“AI-designed versus human-designed recommendation systems in symbolic consumption contexts”

Stefania Kokaraki (577834)

Erasmus School of Economics

Specialization: Marketing (2020-2021)

Master Thesis | 14 August 2021

Supervisor: N.M. Almeida Camacho

Second assessor:

Table of Contents

1. Introduction

1.1 Context of the research and research questions

The substantial growth of Artificial Intelligence (AI) is influencing the present and future of each individual, industry, and -more widely- the economy globally. Although AI has been considered an innovative research field for over fifty years, its considerable prevalence began within the last decade (Anyoha, 2017). Going forward, AI will be the technological leader and the core of novel marketing applications, such as personalized content recommendations, ad targeting, predictive analytics, and chat bots, among others. Some of these applications are likely to play an essential role in our evolution process (Leung et al, 2018).

In recent years, marketers, researchers, and policy makers have shown an increasing interest in AI-based technologies and predictive analytics, as they accrue huge advantages by collecting and analyzing consumers' data. The considerable growth of AI marketing applications has facilitated the understanding and more effective targeting of customers, and has helped companies to make more informed marketing and strategic decisions. For instance, these tools allow online marketers to serve only the right product or service through platforms like Facebook, while they simultaneously liberate them from the costs of experimenting with unfound models and strategies (André et al, 2018).

Given the incrementally growing amount of information, it has become increasingly difficult for a consumer to make choices. The exponential growth of websites, search engines, ratings, and online services disorients consumers and limits their ability to select. There are various system scholars that identify this phenomenon as a source of virtue (variety of options) and menace (information overload) (Swaminathan, 2003; Chiasson et al, 2002; Hanani et al, 2001).

Among the most utilized marketing applications - that emerged in the 1990s with the aim to solve the 'menace' of information overload - are recommendation systems. In the past decades, recommendation systems evolved through AI and are now an indispensable feature of several popular websites, such as Amazon, YouTube, Netflix, Facebook, Last.fm, and Pandora.

Particularly, an AI-designed recommendation system is often described as a subset of an information filtering system that collects data from different sources through algorithms, predicts consumer preferences for products or services, and finally provides them with related indications in a form of advice (Isinkaye, Folajimi, & Ojokoh, 2015). The intelligent and efficient design of recommendation engines has provided companies with convenience, but most importantly with a huge amount of data about customers' preferences and purchases. Subsequently, these data can be used to augment customer interaction and enrich shopping potential. Moreover, recommendation systems can provide customers with personalized advice, which can alleviate the difficult part of decision-making and enhance their purchasing experience. The rapid integration of AI-designed recommendation systems by several industries can be justified by the fact that they are quite apt at generating tailored suggestions easily and effectively both for customers and the company itself.

Despite the beneficial aspects of recommendation systems, there are certain potential drawbacks, which are mostly related to their design process. Before the advent of AI, recommendations had an entirely different form, as they were created solely by humans. In this thesis, these recommendations will be defined and labeled as 'human-designed recommendations'. In fact, consumers not long ago were making decisions based on other humans' advice. For instance, in the past, employees often knew their customers personally and made recommendations to them according to their intuition or previous purchases. This transition from interpersonal conduct to the interaction with content created by machines can cause people to doubt AI recommendations' ability to provide accurate and emotionally-connected suggestions, as human-designed recommendations do (Ekstrand et al, 2014).

However, each consumer's personal perspective and psychological forces also shape the weighting between their opinion and a given advice. In particular, consumers tend to solicit opinions of worthy advisors, evaluate the merit of each opinion, and then combine them (Van Swol & Sniezek, 2005). Therefore, in order to examine consumers' perception and their willingness to accept advice from the different recommendation system designs

(AI vs. human), it is necessary to understand how consumers make choices and whether these choices vary according to the consumption situation.

Granulo, Futch, and Puntoni (2021) have demonstrated that 'consumption is often symbolic'. Products with symbolic value can be defined as those with socially acceptable ability to function as a symbol. In fact, symbolic consumption is a convention that can arise on the basis of a socially common understanding of the meaning of symbols. Material objects embody a system of meanings through which individuals can express their selves and communicate with others (Wattanasuwan, 2005). Such typical examples are the need for sensory stimulation, social recognition or self-esteem, and consistency in the self-image of an individual (Witt, 2010). Therefore, the choice of a product can symbolically constitute a sense of who we are.

The degree of symbolic value may differ depending on the product. For example, tattoos are generally products with higher symbolic value compared to pencils. Similarly, symbolic differentiation can even be observed in the consumption of the same products depending on the situation (e.g. when someone uses his/her PC for work versus for leisure time). Generally, people often choose products not only for their utility, but also for what they symbolize (Granulo, Futch, & Puntoni, 2021).

In light of the above, the main research question of this thesis is:

'*Which is the consumers' willingness to accept advice from AI-designed versus human-designed recommendations in high vs. low symbolic consumption contexts?'*

1.2 Relevance of the subject and research objectives

Due to the explosive development of AI recommendation systems during the last decade, this research topic is important in the sense that such technologies are an integral part of our lives and are therefore of great business and economic interest. Nevertheless, if companies seek to facilitate consumers' lives and improve their experiences through AI, it is necessary to overcome the difficult task of integrating users' behavioral knowledge (Puntoni et al, 2020). Thus, it is imperative for marketers to understand their customers' perceptions and interactions with AI-based systems in order to provide them with the highest value (Zinkhan & Parasuraman, 2002). If the design of AI vs. human-designed recommendations can influence the advice acceptance and consequently the decision-making process, then marketers should take it into account.

Simultaneously, by considering if the symbolic value of a product can influence consumers' preference of an AI vs. human-designed recommendation, businesses and marketers can become more (or less) conservative with the usage of recommendation systems for certain products, depending on the context. Thus, the comparison of consumers' willingness to accept advice with regard to recommendation design under high vs. low symbolic consumption context can provide insights into individuals' preferences and attitudes towards those systems.

This research indicates a first attempt to discover if the design process (AI vs. human) of recommendations can influence the perception of consumers when they are exposed to a high vs. low symbolic consumption context. Specifically, the goal of this thesis is to identify research gaps regarding consumers' perception about recommendations' design and to illuminate if marketers and enterprises can adapt their use based on the level of symbolism in the consumption context.

In particular, this research will consider: (a) to what extent consumers accept advice from an AI-designed compared to a human-designed recommendation; (b) whether consumers' perception or responses change based on the level of a product's symbolic value; (c) whether consumers perceive a recommendation system as more accurate if it provides the same recommendation with their choice; (d) and to what extent consumers feel confident with the quality of their choice after receiving an (AI vs. human) recommendation. By examining these objectives, this research can provide a more nuanced understanding of how consumers behave with respect to recommendation systems under varying symbolic contexts.

1.3 Previous research on the topic

While extensive research has been conducted on peoples' attitudes towards AI recommendation systems and identity-based consumer behavior, there is only scarce literature dedicated to the specific topic, which combines consumer preferences for AI versus human-designed recommendations in symbolic consumption contexts.

Consumers' attitudes towards AI diverge from each other, according to the situation and the wider context. In 2018, Leung, Paolacci, and Puntoni examined consumer's perception of automated products that functioned based on AI. They demonstrated that, although automation provides benefits to the consumption process, often the automated products can be unattractive, especially when identity-based motivations drive consumers' consumption preferences. Indeed, there are certain conditions under which individuals tend to be less open, conscientious, and self-revealing in their interactions with AI vs. humans. Nevertheless, there are also studies that have investigated situations where consumers do not prefer humans but algorithms (Nadimpalli, 2017; Bogert, Schecter, & Watson, 2021; Logg, Minson, & Moore, 2019).

Several previous studies have argued that a consumer's perception is determined by identity-related aspects, which form the basis of the concept of symbolic consumption (Wattanasuwan, 2005; Reed II et al, 2012). The first historical references in consumer research of symbolic consumption as a fundamental concept appeared at the end of the 19^{th} century. Symbolic consumption is closely related to identity-based consumption, which focuses on how consumers express themselves and where they belong according to what product they buy. Berger and Health (2007) state that consumers often choose products that are identity-relevant to separate their selves from majorities and ensure that they effectively communicate their desired identities.

However, identities are dynamically formed by situational factors and this configuration process can occur unconsciously (Oyserman, 2009). Thus, there is both a possibility that one makes conscious decisions influenced by his identity, but also the potential that one's behavior is determined by his identity unconsciously. The above highlights the need to further investigate what triggers consumer preferences for AI vs. human-designed recommendations by considering identity-related factors, which lie at the core of symbolic consumption.

Moreover, closely linked to the specific topic is the research of Chung et al. (2020), who examined the naturalness of the AI vs. human recommendation agents in the context of symbolic consumption by using visual functionality. They showed that consumers had higher perceived unnaturalness when the symbolic brand was recommended by AI vs. human agents. Another relevant approach to this topic is the research of Granulo, Futch, and Puntoni (2021), who found that people have a higher preference for humans compared to robotic labor when they are exposed to symbolic consumption contexts. Also, Smith, Menon, & Sivakumar, (2005) investigated that in symbolic consumption contexts, consumers' preferences for peer versus editorial recommendations are determined by several factors, including recommender and product characteristics (i.e. high vs. low symbolic products).

This brief overview indicates that this thesis can contribute to the literature on the subject by providing an up-to-date overview of consumers' perception and willingness to accept advice between the different designs of recommendation systems under symbolic consumption contexts.

1.4 Structure of the Thesis

This section provides an overview of the thesis' structure. The following Chapter (2) aims to review existing theory on advice (2.1), AI recommendation system designs (2.2), consumer's perceptions and interactions with AI (2.3), and human-designed recommendation systems (2.4). Afterward, a comparison is conducted with regard to the symbolic value of the products (2.5) and the handmade effect is analyzed (2.6). The subsequent subchapter summarizes all of these into a conceptual framework (2.7). Chapter 3 focuses on the experimental design and, specifically, on which methods are used (3.1), the procedure (3.2), and how the hypotheses are tested (3.3). In Chapter 4, the experiment's data and results are analyzed. This analysis aims to assess which are the essential features that could influence consumers' perception and advice acceptance. Finally, Chapter 5 summarizes the outcomes and attempts to answer the research question posed in the introduction. It also demonstrates the academic contribution of this thesis (5.1), outlines its limitations, and makes suggestions for future research (5.2).

2. Theory and Hypothesis

2.1 Acceptance of advice

Both AI and human-designed recommendations entail a form of advice. Seeking advice is a fundamental practice in many real-life decisions. An important motivation for an advice-taker to solicit advice from an advice-giver is the need to improve judgment accuracy and the expectation that such advice will help the advice-taker make a better decision. Prior research indicates that in general, people perceive advice as useful and have a tendency to follow it (Yaniv & Kleinberger, 2000). However, in order to be more precise is necessary to focus on people's behavior and attitude towards advice acceptance that depends on at least two main factors.

First, advice acceptance depends on the extent to which an advice-taker trusts the advice-giver and his/her intentions. Previous research demonstrates the prominent influence of consumers' trust for recommendations in the context of advice adoption (e.g. Wang and Benbasat, 2005; Choi et al., 2011; Dabholkar and Shen, 16 2012). Trust implies the discretion of an individual to influence one's interests. Individuals usually trust others in situations that involve uncertainty, where uncertainty precedes the decision to trust someone else and another person's trust acts as a way to limit that uncertainty (Van Swol & Sniezek, 2005).

Second, advice acceptance depends on the advice-taker's confidence which can be characterized as a persons' belief that their opinion is accurate and correct. People are more likely to reject advice –even expert advice- when they are overconfident or overestimate their own initial decisions. This phenomenon is called 'egocentric discounting' and occurs in situations where people combine advice with their own judgment, even if the advice was given by a more experienced advisor. This process can lead to poorer decisions than fully accepting advice from an expert but people often underestimate the benefits that advice can provide (Yaniv & Kleinberger, 2000).

Third, the degree of the advice giver's expertise also plays an important role in the advice-taker's acceptance of advice. Thus, the assessment of advice impact should take into account, not only the informational effects but also the impact on individuals' identities and relationships between donor and recipient (Van Swol & Sniezek, 2005).

In sum, the advice-taker’s trust in the advice-giver, his/her confidence, and the advice-giver’s expertise, may determine the consumer’s willingness to accept or not a piece of advice.

Importantly, an advice-taker not accepting an advice-giver’s recommendation is not a “binary” outcome. Especially when the advice conflicts with the advice-giver’s beliefs or decision, one can distinguish between at least four levels of adherence to advice (see Figure 1):

1) *Strong non-adherence:* The advice-taker does not change his/her decision and shows relatively high confidence in his/her final decision;
2) *Weak non-adherence:* The advice-taker does not change his/her decision but shows relatively low confidence in his/her final decision;
3) *Weak adherence:* The advice-taker changes his/her decision but has low confidence in his/her final decision;
4) *Strong adherence:* The advice-taker changes his/her decision and has high confidence in his/her final decision.

- No change in decision	- No change in decision	- Change in decision	- Change in decision
- High confidence in final decision	- Low confidence in final decision	- Low confidence in final decision	- High confidence in final decision

Figure 1 Four levels of adherence to advice

2.2 AI-designed Recommendation Systems

There are several different approaches to the design of AI-based recommendation systems with different methodologies and concepts. The most commonly used types are collaborative filtering, content-based filtering, and hybrid models. In particular, collaborative filtering generates recommendations for customers by collecting information, not only from the user itself but also from different users' past behavior with similar purchases and history ratings for items. A content-based filtering system recommends alternative items similar to previous users' preferences that could be attractive for him/her. This system uses keywords to describe the items and draws information from the user's profile to identify the type of items that this user liked in the past (Fayyaz, 2020).

Both types of systems described above suffer from the problem of 'cold-start'. Cold-start is a situation where recommendations are unfounded, given that users or items are new and subsequently the engine lacks historical data to extract information. Another similar problem is data sparsity, which is the lack of information for a user. This phenomenon mainly appears in cases where a user has limited evaluations and ratings of items and limited information about their preferences.

A hybrid model is the combination of the systems above. This can improve the accuracy of recommendations, while it can also be used to overcome the issues of cold start and data sparsity. Several studies that empirically compare the hybrid model's performance with collaborative and content-based methods have shown that hybrid methods can provide more accurate advice and improve decision quality.

In addition, there are several other models, the majority of which focus on recommending the most relevant content to consumers by using contextual information (e.g. constraint-based methods, case-based methods, knowledge-based methods, etc.). Each model provides an alternative set of costs and benefits to the consumer, which in turn leads to different outputs.

Regardless of their type, all AI-designed recommendation systems have a mechanism that is mainly supported by a machine-learning algorithm. The integration of big data and machine-learning into recommendation engines has made them direct and effective systems. The use of AI in recommendation systems can be beneficial for consumers but also for the system itself, as it can elicit information about individual consumers' preferences and store huge amounts of data (Diehl, Kornish, & Lynch, 2003; Senecal & Nantel, 2004; Urban & Hauser, 2004). This technology has made user navigation easier by relieving them from the time and inconvenience of searching (Lee & Hosanagar, 2014).

Consumer's data generated by recommendation systems can also be harnessed to create relevant strategic recommendations for marketers, in order to help them make more accurate and reliable managerial decisions (Schrage, 2018). Many businesses have integrated recommendation systems in their marketing strategies, with the aim to remain relevant in the market, increase the amount of their sales, engage with their consumers, and subsequently build brand loyalty. Industry reports have claimed considerable increases in revenue due to the use of recommendation systems (Lee & Hosanagar, 2014). Recommendation engines are updated on a regular basis, to reflect the activity of each user on the platform and at the same time highlight the wide range of content available.

Companies such as Amazon, YouTube, and Spotify make extensive use of AI recommendation systems by using combinations of the methods mentioned above, tailored to their needs. The most typical example that has equipped its platform with a recommendation engine is Netflix. Netflix uses a personalized recommendation engine: almost 80% of its viewing activity comes from recommendations and only 20% from searches (Hallinan & Striphas, 2016). The widespread use of such systems from well-known companies can be attributed to the fact that they can combine three key managerial pillars: data generation process, analytics enhancement, and choice empowerment (Schrage, 2018). But how do consumers perceive those systems?

2.3 Consumer's perception for AI-designed recommendation systems

Over the years, several researchers from marketing, sociology, and psychology domains have discovered important aspects of how consumers interact with and perceive such technologies. The various types of AI-designed recommendation systems have different impacts on consumers, whose opinions diverge. There are many situations where consumers have a positive attitude towards AI-designed recommendation systems, but studies have also highlighted situations where people are more conservative with their use.

According to a study by Accenture Interactive, the majority of consumers prefer buying from companies that provide recommendation systems (Lee & Hosanagar, 2014). Consumers become more confident in their decision-making and perceive higher interactivity with e-stores when they comply with product recommendations (Aljukhadar, Senecal, & Daoust, 2012). In 2018, Schmit and Requelme examined the dynamics between recommendation systems and users and found that consumer's preferences are determined by the degree of recommendation systems' consistency and efficiency.

Another relevant approach is that consumers treat recommendation agents as "social actors". Both usefulness of recommendation systems as "tools" and consumers' trust in the systems as "virtual assistants" are significant in consumers' intentions to adopt the advice of online recommendation agents (Benbasat & Wang 2005). Most recently, Shin (2020), investigated that consumers perceive an AI recommendation system as trustworthy and useful when it is fairer, accountable, transparent, and interpretable. This demonstrates that trust is valuable to users and further implies the heuristic roles of algorithmic attributes with respect to their underlying links to trust and the consequent attitudes toward algorithmic decisions.

Furthermore, several AI-designed recommendation systems use a mechanism called "classification" in order to offer personalized suggestions. The classification method divides consumers into categories that can be valuable to affirm their self and may help them satisfy identity motives by functioning as social labels. Classification experiences can be positive for consumers because through this personalization as a certain type of person, they feel more understood, either objectively or subjectively (Puntoni et al, 2021).

In 1994, Markus and Keil posed the question: '*Why are some information systems that companies have invested millions of dollars in developing never used or avoided by the* *very people who are intended to use them?*' Several studies have tried to find an answer, but even today the answer is neither specific nor simple.

Past literature has focused on technical influential factors, mainly related to the methods and processes followed by recommendation systems, such as their type, evaluation, functionality, and performance (Pu et al., 2012). Luo et al. investigated that certain consumers become more negative when they are told in advance that they will interact with AI and not with a human. In many cases, the AI-designed recommendation systems' capacity to assist consumers decreases as the complexity of the decision-making process increases (Breugelmans et al, 2012).

In terms of functionality, in 2019, Castelo, Bos, & Lehmann found that people stop relying on an algorithm when they notice an error in it or after receiving bad advice. This phenomenon is called 'algorithmic aversion'. Algorithmic aversion is determined by the degree of people's experience with algorithms. Another research found that, to a certain extent, people's aversion is due to the lack of functionality of particular recommendation systems' types and algorithms (Van der Heijden, 2004; Kim & Kankahalli, 2009). Conversely, consumers tend to increase their dependence on the algorithm when the information provided by the algorithm output is modifiable, referring to the 'algorithm appreciation' phenomenon (Logg et al, 2019).

Although algorithms are becoming increasingly capable, people have still a tendency to be reluctant with AI, when it comes to tasks that are usually performed by humans. For instance, the influence of the human factor in social media, online reviews, and personal networks is higher than automatic recommendations and is more powerful to excel in people's decision-making (Castelo, Bos, & Lehmann, 2019). At the same time, consumers have a tendency to use established routes of searching and are reluctant to change them (Ratchford, Talukdar, & Lee, 2007).

Another research showed that consumers have a tendency to strongly ignore inaccurate advice from algorithms compared to corresponding inaccurate advice from peers (Bogert, Schecter & Richard, 2021). Additionally, consumers avoid relying on algorithms to perform tasks that are normally performed by humans, despite the fact that algorithms often have better performance. For example, Yeomans et al (2019) found that participants relied less on an algorithm than on humans for specific types of tasks (i.e. foretelling joke funniness).

Moreover, it has been observed that consumers often make choices impulsively and react spontaneously or decide based on their emotions. Even if people prefer automation when they seek to maximize convenience, there are situations where automation is not perceived as inherently valuable for them, especially in identity-based consumption contexts (Reed et al, 2012).

Importantly, people's negative perception of AI is mainly influenced by two main factors. As mentioned in the theory of advice acceptance, people's trust and confidence play a vital role and subsequently, may have a significant impact on their behavior and attitude towards AI. Specifically, there is evidence that people are less likely to trust an AI recommendation versus a human recommendation due to the lack of transparency, uncertainty, data capture exploitation, and social experience alienation (Zhang, Liao, & Bellamy, 2020; Puntoni et al, 2021). Correspondingly, in many cases, people are overconfident about their own estimates and predictions when they interact with AI. The AI potential mistakes, the consumers' absence of experience with it, and their effort to maintain internal consistency contribute to increase the 'egocentric discounting' phenomenon (Yaniv & Kleinberger, 2000).

To conclude, the automation that AI-recommendations provide is not universally desirable. Considering the dedicated literature for people's aversion towards AI, the common denominator is that the human factor is missing and the various psychological dimensions affect people's perceptions and drive their behavior.

2.4 Human-designed recommendations

Human-designed recommendations existed long before the emergence of AI. People used to seek advice from other people when they needed help in their purchases. Their role is comparable to AI-designed recommendation systems, as both of them give advice. The main difference is with regard to their functionality (AI vs. human). Human recommendation systems compared to AI-designed recommendation systems are able to serve their customers as unique individuals. Even if the AI-designed recommendation systems' methods have high performance, the interpersonal relationship that human recommendation systems provide cannot be replaced (Ekstrand et al, 2014).

So far, AI technology does not function by considering humans as individuals. Despite that algorithms can draw highly accurate predictions for individual behaviors and preferences based on data, humans tend to feel that their sense of individuality is threatened. In 2006, Haslam found that those systems are using standardized procedures which lack cognitive flexibility. Furthermore, people tend to rely more on certain heuristics, when it comes to algorithmic judgments. In fact, individuals tend to be less open, conscientious, and self-revealing in their interactions with AI versus humans, and thus, this can trigger feelings of alienation (Puntoni et al, 2020).

However, past literature has identified that often advice-takers doubt the expertise of human recommendations, as well. Theoretically, a human expert has the necessary knowledge and can solve a problem or help in a decision-making process. Correspondingly, the advice-taker trusts the advice-giver and he/she intent to follow the given recommendation. Even though people trust human advisors and they do not present a high degree of overconfidence as with AI recommendations, in terms of expertise, people's acceptance and subjective attitudes toward human-designed recommendations is lower than in AI-designed recommendations. People often follow their intuition and are reluctant to change their opinion and thus, may underestimate human advice. Conversely, AI can give them more unbiased suggestions and can provide recommendations by utilizing past preferences or knowledge about consumers with a more nuanced understanding. The machine nature of AI recommendations is often perceived as more expertized, than humans.

Therefore, consumers' behavioral and psychological intentions are able to determine their willingness to accept or not a piece of advice. In light of the above theory, we conclude in two opposing effects. The first effect is the *'negative psychological effects of AI'* where it is assumed that advice-takers typically trust AI advice less than human advice and that advice-takers are typically more overconfident when they receive advice from AI than from humans. The second opposing effect is the '*negative psychological effect of human* *advice'* where it is assumed that advice-takers are more likely to doubt the expertise of human vs. AI advice-givers. Considering the relevant theory, it is expected that the *'negative psychological effect of AI advice'* to be stronger than the *'negative psychological effect of human advice'.* Thus:

H1: Consumers accept to greater extent advice from a human-designed recommendation system versus an AI-designed recommendation system.

2.5 Symbolic consumption context

In the prior section, two opposing psychological effects were reviewed, namely the *'negative psychological effect of human advice'* and the *'negative psychological effect of AI advice'*. These opposing effects suggest that the ultimate effect of the type of advice-giver (AI vs. Human) on advice acceptance is complex and possibly contingent on moderating factors. Prior research (e.g., Granulo, Futch, & Puntoni, 2021; Wattanasuwan, 2005; Khalil, 2000) suggests that the symbolic consumption context may be an important moderator. Therefore, in this section, this moderating effect will be discussed.

Consumption is instrumental to the satisfaction of needs. The enormous variety of products and services, combined with a multitude of incentives that consumers seek with their purchasing decisions, make consumption a highly complex phenomenon. However, the extent to which products and services can serve this purpose depends on their properties. Usually, a product's properties depend on its attributes. These attributes could be tangible or intangible. Specifically, in some cases, consumers strive for social recognition and social status which apparently comply with their identity, including one's self-image and self-esteem. For example, there are cases where consumers buy products because they project their self-image and not because of their utility function (Witt, 2010). Berger and Health (2007) argue that individuals are more likely to diverge in specific domains which are identity relevant. Our memories, personality features, attitudes, and beliefs constitute the concept of identity. From a physiological perspective, identity is related to individuals' self-image, self-esteem, and individuality. Thus, people's attitudes, preferences, and purchasing behavior can act as signals of identity (Singer et al, 2013).

Based on this functional differentiation, products can be distinguished as “symbolic” versus “substantive”, or as products with “high” versus “low” symbolic value. While substantive products confer beneficial prosperity in the sense of monetary benefits, symbolic products provide self-regarding utility (Khalil, 2000). Thus, there are cases where the consumption of products is not limited to our needs satisfaction but also carries, consciously or unconsciously, symbolic meanings. Whenever consumer attitudes are motivated in the latter way, consumption is an activity that can be characterized as socially contingent.

As mentioned above, the role of identity seems to influence at a high-level consumer’s perception. Simultaneously, in high symbolic consumption contexts where products are identity relevant, people prefer human recommendations because symbolic motives represent the inherent realm of humans (Chung et al, 2020). Thus, it is reasonable to assume that in high symbolic contexts, consumers prefer more human-designed recommendations because humans are able to understand consumers’ needs, respect their identity, and treat them as unique individuals compared to AI. Alongside, the AI-designed recommendations may be more useful in low symbolic contexts for consumers, where usually their ultimate purpose is to maximize the utility function of products. Thus:

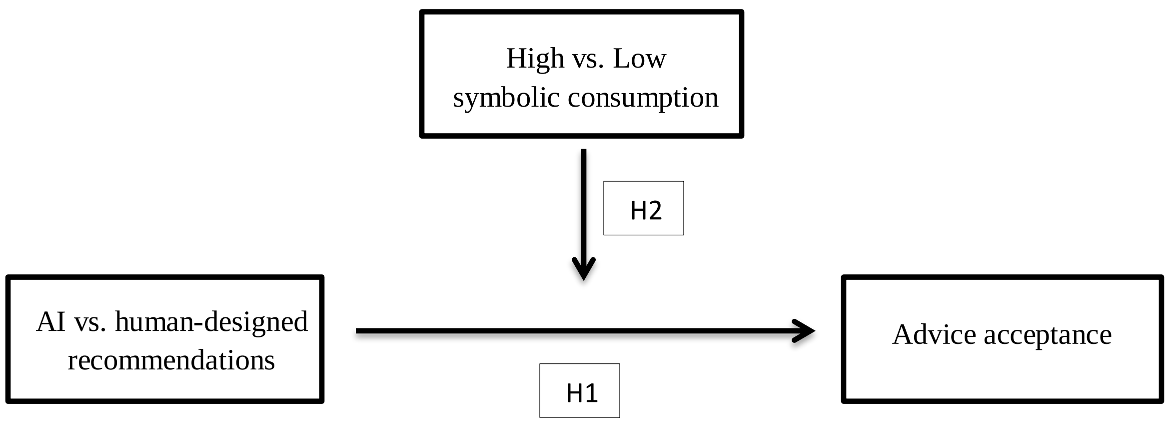
H2: In high compared to low symbolic consumption contexts, consumers tend to accept more the human-designed recommendation advice than the AI-designed recommendation advice.

2.6 Hand-made effect

AI-designed recommendations function based on algorithms, while human-designed recommendations are formed by humans. Therefore, the type of advice that each recommendation system design provides is differentiated based on their machine-made versus human-made nature. An analogous approach can be sought in the “handmade-effect”, which indicates that handmade products are considered more attractive than corresponding machine-made products because it is perceived that handmade products symbolically ‘contain love’.

In this context, “contains love” refers to consumers who perceive that a product and its production process are made with artisanal love. Artisanal love is considered as an emotional attachment to the product and its production process and is symbolically embedded in the product. This effect indicates that customers evaluate a product or service, not only according to the output but also by considering the design process (Fuchs et al, 2015). In the case of recommendation system designs, it is expected that AI is not able to express artisanal love, as it is machine-made. Instead, human recommendations that are supported by humans can express artisanal love.

2.7 Conceptual Framework



Model 1 Direct and Moderator effect

Table 1 Overview of hypotheses

H1	Consumers accept to a greater extend advice from a human-designed recommendation system versus AI-designed recommendation system.
H2	In high compared to low symbolic consumption contexts, consumers tend to accept more the human-designed recommendation advice than the AI-designed recommendation advice.

3. Research Methodology

3.1. Participants and Experimental Design

In order to empirically test the hypotheses, a quantitative research approach and specifically a between-subjects design experiment was conducted. Experiments are able to manipulate one or more independent variables and collect data on the dependent variable while controlling for other variables that may influence the dependent variable. Additionally, experiments are the only means by which causal inferences can be established and, subsequently, confounding effects can be overcome.

A between-groups design was chosen because each of the observations was needed to be assigned to different conditions. This design is divided into treatment and control groups, where the treatment groups receive "special treatment" and control groups receive no variable treatment and are mainly used as a reference.

If a within-subjects design experiment had been selected instead, where respondents participate in all scenarios, they would have understood that part of the experiment was manipulated. This could have caused inaccurate and/or socially desirable answers. Also, a within-subjects design would require six products instead of two, because each product can only meet one of the conditions. In this case, interpretation of results would be more difficult, because people's preferences for certain high versus low symbolic products would probably be hard to control. Even if the order of products and the assignment of different recommendation systems to treatments were randomized, this would complicate the design of the experiment significantly. In contrast, in a between-group design, only two products, one with high and one with low symbolic value, were needed and respondents were less likely to figure out the purpose of the experiment.

The experiment consisted of two phases. Specifically, two hundred two subjects (N = 202, 56.7% female) participated in the experiment. In the first phase, 50% of the participants were randomly assigned into one of the two groups, where the first group was exposed to a product with high symbolic value and the second group to a product with low symbolic value. The product chosen was sunglasses because it combines both symbolic and substantive values into one product. Specifically, the sunglasses' frame can be characterized as a high symbolic product, because it can act as a signal of identity and is closely related to an individual's personality, while the lenses can be characterized as a low symbolic product because they mainly have a utility function. In order to take into account individual preferences, three different products were provided to each group. In the first group, three sunglasses' frames were presented with different shapes, colors, and features. Correspondingly, in the second group, three lenses were presented with different features and intentionally without color, to avoid any identity-related choice.

In the second phase, participants were randomly reassigned into one of the three following groups: treatment A, treatment B, and control group. Specifically, treatment A included an AI-designed recommendation system, treatment B included a human-designed recommendation system, and the control group included a voucher for a future purchase, instead of a recommendation. The number of observations allocated in each group was 40%, 40%, and 20% respectively. Since a between-subjects design was selected, this separation was necessary to obtain independent observations, and to ensure that subjects will not influence each other. Also, this separation confirms the double-blind aspect of the experiment, meaning that subjects were anonymous both towards other subjects and the experimenter.

The uses of monetary incentives immediately establish a reward structure to be specified that conforms to the five precepts of Smith (1982). Institutional researchers widely use lottery incentives with the aim to increase response rates. A lottery incentive is offered as a postpaid reward to experiment participants, where each of them enters a lottery for monetary or other prizes. However, it has been found that occasionally there is no linear relationship between response rates and incentive amounts (Porter & Whitcomb, 2003). Specifically, small amounts may have little impact on participants, who may feel that they do not sufficiently justify their expenditure of time or even consider it an insult. Nevertheless, large amounts may have less impact, because participants are skeptical that they will receive the award. In addition, large amounts can be seen as compensation rather than as a symbolic benefit, thus altering the relationship from mutual to an economic one. Consequently, small amounts are to a greater extent apt to invoke reciprocity and increase the probability of responding. Simultaneously, they can improve the labor framework, which means that participants are likely to make a higher mental effort and have better performance. Considering the lottery mechanism incentives, subjects were provided with a choice to participate in a lottery for the monetary amount of 25 euro at the beginning of the experiment.

3.2 Procedure

The experiment started with the participant's agreement to participate. At the beginning of the experiment, subjects were asked demographic questions, which function as control variables. Subjects were asked to specify their gender, age, educational level, and nationality. After that, participants were randomly allocated to one of the two following groups: high symbolic product (sunglasses' frames), low symbolic product (sunglasses' lenses). Each condition included a question related to sunglasses' frames or lenses, respectively, with the aim to understand how important the style of frames or the quality of lenses is for subjects, respectively.

A scenario-based question followed. All respondents were presented with the same background information regarding a hypothetical situation of online shopping. Specifically, the scenario indicated that participants won a free new frame (or lenses) for sunglasses from a well-known optical shop named "F&R Optical". They had to go to the F&R Optical website to choose a frame (or lenses) and come up with three choices of frames (or lenses). After that, three different products - frames (or lenses) - with pictures and their characteristics were presented to the participants, who had to choose one of them.

As soon as they concluded their choice, participants were randomly reassigned to one of the following three groups: AI-designed recommendation system, human-designed recommendation system, and control group. Both the first and the second condition included a description that F&R Optical wants to provide its customers with the best shopping experience and thus in the next stage of the purchasing process they will be offered personalized advice.

The two different recommendation designs used had the same format. Each condition included an explanation of how the recommendation was powered. The first group was told that the recommendation system was powered by AI, while the second group was told that it was powered by a human. Both recommendation systems were presented as capable to identify the best frames (or lenses) based on individual characteristics and preferences. As an extra stimulus, a picture (robot in AI -designed recommendation system and human employee in human-designed recommendation system) was used to visualize and consequently enhance the experience, as well as to overcome potential weak effects. This also corrects for any possible confounding effects.

The last condition was the control group. In the control group, instead of advice, there was a descriptive text that F&R Optical wants to provide its customers with the best shopping experience and thus in the next stage, it will offer a 20 euro voucher for a future purchase of one of the products shortlisted in the first stage. This condition did not include any picture, in order to be consistent with the neutral aspect of control group functionality.

On the next page, all participants were provided with a recommendation for a certain product, which was always different from their initial choice. This step was needed to test the research question. In other words, by recommending an alternative option on purpose, it was possible to examine to what extent consumers accept (or not) an AI versus a human recommendation. The same process was followed in the control group, so as to be consistent and comparable with the treatment groups. Also, the time for the first and second decision was recorded separately, in order to examine if there is any difference between them, as the first choice was taken individually and the second one after a personalized recommendation or a voucher was preceded.

After making the second choice, to switch or not to the recommended choice, participants evaluated the recommendation design with regard to the accuracy, confidence about their choice, likelihood to purchase in the future and to recommend the brand to a friend/colleague, and perception of others' attitude towards the acceptance of advice. Also, participants had to indicate if the service contains love, considering the purchase process they experienced.

The experiment ended with an explanation about the recommendation process. Specifically, it was explained that the experiment was about their reaction to the advice given by a recommendation system and that in reality no actual system was involved in the recommendation. The hypothetical scenario that was presented at the beginning and the debriefing at the end confirm that no deception was used in this experiment. The full questionnaire is depicted in Appendix A.

3.3 Power Analysis

The power calculation provided by G*Power is used to determine the optimal sample size. The sample size is sufficiently large when the power (β) is at least 0.8, as there is an 80% chance to detect if an effect genuinely exists (Field and Hole, 2002). Also, a standard level of significance (α) of 0.5 and effect size (d) of 0.5 was assumed. This entails that a total of 192 independent observations were needed. Nevertheless, the obtained observations were above the necessary amount, and specifically 202 independent observations (Appendix B1).

3.4 Measures

Advice acceptance and confidence towards advice adherence

The dependent variable was measured in two different parts: i) advice acceptance and ii) confidence towards advice adherence. Specifically, for the first part participants after receiving a recommendation from AI vs. human-designed recommendation were asked if they want to switch from their initial choice: *'Our personalized advice suggests that you should switch to 'option x'. We know this was not the option you chose, but given this new information, do you want to change your choice?'* Based on this, a dummy was used for 'advice acceptance'. Specifically, participants who decided to switch their choice were coded as 0, and participants who kept their initial choice - did not accept the advice – were coded as 1. The second part examined based on the model with the four different 'levels' of no-adherence in relation to the confidence that discussed in the theory adapted from Yaniv & Kleinberger (2000): *'To what extent do you feel confident about the quality of the final choice you made?'* Particularly, participants' confidence for their final choice was measured by a 5-point Likert scale, where (1) means "Not confident at all confident" and (5) means “Extremely confident”. Thereafter, in order to measure the ‘adherence to advice’ in a 1-4 scale as discussed in the theory (see Figure 1), a 2x2 table was created (see Table 2). Confidence is divided into 2 levels -high and low confidence- by taking into account the mean which was 3.63. Thus, all responses that were lower than 3.63 were transformed as a dummy namely ‘low confidence’ and coded as 0 and the responses which were higher than the mean were labeled as ‘high confidence’ and coded as 1.

	Low confidence	High confidence
Switch choice (YES)	3	4
Switch choice (NO)	2	1

Table 2

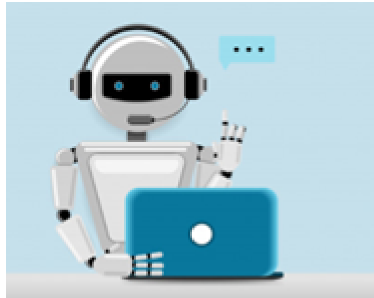
High versus low symbolic value

As discussed in the procedure, in order to measure the moderator ‘high versus low symbolic value’, the product used was sunglasses and divided into frames (high symbolic value) and lenses (low symbolic value). From the beginning of the experiment, participants randomly were assigned to one of the two conditions. As the moderator is categorical, the variable was transformed into a dummy variable, and specifically, the ‘high symbolic value’ coded as (0) and the ‘low symbolic value’ coded as (1).

AI vs. human-designed recommendation system

Following the between-subject design with a moderating variable (high vs. low symbolic products), respondents were reassigned to one of the three treatment and control groups. The participants in treatment groups A and B were exposed to a manipulated recommendation from AI (see Figure 2) and human (see Figure 3) respectively, and participants in the control group were given an offer for a future purchase (see Figure 4).

NEED STYLE ADVICE?



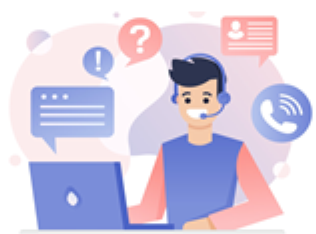
At "F&R Optical" we want our customers to always have the best shopping experience. Therefore, we will now offer you **personalized advice**. Then, based on that advice, you can either revise or keep your choice. It is entirely up to you.

This service is powered by AI. Specifically, it uses a large dataset with purchases and satisfaction scores frommore than 10,000 customers and a machine-learning algorithm to identify **the best frames for you, based on your characteristics and preferences**.

Please press the "next" button to see our suggestion for you.

Figure 2 Treatment group A

NEED STYLE ADVICE?



At "F&R Optical" we want our customers to always have the best shopping experience. Therefore, we will now offer you **personalized advice**. Then, based on that advice, you can either revise or keep your choice. It is entirely up to you.

This service is powered by an expert employee. Specifically, we rely on frontline sales employees with more than 15 years of experience, meaning they have helped and observed the satisfaction of more than 10,000 customers and are thus able to quickly identify **the best frames for you, based on your characteristics and preferences**.

Please press the "next" button to see our suggestion for you.

Figure 3 Treatment group B

TIME FOR A VOUCHER?

At "F&R Optical" we want our customers to always have the best shopping experience. Therefore, we will now offer you a **20€ voucher for a future purchase.** This offer is applicable only for one of the items you had shortlisted. Then, based on that offer, you can either revise or keep your choice. It is entirely up to you.

Please press the "next" button to see our offer for you.

Figure 4 Control group

Control Variables

With the aim to acquire a more precise prediction variance of the independent variables on the dependent variable, covariates were added to the analysis of the conceptual model. Demographic variables are controlled by measuring gender, age, educational level, and nationality. Four additional control variables are identified for this research.

To control for respondents' perception for recommendation systems' accuracy, respondents indicated on a 5-level Likert scale, from 'definitely not' (1) to 'definitely yes' (5) their agreement on the statement: *'If your choice was the same as the recommended choice, would you consider the system more accurate?'*

Furthermore, to control for differences in the willingness to recommend the brand to a friend or colleague, subjects were asked to rate on a 10-point scale, from 'not likely' (1) to 'extremely likely' (10) the following statement: *'If "F&R Optical" was a real store, how likely would you be to recommend it to a friend or colleague?'*.

Subsequently, the likelihood to buy in the future from this brand was measured on a 5-point scale, from 'extremely unlikely (1) to 'extremely likely' (5). In particular, respondents had to answer the question: *'If "F&R Optical" was a real store, how likely would you be to do any purchase from this brand in the future?'*.

Also, in order to examine if people perceive that others people's decision is differentiated from their decision, subjects rated their argument on the statement *'If you think of other people, how likely do you think they are to accept advice on their* *purchase?'* on a 5-point Likert scale and specifically, from 'extremely unlikely (1) to 'extremely likely' (5).

Lastly, the 'hand-made' effect was examined by asking participants to what extent they agreed or disagreed on three statements. Specifically, in line with Fuchs et al., 2015, the 'contains love' variable is measured by three items. This service is provided with 'warm', 'is offered with love', and 'is offered with passion', all measured by a 7-point Likert scale, where (1) means "strongly disagree" and (7) means "strongly agree".

4. Data analysis and Results

A descriptive and a sample characteristics table were created in order to get a better perception of the data (Table 2 & 3). The total sample consisted of 202 participants, with 73 subjects in AI condition, 75 subjects in the human condition, and 50 subjects in the control group, respectively. Most of the participants were from a country inside Europe (56.7%) and were female (56.7%). Also, most of them have a bachelor's (34.8%) or a master's degree (45.8%). Considering the personal characteristics between conditions, the sample randomization was performed successfully.

Table 3 Sample descriptive statistics

	N	Minimum	Maximum	Mean	Std. Deviation
Gender	202	1	4	1.60	.539
Age	202	1	6	2.78	.939
Educational level.	202	1	5	3.23	.942
Nationality.	202	1	3	2.10	.651
Valid N (listwise)	202				

Table 4 Sample Characteristics

Condition		AI	Human	Control	Total
Sample Size		75	77	50	202
Gender	Male	43.8%	37.4%	50.0%	41.8%
	Female	56.2%	61.3%	50.0%	56.7%
	Other	0.0%	4.0%	0.0%	1.5%
Age	Under 18	1.4%	1.3%	4.0%	2.0%
	18 – 24	32.9%	49.3%	42.0%	41.8%
	25 – 34	39.7%	36.0%	46.0%	39.8%
	35 – 44	15.1%	10.7%	6.0%	10.9%
	45 – 54	6.8%	1.3%	2.0%	3.5%
	55 +	4.1%	1.3%	0.0%	2.0%
Education	High-school graduate	9.6%	6.7%	8.0%	8.0%
	Some college, no degree	5.5%	14.7%	10.0%	10.0%
	Bachelor Degree	28.8%	40.0%	36.0%	34.8%
	Master Degree	53.4	37.3%	46.0%	45.8%
	PhD	2.7%	1.3%	0.0%	1.5%
Nationality	Dutch	16.4%	16.0%	18.0%	16.4%
	Other country in Europe	60.3%	58.7%	46.0%	56.7%
	Other country outside of Europe	23.3%	25.3%	36.0%	26.9%
Frames Importance	Not at all important	3.0%	0.0%	0.0%	1.1%
	Slightly important	0.0%	3.1%	8.3%	3.3%
	Moderately important	3.0%	6.3%	12.5%	7.7%
	Very important	48.5%	31.3%	41.7%	40.7%
.	Extremely important	45.5%	59.4%	37.5%	47.3%
Lenses Importance	Not at all important	2.4%	2.4%	0.0%	1.8%

Slightly important	4.9%	2.4%	19.2%	7.3%
Moderately important	14.6%	23.8%	23.1%	20.0%
Very important	58.5%	50.0%	42.3%	50.9%
Extremely important	19.5%	21.4%	15.4%	20.0%

Manipulation checks

In the first phase of the experiment, was performed a manipulation check. Specifically, the participants were randomly divided to one of the two different symbolic contexts, high symbolic context (sunglasses' frames) and low symbolic context (sunglasses' lenses). Thereafter, it was examined how important is the frames (vs. lenses) for the participants. The results showed that in the 'frames' group, most of the participants consider frames as 'very important' (40.7%) and 'extremely important' (47.3%). In the 'lenses' group, more than half of participants consider lenses as 'very important' (50.9%) and 'extremely important' only (20.0%). In addition, a T-test was performed to test whether the importance for frames vs. lenses was higher in the group that received human-designed recommendation versus the group that received AI-designed recommendation. The results of the T-test showed that the overall frame importance was significantly ($t = 49.464$, $p = 0.000$) higher in the human condition ($M = 4.41$, $SE = .783$, $N = 84$) versus the AI condition ($M = 4.32$, $SE = .806$, $N = 68$). In sum, in order to check the symbolic manipulation, we examined whether the participants' answers (high or low symbolic product) corresponded with the recommendation-design manipulation (AI vs. human) that was used in the condition participants were randomly assigned to.

Table 5 One-Sample Statistics

	N	Mean	Std. Deviation	Std. Error Mean
Frame_importance	92	4.29	.833	.087
Lenses_importance	110	3.80	.907	.086

Table 6 One-Sample Test

	t	df	Sig. (2-tailed)	Mean Difference	95% Confidence Interval of the Difference	
					Lower	Upper
Frame_importance	49.464	91	.000	4.293	4.12	4.47
Lenses_importance	43.958	109	.000	3.800	3.63	3.97

Table 7 Frames vs. lenses importance

Condition	M	SD	N
AI-designed Recommendation (Condition 2 & 3)	4.32	.806	68
Human-designed Recommendation (Condition 1 & 4)	4.41	.783	84

Note: During the experiment, the respondents were exposed to one of the four conditions. In conditions 1 (frames) and 4 (lenses) the participants received a human-designed recommendation, whereas in conditions 2 (frames) and 3 (lenses) the participants received an AI-designed recommendation.

Hypotheses testing

For the hypothesis testing, the independent variable and the moderator were recoded into dummy variables: ‘Recommendation Design (Human and AI)’ and ‘Symbolic Value (High or Low)’. Both dummy variables consisted of two categories: for the design of the recommendation the distinction was made between an AI design (‘0’) and a human design (‘1’); and for the symbolic context, the distinction was made between a high symbolic product (‘0’) and a low symbolic product (‘1’). For the analysis, a significance value of $\alpha = 0.05$ was selected.

Advice acceptance

Hypothesis 1 was created with the aim to test the relationship between the recommendation design and the intention to follow the recommendation. Based on the theory was assumed that consumers accept to a greater extend advice from a human-designed recommendation system versus an AI-designed recommendation system. In order to analyze this, a logistic regression analysis was performed, as both dependent and independent variables were categorical. The dependent variable (advice acceptance) is measured as a dummy. Specifically, participants after received the recommendation from an AI vs. human recommendation had to decide if they want to switch (0) or not (1) their initial choice. The logistic regression results are examined in the following model:

- Advice acceptance = $\alpha 0 + \alpha 1D(AI) + \alpha 2D(Human) + \varepsilon i$

The correspondence between the observed group memberships and the predicted group memberships were tested based on the model and correspondingly the misclassifications of the model based on the logistic regression model. Both in the observed and predicted percentages the 'Yes' represents the participants who switched their initial choice and the 'No' the participants who kept their initial choice. The accuracy rate for those who predicted to switch is 66.7% and for those who predicted to keep their initial choice 61.6%. The overall classification accuracy is 63.8% that means that the sample was predicted correctly by this percentage and it is sufficient.

Table 8 Classification Table

	Observed		Yes	No	Percentage Correct
Step 0	Choice_acceptance	Yes	44	22	66.7
		No	33	53	61.6
	Overall Percentage				63.8

a. Constant is included in the model.
b. The cut value is .500

Furthermore, the Omnibus tests of model coefficients can give information of whether the model includes the full set of predictors if it is significant. Therefore, it is clear that the model is a significant improvement and fit over the null model because significance is .000 < p and subsequently we can reject the null hypothesis.

Table 9 Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	12.143	1	.000
	Block	12.143	1	.000
	Model	12.143	1	.000

The proportion of variation in the dependent variable is accounted for by the predictors. Considering the Nagelkerke R Square, which has a range between 0 and 1, is above 1.

Table 10 Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	195.934[a]	.077	.103

a. Estimation terminated at iteration number 3 because parameter estimates changed by less than .001.

Considering the Hosemr and Lemeshow Test we examine the fit of the model to the data by using non-significance as an indicator of right fit. Thus, as p-value < 1.000 the model has a good fit.

Table 11 Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	.000	1	1.000

In the first model used for the first hypothesis, the independent variable -human or AI design- has a significant effect on the dependent variable (.000 < p). Considering the

Exp(B), the participants in the AI condition are likely to keep their initial choice 3.212 times more than in the Human condition with a lower bound 1.753 and upper bound 5.736 probability. In other words, when participants receive a recommendation that is human-designed, they are more likely to accept the advice than when they receive an AI-designed recommendation.

Table 12 Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C I for Exp(B)	
								Lower	Upper
Step 1[a]	Human vs. AI	1.167	.343	11.604	1	.001	3.212	1.753	5736
	Constant	-.288	.230	1.561	1	.212	.750		

a. Variable(s) entered on step 1: Condition_2.

In addition, table 13 indicates the numbers and percentages of each group in relation to the participant's responses on the dependent variable, to switch or not their choice. It is clear, that participants in treatment group A (AI) and a control group were less than participants in treatment group B (Human), for those who switched their choice (Yes). Specifically, in the AI group, 22 participants switched (29.3%), in the control group 15 (30.0%), and in the human group 44 (57.1%). For those who did not switch their initial choice (No), the highest percentages are represented in AI and control group, 70.7% and 70.0%, respectively, and only 42.9% in the human condition.

Furthermore, at the second part of the results, viewing the advice acceptance as outcome variable, the AI vs. human condition as independent variable had a significant negative effect on the advice acceptance, shown in table 16 (B = -2.221, p = 0.000). This means that the AI condition will result in a lower intention to accept advice.

Table 13 Advice acceptance * Condition Crosstabulation

			Condition			
			AI	Human	Control	Total
yes or no	YES	Count	22	44	15	81
		% within yes or no	27.2%	54.3%	18.5%	100.0%
		% within Human or AI	29.3%	57.1%	30.0%	40.1%
		% of Total	10.9%	21.8%	7.4%	40.1%
	NO	Count	53	33	35	121
		% within yes or no	43.8%	27.3%	28.9%	100.0%
		% within Human or AI	70.7%	42.9%	70.0%	59.9%
		% of Total	26.2%	16.3%	17.3%	59.9%
Total		Count	75	77	50	202
		% within yes or no	37.1%	38.1%	24.8%	100.0%
		% within Human or AI	100.0%	100.0%	100.0%	100.0%
		% of Total	37.1%	38.1%	24.8%	100.0%

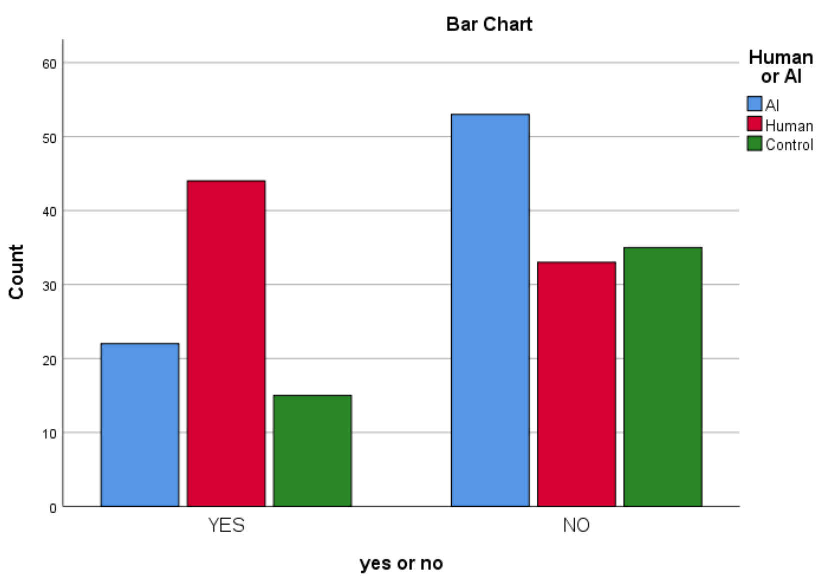


Figure 4 Percentages between the three conditions and dependent variable

Confidence

Based on Figure 1 and table 2 that created with the aim to analyze the four levels of confidence in relation to adherence to advice, a crosstabulation table was implemented to examine each level separately and compare to each other.

The first level of confidence is the 'Strong non-adherence: The advice-taker does not change her decision and shows a relatively high confidence in her final decision'. This level had the highest percentage, 38.6% with 78 respondents. This is in line with the theory of 'egocentric discounting', where people are reluctant to change their opinion, regardless of the recommendation source, and simultaneously have high confidence.

The second level is the 'Weak non-adherence: The advice-taker does not change her decision but shows a relatively low confidence in her final decision'. Participants who belong in this category are much less than in the other categories, and specifically 21.3% of the whole sample. The fact, that this category has a relatively small percentage is complementary with the first category. Specifically, we could argue that if someone keeps his/her choice it is less likely that he/she will show low confidence.

The third level is the 'Weak adherence: The advice-taker changes her decision but has low confidence in her final decision'. In this category, participants were 35, with the least percentage of 17.3%. This can be explained by contemplating that those who switched to the recommended choice have a higher willingness to accept advice compared to those who did not switch. However, their low level of confidence can be attributed to several factors. For example, there is a possibility that they do not trust the recommendation source, have doubts about it, or have other personal traits.

The fourth and last level is the 'Strong adherence: The advice-taker changes her decision and has high confidence in her final decision'. The percentage in this category is 22.8%. As the percentage is higher than the third level, we conclude that there is a higher probability, people who accepted a recommendation to feel confident. Consequently, in this case, people are more likely to trust the recommendation source.

In addition, in order to test if the variable 'advice adherence' that discussed in the theory is statistically significant, a linear regression was conducted. The results showed that the overall regression is significant with (F= 826.069, 0.000<p, R^2 = .845) and thus, the direct effect of independent variable on adherence to advice is statistically significant.

Considering the model of mediation (Appendix, B2), the mediator 'confidence' is examined in two steps. As the direct effect of the independent to the dependent variable has already been identified, it examined the direct effect between X and M (independent and mediator) that was significant (F = 826.069, p > .000). Finally, the direct effect between M and Y was examined, by using multiple regression again with X and M as predictors and Y as an independent variable. Unfortunately, the direct effect between advice adherence and confidence was not significant (Exp(B) = .692, .315 > p). The relevant tables are depicted below.

Table 14 Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.920[a]	.846	.845	.47623

a. Predictors: (Constant), Condition_2

Table 15 ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	187.349	1	187.349	826.069	.000[b]
	Residual	34.019	150	.227		
	Total	221.368	151			

a. Dependent Variable: Adherence_to_advice

b. Predictors: (Constant), Condition_2

Table 16 Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	3.493	.055		63.526	.000
	Condition_2	-2.221	.077	-.920	-28.741	.000

a. Dependent Variable: Adherence_to_advice

Table 17 Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	Adherence_to_advice	-.369	.367	1.008	1	.315	.692
	choice_acceptance	-1.263	.895	1.991	1	.158	.283
	Constant	2.239	1.323	2.867	1	.090	9.388

a. Variable(s) entered on step 1: Adherence_to_advice, choice_acceptance.

Table 18 Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change
1	.920[a]	.846	.845	.47623	.846

a. Predictors: (Constant), Condition_2

Table 19 ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	187.349	1	187.349	826.069	.000[b]
	Residual	34.019	150	.227		
	Total	221.368	151			

a. Dependent Variable: Adherence_to_advice
b. Predictors: (Constant), Condition_2

Table 20 Coefficients[a]

Model	Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.	95.0% Confidence Interval for B Lower Bound	Upper Bound
(Constant)	3.493	.055		63.526	.000	3.385	3.602
Condition (0)	-2.221	.077	-.920	-28.741	.000	-2.373	-2.068

Table 21 Coefficients[a]

Model	Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.	95.0% Confidence Interval for B Lower Bound	Upper Bound
(Constant)	3.493	.055		63.526	.000	3.385	3.602
choice_acceptance	-2.221	.077	-.920	-28.741	.000	-2.373	-2.068
(Constant)	3.553	.081		43.842	.000	3.392	3.713
choice_acceptance	-2.229	.078	-.923	-28.691	.000	-2.382	-2.075
Dummy_confidence	-.082	.083	-.032	-.995	.321	-.246	.081

a. Dependent Variable: Adherence_to_advice

High symbolic versus low symbolic context

Based on the theory, hypothesis 2 was configured by adding a symbolic consumption context as a moderator to the main model. Specifically, a moderator analysis is used to determine whether the relationship between two variables depends on (is moderated by) the value of a third variable (Appendix B2). The logistic regression model that is used is the following:

- Advice acceptance = β0 + β1D(AI vs. human) + β2D(symbolic_consumption) + β3D[(AI vs. human) * (symbolic_consumption)] + εi

As mentioned above, the overall regression model is significant ($p < .05$). In addition, the effect of the interaction 'symbolic consumption' and independent variable 'AI vs. human' is statistically significant (.000 < p-value) as expected. Specifically, in high symbolic group, participants were more likely to accept a human-designed recommendation compared to AI-designed recommendation. This can be confirmed from the interaction between symbolic consumption and AI vs. human condition which is significant (Exp(B) = 20.595, $p < .005$). Also, the B is -1.170, that means that in low symbolic context people are less likely to accept advice compared to high symbolic context. Thus, both H1 and H2 are supported which indicates that people are more likely to accept advice when the recommendation is human-designed compared to AI-designed.

In order to compare the strength of the effect of each individual independent variable to the dependent variable 'advice acceptance', the beta coefficient was used. In particular, when the absolute value of the beta coefficient is high, the effect is strong. The exponentiation of the B coefficient is an odds ratio. This means the variables of the logistic regression can easily be compared to each other. The exponentiation of the B coefficient indicates that the moderator has the highest impact on participants' choices (B = 3.025).

Table 22 Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1	Constant	3.025	.162	.026	1	.000	1.027

Table 23 Variables not in the Equation

			B	S.E.	Wald	df	Sig.	Exp(B)
Step 1	Variables	Condition (AI vs. human)	-3.037	.659	8.191	1	.000	.170
		Symbolic_consumption	-1.770	.618	21.224	1	.004	.048
		interaction	3.025	.792	14.577	1	.000	20.595
		Constant	2.015	.532	14.329	1	.000	7.500

Post hoc analysis

In addition to widely used demographic variables (age, gender, educational level, and nationality), the conceptual construct proposed four control variables that could potentially influence respondents' acceptance of advice. At the end of the experiment, participants were asked some questions relevant to the online purchasing situation they experienced. These control variables can provide a better understanding of people's perceptions of the recommendation systems.

Participants in Treatment group A (AI) and treatment group B (human) were asked the following question: *'If you think of other people, how likely do you think they are to accept advice on their purchase?'* The results showed that the highest percentage both of AI and human condition was in 'somewhat likely' scale. To test whether the variable was statistically significant an ANOVA test was conducted (Table 24). It is found that there was not a significant effect of the variable goal congruence on positive and negative anticipatory emotions ($F = 1.009$, $p = .317 > .05$).

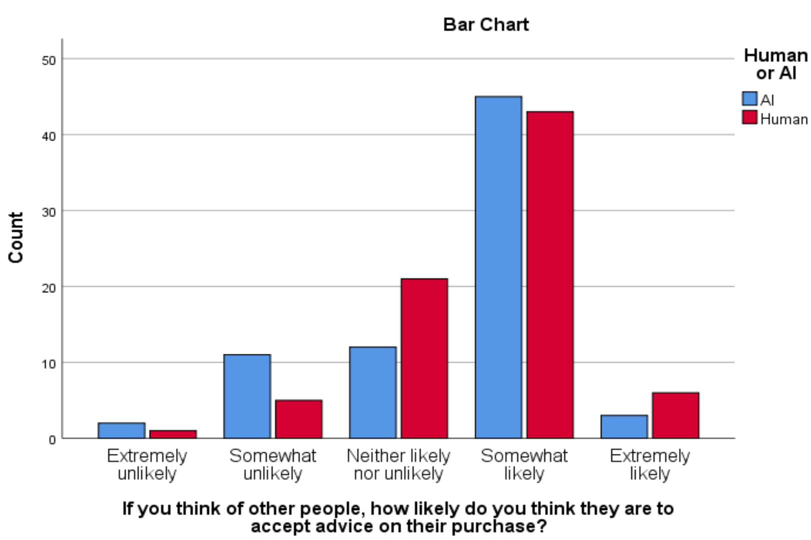


Figure 5

Table 24 ANOVA

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	.714	1	.714	1.009	.317
Within Groups	103.931	147	.707		
Total	104.644	148			

Thereafter, participants were asked *'If "F&R Optical" was a real store, how likely would you be to recommend it to a friend or colleague?'* Figure 6 indicates that Treatment B (human) is much more likely to recommend the brand compared to other groups (Table 25 & 26; Figure 6). Also, the ANOVA showed that F = 2.674, p = .104 > .05 that means that is not statistically significant.

Table 25

If "F&R Optical" was a real store, how likely would you be to recommend it to a friend or colleague?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	4	1	.5	.5	.5
	Not likely 1	6	3.0	3.0	3.5
	3	6	3.0	3.0	6.6
	4	11	5.4	5.6	12.1
	2	6	3.0	3.0	15.2
	5	25	12.4	12.6	27.8
	6	42	20.8	21.2	49.0
	7	47	23.3	23.7	72.7
	8	35	17.3	17.7	90.4
	9	17	8.4	8.6	99.0
	Extremely likely 10	2	1.0	1.0	100.0

Table 26 ANOVA

If "F&R Optical" was a real store, how likely would you be to recommend it to a friend or colleague?

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	61.198	1	61.198	2.674	.104
Within Groups	3341.883	146	22.890		
Total	3403.081	147			

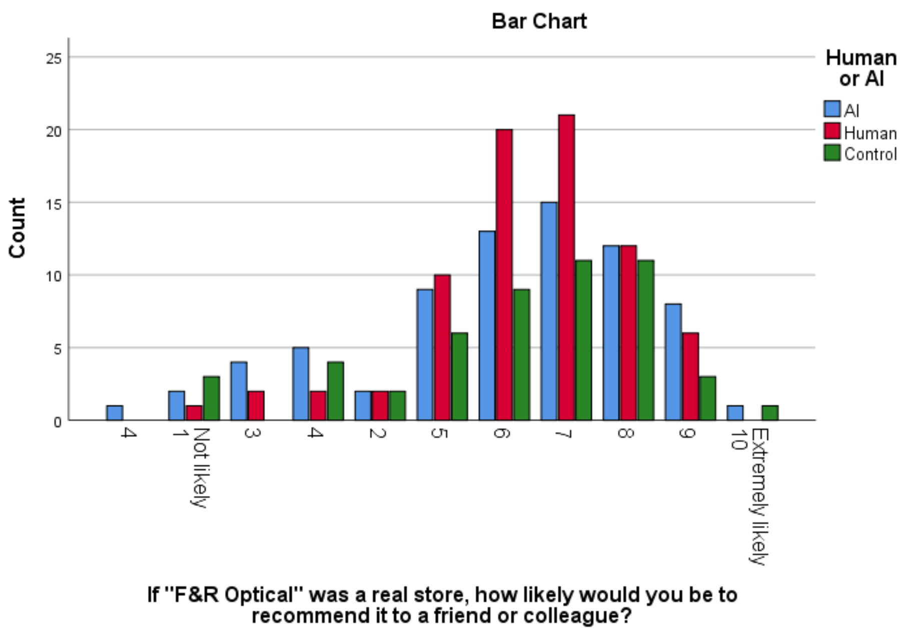


Figure 6

In addition, participants were asked *'If "F&R Optical" was a real store, how likely would you be to do any purchase from this brand in the future?'* Unexpectedly, the results showed that most of the participants who were 'somewhat likely' to buy from this brand in the future were from Treatment A (AI). Even though, participants in Treatment B (human) have relatively high percentages on scales 'neither likely nor unlikely' and 'somewhat likely'. However, the results showed that the variable is not significant with $F = 1.422$, $p = .235 > .05$.

Table 27 ANOVA

If "F&R Optical" was a real store, how likely would you be to do any purchase from this brand in the future?

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	1.064	1	1.064	1.422	.235
Within Groups	110.050	147	.749		
Total	111.114	148			

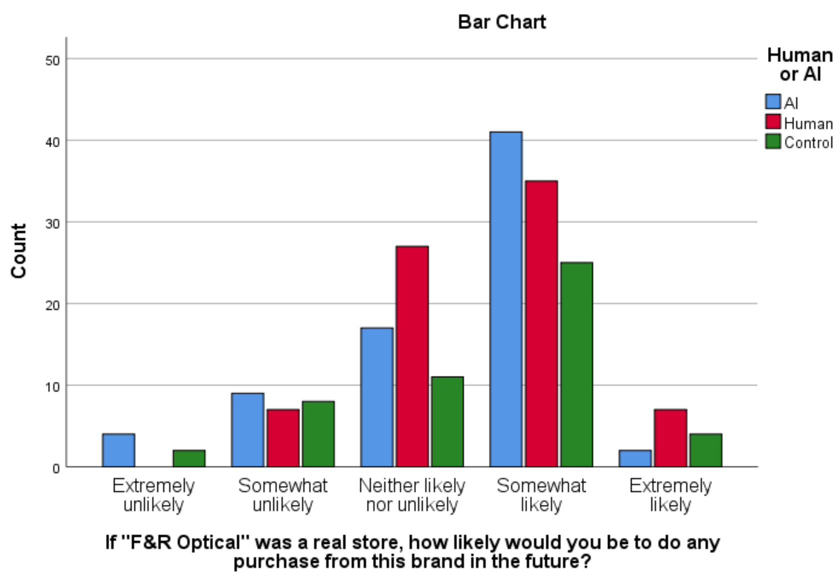


Figure 7

Finally, in order to test if the 'hand-made effect' that discussed in the theory in line with the study of Fuchs et al., 2015, the 'artisanal love' variable was measured by asking respondents to state the extent that perceive that the service provided with 'warm', 'is offered with love', and 'is offered with passion'. Each of them was tested separately by conducting ANOVA. The results showed that the 'warm' was not significant (F = 2.953, .088 > p). However, the 'offered with love' and 'offered with passion' variables was statistically significant with (F = 5.819, .017 < p) and (F = 4.621, 0.33 < p), respectively.

Thus, we can conclude that the hand-made effect is also appeared in recommendation systems' design.

Table 28 ANOVA

Considering the purchase process I just experienced, I consider that - the service provided by "F&R Optical is 'warm'

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	5.581	1	5.581	2.953	.088
Within Groups	277.841	147	1.890		
Total	283.423	148			

Table 29 ANOVA

Considering the purchase process I just experienced, I consider that - the service provided by "F&R Optical is 'offered with love'

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	11.663	1	11.663	5.819	.017
Within Groups	294.619	147	2.004		
Total	306.282	148			

Table 30 ANOVA

Considering the purchase process I just experienced, I consider that - the service provided by "F&R Optical is 'offered with passion'

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	9.410	1	9.410	4.621	.033
Within Groups	299.329	147	2.036		
Total	308.738	148			

5.1 General Discussion and Academic Contribution

Artificial intelligence is becoming increasingly significant both for companies and humans. Specifically, AI-designed recommendation systems are an indispensable part of our daily routines. Several studies have identified that algorithms are quite apt to accomplish complex and analytical tasks in a time and cost-efficient manner (Hussain & Manhas, 2016) and have the ability to surpass humans (Efendic et al., 2020). Nevertheless, even though algorithms often outperform humans on certain tasks, people still have a tendency to be averse to the usage of algorithms (Longoni et al, 2019).

This thesis aimed to examine and acquire a deeper understanding of the consumer's willingness to accept an AI-designed recommendation vs. a human-designed recommendation under a symbolic consumption context. By implementing an online experiment, the relationship between the recommendation design (AI vs. human) and the extent of people's intention to follow the recommendation was examined. Thereby, the context of symbolism (high vs. low) was expected to have a moderating effect on the relationship between the recommendation design and the advice acceptance. This was in line with the research of Chung et al. (2020), who found that people typically prefer advice from human-designed instead of AI-designed recommendations. Most of the outcomes of the initial analyses turned out to be significant and therefore the hypotheses can be confirmed. In line with previous studies (Chung et al., 2020; Granulo, Futch, and Puntoni, 2021; Smith, Menon, & Sivakumar, 2005) and our expectations, the results showed a positive significant effect of the human recommendation on the advice acceptance. Additionally, the statistical analysis showed a significant interaction effect of the recommendation design and the symbolic context on the advice acceptance, as well. This is an interesting finding since this outcome suggests that participants accept advice from a human recommendation to a wider extent as opposed to an AI recommendation in products with high symbolic value compared to products with low symbolic value. The fact that people prefer human advice for high symbolic products compared to low symbolic products is in line with the identity-based theory.

Furthermore, the results showed that people who did not change their initial choice are more overconfident as opposed to people who change their choice. This finding is in line with the ‘egocentric discounting’ effect and confirms that personal and psychological characteristics can influence their perception and drive their decisions.

Overall, this thesis provided an up-to-date overview of consumers’ perception and willingness to accept advice between the different designs of recommendation systems under symbolic consumption contexts. Thus, it opens new light to future research to further investigate whether algorithms, and more precisely whether AI-designed recommendations should be used.

5.2 Limitations and future research

I acknowledge several limitations in this study that suggest opportunities for future research.

Firstly, this research focused on people’s perception of advice accuracy but did not examine to what extent people trust recommendation systems. Trust is a predictor that has received much attention from researchers in the area of advice acceptance. Thus, further research could study the effect of trust on recommendation systems and specifically under symbolic consumption contexts, as they include identity-relevant elements and consequently may determine people’s trust.

Secondly, rather than providing participants with a real recommendation system or a technology to imitate the operation of recommendation systems in an online environment, the experiment was conducted in a fictitious scenario, and participants were asked to imagine themselves subjecting to a specific situation. Future research could conduct a lab or field experiment by using an actual recommendation system to obtain more representative results of consumer’s perception and decision-making.

Furthermore, at the beginning of the experiment, participants had to select between three default frames or lenses. Hence, they did not have many choices as in an actual website and is possible this limitation to had an impact on the advice acceptance. For example, participants may did not switch their choice because of the recommendation but because the choices were limited. Thus, future research could investigate if the results influenced by adding more options which is in accordance with the ultimate objective of recommendation system use, to solve the information overload.

In addition, the study found that people under certain circumstances are overconfident. However, there is a wide theory on confidence which was not considered in this thesis. Thus, further research can study additional dimensions of individuals' confidence in respect to recommendation system designs.

Finally, supplemental research is needed to access and review how consumers' acceptance of AI recommendations depends on the way that the recommendation is presented. This acceptance might be higher when the AI recommendation is given in a way that is more humanized, especially for products with high symbolic value. Researchers might also explore other consumption contexts where AI recommendation systems are disliked by consumers and also whether the acceptance of AI advice for symbolic products increases when algorithms provide unique individual recommendations. For instance, consumers might feel more comfortable when receive an AI recommendation for a symbolic product that is personalized and adapted to their needs.

To conclude, the thesis' findings suggest that people prefer human advice to AI advice, especially for identity-relevant products. Even if the AI will continue to have rapid technological progress in purchasing-related activities, its use and success depends not only on cost and efficiency, but also on consumers' perception and various consumption contexts.

Appendices

Appendix A - Experiment

Dear Participant,

Thank you in advance for taking part in this research. This experiment will be used for my master's thesis in Marketing at the Erasmus University Rotterdam.

The questionnaire will take approximately 5 minutes. All responses will remain anonymous and you will only be able to participate once.

Questions
If you have any questions regarding this study, please contact me at 577834sk@eur.nl.

Consent
Please click on the 'I Agree' button below, if you have understood the information regarding the participation in this experiment, you are aware that all records are confidential, you agree to participate, and you may discontinue participation at any point of the experiment.

○ I Agree

Please select your gender.

○ Male

○ Female

○ Non-binary / third gender

○ Prefer not to say

Please select your age range.

- ○ Under 18
- ○ 18 - 24
- ○ 25 - 34
- ○ 35 - 44
- ○ 45 - 54
- ○ 55 - 64
- ○ 65 +

Please select your educational level.

- ○ High school graduate
- ○ Some college, no degree
- ○ Bachelor Degree
- ○ Master Degree
- ○ PhD

Please select your nationality.

- ◯ Dutch
- ◯ Other country in Europe
- ◯ Other country outside of Europe

Treatment A

If you were looking for new sunglasses, how important would the style of the frame be to you?

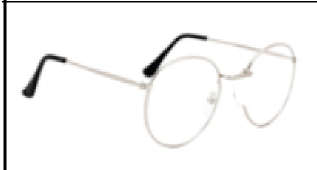
- ◯ Not at all important
- ◯ Slightly important
- ◯ Moderately important
- ◯ Very important
- ◯ Extremely important

Imagine that you won a free new frame for sunglasses from a well-known optical shop, named “F&R Optical”. You go to the F&R Optical website to choose a frame. After searching for a while you come up with the following choices.

If you have to choose one of the frames below, which of them would you select?

1

Material: Plastic
Color: Brown
Light-weight
Flexi hinge

2

Material: Metal (titanium)
Color: Silver
Light-weight
Durable/Strong
Corrosion-resistant

3

Material: Metal (aluminum)
Color: Black
Durable/Strong
Corrosion-resistant

NEED STYLE ADVICE?

At "F&R Optical" we want our customers to always have the best shopping experience. Therefore, we will now offer you **personalized advice**. Then, based on that advice, you can either revise or keep your choice. It is entirely up to you.

This service is powered by AI. Specifically, it uses a large dataset with purchases and satisfaction scores from more than 10,000 customers and a machine-learning algorithm to identify **the best frames for you, based on your characteristics and preferences**.

Please press the "next" button to see our suggestion for you.

NEED STYLE ADVICE?

At "F&R Optical" we want our customers to always have the best shopping experience. Therefore, we will now offer you **personalized advice**. Then, based on that advice, you can either revise or keep your choice. It is entirely up to you.

This service is powered by an expert employee. Specifically, we rely on frontline sales employees with more than 15 years of experience, meaning they have helped and observed the satisfaction of more than 10,000 customers and are thus able to quickly identify **the best frames for you, based on your characteristics and preferences**.

Please press the "next" button to see our suggestion for you.

Treatment B

If you were looking for new sunglasses, how important would the quality of lenses be to you?

○ Not at all important

○ Slightly important

○ Moderately important

○ Very important

◯ Extremely important

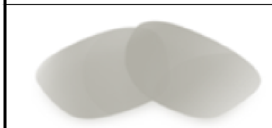
Imagine that you won a free pair of new lenses for sunglasses from a well-known optical shop, named “F&R Optical”. You go to the F&R Optical website to choose lenses. After searching for a while you come up with the following choices.

If you have to choose one pair of the lenses below, which of them would you select?

*All of the lenses can be adjusted to a frame of your choice.

1

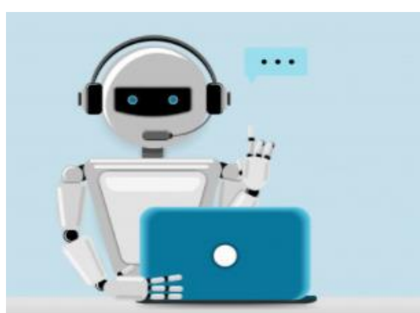
Glass
100% UV Protection
Interchangeable
40+% VLT
Anti-reflective coating
Anti-scratch coating

2

Glass
100% UV Protection
Polarized
0–19% VLT
Tinted lenses
Anti-scratch coating

3

Polycarbonate
100% UV Protection
Polarized
20–40% VLT
Anti-reflective coating
Photochromic

NEED STYLE ADVICE?

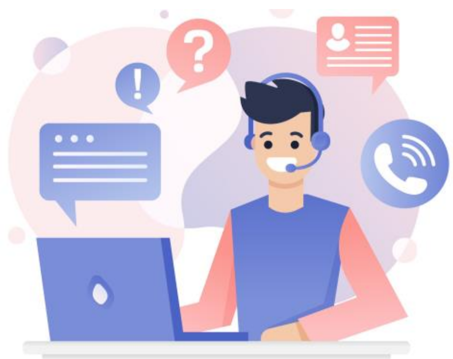


At "F&R Optical" we want our customers to always have the best shopping experience. Therefore, we will now offer you **personalized advice**. Then, based on that advice, you can either revise or keep your choice. It is entirely up to you.

This service is powered by AI. Specifically, it uses a large dataset with purchases and satisfaction scores from more than 10,000 customers and a machine-learning algorithm to identify **the best lenses for you, based on your characteristics and preferences**.

Please press the "next" button to see our suggestion for you.

NEED ADVICE?



At "F&R Optical" we want our customers to always have the best shopping experience. Therefore, we will now offer you **personalized advice**. Then, based on that advice, you can either revise or keep your choice. It is entirely up to you.

This service is powered by an expert employee. Specifically, we rely on frontline sales employees with more than 15 years of experience, meaning they have helped and observed the satisfaction of more than 10,000 customers and are thus able to quickly identify **the best lenses for you, based on your characteristics and preferences**.

Please press the "next" button to see our suggestion for you.

Control group

TIME FOR A VOUCHER?

At "F&R Optical" we want our customers to always have the best shopping experience. Therefore, we will now offer you a **20€ voucher for a future purchase.** This offer is applicable only for one of the items you had shortlisted. Then, based on that offer, you can either revise or keep your choice. It is entirely up to you.

Please press the "next" button to see our offer for you.

Imagine that before you conclude your purchase, "F&R Optical" would offer you the following recommendation:
Our personalized advice suggests that you should switch to '**option X**'. We know this was not the option you chose, but given this new information, do you want to change your choice?

○ Yes, I want to switch to option X

○ No, I want to keep my initial choice

If your choice was the same as the recommended choice, would you consider the system more accurate?

- ○ Definitely not
- ○ Probably not
- ○ Might or might not
- ○ Probably yes
- ○ Definitely yes

To what extend do you feel confident about the quality of the final choice you made?

- ○ Not confident at all
- ○ Slightly confident
- ○ Moderately confident
- ○ Very confident
- ○ Extremely confident

If you think of other people, how likely do you think they are to accept advice on their purchase?

- ○ Extremely unlikely
- ○ Somewhat unlikely
- ○ Neither likely nor unlikely

- Somewhat likely
- Extremely likely

If "F&R Optical" was a real store, how likely would you be to recommend it to a friend or colleague?

- Not likely 1
- 2
- 3
- 4
- 5
- 6
- 7
- 8
- 9
- Extremely likely 10

If "F&R Optical" was a real store, how likely would you be to do any purchase from this brand in the future?

- Extremely unlikely

- Somewhat unlikely
- Neither likely nor unlikely
- Somewhat likely
- Extremely likely

Please indicate to what extent you agree or disagree with the following statements:

Considering the purchase process I just experienced, I consider that

	Strongly disagree 1	Disagree 2	Somewhat disagree 3	Neither agree nor disagree 4	Somewhat agree 5	Agree 6	Strongly agree 7
the service provided by "F&R Optical is **'warm'**							
the service provided by "F&R Optical							

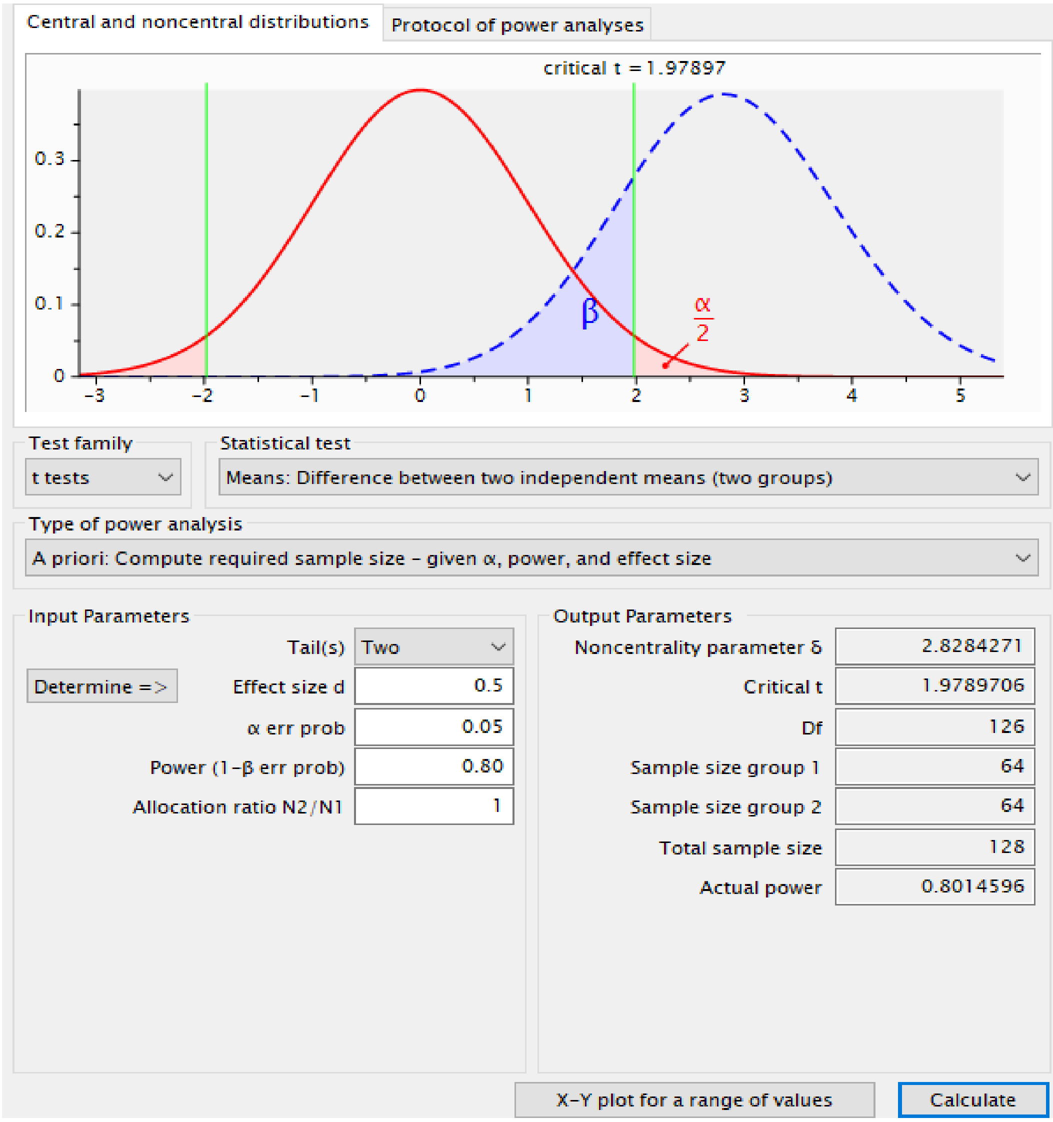
is **'offered with love'**							
the service provided by "F&R Optical is **'offered with passion'**	○	○	○	○	○	○	○

If you are interested in participating in the lottery, please insert your email address below. Once the lottery winner is selected all the data will be deleted.

The experiment was about your reaction to the advice given by a recommendation system. In reality, no actual system was involved in the recommendation.

You have reached the end of the experiment. Thank you for your time! Your response has been recorded.

Appendix B1 Power Analysis



Appendix B2

Moderation

Moderation is used to analyze whether the relationship between the dependent and independent variable is moderated, by another variable that is called 'moderator' variable. The interaction variable -the independent variable multiplied by a moderator variable- demonstrates whether moderation exists and is statistically significant. Also, Yi can explain as a linear function of the explanatory variable Xi, where β is the regression coefficient that measures the impact of independent variable (Xi) on dependent variable (Yi). Lastly, the role of X2 as a moderating variable is achieved by evaluating β3.

In order to examine the moderation analysis, the model equation will be:

$$Yi = \beta 0 + \beta 1X1i + \beta 2X2z + \beta 3\ (X1i * X2z) + \varepsilon i$$

The β3 measures the moderator effect or the interaction between variables Xi and Xz. In other words, the relationship between β1 and Yi could be affected by β2, which is influenced by β3. If the β3 output is significant, then the moderation has occurred.

Mediation

One of the most well-known theories on mediation effect is the study of Baron and Kenny (1986). They found that a variable may be able to function as a mediator that it accounts for the relation between the dependent and independent variable. This is depicted in figure 8.

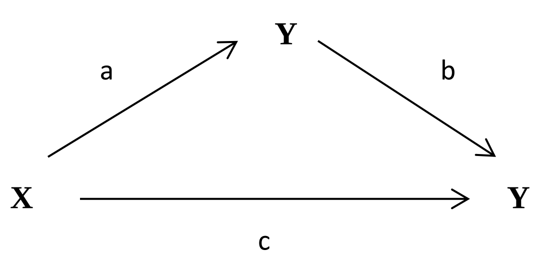


Figure 8

This figure indicates that the outcome variable (advice acceptance) is caused by two paths. First, the direct effect of the independent variable is the path (c). Second, the moderator with is confidence indicated by path (b). Furthermore, path (a) shows the effect of the condition variable on the mediators. Therefore, in order to indicate a variable as a mediator, it must meet the three following criteria in line with Baron and Kenny (1986): (a) the differences in the levels of the independent variable significantly represent the differences in the supposed mediator, (b) mediator's variations significantly represent the variants of the dependent variable, and (c) when paths (a) and (b) are controlled, a previously significant relationship between independent and dependent variables is no longer important and when path (c) is 0, the strongest demonstration of mediation is occurring. Thus, if path (c) is reduced to 0, the presence of a single dominant mediator is very likely.

Bibliography

Aljukhadar, M., Senecal, S., & Daoust, C. E. (2012). Using recommendation agents to cope with information overload. *International Journal of Electronic Commerce, 17*(2), 41-70.

André, Q., Carmon, Z., Wertenbroch, K., Crum, A., Frank, D., Goldstein, W., & Yang, H. (2018). Consumer choice and autonomy in the age of artificial intelligence and big data. *Customer needs and solutions, 5*(1), 28-37.

Anyoha, R., 2017. Can machines think. *Science in the News, special edition: artificial intelligence, summer*.

Benbasat, I., & Wang, W. (2005). Trust in and adoption of online recommendation agents. *Journal of the association for information systems, 6*(3), 4.

Berger, J., & Heath, C. (2007). Where consumers diverge from others: Identity signaling and product domains. *Journal of Consumer Research, 34*(2), 121–34.

Bogert, E., Schecter, A., & Watson, R. T. (2021). Humans rely more on algorithms than social influence as a task becomes more difficult. *Scientific reports*, *11*(1), 1-9.

Breugelmans, E., Bijmolt, T. H., Zhang, J., Basso, L. J., Dorotic, M., Kopalle, P. & Wünderlich, N. V. (2015). *Advancing research on loyalty programs: a future research agenda. Marketing Letters, 26*(2), 127–139.

Castelo, N., Bos, M.W., & Lehmann, D.R. (2019) Task-Dependent Algorithm Aversion. *Journal marketing research*, *56*(5), 809-825.

Chaney, A. J., Stewart, B. M., & Engelhardt, B. E. (2018, September). How algorithmic confounding in recommendation systems increases homogeneity and decreases utility. In *Proceedings of the 12th ACM Conference on Recommender Systems*, 224-232.

Chiasson, T., Hawkey, K., McAllister, M., and Slonim, J. (2002) An Architecture in Support of Universal Access to Electronic Commerce. *Information and Software Technology, 44*(5), 279–289.

Chung, K., Park, J. Y., Park, K., & Kim, Y. (2020). Which Visual Modality Is Important When Judging the Naturalness of the Agent (Artificial Versus Human Intelligence) Providing Recommendations in the Symbolic Consumption Context?. *Sensors*, *20*(17), 5016.

Diehl, K., Kornish, L. J., & Lynch, J. G. (2003). Smart agents: When lower search costs for quality information increase price sensitivity. *Journal of Consumer Research*, *30*(1), 56–71.

Dietvorst, B. J., Simmons, J. P., & Massey, C. (2015). Algorithm aversion: People erroneously avoid algorithms after seeing them err. *Journal of Experimental Psychology: General*, *144*(1), 114.

Ekstrand, M. D., Harper, F. M., Willemsen, M. C., & Konstan, J. A. (2014, October). User perception of differences in recommender algorithms. *In Proceedings of the 8th ACM Conference on Recommender systems* (pp. 161-168).

Efendic, E., Van de Calseyde, P. P.F.M., and Evans, A.M., (2020). Slow response times undermine trust in algorithmic (but not human) predictions. *Organizational behavior and human decisions processes, Elsevier,* 157: 103- 114.

Fayyaz, Z., Ebrahimian, M., Nawara, D., Ibrahim, A., & Kashef, R. (2020). Recommendation Systems: Algorithms, Challenges, Metrics, and Business Opportunities. *Applied Sciences*, *10*(21), 7748.

Fuchs Christoph, Martin Schreier, and Stijn M.J. van Osselaer (2015), "The Handmade Effect: What's Love Got to Do with It?," *Journal of Marketing, 79* (2), 98–110.

Granulo, A., Fuchs, C., & Puntoni, S. (2021). Preference for human (vs. robotic) labor is stronger in symbolic consumption contexts. *Journal of Consumer Psychology*, *31*(1), 72-80.

Hallinan, B., & Striphas, T. (2016). Recommended for you: The Netflix Prize and the production of algorithmic culture. *New media & society, 18*(1), 117-137.

Hanani, U., Shapira, B., & Shoval, P. (2001). Information filtering: Overview of issues, research and systems. *User modeling and user-adapted interaction*, *11*(3), 203-259.

Haslam, N. (2006). Dehumanization: An integrative review. *Personality and social psychology review*, *10*(3), 252-264.

Hussain, M., and Manhas, J. (2016). ARTIFICIAL INTELLIGENCE FOR BIG DATA: POTENTIAL AND RELEVANCE. *International Academy of Engineering and Medical Research,* 1 (1).

Isinkaye, F. O., Folajimi, Y. O., & Ojokoh, B. A. (2015). Recommendation systems: Principles, methods and evaluation. *Egyptian Informatics Journal*, *16*(3), 261-273.

Khalil, E. L. (2000). Symbolic products: Prestige, pride and identity goods. *Theory and Decision*, *49*(1), 53-77.

Kunapuli, G., Odom, P., Shavlik, J. W., & Natarajan, S. (2013, December). Guiding autonomous agents to better behaviors through human advice. *In 2013 IEEE 13th international conference on data mining*, 409-418.

Lee, D., & Hosanagar, K. (2014). Impact of recommender systems on sales volume and diversity.

Leung, E., Paolacci, G. and Puntoni, S., 2018. Man versus machine: Resisting automation in identity-based consumer behavior. *Journal of Marketing Research, 55*(6), 818-831.

Logg, J. M., Minson, J. A., & Moore, D. A. (2019). Algorithm appreciation: People prefer algorithmic to human judgment. *Organizational Behavior and Human Decision Processes, 151*, 90–103.

Longoni, C., Bonezzi, A., Morewedge, C.K. (2019). Resistance to Medical Artificial Intelligence. *Journal of Consumer research,* 46, 629- 650.

Luo, X., Qin, M.S., Fang, Z., & Qu, Z. (2021). Artificial Intelligence Coaches for Sales Agents: Caveats and Solutions. *Journal of Marketing*, *85*(2), 14-31.

Markus, M. L., & Keil, M. (1994). If we build it, they will come: Designing information systems that people want to use. *MIT Sloan Management Review*, *35*(4), 11.

Martínez-López, F. J., Esteban-Millat, I., Argila, A., & Rejón-Guardia, F. (2015). Consumers' psychological outcomes linked to the use of an online store's recommendation system. *Internet Research*.

Melville, P., & Sindhwani, V. (2010). Recommender systems. *Encyclopedia of machine learning*, *1*, 829-838.

Nadimpalli, M. (2017). Artificial intelligence–consumers and industry impact. *International Journal of Economics & Management Sciences*, *6*(03).

Oyserman, D. (2009). Identity-based motivation and consumer behavior. *Journal of Consumer Psychology*, *19*(3), 276-279.

Parasuraman, A., & Zinkhan, G. M. (2002). Marketing to and serving customers through the Internet: An overview and research agenda. *Journal of the academy of marketing science*, *30*(4), 286-295.

Prahl, A., & Van Swol, L. (2017). Understanding algorithm aversion: When is advice from automation discounted?. *Journal of Forecasting*, *36*(6), 691-702.

Puntoni, S., Reczek, R. W., Giesler, M., & Botti, S. (2021). Consumers and artificial intelligence: An experiential perspective. *Journal of Marketing*, *85*(1), 131-151.

Pu, P., Chen, L., & Hu, R. (2012). Evaluating recommender systems from the user's perspective: survey of the state of the art. *User Modeling and User-Adapted Interaction*, *22*(4-5), 317-355.

Ratchford, B. T., Talukdar, D., & Lee, M. S. (2007). The impact of the Internet on consumers' use of information sources for automobiles: A reinquiry. *Journal of Consumer Research*, *34*(1), 111–119.

Reed II, A., Forehand, M. R., Puntoni, S., & Warlop, L. (2012). Identity-based consumer behavior. *International Journal of Research in Marketing*, *29*(4), 310-321.

Schmit, S., & Riquelme, C. (2018, March). Human interaction with recommendation systems. *In International Conference on Artificial Intelligence and Statistics*, 862-870. PMLR.

Senecal, S., & Nantel, J. (2004). The influence of online product recommendations on consumers' online choices. *Journal of retailing*, *80*(2), 159-169.

Shin, D. (2020). User perceptions of algorithmic decisions in the personalized AI system: Perceptual evaluation of fairness, accountability, transparency, and explainability. *Journal of Broadcasting & Electronic Media*, 1-25.

Singer, J. A., Blagov, P., Berry, M., & Oost, K. M. (2013). Self-defining memories, scripts, and the life story: Narrative identity in personality and psychotherapy. *Journal of personality*, *81*(6), 569-582.

Smith, D., Menon, S., & Sivakumar, K. (2005). Online peer and editorial recommendations, trust, and choice in virtual markets. *Journal of interactive marketing*, *19*(3), 15-37.

Swaminathan, V. (2003). The impact of recommendation agents on consumer evaluation and choice: the moderating role of category risk, product complexity, and consumer knowledge. *Journal of Consumer Psychology*, *13*(1-2), 93-101.

Urban, G. L., & Hauser, J. R. (2004). “Listening in” to find and explore new combinations of customer needs. Journal of Marketing, 68(2), 72–87.

Van der Heijden, H. (2004). User acceptance of hedonic information systems. *MIS quarterly*, 695-704.

Van Swol, L. M., & Sniezek, J. A. (2005). Factors affecting the acceptance of expert advice. *British journal of social psychology*, *44*(3), 443-461.

Wattanasuwan, K. (2005). The self and symbolic consumption. *Journal of American Academy of Business*, *6*(1), 179-184.

Witt, U. (2010). Symbolic consumption and the social construction of product characteristics. *Structural Change and Economic Dynamics*, *21*(1), 17-25.

Yaniv, I., & Kleinberger, E. (2000). Advice taking in decision making: Egocentric discounting and reputation formation. *Organizational behavior and human decision processes*, *83*(2), 260-281.

Zeithaml, V. A., Parasuraman, A., & Malhotra, A. (2002). Service quality delivery through web sites: a critical review of extant knowledge. *Journal of the Academy of Marketing Science*, *30*(4), 362–375.

Zhang, Y., Liao, Q. V., & Bellamy, R. K. (2020). Effect of confidence and explanation on accuracy and trust calibration in AI-assisted decision making. *In Proceedings of the 2020 Conference on Fairness, Accountability, and Transparency*, 295-305.