Effectiveness of AI-Based Personalized Recommendations in Reducing Choice Overload on E-Commerce Platforms

Research Thesis

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Abstract

The rapid growth of e-commerce platforms has given consumers opportunities to access an extensive range of options, which can sometimes lead to a phenomenon named choice overload. It means when individuals are faced with an abundance of choices, they will find it difficult to make decisions. This study will examine how AI-based personalized recommendation systems can help people reduce this situation during the online shopping experience. The recommendation system can greatly save decision time and improve the user experience by customizing suggestions based on users' behaviors, preferences, and interactions. The research will adopt a quantitative methodology, collecting data through online surveys. This study will explore metrics like the time it takes to make decisions, how satisfied users are, and the key factors influencing their choices. The findings are expected to contribute valuable insights to existing research on AI in consumer behavior and offer practical recommendations for e-commerce platforms to enhance their recommendation systems.

Key Words: AI; Recommendation system; Choice overload; E-commerce

Submission of Thesis and Dissertation

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Chapter 1: Introduction

1.1 Background

The rapid development of online shopping platforms has reshaped the global retail landscape. Consumers are now faced with an overwhelming variety of products across countless categories. While this abundance of options offers choice freedom and convenience, it also introduces a common cognitive issue: choice overload. First introduced by Alvin Toffler in his book *Future Shock* (1970), this concept describes a situation where users feel overwhelmed due to too many available choices. This mental burden can lead to decision fatigue, regret, lower satisfaction, and even lead to choice rejection.

Choice overload is not only a theoretical concept, but it has also been demonstrated in several empirical studies. For instance, Iyengar and Lepper (2000) found that people who were offered fewer options were more likely to make a decision and report satisfaction with their choice. In contrast, those given more choices often felt less satisfied, even if they made a choice. Schwartz (2004) also emphasized that too many options may increase expectations and self-blame, which ultimately reduce satisfaction. In today's digital marketplace, consumers are constantly faced with such overwhelming choice sets across every product category, from fashion and electronics to entertainment and services.

To address this problem, AI-based personalized recommendation systems have been widely used across e-commerce platforms. These systems aim to simplify the consumer decision-making process by filtering and presenting options based on individual user preferences, behavior, and previous purchase history. Algorithms used in these systems include collaborative filtering, content-based filtering, and hybrid models (Widayanti et al., 2023). Popular platforms like Amazon, Netflix, and Spotify have integrated these tools into their user experience to drive engagement and improve satisfaction.

These recommendation systems are designed to reduce the mental effort and help users make decisions. Instead of manually comparing dozens of products, users are shown a shortlist that aligns closely with their past preferences or predicted interests. According to Bhuiyan (2024), personalized recommendation systems significantly improve user satisfaction by offering relevant and timely product suggestions. Masciari, Umair, and Ullah (2024) state that such systems are normally trained on the MovieLens dataset and social media platforms, which showcases the universal usage and implementation.

In addition to e-commerce, recommendation systems are now essential in social media, content streaming, and mobile apps. According to Selmene and Kodia (2020), platforms such as TikTok and Instagram personalize the content feed, relying on interaction data. The algorithms of these systems can not merely keep a record of viewing history or clicking behavior, but can also recognize preferences by using machine learning. What this demonstrates is that it is not only what people buy that is being influenced by AI recommendation systems, but what they see and experience in the online world.

Although the systems are becoming more prevalent, little is known about their effect on users in terms of cognitive and emotional perspectives. Are they truly making the burden of choice easier or merely moving the issue into a new form-such as algorithmic bias or over-usage? More important is what the perception of users is regarding these systems, as far as trust and usefulness are concerned. This is one of the questions that are not answered in the available literature.

1.2 Problem Statement

While recommendation systems have proven effective in improving personalization and driving sales, there is limited academic research that directly evaluates their psychological impact on consumers, particularly in reducing choice overload. Most existing studies focus on technical or marketing outcomes and overlook user experience factors such as cognitive load, trust, and decision satisfaction.

Moreover, prior research often evaluates recommendation performance based on quantitative metrics like click-through rate, time spent on site, or conversion rate. While these indicators are useful for platform designers, they do not reveal how users feel during the decision-making process. For instance, a user may click on a recommended item not because it was the best option, but simply because it was the least confusing among many irrelevant choices.

Additionally, little attention has been paid to demographic variations, such as how age, gender, or digital experience may influence a user's perception of AI-based systems. Some users may view AI recommendations as helpful assistants, while others may see them as intrusive or manipulative. Mehta and Dave (2024) found that men are more likely to complete purchases based on personalized recommendations, highlighting that gender can influence user behavior. These findings suggest that one recommendation model may not effectively serve all users.

There is also a lack of insight into how algorithm transparency, perceived fairness, and ethical concerns affect user trust. Users may experience distrust if they do not understand how recommendations are generated or if they feel the system is pushing certain products too aggressively. These psychological aspects of recommendation systems are usually overlooked in order to conduct more technical analyses.

Overall, this investigation is not only focused on whether recommendation systems can help reduce choice overload but also tests the user experience of the systems in a real-life setting of online shopping.

1.3 Research Aim and Objectives

The overall aim of this research is to evaluate whether AI-based personalized recommendation systems can effectively reduce choice overload and enhance the online shopping experience. This study intends to explore the psychological effects of personalized recommendations, focusing on user satisfaction, trust, and ease of decision-making.

The specific objectives of the research are:

1. To evaluate the effectiveness of AI-based personalized recommendations in reducing choice overload on shopping platforms.
2. To identify the key factors that contribute to the perceived usefulness and trustworthiness of these systems.
3. To provide actionable insights for e-commerce platforms to optimize their recommendation strategies.

By addressing these objectives, the study aims to provide a comprehensive understanding of how AI recommendations shape consumer decisions and how they can be improved to better serve users' cognitive and emotional needs.

1.4 Research Questions

This study seeks to answer the following research questions:

1. How do personalized recommendations impact users' decision-making processes?
2. To what extent do these systems reduce choice overload?
3. What factors influence user satisfaction and trust in AI-based recommendations?

These questions are designed to guide the research toward measurable, user-centered outcomes. They also reflect a growing interest among e-commerce developers, marketers, and policy-makers in creating more ethical and effective AI systems.

1.5 Significance of the Study

This research holds both practical and theoretical significance. From a practical perspective, the findings will be useful for e-commerce platforms, marketing strategists, and UX designers who are seeking to enhance the effectiveness of recommendation systems. By understanding how users perceive and interact with these systems, platforms can make informed decisions about how to design algorithms, present options, and communicate recommendation logic to users. This could lead to higher customer satisfaction, reduced cart abandonment, and stronger platform loyalty.

Moreover, understanding which user segments are most vulnerable to choice overload can help platforms tailor their strategies. For example, younger users who are more digitally experienced may navigate recommendation systems with ease, while older users or those with limited digital literacy may struggle more. Identifying these differences is essential for building inclusive technologies.

From a theoretical perspective, this study contributes to the literature on consumer decision-making, choice architecture, and AI ethics. While much has been written about the technical implementation of recommender systems, less attention has been given to the user's cognitive experience. This study seeks to bridge that gap by focusing on how AI tools affect users' psychological states during online shopping.

This research also contributes to ethical discussions around algorithmic bias, user autonomy, and manipulation. For example, if a system pushes certain products more often due to commercial interests, users may lose trust or feel that their autonomy is compromised. These are important considerations in a world increasingly shaped by AI.

1.6 Structure of the Dissertation

This dissertation is organized into six main chapters:

Chapter 1: Introduction

Provides the background, research aim, questions, objectives, and outlines the relevance of the study.

Chapter 2: Literature Review

Discusses the key themes related to choice overload, recommendation systems, consumer behavior, and identifies gaps in the current literature.

Chapter 3: Methodology

Describes the research design, data collection methods, analysis tools, and ethical considerations applied during the study.

Chapter 4: Data Analysis

Presents the results of the quantitative survey using descriptive statistics, correlation analysis, and regression models to explore the relationships between variables.

Chapter 5: Discussion

Interprets the findings in light of existing literature, explores their implications, and addresses limitations and future research directions.

Chapter 6: Conclusion and Recommendations

Summarizes the study, offers practical recommendations for e-commerce platforms, and concludes with final reflections on the topic.

Chapter 2 Literature review

2.1 Introduction

In recent years, the rapid development of artificial intelligence (AI) technologies has significantly transformed the e-commerce world. Among all these innovations, AI-based personalized recommendation systems have become a powerful tool for enhancing user experience, driving sales, and boosting customer loyalty. These recommendation systems offer tailored suggestions based on user preferences, past interactions, and behaviour patterns. While much of the existing research emphasizes their impact on sales performance and customer engagement, fewer studies examine their role in alleviating cognitive burdens associated with overwhelming product choices, commonly referred to as choice overload. Therefore, this study seeks to investigate how AI-based personalization systems can reduce the choice overload in the online shopping experience

Choice overload, a concept based on psychological theory, describes the paradox that while more options may seem beneficial, the abundance of choices can lead to confusion, dissatisfaction, and even decision failure. As online platforms continue to expand product selections and try to ensure the customers' access to everything, the need to simplify the decision-making process has become increasingly urgent. Recommendation systems, by narrowing down options and presenting personalized suggestions, have been seen as a potential solution to this growing issue.

This literature review explores three major themes that support this research. First, it investigates the theoretical foundations and psychological consequences of choice overload in consumer decision-making. Second, it reviews the design, functions, and applications of AI-based personalized recommendation systems. Finally, it considers the impact of these systems on consumer behaviour, particularly in terms of trust, satisfaction, and decision-making ease. By critically examining existing research across these areas, this review identifies key gaps in knowledge and lays the foundation for investigating how personalized recommendations can help mitigate choice overload in e-commerce environments.

2.2 Choice overload

Choice overload, also known as 'overchoice', occurs when people face too many available options, which may lead to various consequences, like cognitive burden and decision fatigue (Chernev, Böckenholt, and Goodman, 2015). The history of this phenomenon can be traced to the Middle Ages, when a French philosopher, Jean Buridan, theorized that when intelligent beings faced with the choice of two similar-valued options, they delay making a choice and eventually choose randomly (Scheibehenne, Greifeneder and Todd, 2010) In modern times, psychologists like Millier (1944), Lewin (1951), and Festinger (1957) have all proved that appealing choices often lead to cognitive conflict. Then, in 1970, this concept was formally introduced by Alvin Toffler in his book, *Future Shock* (Manolică et al., 2021), which the idea is about with the development, people in the future will inevitably suffer from the abundance of choices.

Iyengar and Lepper (2000) conducted 2 studies about purchasing jam and chocolate, which showed that although participants were more attracted to the larger display, they were more likely to buy from the smaller selection, indicating that more choices can cause dissatisfaction. In Schwartz's (2004) book, *The Paradox of Choice*, he also explains the psychological process when more choices are provided: many people will regret their choice by imagining the goodness of the missing choice. This finding has been replicated in various domains, including business investment, consumer electronics, and online shopping (Chernev et al., 2015).

Through the choice overload literature, the assortment size is normally one of the main considerations. When customers hesitate whether to buy rather than which to select, increasing the assortment size is likely to boost purchase behaviour (Gao & Simonson, 2016), however, the large amount of choice would look more appealing at first, then consumers will feel overwhelmed and frustrated while making a decision (Benoit & Miller, 2017). It has been proven that when too many options are provided, it is likely to cause a failure in decision-making (Adriatico et al., 2022). Also, several consequences of the choice overload need to be considered, such as choice satisfaction, decision difficulty, and regret. Customers always prefer more options, although it may lead to regret (Sthapit, 2018), and the realization of product satisfaction comes from a large number of choices (Messner & Wänke, 2011). This seemed to raise a question of how organizations can provide enough choices while at the same time not lowering the degree of customers' satisfaction. Misuraca et al. (2022) explain that the ideal number of choices depends on contextual and demographic factors, and while identifying it can be challenging, it is valuable for important or recurring decisions like pensions, health plans, or careers. According to Polman (2012), for an individual, fewer choices lead to dissatisfaction, whereas for the proxy is the opposite, which reveals the different needs for different segments. When many choices are offered, the alternatives become more similar, making it hard to distinguish, therefore causing difficulty in decision making (Scheibehenne et al., 2009). Meanwhile, it often leads to consumer regret; this situation happens everywhere, especially in e-commerce, with the development of society, people are facing several choices compared to a couple of decades ago (Park and Jang, 2013). People are trying to make the best choice for themselves, but more considerations in mind only make decisions harder.

Recent research has highlighted several key moderators that shape how consumers experience choice overload. Categorization is shown to ease decision-making by enhancing perceived variety and structure, as seen in the work of Mogilner et al. (2008) and Yun & Duff (2017), though excessive categorization may reverse this benefit (Yan et al., 2015). Time pressure generally worsens overload, increasing stress and regret during decision-making (Inbar et al., 2011; Mahmood et al., 2016), although some studies suggest time-constrained decisions may remain effective if motivation is high

(Fasolo et al., 2009). The role of ideal points or articulated preferences is also critical; individuals with clear preferences benefit from large assortments, while those without experience heightened difficulty (Chernev, 2003; Diehl & Poynor, 2010). Brand familiarity acts as a simplifying cue, reducing regret and perceived difficulty (Misuraca et al., 2019, 2021), whereas its absence tends to intensify overload. Similarly, product knowledge helps filter and evaluate options efficiently, making larger assortments less overwhelming for experts (Hadar & Sood, 2014; Morrin et al., 2012). Choice justification emerges as a key cognitive mediator, with larger assortments making justification more complex and mentally demanding (Sela et al., 2009; Scheibehenne et al., 2009). Lastly, presentation style, particularly horizontal visual displays, can improve processing fluency and perceived variety but may also increase the cognitive complexity of decisions (Deng et al., 2016; Townsend & Kahn, 2014). Together, these studies underscore that the experience of choice overload is not universal but is strongly influenced by contextual, cognitive, and perceptual moderators.

Besides, choice overload in digital settings is more than just a theoretical concern. E-commerce platforms are becoming more and more integrated into daily life; with the fast-paced life, customers not only want quick and easy transactions, but also want individualized and meaningful experiences. Therefore, AI-based personalized recommendation systems bring great value to the business (Alrashidi et al., 2023)

In summary, the literature on choice overload indicates a paradox within modern consumer behaviour: while the variety of products brought freedom and consumer empowerment, too much choice can impair decision-making and decrease satisfaction. In the next section of this review, the AI-driven recommended system design will be explored, and the potential applications of such recommended systems to mitigate this mental effect under e-commerce scenarios.

2.3 AI-Based Personalized Recommendation Systems

The evolution of AI-based personalized recommendation systems has significantly influenced the way consumers interact with digital platforms, particularly in e-commerce. They have become one of the solutions to help users overcome choice overload (Zhang et al., 2019). These systems process large volumes of data to predict user preferences and suggest products, services, or content, often with remarkable accuracy. Common techniques include collaborative filtering, content-based filtering, and hybrid methods (Widayanti et al., 2023). These systems aim to improve user experience by presenting tailored options, thereby simplifying decision-making (Amin et al., 2020).

According to Masciari et al. (2024), the AI-based personalized recommendation system is being applied in many fields, such as natural language processing, computer vision, healthcare, finance, or any other industry where the created algorithms or models are meant to be applied could be the application area. Among all these fields, healthcare and movie recommendations are the two main application fields. Recommendation systems offer mutual benefits for both firms and consumers. They enhance the customer experience and influence purchasing decisions, while also providing businesses with valuable data to deliver personalized offers effectively (Kliestik et al., 2022; Rausch et al., 2022). One of the other most cited benefits is improved consumer engagement. Alrashidi et al. (2023) found that users who interact with personalized systems tend to spend more time on websites and are more likely to make purchases because it fosters a sense of individual attention, which enhances satisfaction and boosts trust in the platform. Moreover, businesses experience increased revenue due to better product discoverability and higher conversion rates (Ding, 2018)

However, these benefits are accompanied by ethical considerations. First, the “black box” nature of many algorithms poses a transparency problem. Users usually do not know how the recommendations are generated (Masciari et al., 2024). Second, recommendation systems can be designed to influence user behavior by serving the platform's interest first, but not considering the user's best interest (Figà-Talamanca, 2024). These risks reinforce existing biases and preferences. Over-reliance on recommendations is another concern. Users may become passive consumers, depending entirely on algorithmic suggestions rather than actively exploring available alternatives (Schemmer et al., 2023). Moreover, these systems often collect vast amounts of personal data, which raises ethical and privacy concerns. Although there are regulations like GDPR that aim to protect users, many systems still operate with limited user control over how data is collected and used (Di Noia et al., 2022)

Notably, lots existing literature is mainly focused on technical performance, such as accuracy, relevance, and scalability, rather than psychological or cognitive outcomes. Therefore, it creates a gap in the literature in understanding how recommendation systems affect the user experience beyond efficiency. Moreover, little research explores whether these systems can alleviate psychological burdens like choice overload, decision fatigue, or regret. This is particularly relevant, especially the digital world products become more complex, and the number of products is also increased.

Thus, while AI-based recommendation systems have dramatically changed personalization in digital environments, there is an urgent need to examine their psychological impact on consumer behavior. This study aims to bridge that gap by exploring whether recommendation systems can mitigate choice overload and how users perceive their decision-making experiences in AI-powered environments.

2.4 Consumer Behavior in Response to AI Recommendations

The integration of AI-based recommendation systems has greatly transformed consumer behavior, particularly in digital and content platforms. These systems are designed to reduce the cognitive burden of decision-making, influence not just what users choose, but how they feel about the process of choosing (Raji et al, 2024). There is increasing literature that has studied the behavioral implications of such systems and provided information about user trust, satisfaction, and the convenience of decision-making.

Bhuiyan (2024) explains that AI recommendation systems significantly enhance user trust and satisfaction when they feel the suggestions are accurate and relevant. The perception of relevance boosts user engagement and reduces the cognitive burden due to the large number of choices. Besides, Arora et al (2024) find that by offering faster service delivery and personalized experiences, AI can then greatly enhance customer satisfaction, fostering loyalty, and gaining a competitive advantage in attracting and retaining customers.

Demographic factors also influence how users perceive and respond to AI suggestions. Mehta and Dave (2024) highlight gender differences in recommendation acceptance, suggesting that women are more likely to express stronger emotional responses, such as satisfaction or frustration, while men tend to accept AI advice more functionally. The study also reveals that younger users possess higher levels of trust in AI systems, mainly because of increased exposure to the technology and fluency in manipulating, whereas older adults show hesitation due to lower confidence in digital systems. These findings suggest that one recommendation model may fail to meet the diverse needs of consumer groups.

Besides the benefits, ethical concerns about AI-based recommendations are rising. Masciari et al. (2024) warn that recommendation systems can unintentionally manipulate consumer decisions, prioritizing commercial interests over user needs. Additionally, algorithmic bias and equity are other problems; recommender systems may unintentionally reinforce biases found in their training data, resulting in unfair treatment of certain user groups (Sah, Lian & Islam, 2024). Ensuring fairness across all demographics is a key challenge, requiring bias detection and mitigation strategies during system development (Qian & Jain, 2024)

Beyond behavior, AI recommendations also impact users psychologically. While some studies suggest that these systems reduce regret by guiding users toward satisfying choices, others point to a loss of perceived autonomy. Users may feel manipulated rather than empowered, particularly if they cannot clearly understand how recommendations are generated. Nevertheless, when executed transparently and respectfully, AI systems can increase user confidence, giving them the sense that they are making "smarter" decisions without exerting unnecessary mental effort.

Despite progress, many psychological outcomes remain underexplored. For example, limited research has systematically investigated the relationship between AI recommendation systems and perceived decision ease, decision fatigue, or emotional satisfaction. Although trust is often mentioned, there are few empirical studies on how trust develops or is determined by the transparency features or interface design. These gaps indicate the necessity of more in-depth studies that take into consideration not only demographic variables but also psychological reactions.

2.5 Gaps in Literature

Whereas the psychological phenomenon of choice overload and technological possibilities of the AI-based personalized recommendation system have been discussed in detail, the relationship between the two fields has not been studied in detail. In the majority of cases, the research is based on the performance indicators of recommendation systems, which include accuracy, sales impact, and engagement rates. However, little has been done to explain its mitigation in the case of choice overload in e-commerce. The current literature would also overlook the demographic variables, including age and gender, which could change the user response to and interaction with the recommendation systems (Mehta and Dave, 2024). Also, ethical dimensions, like the transparency of the algorithms and the trust of the users, are still not sufficiently covered. This research aims to fill these gaps by investigating the role of AI-based personalized recommendations in reducing choice overload, particularly in user satisfaction, decision-making ease, and the perceived trustworthiness of the system.

2.6 Summary

The present literature review considered three interdependent topics that are related to AI-based personalized recommendation systems and their use in the mitigation of choice overload. First, studies on choice overload show that although the larger variety may seem to be of value, it is associated with adverse psychological outcomes, including cognitive overload, decision fatigue, and post-decision regret. The important moderators of this overload, which involve categorization, time pressure, brand familiarity, and presentation style, are important, as the recommendation is based on context and differs according to the segments of users.

Second, the part of AI-based personalized recommendation systems discussed the way those technologies simplify the process of decision-making, filtering, and customizing the options to match personal preferences. Most of the current research focuses on technical precision and business results, although it is regularly popular in such fields as e-commerce and healthcare, and very few inquiries consider user-focused psychological implications. Ethical issues like transparency, data privacy, and algorithmic manipulation are other problems that need to be addressed since they form serious concerns.

Third, the consumer behavior literature on responding to AI recommendations shows that the predominant trend is positive reactions. When systems are correct and transparent, there is more trust, satisfaction, and less difficulty in making a decision. Nevertheless, the success of such systems may differ according to age and gender factors as demographic variables. Also, users may lose their independence or resort to excessive dependence on AI when recommendations are biased.

Regardless of the amount of research conducted in this field, there are some serious gaps that need to be filled. These consist of the absence of empirical studies regarding how AI recommendations influence aspects of psychology, like the ease of decision and satisfaction during choice overload, and the lack of investigation of demographic factors and morale. The proposed study will address these gaps by examining the impact of an AI-based recommendation system on user experience of decision-making decisions, particularly in the case of excess product.

Chapter 3 Methodology

3.1 Introduction

This chapter outlines the methodological framework used to examine how AI-based personalized recommendation systems impact consumer decision-making, particularly concerning choice overload. The research is grounded in a positivist paradigm, utilizing a quantitative approach through an online survey to gather empirical data. The methodology aims to address the research questions by exploring user perceptions of AI recommendation systems in e-commerce, the extent to which these systems alleviate decision-making difficulties, and the demographic and psychological factors affecting satisfaction and trust.

This chapter outlines the research philosophy, the research approach, how the research has been designed, how to collect data and analyze it, and ethical considerations are also included.

3.2 Research Philosophy

Research philosophy, which concerns how knowledge is developed and understood, emphasizes that conducting research involves generating new knowledge within a particular field (Saunders, Lewis and Thornhill, 2008). There are two major philosophies, ontology and epistemology. Ontology focuses on the nature of reality, encompassing both objectivism and subjectivism (Saunders et al., 2008). Epistemology is concerned with how we know what we know, what justifies belief, and what standards of evidence are acceptable (Audi, 2010). Under epistemology, positivism, realism, and interpretivism have been discussed. Positivism assumes that reality is objective and measurable, and that valid knowledge is gained through observable and quantifiable facts; realism holds that an external reality exists independently of our perceptions, and our knowledge is shaped by both sensory experiences and social influences; interpretivism emphasizes understanding the subjective meanings and social contexts behind human behavior through empathetic and qualitative inquiry (Saunders et al., 2008).

The study adopts a positivist research philosophy, aiming to ensure objectivity, measurability, and generalizability in understanding how AI-based personalized recommendation systems influence consumer behavior. Positivism emphasizes the use of scientific methods and observable, quantifiable data, asserting that knowledge is derived from empirical evidence rather than subjective interpretation (Saunders et al., 2008). Given that the main focus of this research is to assess the impact of personalized recommendations on user decision-making, perceived choice overload, satisfaction, and trust within e-commerce environments, a positivist stance is most appropriate.

Under the positivist paradigm, the researcher is seen as a neutral observer, separate from the subject of investigation (Saunders et al., 2008). The phenomena being studied, such as user behavior, trust in recommendation systems, and perceived decision ease, are considered to exist independently of the researcher and can be measured objectively. This approach aligns well with the use of a structured questionnaire, where all participants respond to the same set of predefined, closed-ended questions designed to capture consistent and comparable data.

Although the final two questions in the survey are open-ended, the number of meaningful responses was limited and thus insufficient for deep qualitative analysis. Therefore, the core data analysis remains quantitative. This includes descriptive statistics and correlation analysis to examine patterns and relationships among key variables such as satisfaction, trust, and perceived overload. This reliance on quantifiable data is consistent with the positivist belief in discovering patterns and drawing conclusions through logical reasoning based on observable facts.

Positivism also supports hypothesis testing and the identification of cause-and-effect relationships (Saunders et al., 2008). For example, this study explores whether personalized AI recommendations reduce choice overload and whether trust in the system influences user satisfaction. These relationships are investigated using measurable constructs and statistical analysis, which is central to positivist research methodology.

In contrast to interpretivism, which emphasizes subjective meaning and individual interpretation, positivism provides a more standardized and replicable framework (Saunders et al., 2008). This is particularly beneficial when the aim is to produce generalizable insights across a broader population, such as online shoppers on major e-commerce platforms (Park, Konge and Artino, 2020). Moreover, the use of Likert scale questions allows the study to capture the degree of agreement or disagreement with various statements in a numerically analyzable format, further reinforcing the objectivity of the findings.

By choosing a positivist approach, this research ensures that conclusions are drawn from systematic data collection and analysis, rather than personal interpretation. The standardized nature of the survey and the focus on observable behaviors and perceptions strengthen the reliability and validity of the study's findings. Furthermore, the results are intended not only to contribute to academic understanding but also to offer practical insights for e-commerce platforms seeking to optimize their recommendation strategies.

In summary, the positivist philosophy underpins this study by supporting a clear, empirical, and objective investigation into the role of AI recommendation systems in shaping consumer behavior. It allows for structured data analysis, encourages generalization of findings, and aligns well with the overall research objectives focused on quantifying user experiences and behaviors in digital shopping environments.

3.3 Research Approach

Following the selection of a positivist philosophy, this research adopts a deductive approach, which is closely aligned with positivism and quantitative methodology. Deduction involves developing a theoretical framework and hypotheses from existing literature and then testing them through empirical observation (Saunders et al., 2008). This approach is appropriate because this study aims to test assumptions about the effects of AI-based personalized recommendation systems on users' experience, particularly regarding decision-making, choice overload, satisfaction, and trust.

As the research questions are designed to measure user responses to structured survey items rather than explore open-ended perceptions, the deductive approach facilitates clarity, replicability, and objective interpretation. Furthermore, the hypotheses are derived from established literature on recommendation systems and consumer decision-making, which allows the results to contribute to validating or refining existing theories.

Considering an alternative approach, the inductive approach is more about building a theory from data, which is the reverse of the deductive approach. Due to the nature of the research, this approach was not the best option; it is more concerned with the understanding of the world, which will focus on the small contexts and different views of phenomena.

3.4 Research Design and Instrument

This study employs a mono-method quantitative research design using a self-administered survey as the primary research instrument. Quantitative research is particularly effective in producing objective, generalizable insights from a larger sample size (Bryman, 2012). The structured survey consists primarily of closed-ended questions, including multiple-choice, Likert-scale items, and demographic queries, ensuring ease of analysis and consistency in responses.

The survey was designed using Google Forms, which facilitates wide and low-cost distribution and allows for efficient data collection. The structure of the survey aligns with the study's three research questions:

1. How do personalized recommendations impact users' decision-making processes?
2. To what extent do these systems reduce choice overload?
3. What factors influence user satisfaction and trust in AI-based recommendations?

To ensure validity and relevance, the questionnaire was informed by previous academic studies on AI systems, decision fatigue, choice overload, and e-commerce behavior. A 5-point Likert scale (ranging from "Strongly Disagree" to "Strongly Agree") was employed for most opinion-based items, while multiple-choice and checkbox questions were used to capture background information and behavioral patterns. A total of 19 questions were set for the questionnaire, and a copy of the questionnaire is attached in the Appendix.

3.5 Data Collection

The primary data for this research were collected through a structured online questionnaire distributed via convenience sampling. Participants were recruited primarily through university mailing lists, social media platforms (including WhatsApp and Little Rednotes), and peer networks. The target population includes online consumers who have experience shopping on e-commerce platforms that use personalized recommendation systems, such as Amazon, Shein, or Zalando.

Participants were asked to voluntarily complete the survey, which took approximately 5–7 minutes. No incentives were provided to maintain objectivity and avoid biased responses. The questionnaire was live for 10–14 days to allow sufficient time for responses, and reminders were issued midway through the period to encourage participation.

A total of 158 responses were collected; 8 were invalid due to the incomplete survey, and 150 responses will be further analyzed. Responses were automatically compiled in Google Sheets via Google Forms and later exported for statistical analysis.

3.6 Data Analysis

The data collected were subjected to descriptive and inferential statistical analysis using SPSS Version [V.31]. The data analysis was conducted in several stages:

1. Descriptive statistics were used to summarize the demographic information of the respondents and to provide general insights into user behavior and perceptions.
2. Frequency distributions and mean scores were used to evaluate patterns related to user trust, satisfaction, and perceived decision ease.
3. Pearson's correlation analysis was conducted to examine the relationships between key variables such as recommendation relevance, trust, and perceived choice overload.
4. Where applicable, cross-tabulations were used to assess whether demographic factors such as age or gender influenced perceptions.

This analytical approach provides a robust and objective means of addressing the research questions and drawing conclusions based on quantifiable data.

3.7 Ethical Considerations

In line with ethical guidelines provided by the National College of Ireland and the principles of responsible research (Saunders et al., 2008), several measures were implemented to ensure the integrity and ethical soundness of the study.

Participants were first presented with a consent form explaining the purpose of the study, the voluntary nature of their participation, and how their data would be used. Respondents had to acknowledge their understanding and consent before proceeding with the questionnaire.

Participation was anonymous, and no personally identifiable information (e.g., names, emails) was collected. All responses were stored securely and used solely for academic purposes. The data will be retained only for the duration of the project and will be deleted after the final assessment submission.

Moreover, participants were informed that they could withdraw from the survey at any point without penalty. No incentives were offered, ensuring that all data was collected from informed and willing individuals.

The researcher ensured that the questions were neutral, respectful, and did not cause psychological discomfort. The research adhered to GDPR (EU Regulation 2016/679) standards on data protection.

Chapter 4 Data Analysis

4.1 Introduction

This chapter presents the data analysis conducted to examine the effectiveness of AI-based personalized recommendation systems in reducing choice overload and enhancing consumer satisfaction and trust on online shopping platforms. The analysis is based on primary data collected through an online questionnaire distributed via Google Forms, targeting users with recent experience in online shopping. A total of 150 valid responses were collected and exported into SPSS version 31 for statistical analysis.

The data analysis aims to explore three key areas: (1) how AI-based recommendations influence users' decision-making processes, (2) the extent to which such systems reduce perceived choice overload, and (3) what factors contribute to user satisfaction and trust in AI-based recommendation systems.

The chapter begins with a description of data cleaning and variable naming procedures, followed by descriptive statistical analysis to outline the respondent demographics and core variable distributions. Next, reliability analysis (Cronbach's Alpha) is used to assess the internal consistency of the Likert-scale constructs. Pearson correlation analysis is then performed to examine the relationships between variables, while cross-tabulations help explore group differences based on demographic characteristics. Lastly, linear regression analysis is conducted to identify key predictors of satisfaction and perceived decision ease.

4.2 Descriptive results overview

A total of 150 valid responses were collected from the online survey, which consisted of 19 questions, including 11 Likert-scale questions, as well as 2 demographic questions. The demographic items focused on gender and age group. This section provides a descriptive overview of the demographic composition of the sample.

4.2.1 Gender

Figure 4.1 shows the sample consisted of 68% or 102 female respondents, 32% or 48 male. This gender split aligns with existing literature suggesting that women are generally more active in online shopping environments than men (Abumalloh, Ibrahim and Nilashi, 2020).

Figure 4.1 Survey respondents by gender

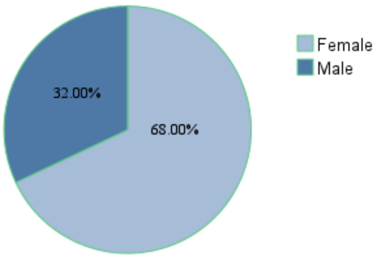

Figure 4.2 Gender frequencies

Gender	Frequency	Percent
Female	102	68.0
Male	48	32.0
Total	150	100.0

4.2.2 Age Group

As shown in Figure 4.3, the age distribution of respondents was more concentrated on younger adults, with the largest proportion (47.3%) falling in the 25–34 age group. This was followed by 38.7% aged 18–24, while smaller proportions were observed among those aged 35–44 (6%), 55+ (6%), and 45–54 (approximately 1%). The dominance of the 18–34 age segment suggests that the sample largely reflects a digitally familiar population, who are more likely to engage in e-commerce activities and interact with personalized recommendation systems regularly. These findings align with prior research indicating that younger users, particularly millennials and Gen Z, are more responsive to online personalization and AI-driven product suggestions (Ozok, Fan and Norcio, 2010; Abumalloh et al., 2020).

Figure 4.3 Survey respondents by age group

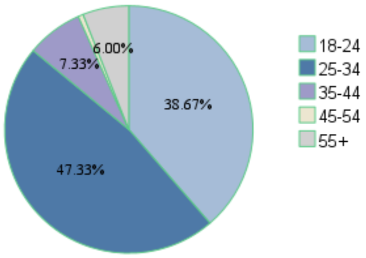

Figure 4.4 Age Frequencies

Age	Frequency	Percent
18-24	58	38.7
25-34	71	47.3
35-44	11	7.3
45-54	1	.7
55+	9	6.0
Total	150	100.0

4.2.3 Descriptive Statistics

To provide an overview of respondents' perceptions regarding personalized recommendation systems, a descriptive statistics analysis was conducted on key survey variables (see Table 4.1).

The variable "NoticeFreq" (how often users notice personalized recommendations) had the highest mean value (M = 4.11, SD = 0.79), indicating that respondents frequently observe personalized recommendations when shopping online. Similarly, "PerceivedBias" (M = 3.89, SD = 0.92) and "DelayDueToOptions" (M = 3.89, SD = 1.06) showed relatively high average scores, suggesting participants are moderately aware of potential bias and delays due to option overload.

In contrast, "Relevance" (M = 3.80), "Usefulness" (M = 3.75), and "Satisfaction" (M = 3.67) demonstrated generally positive user attitudes towards recommendation system performance. Also, "Trust" had a mean score of 3.57 (SD = 0.99), indicating a neutral to slightly positive level of trust in AI-based recommendation systems.

Besides, the variable "ShopFreq" (frequency of online shopping) had the lowest mean score (M = 2.05, SD = 0.74), suggesting that while respondents notice and interact with personalized recommendations, they may not shop online very frequently.

Overall, most variables had mean scores between 3.5 and 4.1, indicating moderate to positive perceptions of personalized recommendation systems, although standard deviations (ranging from 0.74 to 1.06) reveal some variation in individual responses.

Table 4.1 Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
Ease of Decision_Numeric	150	1.00	5.00	3.6133	1.00860
DelayDueToOptions_Numeric	150	1.00	5.00	3.8933	1.06277
Revelance_Numeric	150	1.00	5.00	3.8000	.81923
Usefulness_Numeric	150	1.00	5.00	3.7467	.93541
Trust_Numeric	150	1.00	5.00	3.5733	.99223
PerceivedBias_Numeric	150	1.00	5.00	3.8867	.92349
Satisfaction_Numeric	150	1.00	5.00	3.6667	.85661
NoticeFreq_Numeric	150	1.00	5.00	4.1133	.79035
ClickFreq_Numeric	150	1.00	5.00	3.5133	.92495
ChoiceOverload_Numeric	150	1.00	5.00	3.7333	.87214
NarrowDownHelp_Numeric	150	1.00	5.00	3.6600	1.02865
ShopFreq_Numeric	150	1.00	4.00	2.0467	.74489
Valid N (listwise)	150				

4.3 Reliability Analysis

As revealed in Table 4.2, reliability analysis was conducted on six items (Q10, Q11, Q13, Q14, Q15, and Q16) measuring users' perceived usefulness and trust in AI-based personalized recommendation systems. The Cronbach's Alpha value was 0.857, indicating high internal consistency. According to Saunders et al (2008), a Cronbach's Alpha value above 0.7 is generally acceptable, while values above 0.8 reflect good reliability.

- **Table 4.2 Reliability Results**

Latent Variables	Item Code	Questionnaire Item	Cronbach's Alpha
Perceived Recommendation Value	Q10	To what extent do personalized recommendations help you narrow down your choices?	0.857
	Q11	Personalized recommendations make it easier for me to make a decision.	
	Q13	The recommended products are usually relevant to my interests.	
	Q14	I find personalized recommendations useful when shopping online.	
	Q15	How satisfied are you with the personalized recommendations you receive?	
	Q16	I trust that the platform recommends products that genuinely match my preferences.	

4.4 Pearson's Correlation Analysis

To examine the relationships between key variables related to user experience with AI-based personalized recommendations, Pearson correlation has been conducted across three main variable clusters: (1) recommendation quality and decision-making support, (2) psychological responses such as trust and satisfaction, and (3) interaction frequency with personalized content. Results are presented in Tables 4.3–4.5.

4.4.1 Relationship between Recommendation Quality and Decision-Making Support

Table 4.3 examines the correlation among variables measuring perceived relevance, usefulness, ease of decision-making, delay due to excessive options, perceived choice overload, and assistance with narrowing down choices. Relevance was positively and significantly correlated with usefulness ($r = 0.494$, $p < .001$), ease of decision-making ($r = 0.417$, $p < .001$), and narrowing down help ($r = 0.381$, $p < .001$). These results suggest that when users receive more related recommendations, they are more likely to find them useful and helpful in facilitating decisions.

Additionally, ease of decision-making was strongly correlated with narrowing-down help ($r = 0.694$, $p < .001$), indicating that personalized recommendations play an important role in reducing cognitive load. Usefulness also showed moderate positive relation with both delay due to options ($r = 0.337$, $p < .001$) and narrowing-down help ($r = 0.510$, $p < .001$), while delay due to options had a weaker correlation with ease of decision-making ($r = 0.168$, $p = .042$), suggesting only a partial connection between perceived overload and decision difficulty.

Choice overload itself was not significantly correlated with most other variables, except for a low positive correlation with usefulness ($r = 0.251$, $p = .002$), indicating that even when users feel overwhelmed, they might still appreciate personalized options.

Table 4.3 Correlations

		Revelance_Numeric	Ease of Decision_Numeric	Usefulness_Numeric	DelayDueToOptions_Numeric	ChoiceOverload_Numeric	NarrowDownHelp_Numeric
Revelance_Numeric	Pearson Correlation	1	.417**	.494**	.284**	.009	.381**
	Sig. (2-tailed)		<.001	<.001	<.001	.909	<.001
	N	150	150	150	150	150	150
Ease of Decision_Numeric	Pearson Correlation	.417**	1	.536**	.168*	.157	.694**
	Sig. (2-tailed)	<.001		<.001	.040	.056	<.001
	N	150	150	150	150	150	150
Usefulness_Numeric	Pearson Correlation	.494**	.536**	1	.337**	.056	.510**
	Sig. (2-tailed)	<.001	<.001		<.001	.492	<.001
	N	150	150	150	150	150	150
DelayDueToOptions_Numeric	Pearson Correlation	.284**	.168*	.337**	1	.251**	.145
	Sig. (2-tailed)	<.001	.040	<.001		.002	.077
	N	150	150	150	150	150	150
ChoiceOverload_Numeric	Pearson Correlation	.009	.157	.056	.251**	1	.175*
	Sig. (2-tailed)	.909	.056	.492	.002		.032
	N	150	150	150	150	150	150
NarrowDownHelp_Numeric	Pearson Correlation	.381**	.694**	.510**	.145	.175*	1
	Sig. (2-tailed)	<.001	<.001	<.001	.077	.032	
	N	150	150	150	150	150	150

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

4.4.2 Trust and Satisfaction

In Table 4.4, the correlation between relevance, trust, satisfaction, and perceived bias was investigated. Relevance significantly correlated with both trust ($r = 0.497$, $p < .001$) and satisfaction ($r = 0.478$, $p < .001$), highlighting the importance of recommendation accuracy in building user trust and satisfaction.

Trust was also highly correlated with satisfaction ($r = 0.550$, $p < .001$), indicating a strong connection between the user's belief in the recommendation system and their overall contentment with the recommendations. However, perceived bias did not show significant relationships with any of the other variables, suggesting that users' perception of recommendation bias might be independent of their overall trust or satisfaction levels.

Table 4.4 Correlations

		Revelance_Numeric	Trust_Numeric	Satisfaction_Numeric	PerceivedBias_Numeric
Revelance_Numeric	Pearson Correlation	1	.497**	.478**	.103
	Sig. (2-tailed)		<.001	<.001	.210
	N	150	150	150	150
Trust_Numeric	Pearson Correlation	.497**	1	.550**	-.068
	Sig. (2-tailed)	<.001		<.001	.410
	N	150	150	150	150
Satisfaction_Numeric	Pearson Correlation	.478**	.550**	1	.020
	Sig. (2-tailed)	<.001	<.001		.810
	N	150	150	150	150
PerceivedBias_Numeric	Pearson Correlation	.103	-.068	.020	1
	Sig. (2-tailed)	.210	.410	.810	
	N	150	150	150	150

**. Correlation is significant at the 0.01 level (2-tailed).

4.4.3 Recommendation Interaction Frequency and Satisfaction

As shown in Table 4.5, click frequency was significantly correlated with both notice frequency ($r = 0.361$, $p < .001$) and satisfaction ($r = 0.472$, $p < .001$). This suggests that users who are more likely to notice and click on personalized recommendations also report higher levels of satisfaction. However, notice frequency itself was not significantly related to satisfaction ($r = 0.126$, $p = 0.126$), implying that awareness alone is not sufficient—engagement, like the clicking behavior, plays a more decisive role in shaping user satisfaction.

Table 4.5 Correlations

		ClickFreq_Numeric	NoticeFreq_Numeric	Satisfaction_Numeric
ClickFreq_Numeric	Pearson Correlation	1	.361**	.472**
	Sig. (2-tailed)		<.001	<.001
	N	150	150	150
NoticeFreq_Numeric	Pearson Correlation	.361**	1	.126
	Sig. (2-tailed)	<.001		.126
	N	150	150	150
Satisfaction_Numeric	Pearson Correlation	.472**	.126	1
	Sig. (2-tailed)	<.001	.126	
	N	150	150	150

**. Correlation is significant at the 0.01 level (2-tailed).

4.5 Crosstabulation Analysis

This section examines the relationship between demographic variables, such as age and gender, and consumer behaviors within the context of personalized recommendation systems. Three crosstabulation analyses were conducted to examine associations between (1) gender and perceived choice overload, (2) gender and click frequency, and (3) age and shopping frequency. The Pearson Chi-Square test was used to assess the significance of these associations.

4.5.1 Gender and Perceived Choice Overload

In Table 4.6 and Table 4.7, a significant association was found between gender and perceived choice overload (χ^2 (4, N = 150) = 10.827, p = 0.029). Female participants were more likely to report feeling “somewhat overwhelmed” (67.6%) compared to males (45.8%). Conversely, male respondents showed higher proportions of “neutral” or “not overwhelmed” responses. These results suggest that women may be more easily to experience choice overload when shopping with abundant product options.

Table 4.6 Gender and Choice Overload

			Choice overload					
			Neutral	Not overwhelmed at all	Not very overwhelmed	Somewhat overwhelmed	Very overwhelmed	Total
Gender	Female	Count	8	0	12	69	13	102
		% within Gender?	7.8%	0.0%	11.8%	67.6%	12.7%	100.0%
		% within Choice overload	42.1%	0.0%	63.2%	75.8%	65.0%	68.0%
	Male	Count	11	1	7	22	7	48
		% within Gender?	22.9%	2.1%	14.6%	45.8%	14.6%	100.0%
		% within Choice overload	57.9%	100.0%	36.8%	24.2%	35.0%	32.0%
Total		Count	19	1	19	91	20	150
		% within Gender?	12.7%	0.7%	12.7%	60.7%	13.3%	100.0%
		% within Choice overload	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%

Tablle 4.7 Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	10.827[a]	4	.029
Likelihood Ratio	10.627	4	.031
N of Valid Cases	150		

a. 2 cells (20.0%) have expected count less than 5. The minimum expected count is .32.

4.5.2 Gender and Click Frequency on Recommended Products

There was no statistically significant relationship between gender and the frequency of clicking on recommended products (χ^2 (4, N = 150) = 2.212, p = 0.697). Both male and female respondents exhibited similar patterns in their likelihood to interact with personalized recommendations.

Table 4.8 Gender and Click Frequency

			Click Frequency					
			Never	Often	Rarely	Sometimes	Very often	Total
Gender	Female	Count	1	44	13	31	13	102
		% within Gender	1.0%	43.1%	12.7%	30.4%	12.7%	100.0%
		% within Click Frequency	100.0%	68.8%	56.5%	72.1%	68.4%	68.0%
	Male	Count	0	20	10	12	6	48
		% within Gender	0.0%	41.7%	20.8%	25.0%	12.5%	100.0%
		% within Click Frequency	0.0%	31.3%	43.5%	27.9%	31.6%	32.0%
Total		Count	1	64	23	43	19	150
		% within Gender	0.7%	42.7%	15.3%	28.7%	12.7%	100.0%
		% within Click Frequency	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%

Table 4.9 Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	2.212[a]	4	.697
Likelihood Ratio	2.452	4	.653
N of Valid Cases	150		

a. 2 cells (20.0%) have expected count less than 5. The minimum expected count is .32.

4.5.3 Age and Shopping Frequency

The chi-square test revealed no significant association between age group and shopping frequency (χ^2 (12, N = 150) = 14.333, p = 0.280). Although younger respondents aged 18–34 were more likely to shop more frequently (weekly or monthly), the differences were not statistically significant. This suggests that shopping frequency patterns are relatively consistent across age groups in this sample.

Table 4.10 Age Group and Shopping Frequency

			Shopping Frequency				
			Daily	Less than once a month	Monthly	Weekly	Total
Age Group	18-24	Count	1	8	33	16	58
		% within Age Group	1.7%	13.8%	56.9%	27.6%	100.0%
		% within Shopping Frequency	33.3%	22.9%	43.4%	44.4%	38.7%
	25-34	Count	2	18	33	18	71
		% within Age Group	2.8%	25.4%	46.5%	25.4%	100.0%
		% within Shopping Frequency	66.7%	51.4%	43.4%	50.0%	47.3%
	35-44	Count	0	4	7	0	11
		% within Age Group	0.0%	36.4%	63.6%	0.0%	100.0%
		% within Shopping Frequency	0.0%	11.4%	9.2%	0.0%	7.3%
	45-54	Count	0	0	1	0	1
		% within Age Group	0.0%	0.0%	100.0%	0.0%	100.0%
		% within Shopping Frequency	0.0%	0.0%	1.3%	0.0%	0.7%
	55+	Count	0	5	2	2	9
		% within Age Group	0.0%	55.6%	22.2%	22.2%	100.0%
		% within Shopping Frequency	0.0%	14.3%	2.6%	5.6%	6.0%
Total		Count	3	35	76	36	150
		% within Age Group	2.0%	23.3%	50.7%	24.0%	100.0%
		% within Shopping Frequency	100.0%	100.0%	100.0%	100.0%	100.0%

Table 4.11 Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	14.333[a]	12	.280
Likelihood Ratio	17.209	12	.142
N of Valid Cases	150		

a. 13 cells (65.0%) have expected count less than 5. The minimum expected count is .02.

4.6 Regression Analysis

This section presents the findings from three multiple linear regression models that were conducted to examine the relationships between key psychological and behavioral variables in the context of AI-based personalized product recommendations. Each model tested a distinct dependent variable based on the study's objectives: Ease of Decision, Choice Overload, and Satisfaction.

4.6.1 Factors Influencing Ease of Decision

The first model examined factors influencing the ease of the decision, the factors include the narrowing-down help, usefulness, and relevance of the AI recommendations.

Model Summary

The regression model presents an R value of 0.731 and an R^2 of 0.535, indicating that the three independent variables could explain 53.5% of the variance in Ease of Decision. The adjusted R^2 was 0.525, and the model was statistically significant ($F = 55.987$, $p < 0.001$), showing strong explanatory power.

Table 4.11 Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.731[a]	.535	.525	.69482	.535	55.987	3	146	<.001

a. Predictors: (Constant), NarrowDownHelp_Numeric, Revelance_Numeric, Usefulness_Numeric

ANOVA and Model Fit

The ANOVA table further supports the model's validity, with a significant p-value (<

0.001), indicating that the model makes a significant prediction of the dependent variable. The regression sum of squares (81.088) is larger than the residual sum of squares (70.486), which supports that the predictors contribute substantially to the model.

Table 4.12 ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	81.088	3	27.029	55.987	<.001[b]
	Residual	70.486	146	.483		
	Total	151.573	149			

a. Dependent Variable: Ease of Decision_Numeric

b. Predictors: (Constant), NarrowDownHelp_Numeric, Revelance_Numeric, Usefulness_Numeric

Coefficient Analysis:

NarrowDownHelp was the strongest predictor (B = 0.539, $p < 0.001$), suggesting that users who feel the recommendation system helps reduce the number of options find decisions easier.

Usefulness was also significant (B = 0.218, $p = 0.005$), showing that users who perceive recommendations as useful experience improved decision-making.

Relevance had a positive but non-significant effect (B = 0.134, $p = 0.102$).

Table 4.13 Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	.317	.301		1.054	.294		
	Revelance_Numeric	.134	.081	.108	1.646	.102	.734	1.363
	Usefulness_Numeric	.218	.076	.202	2.850	.005	.635	1.575
	NarrowDownHelp_Numeric	.539	.065	.550	8.255	<.001	.718	1.392

a. Dependent Variable: Ease of Decision_Numeric

Multicollinearity

The Variance Inflation Factor (VIF) values for all predictors were well below the threshold of 5 (VIF < 1.6), indicating no multicollinearity concerns. Additionally, the condition indices in the collinearity diagnostics table were below the critical value of 30, further confirming that multicollinearity is not a threat to the model's validity.

Table 4.14 Collinearity Diagnostics[a]

Model	Dimension	Eigenvalue	Condition Index	Variance Proportions (Constant)	Revelance_Numeric	Usefulness_Numeric	NarrowDownHelp_Numeric
1	1	3.908	1.000	.00	.00	.00	.00
	2	.042	9.655	.15	.13	.00	.82
	3	.029	11.675	.29	.00	.87	.16
	4	.022	13.437	.56	.87	.12	.02

a. Dependent Variable: Ease of Decision_Numeric

This model emphasizes the importance of AI recommendations' functional and filtering capabilities in reducing user cognitive burden. Specifically, perceived usefulness and narrowing assistance significantly enhance decision ease, even more than content relevance.

4.6.2 Determinants of Choice Overload

The second model aimed to predict users' perception of choice overload based on their experiences with decision delays, system support in narrowing options, and decision ease.

Model Summary

This model produced an R^2 of 0.084, with an adjusted R^2 of 0.065, indicating that only 8.4% of the variance in Choice Overload was explained. Despite its modest explanatory power, the model was statistically significant ($F = 4.442$, $p = 0.005$).

Table 4.15 Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change
2	.289[a]	.084	.065	.84340	.084	4.442	3	146	.005

a. Predictors: (Constant), Ease of Decision_Numeric, DelayDueToOptions_Numeric, NarrowDownHelp_Numeric

ANOVA and Model Fit

The ANOVA table confirms that the regression model is statistically significant ($p = 0.005$), implying that the independent variables together contribute meaningfully to predicting users' sense of being overwhelmed by product choices. However, the regression sum of squares (9.479) is small relative to the residual sum of squares (103.854), which explains the low R^2.

Table 4.16 ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
2	Regression	9.479	3	3.160	4.442	.005[b]
	Residual	103.854	146	.711		
	Total	113.333	149			

a. Dependent Variable: ChoiceOverload_Numeric

b. Predictors: (Constant), Ease of Decision_Numeric, DelayDueToOptions_Numeric, NarrowDownHelp_Numeric

Coefficient Analysis:

DelayDueToOptions was the only significant predictor (B = 0.187, p = 0.005), positively associated with choice overload.

NarrowDownHelp (B = 0.098, p = 0.296) and Ease of Decision (B = 0.033, p = 0.731) were not statistically significant.

Table 4.17 Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
2	(Constant)	2.526	.348		7.262	<.001		
	DelayDueToOptions_Numeric	.187	.066	.228	2.840	.005	.970	1.031
	NarrowDownHelp_Numeric	.098	.093	.116	1.049	.296	.518	1.932
	Ease of Decision_Numeric	.033	.096	.038	.345	.731	.514	1.947

a. Dependent Variable: ChoiceOverload_Numeric

Multicollinearity

The VIF values for all predictors ranged from 1.03 to 1.95, which is well below the common cutoff of 5, indicating no multicollinearity issues. The condition indices in the collinearity diagnostics were also below 30, confirming model stability.

Table 4.18 Collinearity Diagnostics[a]

Model	Dimension	Eigenvalue	Condition Index	Variance Proportions (Constant)	DelayDueToOptions_Numeric	NarrowDownHelp_Numeric	Ease of Decision_Numeric
2	1	3.875	1.000	.00	.00	.00	.00
	2	.074	7.218	.02	.48	.11	.10
	3	.028	11.666	.97	.51	.03	.07
	4	.022	13.248	.00	.01	.85	.83

a. Dependent Variable: ChoiceOverload_Numeric

Findings suggest that decision delays due to excessive options are a key driver of perceived overload, whereas ease of decision and recommendation system assistance do not directly reduce choice overload. This indicates that behavioral outcomes (delays) may better capture the overload experience than perceptual ease alone.

4.6.3 Factors Influencing User Satisfaction

The final regression model assessed the effects of perceived relevance, trust, perceived bias, and click frequency on user satisfaction with AI recommendations.

Model Summary

The model showed an R value of 0.644 and an R^2 of 0.414, meaning 41.4% of the variance in satisfaction could be explained. The adjusted R^2 was 0.398, with a significant F-statistic ($F = 25.662$, $p < 0.001$), demonstrating good model fit.

Table 4.19 Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics R Square Change	F Change	df1	df2	Sig. F Change
3	.644[a]	.414	.398	.66444	.414	25.662	4	145	<.001

a. Predictors: (Constant), ClickFreq_Numeric, PerceivedBias_Numeric, Revelance_Numeric, Trust_Numeric

ANOVA and Model Fit

The ANOVA results support the model's overall validity ($p < 0.001$), with the regression sum of squares (45.318) showing a substantial portion of explained variance compared to the residual (64.016).

Table 4.20 ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
3	Regression	45.318	4	11.329	25.662	<.001[b]
	Residual	64.016	145	.441		
	Total	109.333	149			

a. Dependent Variable: Satisfaction_Numeric

b. Predictors: (Constant), ClickFreq_Numeric, PerceivedBias_Numeric, Revelance_Numeric, Trust_Numeric

Coefficient Analysis:

Trust emerged as the strongest predictor (B = 0.296, $p < 0.001$), confirming its critical role in enhancing satisfaction.

Click Frequency was also significant (B = 0.243, $p < 0.001$), suggesting that active interaction with recommendations increases satisfaction.

Relevance showed a moderate, positive, and significant influence (B = 0.223, p = 0.005).

Perceived Bias had no significant effect (B = 0.005, p = 0.936), indicating that it may not factor into satisfaction judgments.

Table 4.21 Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
3	(Constant)	.889	.360		2.471	.015		
	Revelance_Numeric	.223	.079	.213	2.820	.005	.706	1.416
	Trust_Numeric	.296	.066	.343	4.476	<.001	.687	1.455
	PerceivedBias_Numeric	.005	.060	.005	.080	.936	.967	1.034
	ClickFreq_Numeric	.243	.065	.262	3.717	<.001	.811	1.233

a. Dependent Variable: Satisfaction_Numeric

Multicollinearity

No multicollinearity was detected, as all VIF values were below 1.5 and the condition indices remained under 17. These metrics confirm the model's reliability and the independence of predictors.

Table 4.22 Collinearity Diagnostics[a]

Model	Dimension	Eigenvalue	Condition Index	Variance Proportions (Constant)	Revelance_Numeric	Trust_Numeric	PerceivedBias_Numeric	ClickFreq_Numeric
3	1	4.844	1.000	.00	.00	.00	.00	.00
	2	.071	8.231	.01	.01	.22	.41	.04
	3	.042	10.783	.00	.04	.24	.01	.91
	4	.025	13.825	.01	.76	.52	.19	.01
	5	.017	16.685	.97	.19	.02	.39	.03

a. Dependent Variable: Satisfaction_Numeric

User satisfaction is primarily driven by trust and click frequency, with relevance also playing a role. However, perceived bias did not diminish satisfaction, potentially indicating that users tolerate or overlook minor bias if the system is otherwise useful and trustworthy.

4.7 Finding Summary

The analysis of 150 valid survey responses reveals several key findings regarding the effectiveness of AI-based personalized recommendations in the online shopping context. Demographic insights show a predominantly female respondent base (68%) and a majority aged between 25–34 years, aligning with the typical demographic of active online shoppers.

Descriptive statistics show that participants generally held positive perceptions toward personalized recommendations, particularly in terms of usefulness, relevance, and their ability to reduce decision-making effort. Respondents reported moderate levels of choice overload, suggesting that while personalization helps, it does not eliminate the burden of excessive options.

A reliability analysis confirmed internal consistency among key items measuring perceived recommendation quality (Cronbach’s Alpha = 0.857). Correlation analysis further demonstrated that the relevance and usefulness of recommendations were positively associated with decision ease and satisfaction, while perceived bias was negatively correlated with trust and satisfaction.

Crosstab analyses revealed no significant gender differences in click frequency. However, the data analysis indicates that female respondents are more likely to feel overwhelmed in the online shopping context.

Three regression models were conducted. The first model found that perceived narrow down help and usefulness significantly predicted decision ease, accounting for 53.5% of the variance ($R^2 = 0.535$). The second model showed that only decision delays significantly affected perceived choice overload ($R^2 = 0.084$). The third model indicated that trust was the strongest positive predictor of satisfaction, click frequency, and relevance showed a moderate influence, while perceived bias was a negative predictor, explaining 41.4% of the variance ($R^2 = 0.414$).

In conclusion, these findings suggest that personalized recommendations, when perceived as relevant, useful, and trustworthy, can reduce cognitive load, improve user satisfaction, and positively influence consumer behavior in online shopping platforms. These insights will be further examined in Chapter 5 in light of existing literature.

Chapter 5 Discussion

5.1 Introduction

This chapter discusses the key findings of the study with the existing literature on AI-based personalized recommendation systems and consumer decision-making, with a particular focus on choice overload, satisfaction, and trust. The purpose is to interpret and critically evaluate the statistical results presented in Chapter 4, while highlighting their theoretical and practical implications.

By examining the relationships between perceived relevance, usefulness, interaction frequency, decision ease, and satisfaction, this chapter aims to provide a different understanding of how personalized recommendation systems influence user behavior in e-commerce environments. Particular attention is given to explaining unexpected or statistically weak findings, such as the limited role of perceived bias and the modest predictive power of the model for choice overload.

The discussion also compares these results with prior studies and theoretical perspectives introduced in the literature review. Through this comparison, the chapter explores whether the empirical data support, extend, or challenge existing knowledge. Finally, the broader implications for platform designers, marketing strategists, and future academic research are outlined.

5.2 Personalized Recommendations Enhance Decision Ease

Decision ease is always one of the evaluation elements in the recommendation system, which can also be referred to as efficiency. It has been defined as the degree to which a recommender system enables users to efficiently locate their preferred items (Pu, Chen and Hu, 2011). The regression model investigating factors influencing ease of decision-making revealed that narrowing down help and the usefulness of the recommendation system had a significant impact on the decision stage. Among them, narrowing down help had the strongest influence, indicating that users are more likely to find decisions easier when the system can effectively filter and target relevant options. This result also aligns with existing literature emphasizing the role of recommendation systems in reducing cognitive effort by simplifying complex decision environments (Nimbalkar and Berad, 2021; Zhang and Xiong, 2024). Besides, the usefulness of recommendations also contributes a lot to the ease of decision-making. Mican, Sitar-Tăut, and Moisescu (2020) found that the perceived usefulness positively influences the willingness to share data with the RS developer, which in turn improves future recommendations and encourages further data sharing, and then better enhances the ability to simplify the decision-making.

In contrast, while relevance showed a positive effect, it was not statistically significant in the model. This may suggest that although content relevance is important, the functional value, like how well the system helps the decision making that plays a more important role in easing cognitive burden during the shopping experience. Therefore, for better optimizing recommender systems, only focusing on accurately matching users' interests may be insufficient to improve decision efficiency; instead, enhancing decision-support capabilities, such as narrowing the range of options and providing clear recommendations, may be more critical.

Overall, these findings expand our understanding of the mechanisms by which personalized recommender systems operate, particularly in terms of their role in enhancing decision efficiency. From a practical perspective, e-commerce platforms should prioritize strengthening the usefulness and filtering functions of their recommender systems, rather than solely emphasizing content relevance, to further enhance user experience and satisfaction.

5.3 Choice Overload Persists Despite Personalization

Although some researchers propose reducing the choice overload by restricting the choice set (Schwartz, 2004), this would also trigger a criticism of being paternalistic, because the decision was made and not chosen by the users (Besedeš et al., 2015). Besedeš et al. (2015) suggest that breaking large decisions into smaller, well-structured stages, particularly through the sequential tournament process, can enhance decision quality without reducing overall choice availability.

However, the regression analysis on choice overload in this study presents an unexpected finding, indicating only a small proportion of the variance ($R^2 = 0.084$). Among all three predictors, only delay due to excessive options showed a significant association with perceived overload. Neither ease of decision nor narrowing down significantly helped predict lower choice overload. This may suggest that even though recommendation systems provided some support during the decision-making process at a certain level, they do not fully eliminate users' sense of being overwhelmed by abundant options.

This finding challenges some assumptions in the literature that personalization inherently resolves overload (Shani and Gunawardana, 2010). Instead, the results show that behavioral delays, such as the time spent evaluating options or even decision-making delays, may be a more reliable indicator of overload. It also suggests that personalization may help users feel more confident in the decision-making process, but would not necessarily reduce the actual burden of the choice.

5. 4 Trust and Click Frequency Drive Satisfaction

The research question tries to figure out what factors influence the user's satisfaction. In the regression model, the strongest predictors of user satisfaction with recommendations were trust and click frequency. This emphasizes the idea that trust is an important component of human-AI interaction, particularly when it involves decision support (Herse et al., 2018). When users perceive the system as trustworthy, accurate, fair, and consistent, they are more likely to feel satisfied with the recommendation systems. Tintarev and Masthoff's (2007) study also proved this point, indicating seven key goals of explanation in recommender systems that are transparency, scrutability, trust, effectiveness, persuasiveness, efficiency, and satisfaction; all of these contribute a lot to enhancing the overall user experience.

In addition, active engagement, like the higher click frequency, was also positively associated with satisfaction. It was assumed that the higher click frequency reflects the attractiveness and relevance of the recommendation system (Jannach and Jugovac, 2019), therefore leading to higher satisfaction. The result of this model suggests that satisfaction is not only driven by passive exposure to recommendations, but also by interactive behaviors that reflect user agency and interest. In the "you may also like" context, the change of the algorithm from simple title-based recommendations to related product recommendations brought 38% click frequency on eBay(Katukuri et al., 2014). These results support previous studies emphasizing the role of perceived meaningful interaction in shaping positive attitudes toward algorithmic systems (Arora et al., 2024).

Notably, perceived bias did not significantly influence satisfaction, which may suggest that users are either unaware of subtle bias or willing to overlook it if the system is able to provide useful and accurate suggestions. From the literature, many different biases have been discussed: inductive bias, popularity bias, unfairness, conformity bias, position bias, selection bias, and exposure bias (Chen et al., 2023). With so many kinds of bias and the existence of information cocoons, it is difficult for users to truly recognize bias. This finding points to a potential blind spot in user perception that has implications for ethical system design, discussed further in Section 5.6.

5. 5 Additional Observations – Demographics

5.5.1 Gender

Mehta and Dave (2024) identified gender-based differences in online purchasing behavior, with men more likely to make purchase decisions solely based on personalized recommendations, whereas women tended to report stronger emotional responses, including satisfaction or frustration.

From the 150 respondents in this study, 68% were female and 32% were male. The crosstabulation results revealed a significant association between gender and perceived choice overload (χ^2 (4, N = 150) = 10.827, p = 0.029). Female respondents were more likely to report feeling “somewhat overwhelmed” (67.6%) compared to male respondents (45.8%), whereas male participants had a higher proportion of “neutral” or “not overwhelmed” responses. This suggests that women in this sample experienced a greater cognitive burden when faced with abundant product options in e-commerce environments.

No significant association was found between gender and the frequency of clicking on recommended products (χ^2 (4, N = 150) = 2.212, p = 0.697), indicating that despite differences in overload perception, both male and female respondents engaged with personalized recommendations at similar levels.

5.5.2 Age Group

The age distribution of respondents was concentrated among younger adults, with 47.3% aged 25–34 and 38.7% aged 18–24, while only 14% were aged 35 or above. Crosstabulation results showed no significant association between age group and shopping frequency (χ^2 (12, N = 150) = 14.333, p = 0.280). While descriptive data indicated that younger participants were more likely to shop online on a weekly or monthly basis, these differences were not statistically significant.

The large proportion of younger respondents in the sample suggests that the results mainly reflect the habits and attitudes of a technology-proficient group who are more used to engaging with AI-based recommendations.

5.6 Practical Implications

The research question asked how AI-based personalized recommendation systems influence consumer decision-making, particularly in reducing choice overload and enhancing satisfaction and trust. Based on the findings from this study and the empirical evidence gathered, these questions have been answered while also adding to the existing literature on personalization in e-commerce.

Firstly, this study adds to the work of Nimbalkar and Berad (2021) and Zhang and Xiong (2024), which highlight the importance of functional decision-support features in recommender systems. The results from this research confirm that narrowing down help and usefulness are more influential than mere content relevance in enhancing decision ease. This reinforces the notion that effective filtering and structuring of product options are central to improving the consumer decision-making process, a finding that applies in both the Irish e-commerce context and potentially in other online retail markets.

Secondly, this study shows different results from the prior research, such as those suggested by Shani and Gunawardana (2010), that personalization systems can inherently resolve choice overload. However, the results show that overload can persist despite personalization, with decision delays being the only significant predictor. This points to a need for e-commerce platforms to integrate additional choice architecture techniques, such as staged product disclosure or summary comparisons, to complement personalization algorithms.

From a managerial and design perspective, the findings highlight the importance of building and maintaining trust, as it emerged as the strongest predictor of satisfaction. This aligns with the arguments of Tintarev and Masthoff (2007) that transparency and explainability are crucial to fostering user confidence. Platform managers should therefore invest in policies and interface designs that communicate recommendation logic clearly, monitor for potential bias, and promote fair exposure of products. Furthermore, the study's results on gender differences in overload perception suggest that personalization strategies may need to be adjusted to specific user segments, rather than relying on one model to fix all the problems

Overall, the empirical evidence confirms that platform designers, marketers, and product managers can significantly improve decision ease and satisfaction by enhancing usefulness, narrowing down capabilities, and trust-building mechanisms within recommendation systems, while also recognizing that personalization alone may not fix the challenge of choice overload.

5.7 Theoretical Contributions

The study also leads to a number of theoretical contributions to recommender system literature, consumer decision-making literature, and the choice overload literature.

First, it builds on the literature available on choice overload theory by proving that personalization enhances ease of choice, but it is not always associated with the perception of reduced overload. The finding expands and provides details to the previous research on the topic, like Schwartz (2004) and Diehl and Poynor (2010), by demonstrating that cognitive relief and overload reduction can be two separate processes. The fact that the decision delay, a behavioral indicator, predicts overload far better than the perception of ease of decision making indicates a change to existing theoretical frameworks.

Secondly, the research contributes to the paradigm of trust and satisfaction in the AI recommendation system. Although previous studies (Herse et al., 2018) have determined the importance of trust as a factor of satisfaction, the present results indicate that engagement in behaviors like the number of clicks is an essential factor as well. This impact implies that the theoretical models of recommender system acceptance need to incorporate the metrics of interaction with attitudinal variables.

Third, the lack of a significant correlation between perceived bias and satisfaction introduces a new dimension to the algorithmic fairness. This observation indicates that the users might be more concerned with the usefulness and relevance than with the issue of fairness when rating the system of recommendations. This creates possibilities of future theory-building about the interaction of the system's perceived benefits and ethics in the interaction between a human and the AI.

Lastly, the research has added to the literature on the issue of user diversity in personalization effects, which determines the gender differences in the perception of overloads. It supports emerging theoretical perspectives advocating for segment-aware personalization, suggesting that demographic factors can shape cognitive and emotional responses to recommender systems in meaningful ways.

5.8 Limitations of the Study

Although this research offers valuable insights into the role of AI-based personalized recommendation systems in mitigating choice overload and enhancing satisfaction and trust, several limitations should be acknowledged.

First, the study employed a convenience sampling strategy, recruiting respondents primarily through social media and personal networks. As a result, the sample had a higher proportion of younger, digitally literate users, particularly those aged 18–34. This demographic concentration limits the generalizability of the findings to broader populations, especially older adults or those with limited e-commerce experience.

Second, the data collection relied on self-reported survey responses, which are subject to recall bias and social desirability bias. While Likert-scale questions provided a consistent measurement framework, they may not fully capture the subtle differences in user behavior, especially in real-time decision-making contexts.

Third, the research design was cross-sectional, capturing user perceptions at a single point in time. Therefore, it cannot establish causal relationships between personalization, choice overload, trust, and satisfaction. Longitudinal or experimental designs would be necessary to track changes over time and infer causality.

Fourth, although this research measured perceived bias, it did not differentiate between specific types of bias, such as popularity bias, position bias, or confirmation bias, among others. As Chen et al. (2023) noted previously, there are various algorithmic biases; using more specific metrics could lead to deeper insights into how each factor operates alone and in combination with others

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Finally, due to the limitations of time and resources, the study did not include behavioral tracking data, such as actual clickstream, which could have complemented self-reported perceptions with objective measures of engagement.

5.9 Suggestions for Future Research

Building on the findings and limitations of this study, there are a few suggestions for future research. First, future studies could aim to collect data across different age groups, cultural backgrounds, and different levels of familiarity with the technology. This would enable a more comprehensive understanding of how personalization impacts different user segments and would also test the gender differences observed in choice overload perception. Second, constructing a longitudinal or experimental research design would be beneficial in figuring out the connection between recommendation system features, user trust, ease of decision, and contentment. For example, controlled variable experiments could be adopted by establishing levels of narrowing down help or transparency and then calculating their direct impacts on users. Third, additional studies, like the clickstream data, time-to-decision measures, and purchasing conversion rates, would also be a great supplement to the behavioral analytics. This would not only complete self-report measures but also conduct a more comprehensive analysis of user behavior patterns. Fourth, future work could explore different bias types separately, investigating whether certain biases are more tolerable or detectable to users compared to the other bias, and how this impacts trust and satisfaction. This could bring some valuable insights to the design of fairness-aware algorithms and bias mitigation strategies. Finally, examining contextual moderators, such as product category complexity, purchase frequency, or platform interface design, could refine our understanding of when and how personalization alleviates or worsen choice overload.

5.10 Summary

This chapter discussed the empirical findings of the study about existing literature, identifying both consistencies and divergences. The analysis revealed that narrowing down helps and usefulness significantly enhance decision ease, while trust and click frequency strongly predict satisfaction. However, personalization did not substantially reduce perceived choice overload, with decision delays emerging as the only significant predictor of overload.

These results challenge the assumption that personalization inherently eliminates overload, suggesting instead that behavioral indicators may be more telling than self-reported ease. The discussion also highlighted the limited impact of perceived bias on satisfaction, raising questions about user awareness and tolerance of algorithmic bias.

Practical implications were outlined for platform designers and marketers, emphasizing the need for enhanced decision-support features, transparency, and segment-specific personalization. Theoretical contributions included extending choice overload theory, refining the trust-satisfaction paradigm, and suggesting that users may prioritize usefulness and relevance over fairness concerns when evaluating recommendation systems.

Limitations were acknowledged, including sampling bias, self-reported measures, cross-sectional design, and lack of behavioral data. Future research directions were proposed to address these limitations and deepen the understanding of personalization's psychological and behavioral effects.

Overall, this chapter positions the study's findings within the broader discourse on AI-driven personalization, offering both actionable insights and avenues for continued scholarly exploration. The next chapter will present the overall conclusions of the research, synthesizing key contributions and implications.

Chapter 6 Conclusion and Recommendation

6.1 Conclusion

This study examined how AI-based personalized recommendation systems affect online consumer decision-making and whether the recommendation system can help alleviate the choice overload. The focus was on decision ease, satisfaction, and trust. The research adopted a positivist, deductive design and a quantitative survey with 150 valid responses.

Three main results were explored under the analysis. First, when the recommendation system offered strong narrowing-down help, then it would be recognized as useful, thus improving the decision ease. Content relevance also shows some connection, but is not the main predictor in the model. Second, although recommendation systems offered help but the choice overload persisted. Only decision delays predicted overload, which suggests that overload is a behavioral and experiential problem, not only a perception problem. Third, trust and click frequency were the strongest drivers of satisfaction, which indicated that users felt satisfied when they trusted the recommendation system and actively engaged with its suggestions.

This research also observed demographic differences. According to the analysis, female respondents were more likely to feel overwhelmed compared to males, while gender and age did not explain differences in clicking or shopping frequency. These patterns point out the user diversity and the need for segment-aware design.

Examining the literature and the data collected reveals deeper problems contributing to the recommendation systems. The study shows that decision-support features reduce cognitive effort more than relevance alone. Also, the study shows that personalization does not automatically reduce the overload in complexity choice environments. Besides, the study also shows that trust and engagement work together to raise satisfaction. These results give platform teams a clear agenda: design for decision support, monitor overload behavior, and build trust into every step of the experience.

6.2 Recommendations

Following the findings and discussion presented in this study, it is important to offer practical recommendations for e-commerce companies and digital platform teams. These recommendations aim to improve the design, evaluation, and performance of AI-based recommendation systems, particularly with a focus on consumer satisfaction, decision efficiency, and trust.

Four recommendations are provided below. Each is designed for application by UX designers, data science teams, and digital marketing managers involved in recommender system development and deployment.

1. Prioritize Decision Support Functions in System Design

The study found option narrowing and recommendation utility more influential than pure relevance in supporting user decision-making. Therefore, sites should shift their design paradigm from mere preference-matching towards dynamic decision support.

As a best practice, we advocate that recommendation pages incorporate elements like “Top 5 picks”, custom filters (e.g., by budget, brand awareness), and category shortcuts. These resources allow users to more easily browse through extensive product sets and minimize the time spent on decisions.

Timeframe and Cost Considerations: User interface updates can be prototyped within 2–4 weeks and tested through A/B testing platforms like Optimizely or Google Optimize. Implementation may require design, frontend development, and testing resources. The estimated cost ranges between €3,000 to €10,000, depending on internal capacity and complexity.

2. Improve Transparency and Control to Establish Trust

Trust emerged as a strong driver of user satisfaction. Platforms must explain explicitly why they recommend things and provide users with more control over the experience.

Suggest brief, friendly summaries like "Recommended since you searched for X" or "Popular amongst users with similar tastes." Allow controls such as suppressing certain category results, preference weight adjustments, or feedback options (e.g., "Not related").

Timeframe and Cost Considerations: Establishing a simple explanation layer and user control panel will involve 4–6 weeks. It will involve communication between backend logic and frontend presentation. Prices will range between €5,000 and €15,000 based on the degree of personalization logic implemented and the complexity of the interface.

3. Monitor Choice Overload through Behavioral Signals

This research reveals that perceived overload has the strongest relationship with option abundance-based delay. Platforms must not depend on questionnaires to identify overload. Real-time behavioral signals can instead be monitored.

It is advised that you utilize measures like dwell time, option reversal patterns, session loops, or abandoned carts as signs of decision fatigue. These will then activate streamlined forms of the recommender, such as a shorter option list or guided assistant.

Timeframe and Cost Analysis: Behavioral tracking is offered through analytics products like Google Analytics 4, Heap, or Mixpanel. Overload-trigger rules and simplified fallback flows will require 3–5 weeks of setup. Estimated price: €2,000–€8,000, depending on the necessary data integration.

4. Tailor Recommendation Complexity Based on User Segments

The study found that younger and more digitally experienced users may handle the complexity of recommendation systems differently from older or less experienced ones. Therefore, improving and personalizing the recommendations based on the user segments could reduce overload and improve users' engagement.

Platforms are advised to develop adaptive interfaces that adjust the number of recommendations, level of explanation, and decision support features based on user profiles or behavioral history. For example, new users could see a simplified interface, while returning users get more detailed options.

Timeframe and Cost Considerations:
This strategy requires both UX design and algorithmic segmentation work. A first phase rollout targeting two user groups could be tested in 6–8 weeks. Costs may vary from €6,000 to €20,000, depending on the segmentation method, personalization engine, and internal tooling.

Overall, these recommendations aim to help organizations build more effective and ethical AI-based recommendation systems. Platforms that prioritize trust, user control, and decision efficiency are more likely to retain customers, increase satisfaction, and reduce the negative effects of choice overload. Future work should focus on evaluating the long-term outcomes of these strategies across different consumer segments and market categories.

6.3 Personal Learning Statement

This dissertation journey has been one of the most challenging but also a rewarding experience of my academic life. Through my dissertation on AI recommendation and choice overload, I have gained extensive knowledge about these factors and their interplay, as well as the various ways in which recommendation systems impact users and offer assistance in different industries.

My inspiration and motivation for this topic comes from my personal experience with the overwhelming abundance of choice online and offline, and then I was surprised to find out how accurate the recommendation systems could be; sometimes it even shows the relevant products that I was interested in on other platforms, which also triggers my worries about personal information safety and the potential bias. In terms of AI, I have learned lots of advanced AI tools through my elective course: Doing Business on the Cloud. From this course, I learned how to code and then build a webpage with the help of AI, and also learned to edit video by AI. All these knowledge I absorbed, turning to my strong interests in AI. Therefore, all these elements combined to drive me to choose this topic for my thesis.

Throughout the process, I have also improved my research skills. At the beginning, I found it difficult to formulate clear research questions and structure the literature review. However, after deep learning of some excellent articles and the overall research trends, I learned how to critically evaluate the different article resources and build my thesis. During the research, I have learnt the origin and the development of the choice overload, and have a better understanding of recommendation systems. I learned the various applications of RS, which methods they adopted, and how it works.

One of the biggest challenges I faced was in the data collection stage. Due to limited resources and time, I had to rely on online surveys and share them on different platforms. At first, I did not get many responses and felt discouraged, but with the help of friends, family, and kind unknown Netizens, I collected all the responses that I needed. The social media users on Little Red Book are very friendly and helpful; they contribute a lot to my research.

I also developed strong skills in using SPSS to analyze survey data. Before this project, I had no experience with statistical software, nor did I know how to download it or which version to choose. Luckily, we are now living in the digital age, so I can access all the knowledge online, learning step by step. After this project, I am comfortable running descriptive statistics, correlation tests, and regression analysis. These skills will undoubtedly be valuable for future work in data-driven business environments.

Besides, doing this research alongside part-time work taught me how to manage time effectively, prioritize tasks, and stay focused under pressure. Although two weeks of illness interrupted my plan, I still finished this project on time. These are valuable skills that will support me in both further study and in a professional setting.

In conclusion, this dissertation was not only an academic requirement but also a personal learning experience that pushed me beyond my comfort zone. It taught me how to think critically, plan systematically, and work independently. I also really enjoyed this whole learning journey; the passion for this topic fuels my progress.

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Appendix

Appendix 1: Participant Information and Consent Form

Title of Study: Effectiveness of AI-Based Personalized Recommendations on Shopping Platforms

Researcher: Mengdie Hu

[National College of Ireland]

Purpose of the Study:

This study aims to explore how personalized recommendations powered by artificial intelligence (AI) affect consumer decision-making, choice overload, and trust in online shopping environments.

Participation Information:

- Your participation is entirely voluntary.

- You must be 18 years or older to take part.

- The questionnaire will take approximately 5–8 minutes to complete.

- All responses will remain anonymous and confidential.

- You have the right to withdraw at any time before submitting the form, without providing a reason.

- The data collected will be used strictly for academic purposes (e.g., research paper or dissertation) and will not be shared with third parties.

Data Protection and Privacy:

- No personal identifiers (such as name or email) will be collected.
- Data will be stored securely and in compliance with relevant data protection laws.

Consent Statement:

By proceeding with the questionnaire, you confirm that:

☑ You are 18 years of age or older.

☑ You understand the purpose of this research and what your participation involves.

☑ You voluntarily agree to participate in this study.

Please click "Next" or "Continue" if you agree to participate.

Appendix 2: Research Study Question

1. Have you shopped online in the past 6 months?

○ Yes

○ No

2. Have you noticed or interacted with personalized recommendations (e.g., 'Recommended for you', 'You may also like') during online shopping?

○ Yes

○ No

3. What is your age?

○ 18–24

○ 25–34

○ 35–44

○ 45–54

○ 55+

4. What is your gender?

○ Male

○ Female

5. How often do you shop online?

○ Daily

○ Weekly

○ Monthly

○ Less than once a month

6. Which platforms do you frequently use for online shopping? (Select all that apply)

○ Amazon

○ eBay

○ Shein

○ Zalando

○ Temu

○ Other (please specify): ___________

7. How often do you notice personalized recommendations while shopping online?

○ Very frequently

○ Frequently

○ Occasionally

○ Rarely

○ Never

8. How often do you click on or explore these recommended products?

○ Very often
○ Often
○ Sometimes
○ Rarely
○ Never

9. When shopping online, how overwhelmed do you feel by the number of product choices available?

○ Very overwhelmed
○ Somewhat overwhelmed
○ Neutral
○ Not very overwhelmed
○ Not overwhelmed at all

10. To what extent do personalized recommendations help you narrow down your choices?

○ A great deal
○ Somewhat
○ Neutral
○ Very little
○ Not at all

11. Personalized recommendations make it easier for me to make a decision.

○ Strongly agree
○ Agree
○ Neutral
○ Disagree
○ Strongly disagree

12. I often delay or avoid purchases because I can't decide among too many options.

○ Strongly agree
○ Agree
○ Neutral
○ Disagree
○ Strongly disagree

13. The recommended products are usually relevant to my interests.

○ Strongly agree
○ Agree
○ Neutral
○ Disagree
○ Strongly disagree

14. I find personalized recommendations useful when shopping online.

○ Strongly agree
○ Agree
○ Neutral
○ Disagree
○ Strongly disagree

15. How satisfied are you with the personalized recommendations you receive?

○ Very satisfied
○ Satisfied
○ Neutral
○ Dissatisfied
○ Very dissatisfied

16. I trust that the platform recommends products that genuinely match my preferences.

○ Strongly agree
○ Agree
○ Neutral
○ Disagree
○ Strongly disagree

17. Sometimes I feel the recommendations are biased or influenced by advertising rather than my preferences.

○ Strongly agree
○ Agree
○ Neutral
○ Disagree
○ Strongly disagree

18. What do you like most about personalized recommendations on shopping platforms? (Optional)

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19. What could be improved in the current recommendation systems you encounter? (Optional)