experiment Survey

Dear Participant,

First of all, thank you in advance for your participation in this dissertation research project.

My name is Francisco Santos and I am currently developing my Master's Thesis on the topic of Optimal Decision Making. The goal of this survey is to understand how consumers react to product recommendations within an e-commerce setting and how this may affect the design of Virtual Service Assistants. This survey has an estimated duration of 5-8 minutes. You will start with a block consisting of demographic questions, followed by more specific questions related to your perceptions and behavior within a specific scenario. This questionnaire will be recorded anonymously, so I ask you to answer as honestly as possible. In no question will you be asked

to provide your name, identification number, or any other type of information that might compromise your identity.

In case you have any doubts regarding the survey, or you wish to get more information on the study, please feel free to contact me via email: s-fmfsantos@ucp.pt Completion of this survey implies your consent to serve as a participant in this research. Once again, thank you for your time and availability!

Please specify your gender:

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

What is your age?

_____

What is the highest level of school you have completed or the highest degree you have received?

- ○ Less than high school degree
- ○ High school graduate
- ○ Some college but no degree
- ○ Associate degree in college
- ○ Bachelor's degree in college
- ○ Master's degree
- ○ Doctoral degree
- ○ Professional degree
- ○ Other

What is your nationality?

▼ Afghan ... Zimbabwean

For each stattement, indicate how true it is for you:

	Completely False				Completely True
I don't like to have to do a lot of thinking.	○	○	○	○	○
I try to avoid situations that require thinking in depth about something.	○	○	○	○	○
I prefer to do something that challenges my thinking abilities rather than something that requires little thought.	○	○	○	○	○
I prefer complex to simple problems.	○	○	○	○	○
Thinking hard and for a long time about something gives me little satisfaction.	○	○	○	○	○
I trust my initial feelings about people.	○	○	○	○	○
I believe in trusting my hunches.	○	○	○	○	○
My initial impressions of people are almost always right.	○	○	○	○	○
When it comes to trusting people, I can usually rely on my "gut feelings."	○	○	○	○	○
I can usually feel when a person is right or wrong even if I can't explain how I know.	○	○	○	○	○

How familiar are you with chatbots/and or other conversational interfaces?

- ○ Not at all familiar
- ○ Slightly familiar
- ○ Somewhat familiar
- ○ Moderately familiar
- ○ Extremely familiar

For each of the following statements, please select the option that best represents your level of agreement or disagreement.

	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
I have shopped online extensively.	○	○	○	○	○
I have used the internet to shop for a long time.	○	○	○	○	○
I shop online frequently.	○	○	○	○	○

To me, a cellphone is:

	1	2	3	4	5	6	7	
Important	○	○	○	○	○	○	○	Unimportant
Boring	○	○	○	○	○	○	○	Interesting
Relevant	○	○	○	○	○	○	○	Irrelevant
Exciting	○	○	○	○	○	○	○	Unexciting
Means nothing	○	○	○	○	○	○	○	Means a lot to me
Appealing	○	○	○	○	○	○	○	Unappealing
Fascinating	○	○	○	○	○	○	○	Mundane
Worthless	○	○	○	○	○	○	○	Valuable
Involving	○	○	○	○	○	○	○	Uninvolving
Not needed	○	○	○	○	○	○	○	Needed

To me, a videogame is:

	1	2	3	4	5	6	7	
Important	○	○	○	○	○	○	○	Unimportant
Boring	○	○	○	○	○	○	○	Interesting
Relevant	○	○	○	○	○	○	○	Irrelevant
Exciting	○	○	○	○	○	○	○	Unexciting
Means nothing	○	○	○	○	○	○	○	Means a lot to me
Appealing	○	○	○	○	○	○	○	Unappealing
Fascinating	○	○	○	○	○	○	○	Mundane
Worthless	○	○	○	○	○	○	○	Valuable
Involving	○	○	○	○	○	○	○	Uninvolving
Not needed	○	○	○	○	○	○	○	Needed

For each of the following statements, please select the option that best represents your level of agreement or disagreement.

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
I would consider myself an expert on videogames.	○	○	○	○	○	○	○
My friends and family would refer to me as a videogame expert.	○	○	○	○	○	○	○
People often compliment me on my videogame knowledge.	○	○	○	○	○	○	○
I put a lot of effort into understanding how to play videogames.	○	○	○	○	○	○	○

For each of the following statements, please select the option that best represents your level of agreement or disagreement.

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
I would consider myself an expert on cellphones.	○	○	○	○	○	○	○
My friends and family would refer to me as a cellphone expert.	○	○	○	○	○	○	○
People often compliment me on my knowledge of cellphones.	○	○	○	○	○	○	○
I put a lot of effort into understanding how to use my cellphone.	○	○	○	○	○	○	○

Experience Product & Analytic Appeal - Please imagine the following situation, You are browsing the videogames' category page of an e-commerce website when you receive a message from a Virtual Service Agent (Chatbot) offering its help and wanting to assess what you are looking for. After a two-way interaction with the assistant, where you answer some questions, you receive the following message: Based on our conversation, I believe the most recent release by GameWizard would perfectly match your criteria selection. The game menus were designed to provide you a thorough and detailed navigation experience as well as an in-depth control over all the features it has to offer. The graphical elements it has to offer show even the most minute details and allow you to effectively observe and analyze your environment. The other game characters, powered by AI,

were programmed to be able to collect and assess your inputs, and act based on this data, resulting in a logical gameplay experience.

Experience Product & Intuitive Appeal - Please imagine the following situation, You are browsing the videogame category of an e-commerce website when you receive a message from a Virtual Service Agent (Chatbot) offering its help and wanting to assess what you are looking for. After a two-way interaction with the assistant, where you answer some questions, you receive the following message:
Based on our conversation, I believe the most recent release by GameWizard would perfectly match your needs and will just feel right. The game menus were designed to help you navigate in a fast and intuitive manner and have effortless control over all the features it has to offer. The graphical elements it has to offer allow you to extend your senses and really feel like you are in the game. The other game characters, powered by AI, were programmed to be able to sense and predict your inputs, so that they can react quickly and automatically, resulting in a seamless gameplay experience.

Search Product & Analytic Appeal -Please imagine the following situation, You are browsing the cellphone category page of an e-commerce website when you receive a message from a Virtual Service Agent (Chatbot) offering its help and wanting to assess what you are looking for. After a two-way interaction with the assistant, where you answer some questions, you receive the following message:
Based on our conversation, I believe the most recent release by Cypher would perfectly match your criteria selection. It offers an excellent build quality and a screen that provides thorough, detailed menus allowing for an in-depth control over the full range of applications' features. Its new camera includes a nocturnal mode that collects the smallest detail and helps you identify difficult to observe objects. The phone brings a state-of-the-art processor capable of analyzing data and acting in accordance to deliver optimal performance, and it will be able to effectively observe and analyze your day-to-day usage to maximize battery life.

Search Product & Intuitive Appeal -Please imagine the following situation, You are browsing the cellphone's category page of an e-commerce website when you receive a message from a Virtual Service Agent (Chatbot) offering its help and wanting to assess what

you are looking for. After a two-way interaction with the assistant, where you answer some questions, you receive the following message:
Based on our conversation, I believe the most recent release by Cypher would perfectly match your needs and will just feel right. It offers an excellent build quality and a screen that provides fast, intuitive menus allowing for effortless control over the full range of applications' features. Its new camera includes a nocturnal mode that extends your senses and helps you identify difficult to observe objects. The phone brings a state-of-the-art processor capable of acting effortlessly and automatically to deliver optimal performance, and it will be able to quickly sense and predict your day-to-day usage to maximize battery life.

Keeping the previously described scenario in mind, please select the option that best represents your level of agreement or disagreement:

	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
The product recommendation was helpful.	○	○	○	○	○
The product recommendation was relevant.	○	○	○	○	○
I became interested in the product after it was recommended by the Virtual Service Agent.	○	○	○	○	○
I feel that the product recommendation helped me decide what product to buy.	○	○	○	○	○

Keeping the previously described scenario in mind, please select the option that best represents your level of agreement or disagreement:

	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
The information provided by the Virtual Service Agent is accurate.	○	○	○	○	○
The information provided by the Virtual Service Agent is credible.	○	○	○	○	○
The information provided by the Virtual Service Agent is factual.	○	○	○	○	○

Considering that you are facing the previously described scenario, please select the option that best represents your level of agreement or disagreement:

	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
I'm likely to purchase this product.	○	○	○	○	○
I would like to have more information on this product.	○	○	○	○	○
I'm interested in this product.	○	○	○	○	○

C. Control variables

Table 96 - *Correlation between control variables and dependent variables*

		Purchase Intention	Recommendation Usefulness	Product Advice Credibility
Online Shopping Experience	Pearson Correlation	.213	.151	.089
	Sig. (2-tailed)	.010	.072	.289
Chatbot Familiarity	Pearson Correlation	.049	.052	.083
	Sig. (2-tailed)	.561	.532	.322
Product Knowledge	Pearson Correlation	.277	.168	.025
	Sig. (2-tailed)	.001	.044	.763

D. Variable analysis

Figure 2 - *Purchase intention distribution*

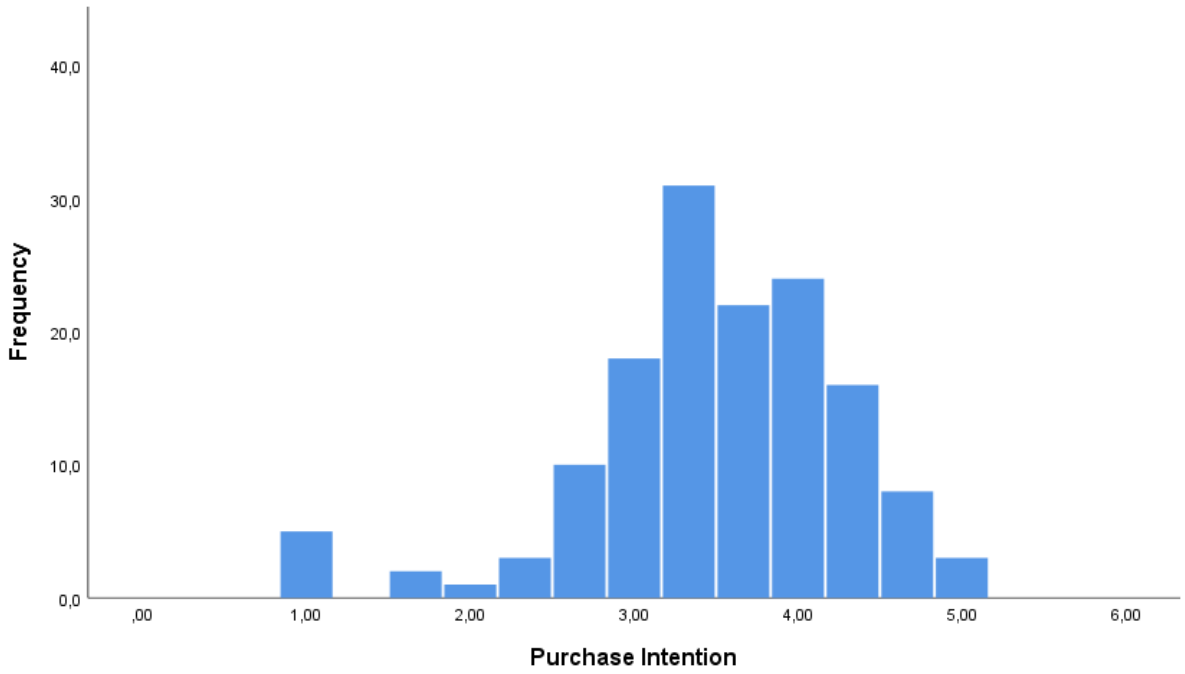

Figure 3 - *Product advice credibility distribution*

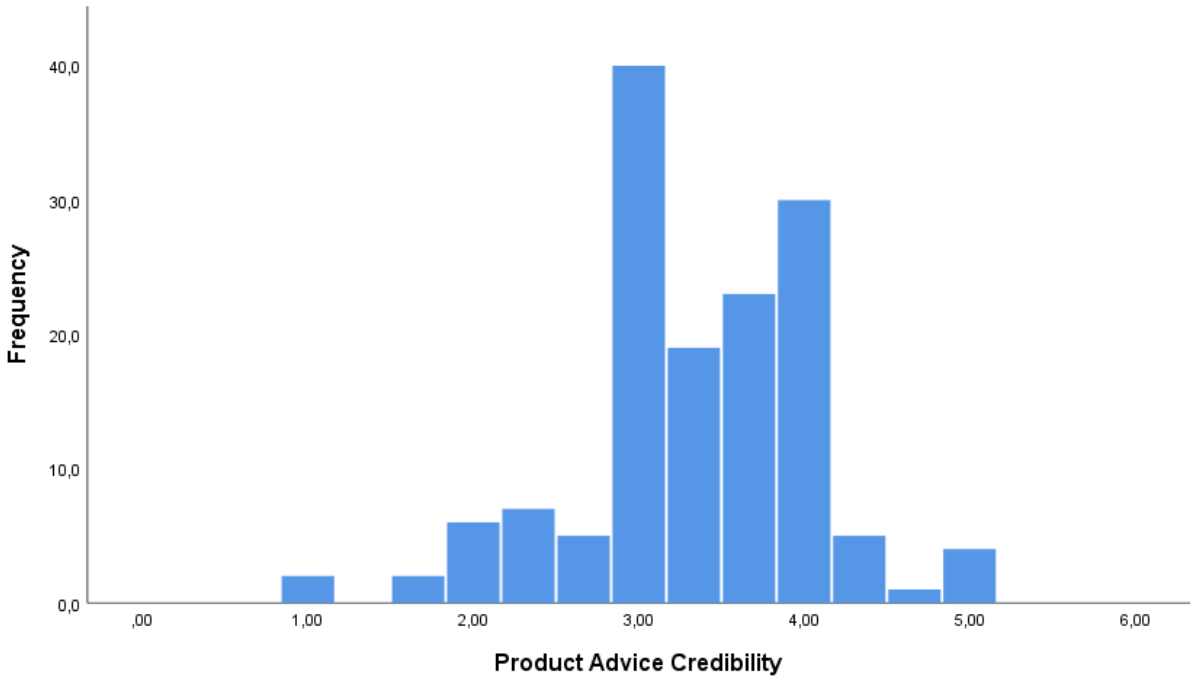

Figure 4 - *Recommendation usefulness distribution*

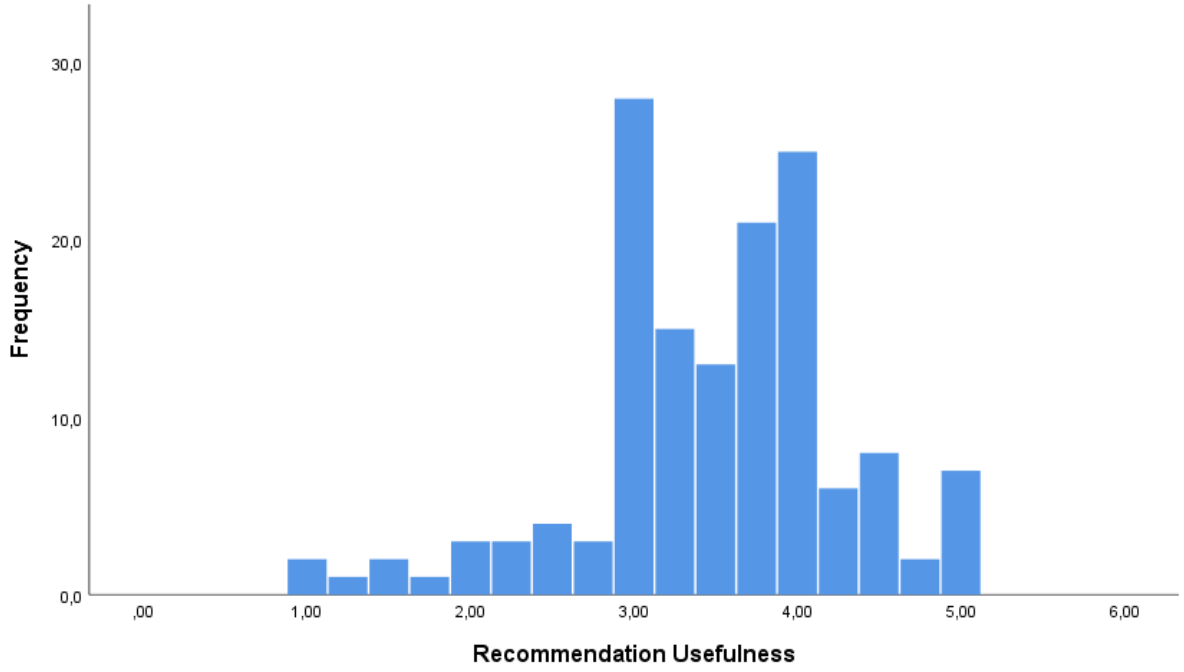

Table 70 - *Variable's mean and SD per condition*

	Condition							
	Experience Product & Analytic Appeal		Experience Product & Intuitive Appeal		Search Product & Analytic Appeal		Search Product & Intuitive Appeal	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
NFC	3.55	.76	3.50	.46	3.36	.67	3.53	.66
FI	3.42	.72	3.71	.67	3.59	.81	3.53	.71
Online Shopping Experience	3.62	1.09	3.86	1.03	3.55	1.00	3.69	1.06
Product Knowledge	3.07	1.74	2.49	1.53	3.81	1.35	4.05	1.40
Chatbot Familiarity	3.02	1.08	2.87	.98	2.61	1.15	3.21	.93
Recommendation Usefulness	3.27	.81	3.62	.81	3.64	.70	3.45	.85
Product Advice Credibility	3.37	.71	3.36	.65	3.40	.66	3.21	.87
Purchase Intention	3.37	.92	3.43	.92	3.71	.58	3.45	.75
Product Involvement	4.40	1.56	4.26	1.59	5.02	.86	5.09	.93

E. The effect of appeal and product type on the dependent variables

Table 11 - *ANOVA Product Advice Credibility*

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	2.157[a]	6	.359	.680	.666
Intercept	52.649	1	52.649	99.638	.000
Product Knowledge	.005	1	.005	.010	.921
Chatbot Familiarity	.742	1	.742	1.404	.238
Online Shopping Experience	.565	1	.565	1.069	.303
Appeal Type	.529	1	.529	1.000	.319
Product Type	.081	1	.081	.154	.696
Appeal Type * Product Type	.489	1	.489	.926	.338
Error	72.392	137	.528		
Total	1,681.222	144			
Corrected Model	74.549	143			

Table 82 - *ANOVA Purchase Intention*

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	11.717[a]	6	1.953	3.310	.005
Intercept	38.618	1	38.618	65.446	.000
Product Knowledge	4.017	1	4.017	6.808	.010
Chatbot Familiarity	.187	1	.187	.317	.575
Online Shopping Experience	2.735	1	2.735	4.635	.033
Appeal Type	.516	1	.516	.875	.351
Product Type	.104	1	.104	.176	.675
Appeal Type * Product Type	1.372	1	1.372	2.326	.130
Error	80.250	136	.590		
Total	1,837.889	143			
Corrected Total	91.967	142			

Table 93 - *ANOVA Recommendation Usefulness*

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	7.596[a]	6	1.266	2.068	.061
Intercept	48.974	1	48.974	79.992	.000
Product Knowledge	1.713	1	1.713	2.799	.097
Chatbot Familiarity	.300	1	.300	.490	.485
Online Shopping Experience	1.129	1	1.129	1.845	.177
Appeal Type	.132	1	.132	.216	.643
Product Type	.015	1	.015	.025	.874
Appeal Type * Product Type	3.268	1	3.268	5.337	.022
Error	83.876	137	.612		
Total	1,841.500	144			
Corrected Total	91.472	143			

F. The moderating effect of involvement on the interaction between appeal type and the dependent variables

Table 104 - *Linear Regression Purchase Intention*

	Unstandardized Coefficients		Standardized Coefficients		
	B	Std. Error	Beta	t	Sig.
(Constant)	2.030	.342		5.936	.000
Online Shopping Experience	.127	.062	.164	2.037	.044
Product Knowledge	.056	.046	.112	1.236	.219
Chatbot Familiarity	.003	.061	.004	.055	.956
Appeal Type	-.059	.240	-.073	-.245	.807
Involvement	.169	.056	.273	3.035	.003
Involvement * Appeal Type	.001	.049	.006	.020	.984

Table 115 - *Linear Regression Product Advice Credibility*

	Unstandardized Coefficients		Standardized Coefficients		
	B	Std. Error	Beta	t	Sig.
(Constant)	2.906	.332		8.747	.000
Online Shopping Experience	.068	.060	.098	1.126	.262
Product Knowledge	-.006	.043	-.013	-.138	.891
Chatbot Familiriarity	.063	.059	.092	1.053	.294
Appeal Type	-.074	.228	-.103	-.325	.746
Involvement	.004	.052	.007	.069	.945
Involvement * Appeal Type	.003	.047	.017	.054	.957

Table 126 - *Linear Regression Recommendation Usefulness*

	Unstandardized Coefficients		Standardized Coefficients		
	B	Std. Error	Beta	t	Sig.
(Constant)	2.900	.362		8.017	.000
Online Shopping Experience	.086	.066	.112	1.308	.193
Product Knowledge	.077	.047	.155	1.635	.104
Chatbot Familiriarity	.030	.065	.039	.458	.648
Appeal Type	.303	.249	.379	1.221	.224
Involvement	-.015	.056	-.025	-.265	.791
Involvement * Appeal Type	-.057	.051	-.349	-1.121	.264

G. Matching effects between individuals' thinking styles and appeal type

Table 137 - *Linear Regression Purchase Intention*

	Unstandardized Coefficients		Standardized Coefficients		
	B	Std. Error	Beta	t	Sig.
(Constant)	1.665	1.688		.986	.326
Online Shopping Experience	.132	.064	.172	2.062	.041
Product Knowledge	.121	.041	.241	2.967	.004
Chatbot Familiriarity	.028	.063	.036	.440	.661
Appeal Type	-.967	.505	-1.201	-1.915	.058
NFC	-.002	.492	-.002	-.005	.996
FI	.235	.463	.214	.507	.613
NFC * Appeal Type	.051	.105	.225	.486	.628
FI * Appeal Type	.201	.091	.909	2.209	.029
FI * NFC	.002	.133	.010	.018	.986

Table 148 - *Linear Regression Product Advice Credibility*

	Unstandardized Coefficients		Standardized Coefficients		
	B	Std. Error	Beta	t	Sig.
(Constant)	-.165	1.572		-.105	.917
Online Shopping Experience	.046	.060	.068	.779	.437
Product Knowledge	-.008	.038	-.018	-.207	.836
Chatbot Familiriarity	.059	.058	.086	1.012	.313
Appeal Type	-1.113	.469	-1.548	-2.373	.019
NFC	.691	.459	.627	1.506	.134
FI	.798	.431	.812	1.850	.066
NFC * Appeal Type	.083	.097	.412	.858	.393
FI * Appeal Type	.208	.085	1.051	2.448	.016
FI * NFC	-.167	.124	-.790	-1.353	.178

Table 19 - *Linear Regression Recommendation Usefulness*

	Unstandardized Coefficients		Standardized Coefficients		
	B	Std. Error	Beta	t	Sig.
(Constant)	-2.215	1.666		-1.329	.186
Online Shopping Experience	.049	.063	.064	.773	.441
Product Knowledge	.063	.040	.128	1.575	.118
Chatbot Familiriarity	-.006	.062	-.007	-.092	.927
Appeal Type	-1.055	.497	-1.325	-2.123	.036
NFC	1.190	.486	.975	2.450	.016
FI	1.344	.457	1.234	2.940	.004
NFC * Appeal Type	.143	.103	.638	1.388	.167
FI * Appeal Type	.160	.090	.729	1.775	.078
FI * NFC	-.291	.131	-1.241	-2.223	.028