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Master Thesis

Exploring the Impact of AI-Powered Personalization on Customer Relationship Marketing in the Retail Industry

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ABSTRACT

In the evolving retail landscape, the effectiveness of AI-driven personalization and its implications on relationship marketing outcomes are critical. Investigating how cognitive elaboration interacts with the effectiveness of personalized AI product recommendations, this study maps their influence on customer satisfaction, trust, and purchase intention. Quantitative data were gathered from 130 survey participants and analyzed via regression using PROCESS Macro Model 6. The findings reveal that while personalization effectiveness significantly impacts customer satisfaction and trust, its direct effect on purchase intention is non significant, suggesting a more multifaceted role. Specifically, customer satisfaction was found to directly influence both trust and purchase intention, thereby reinforcing CRM theory. Future research should explore the indirect impact of personalization on purchase intention and the role of cognitive elaboration in depth. Investigating potential moderating factors such as customer experience and the quality of personalized recommendations could further enrich our understanding. As AI technology continues to evolve, conducting longitudinal studies will be critical to understand changing dynamics and optimize business strategies.

Keywords*: Artificial intelligence, AI personalization, personalization effectiveness, customer satisfaction, trust, purchase intention, product recommendations*

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Ohanes Muradian

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LIST OF ABBREVIATIONS

SPSS	Statistical Package for the Social Sciences
N	Number of respondents
a	Cronbach's alpha
p	Significance
t	t-value
R	Multiple correlation coefficient
B	Standardized beta coefficient
SE	Standaard error
KMO	Kaiser-Meyer-Olkin (suitability)
VIF	Variance Inflation Factor
Q-Q plot	Quantile-quantile plots
CE	Cognitive Elaboration (construct)
PE	Personalization Effectiveness (construct)
PE_N	Personalization Effectiveness after the deletion of item PE3 (construct)
CS	Customer Satisfaction (construct)
TR	Trust (construct)
PI	Purchase Intention (construct)

1. INTRODUCTION

The application of Artificial Intelligence (AI) within the retail sector has been witnessing substantial growth in recent times, promising to significantly augment the customer experience and shopping practices (Dwivedi et al., 2021). Retailers extensively employ AI in the area of personalization, as it plays a crucial role in enhancing customer experience and delivering superior outcomes for customers (Nimbalkar & Berad, 2021; Thirumalai & Sinha, 2011). Using AI technology, retailers can gather and analyze large customer data, such as demographic details, purchase history, browsing patterns, and more. This helps them identify customer habits and preferences (Kietzmann et al., 2018). As a result, the data obtained is used to generate product recommendations matching the customer's preferences and needs. AI algorithms are used to continuously learn and adapt to changing customer preferences, improving the accuracy of recommendations over time. As an illustration, in an e-commerce platform, registered users receive personalized product recommendations based on their individual preferences, browsing, and purchase history (Salonen & Karjaluoto, 2016).

AI-powered personalization techniques differ from regular recommendation systems, which typically involve recommending a fixed set of products or suggesting items based on their relevance to a customer's previous purchases. For instance, a traditional recommendation system may suggest milk powder to a customer after they purchase a drink bottle from an online webshop (Zhou, 2020). In contrast, AI-powered personalization techniques use a more dynamic approach that adapts to each customer's unique preferences and behaviors (Salonen & Karjaluoto, 2016). Personalized product recommendations in the context of an online clothing retailer can extend beyond recommending a complementary item to a previous purchase. For instance, if a customer previously bought a floral dress, an AI-powered personalization system might not only recommend a matching pair of shoes but also take into account the customer's preferred color palette, fabric preferences, and favorite designers. As a result, the system could suggest a range of coordinated accessories, such as handbags, scarves, or jewelry, that not only match the dress but also align with the customer's overall style preferences. This allows retailers to transform from a one-size-fits-all approach and instead offer a personalized and effective shopping experience (Ameen et al., 2021). Accordingly, personalization has the potential to enhance the efficiency of the purchasing experience for customers (Roggeveen & Sethuraman, 2020). Customers who receive personalized product recommendations experience a curated selection of goods that are tailored to their preferences. This can save them time and increase the likelihood of them finding something they like, resulting in increased sales and customer satisfaction (Parise et al., 2016). Personalization also plays a significant role in fostering trust and enhancing purchase intention, which is crucial for maintaining a competitive edge in the market (Morgan & Hunt, 1994; Dodds et al., 1991). The application of AI in personalization could potentially revolutionize the way brands or retailers instill trust and encourage purchase intention among customers (Kumar et al., 2019).

Personalization has been shown to have a favorable impact on customer loyalty as it makes customers feel understood and valued by the retailer. This, in turn, can lead to repeat customers who are more likely to make additional purchases and positive word-of-mouth recommendations (Tyrväinen et al., 2020). Furthermore, personalization fosters a deeper relationship between the customer and the brand (Hildebrand & Bergner, 2019). Several studies have demonstrated that integrating AI personalization mechanisms into customers' shopping processes promotes more intimate customer-brand relationships and enhances trust between brands, retailers, and customers (Kumar et al., 2019). In addition, AI techniques have been identified as a powerful tool that retailers can use to upsell their products and services, thereby increasing their revenue (Hildebrand & Bergner, 2019). Personalization additionally has the potential to improve the effectiveness of marketing campaigns by providing personalized product recommendations that target specific customer segments with tailored messages, leading to increased conversion rates and sales (Kumar et al., 2019).

While AI's application in the retail industry has garnered increasing interest and adoption, a significant theoretical gap remains in understanding how AI-powered personalized recommendations affect customer relationship marketing, in terms of their effectiveness in shaping customer perceptions and behaviors (Trawnih et al., 2022; Pillai et al., 2020). Specifically, the detailed mechanisms of how AI personalization influences customer satisfaction, trust, and purchase intention are under-explored (Adapa et al., 2020; Khan & Iqbal, 2020). Furthermore, current literature does not extensively investigate the psychological factors, such as cognitive assessment and emotional reactions that impact customers' behavior on AI recommendation services, as research on AI recommendation services from the customer perspective is still limited (Yoon & Lee, 2021, p. 1913). Nevertheless, a study conducted by Lee et al. (2022) explores the impact of personalization on customers' purchase intention in social media campaigns, however not in retail. The retail sector is unique due to its direct customer interactions and elements like service quality and store layout. Accordingly, a research gap exists regarding the role of AI-powered personalized recommendations in fostering customer relationship marketing and its potential to revolutionize the retail industry (Moore et al., 2022).

In response to the identified research gap in the literature, the central research question guiding this thesis is:

RQ: How does AI personalization effectiveness influence the relationship marketing outcomes in the retail industry?

To address the aforementioned research gap, the objective of this master thesis is to investigate the effectiveness of AI-powered personalized recommendations in enhancing customer satisfaction, trust, and purchase intention in the retail industry, with a focus on the cognitive level of elaboration. This thesis considers the impact of customers' previous purchasing behavior on their perceptions of personalized recommendations. A quantitative research methodology is employed, using surveys to collect data and assess customer attitudes toward AI-powered personalized recommendations. The research is focused on exploring the current state of personalization in the retail industry, including the benefits and challenges of using AI-powered personalized recommendations (Cao, 2021; Anica-Popa et al., 2021).

The findings of this research significantly impact retailers planning to utilize AI-based personalized recommendations, as well as academics and professionals interested in exploring AI's use in the retail sector.

The scientific relevance of this master thesis is based on the gap in the existing literature related to the effectiveness of AI-powered personalized recommendations in the retail industry. This thesis contributes to a deeper understanding of how these recommendations affect customer satisfaction, trust, and purchase intention (Pillai et al., 2020). Furthermore, it expands upon limited existing research regarding customer behaviors toward AI recommendation services (Yoon & Lee, 2021; Guha et al., 2021). By investigating these elements within the context of the retail industry, this study not only enhances the current body of knowledge but also encourages further exploration in this rapidly evolving field. The use of a quantitative research methodology has enabled empirical data to be collected to support the thesis findings. This study enriches the under-researched literature by examining the effectiveness of AI-based personalized recommendations in fostering customer marketing relationships. It offers insights into the current state of personalization in the retail industry and highlights the benefits of utilizing AI-powered personalized recommendations (Riegger et al., 2021).

Furthermore, there is a major practical significance due to the increasing use of AI technology in the retail industry and its effect on customers' purchase intention, trust, and satisfaction. Firstly, the findings of this thesis can educate retailers about the possible advantages of using AI-powered personalized recommendations to improve customer satisfaction, trust, and purchase intention. This data can be especially useful for companies seeking to improve their competitiveness in the market and gain a better understanding of customer behavior (Secinaro et al., 2021). Second, the thesis can help retailers understand the significance of using customer data to guide personalized recommendations of products by exploring the impact of customers' previous purchasing behavior on their perceptions of personalized recommendations. Retailers will have the potential to transform the shopping experience and level of personalization received by customers (Nguyen et al., 2022). This can lead to more effective marketing strategies, turning to increased customer loyalty and sales. Third, the study can shed light on the advantages of using AI-powered personalized recommendations in the retail industry. The study emphasizes possible barriers to the successful implementation of personalized AI techniques while identifying areas for development by examining the present status of personalization in the retail sector (Dwivedi et al., 2021). This can assist retailers' decision-making processes when considering the use of AI-powered personalized recommendations.

This research is divided into five chapters for structured reporting. The subsequent chapter presents the theoretical framework, supported by relevant literature, and introduces a conceptual model and hypotheses. Chapter three details study methods, data collection, variable operationalization, and analysis techniques. Analysis results are explored in chapter four, and chapter five concludes with a summary of findings, recommendations, and study limitations.

2. THEORETICAL FRAMEWORK

2.1 AI Personalization

AI, or artificial intelligence, refers to the ability of machines to perform tasks that typically require human-like intelligence, such as learning, problem-solving, and decision-making (Esh & Back, 2021). AI technology, particularly personalization, is reshaping the retail industry by influencing customer behavior and creating new opportunities for firms and customers alike (Fedorko et al., 2022; Dwivedi et al., 2021). This is because customers consider personalized interaction with retailers to be relevant and engaging (Ikumoro et al., 2019). According to Riemer and Totz (2003), the essence of personalization lies in building a meaningful one-to-one relationship by understanding individual needs and fulfilling them effectively and intelligently within a given context. Utilizing AI-powered personalization technologies is recommended to achieve personalized results for each customer (Khan & Iqbal, 2020). Chandra et al. (2022) defines personalization as “offering the right product and service to the right customer at the right time and the right place” (p. 1531). By employing AI-powered personalization, retailers can effectively utilize data analytics and machine learning to offer tailored recommendations and experiences. This leads to enhanced customer satisfaction and loyalty (Roggeveen & Sethuraman, 2020; Kietzmann et al., 2018).

A study conducted by Gao and Liu (2022) mentions that AI personalization can be implemented at different stages. In the context of retail e-commerce, it entails integrating AI algorithms to provide personalized product recommendations, customized customer support, and targeted marketing communication (Kumar et al., 2019). Customer data such as previous purchases, search history, and browsing activity must be collected and analyzed to provide personalized recommendations (Schafer et al., 2001). Those activities are collectively referred to as customer online behavior. Customer behavior is broadly defined as the study of how individuals acquire, use, and dispose of goods and services, including the examination of their search, evaluation, purchase, consumption, and post-purchase behaviors, as well as personal characteristics (Barmola & Srivastava, 2010, p .80). In this digital era, customer behavior is shifting towards online purchases, necessitating research into online behavior for businesses to align their offerings with customer needs (Yap et al., 2022; Kietzmann et al., 2018). Nonetheless, as customers gain experience with e-commerce, their behavior in the online marketplace may change (Hernández et al., 2010). This could involve developing a deeper familiarity with the platform and establishing preferences for certain features or types of online shopping experiences. The findings of the Hernández et al. (2010) research also indicate that customer behavior is not consistent because prior e-commerce experiences can influence and change one's perceptions. Implementing AI techniques in e-commerce, for instance, personalized product recommendation systems, serves various purposes, including reducing operating costs, increasing productivity, boosting revenue, and improving customer experience, either individually or collectively (Dang, 2022; Thongpapanl & Ashraf, 2011). The process of creating personalized product recommendations starts with using data from browsing history, search queries, and purchase history to understand customer preferences and behaviors (Schafer et al., 2001).

Further, personalized marketing, enabled by algorithms that analyze customer data, helps businesses establish meaningful connections with their customers (Anshari et al., 2019; Rafieian & Yoganarasimhan, 2023). Zimmermann et al. (2022) note that explanations in recommender systems aim to enhance the shopping experience through high-quality, interactive, and intuitive suggestions while keeping recommendations easy to understand for customers (p. 6). Despite challenges such as data availability and system scalability, effective recommender systems can lead to higher conversion rates for online shoppers (Konstan & Riedl, 2012; Nimbalkar & Berad, 2021). Nevertheless, the success of an AI-powered website in the market depends on its user-friendliness and flawless operation as essential prerequisites (Nagy & Hajdú, 2021). AI tools offer a personalized approach to narrowing down endless options and information available to customers, hence improving their shopping experience and strengthening customer relationships (Kumar et al., 2019; Nagy & Hajdú, 2021). Consequently, this thesis proposes an investigation of the influence of personalized product recommendations generated by AI on customer satisfaction, trust, and purchase intention. The framework structure initially evaluates the relationship between these three variables, using existing research (Steinhoff et al., 2019), and subsequently examines the level of cognitive elaboration and personalization effectiveness on customer marketing relationships.

2.2 Customer Relationships Marketing

Retailers are constantly striving to improve their effectiveness and maximize profits by following the latest trends and implementing the most innovative technologies into their practices (Grewal et al., 2018). Personalization, which significantly impacts marketing outcomes such as satisfaction, trust, and purchase intention, is considered crucial in determining product success (Thongpapanl & Ashraf, 2011). This aligns with the Customer Relationship Marketing (CRM) theory, which is about "all marketing activities aimed at establishing, developing and maintaining successful relational exchanges between customers and organizations" (Steinhoff et al., 2019, p. 370). Personalization, as an essential component of CRM, helps businesses achieve these relational exchanges by matching product recommendations with individual customer preferences.

2.2.1 Customer Satisfaction

One of the primary elements of relationship marketing is customer satisfaction. Customer satisfaction can be defined as the result of meeting the expectations and experience that customers are looking for (Vasić et al., 2019). This definition of satisfaction is applicable to the thesis, as satisfaction signifies that a business has effectively tailored its product recommendations to the customer's tastes, leading to increased satisfaction. Customer satisfaction is therefore important to determine the success of the marketplace. In other words, offering and recommending the products that customers are willing to be exposed to and interested in increases customer satisfaction. The process of recommending products that resonate with a customer's preferences holds significant business value. By doing so, businesses can not only increase customer satisfaction but also improve their market standing (Kim et al., 2021). The implementation of sophisticated AI algorithms, for instance, to generate personalized product recommendations, exemplifies a proactive approach to understanding and serving customers' needs, thereby improving customer satisfaction. This cycle of recommendation, satisfaction, and repeat business is a pivotal driver of ongoing success for businesses in the competitive retail industry (Tyrväinen et al., 2020). Therefore, a comprehensive understanding and strategic use of customer satisfaction metrics, combined with effective personalization strategies, are key to a business's sustainable growth and success (Azizan & Yusr, 2019).

2.2.2 Trust

Understanding customer satisfaction also means examining its relationship with customer trust. Marketing theories highlight a clear, positive relationship between customer satisfaction and trust (Chu & Zhang, 2016; Leninkumar, 2017). Trust in the concept of marketing is defined from different perspectives. Leninkumar (2017) used an article by Patrick (2002) to define customer trust as “thoughts, feelings, emotions, or behaviors manifested when customers feel that a provider can be relied upon to act in their best interest when they give up direct control” (p. 451). Importantly, trust manifests in the context of AI-powered personalization when a customer trusts the product recommendations provided by AI algorithms. In this thesis, Hsiao et al. 's (2010) definition of trust in recommendation is adopted, which defines it as “the willingness of a consumer to trust the product recommendations of shoppers” (p.938).

The relationship between customer satisfaction and trust is complex and multifaceted, especially in AI-driven environments. While exploring this relationship, many studies including Leninkumar (2017), state that the relationship of customer satisfaction is an antecedent of customer trust. When customers feel satisfied with a service or product, they develop a trustful relationship with the provider, assuming the same level of satisfaction in future exchanges. Customers trust the provider to consistently meet their expectations and recommended preferred products, leading to a virtuous cycle where satisfaction feeds into trust, which in turn drives more satisfaction. While other studies mention the opposite, where without trust there is no satisfaction (Setiawan & Sayuti, 2017). From this perspective, trust is a prerequisite for satisfaction. Customers enter into a business interaction with a certain level of trust, whether based on past experiences, word-of-mouth, or brand reputation. If a brand is not trusted, it may not even get the opportunity to deliver satisfaction, making trust crucial in the engagement process. Regardless of this causal direction, trust is widely accepted as a crucial bond between a brand and its customers, and this applies even more in a digital world where customer-brand interactions are often virtual (Leninkumar, 2017). Without trust, societal interactions would fail or operate irregularly, as trust is an important element that reduces uncertainty and perceived risk in transactions (Patrick, 2002). In the context of AI-driven personalization, this trust translates to faith in the AI system's ability to understand customers' needs and offer personalized and accurate recommendations (Zimmermann et al., 2022). Understanding the needs of the customer and improving the service based on responsive input enhances satisfaction and fosters trust. When businesses truly understand their customers' needs and expectations, they can tailor their services to meet these demands. This not only drives satisfaction as customers feel their needs are being met but also fosters trust as customers feel understood and valued (Kassim & Asiah Abdullah, 2010). Having said that, satisfaction is a prerequisite for the establishment of profound trust (Sitorus & Yustisia, 2018). Therefore, it is important to test this interplay further, leading to testing the following hypothesis:

H1: *There is a positive relationship between customer satisfaction and trust.*

2.2.3 Purchase Intention

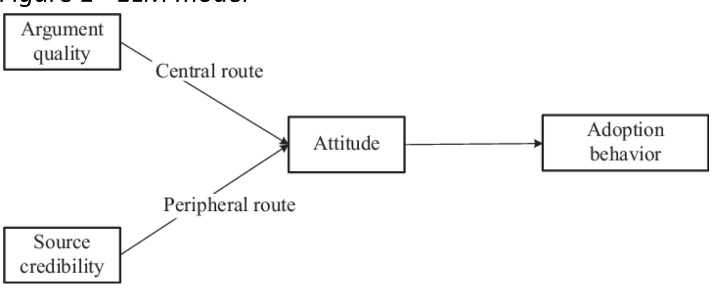
The relationship between customer trust and purchase intention is important for business operations. Purchase intention, or more specifically in this thesis, online purchase intention can refer to the customer's intention to shop online based on personalized services (Pappas et al., 2017, p. 978). A key facet contributing to these intentions is the level of trust a customer has towards a specific online retail platform, which is often built and strengthened by effective AI-driven personalized services and product recommendations. Several studies have found that there is a positive relationship between customer trust and purchase intention. For instance, Gao (2011) shows a positive correlation between trust and purchase intention. Customers with a high level of trust in a website are more likely to have the intention to purchase from it. This is because trust decreases the perceived risk and uncertainty connected with online transactions, resulting in a greater degree of trust in making a purchase (Ling et al., 2011). Furthermore, customer trust is also a useful predictor of repeat purchase intention. Customers are more inclined to trust a website and intend to make more purchases if they have a positive experience with it (Hsu et al., 2015). Such intention further underscores the instrumental role of trust as a driver for purchase decisions, especially in the context of online transactions. Businesses prioritizing the use of AI in building trust with their customers are likely to witness an increase in both initial and repeat purchases, contributing to the long-term sustainability and growth of the business (Azizan & Yusr, 2019). Based on the extensive evidence supporting the relationship between customer trust and purchase intention, the following hypothesis is advanced:

H2: *There is a positive relationship between trust and purchase intention.*

2.3 Effectiveness of Personalized Recommendations

Effectiveness is considered the measure of success in influencing customer decisions through personalized product recommendations, resulting in desired outcomes such as increased purchases, customer satisfaction, or trust (Riegger et al., 2021; Khadka & Maharjan, 2017). For instance, increased purchases signify a direct and positive outcome of an effective recommendation system (Guha et al., 2021). When an online retailer suggests products based on a customer's prior activity, and this leads to a purchase, it demonstrates the effectiveness of the personalization system. Moreover, effectiveness extends beyond immediate sales to include customer satisfaction and trust. According to Shanahan et al. (2019), a recommendation system fosters a long-lasting relationship between the customer and the retailer when it continually caters to the preferences of the customer. The roots of this effectiveness issue can be traced back to the cognitive processes consumers undergo while interacting with these recommendations. This process can be explained with the Elaboration Likelihood Model (ELM) introduced by Petty and Cacioppo (1986). ELM demonstrates how customers process information and make decisions. Specifically, it outlines two distinct routes to persuasion—central and peripheral—that influence attitude change and behavior. The effectiveness of personalized product recommendations can be seen through the ELM framework, as it depends on the level of cognitive elaboration that customers engage in when processing the information. However, the quantity of recommendations that the user explores is not being considered (Ho & Bodoff, 2014). The central route in the ELM corresponds to a high elaboration process in which the customer actively engages with the information and makes a careful evaluation of the product recommendations. Conversely, the peripheral route is a low elaboration process in which the customer is influenced by peripheral cues, such as the brand name or the attractiveness of the product image (Petty & Cacioppo, 1986; Ho & Bodoff, 2014). *Figure 1*, presents the ELM model.

Figure 1 - ELM model



The Elaboration Likelihood Model (ELM) helps explain personalized recommendation effectiveness, depending on the customer's cognitive elaboration level (Tam & Ho, 2006). Level of cognitive elaboration is defined as “the mental efforts that people spend in processing relevant information” (Zhang et al., 2013, p. 792). This includes the level of consideration, analysis, and evaluation that a customer invests in when interacting with product recommendations. Customers who engage in a high level of cognitive elaboration are more likely to be influenced by the central route of persuasion and will carefully evaluate the product recommendations before making a purchase decision. In contrast, customers with low cognitive elaboration tend to base decisions on peripheral factors, like product image attractiveness or brand name, rather than the product's intrinsic qualities (Gammoh et al., 2006). Therefore, recommendation effectiveness is tied to the customer's information-processing approach (Ho & Bodoff, 2014).

Several factors may affect the level of cognitive elaboration that customers engage in when processing personalized product recommendations. Key among these is the customer's purchase history, including factors like purchase frequency, loyalty, and perceived experience (Bang & Wojdynski, 2016). Frequent and satisfied customers likely have higher cognitive elaboration levels, closely examining recommendations. In contrast, customers with fewer purchases and less favorable experiences may not examine recommendations as closely, indicating lower cognitive elaboration levels (Darley et al., 2010). This process depth influences their purchase likelihood based on the recommendation (Park & Lee, 2008; Yoon & Lee, 2021). Consequently, it is hypothesized that:

H3: *There is a positive relationship between the level of cognitive elaboration and personalization effectiveness.*

2.4 The Influence of Personalization Effectiveness on Customer Relationship

2.4.1 Personalized Effectiveness on Customer Satisfaction

Retailers use personalized AI product recommendation systems to meet their customers' expectations, provide better customer service, and improve customer satisfaction (Thirumalai & Sinha, 2011). Several studies proved a positive relationship between personalization and customer satisfaction in online purchasing behavior (Thirumalai & Sinha, 2011; Chen et al., 2021). Balancing recommendation accuracy and diversity is a crucial measure of customer satisfaction. According to Kim et al. (2021), there is a trade-off between recommendation accuracy and recommendation diversity. Although accuracy is important, continual recommendations of the same item may reduce satisfaction, suggesting the need for diversified, dynamic systems that accommodate novelty and variety (Kim et al., 2021). Not including seasonal product information can also reduce customer satisfaction in e-commerce. As said, customer satisfaction is an essential indicator of product quality since it can result in greater loyalty and favorable word-of-mouth suggestions (Casaló et al., 2008). Improving the design and functionality, as well as including features such as detailed product information, personalization options, and pricing choices, would also improve overall satisfaction (Zimmermann et al., 2022 p. 17). Having said that, personalized recommendations that demonstrate usefulness and user-friendliness can likely heighten customer satisfaction (Tong et al., 2012, p. 107). Based on the arguments above, the following hypothesis has been proposed:

H4: *There is a positive relationship between personalization effectiveness and customer satisfaction.*

2.4.2 Personalized Effectiveness on Trust

Trust plays an essential role in e-commerce, impacting customer attitudes and behaviors toward online purchases (Kassim & Asiah Abdullah, 2010; Saw & Inthiran, 2022). Factors like perceived ease of use, website quality and reputation, and perceived usefulness build trust in a website (Agag & El-Masry, 2017). Customer trust in a website and its recommendations can change customers' attitudes and behaviors regarding online purchasing (Saw & Inthiran, 2022). AI techniques, including personalized product recommendation systems, aim to increase customer trust in the service or recommendation provided (Kumar et al., 2019). E-commerce platforms can tailor recommendations to individual preferences, leading to a more personalized and relevant customer experience. Moreover, customer trust can be increased through positive experiences while using the website, as well as by site quality and perception of market orientation, ensuring a seamless and enjoyable user experience (Corbitt et al., 2003). Transparency and providing relevant information also play a role in establishing trust. Dabholkar and Sheng (2012) emphasize the importance of revealing information to customers, as it helps increase their trust in the e-commerce platform. When customers understand how AI mechanics work and how their data is used, it can enhance their trust in the system and acceptance of AI technologies (Zimmermann et al., 2022, p. 6). Nevertheless, reducing societal bias and discrimination can boost customer trust (Yau et al., 2021). Therefore, this study aims to investigate the relationship between personalization effectiveness and trust in the recommendations provided, as hypothesized in:

H5: *There is a positive relationship between personalization effectiveness and trust.*

2.4.3 Personalized Effectiveness on Purchase Intention

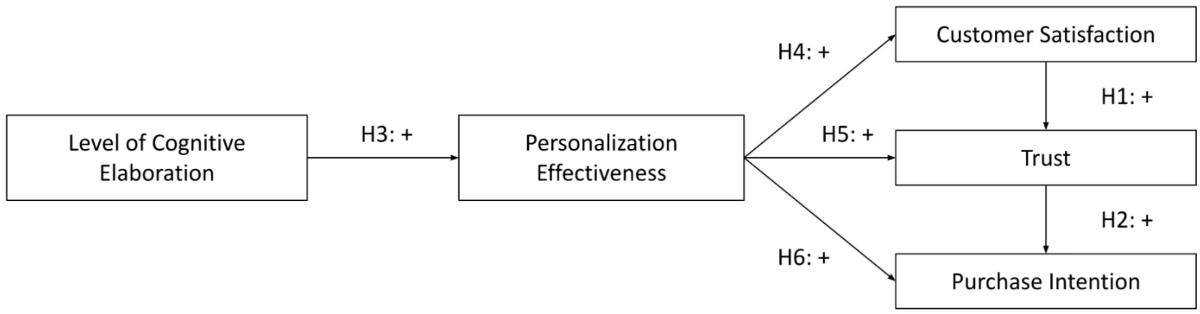
As businesses seek to maximize revenue and optimize their effectiveness, they often follow the latest trends and implement the most innovative technologies (Grewal et al., 2018). One such innovation is personalization, which positively impacts customers' purchase intention by improving their shopping experience and creating a feeling of exclusivity and uniqueness (Pappas et al., 2017). Personalization is effective in influencing purchase intention when customers process information through the central route, which involves in-depth thinking and analysis of information (Hirsh et al., 2012). According to Ho and Bodoff (2014), web customization helps businesses increase both their advertising and sales revenue. This is achieved through the use of big data and artificial intelligence, enabling businesses to collect and analyze customer data to make personalized recommendations and predictions about their preferences (Panigrahi & Karuna, 2021). Personalization not only assists customers in finding what they are searching for, but it also fosters brand loyalty and customer satisfaction, increasing the likelihood that a client would purchase (Shanahan et al., 2019). Based on the aforementioned factors, the relationship between personalization effectiveness and purchase intention is hypothesized:

H6: *There is a positive relationship between personalization effectiveness and purchase intention.*

2.5 Conceptual Framework

The primary objective of this study is to investigate the interplay between customers' online behavior, the personalization effectiveness of product recommendations based on the Elaboration Likelihood Model (ELM), and their impact on customer marketing relationships, such as customer satisfaction, trust, and purchase intention in the retail industry. The proposed conceptual model takes into account the level of cognitive elaboration, which is considered a key factor affecting personalization effectiveness. The degree to which customers engage in cognitive elaboration when processing information plays a critical role in determining the effectiveness of these recommendations. Customers who engage in high levels of cognitive elaboration are more likely to be influenced by the central route of persuasion and carefully evaluate the product recommendations before making a purchase decision. The success of personalized product recommendations will ultimately impact customer satisfaction, trust, and purchase intention.

Figure 2 - Conceptual model



3. METHODOLOGY

This chapter provides an in-depth overview of the thesis methodology, including research strategy, sampling, data collection method, and procedure.

3.1 Research Strategy

The methodology section of a research study is crucial as it explains the process and procedures used to collect, analyze, and interpret data. In this thesis, the effectiveness of personalization on customer marketing relationships is investigated using quantitative research methods. Quantitative research, characterized by the collection and mathematical analysis of numerical data, allows for describing and understanding the phenomena that these observations reflect (Quick, 2015; Sukamolson, 2007, p. 2). The systematic and explicit nature of quantitative methodology allows for independent evaluation and replication of its results, unlike the traditional literature reviews, where the efficiency of data storing and analysis are crucial (Stanley & Jarrell, 2005). The quantitative research method has been selected due to its ability to test hypotheses and to understand the interplay between the five research constructs (Etikan et al., 2016; Sukamolson, 2007). Moreover, this study encompasses a broad target demographic. The application of quantitative research methodologies allows for a more efficient data collection process from a multitude of respondents compared to the utilization of qualitative research methods (Kooiker et al., 2011).

The data collection tool used is an online survey combining multiple-choice questions with statements responses, chosen for its efficiency in terms of time and resources (Kalia et al., 2022; Ball, 2019). According to Roberts (1999), survey questionnaires are a commonly used tool in surveys, as they effectively facilitate outreach to a large number of respondents, minimizing sampling errors. Furthermore, to measure the collected data and ask questions that people elicit have varying opinions, a Likert scale questionnaire has been used (Joshi et al., 2015, p. 398). The Likert scale ensures that respondents can answer faster and are provided with a range of options (Chimi &

Russell, 2009). To optimize the reliability of responses, a 7-point Likert scale is used, with categories ranging from 1 (*strongly disagree*) to 7 (*strongly agree*) (Taherdoost, 2019).

3.2 Sampling

The appropriate sampling method is convenience sampling, a type of non-probability sampling that selects individuals based on factors such as accessibility, availability, and willingness to participate (Etikan et al., 2016, p. 2). In this thesis, respondents were primarily sourced through an online survey, with certain criteria for selection. To ensure reliability, respondents should be aged 18 or over, due to potential inconsistencies in shopping behavior amongst younger individuals (Naudin & Vanwesenbeeck, 2021). Additionally, respondents should also have made an online purchase previously and ideally be exposed to personalized product recommendations on retail websites, ensuring that responses are based on actual interactions with such systems. There were no demographic restrictions to the sample when conducting the research. In order to ensure an adequate sample size for the study, Hair et al. (2018, p. 280) suggested a minimum of 100 respondents for the sample size, if the model contains five or fewer constructs each with more than 3 items. This suggestion can be applied to the conceptual model and the operationalization table of this thesis to ensure sufficient statistical power (*Appendix A*).

3.3 Procedure

The online survey, implemented via Qualtrics, a platform that offers an efficient and user-friendly interface for managing data and monitoring response rates, was disseminated through multiple channels like email, Whatsapp, and social media over a span of two weeks. The survey design, detailed in *Appendix A*, included a Dutch translation to facilitate respondents' comprehension and engagement with the survey. A process of back translation was also employed to ensure linguistic accuracy. Two fellow students have reviewed the Dutch translation of the survey to ensure that it accurately conveys the same meaning as the original item. Furthermore, the survey was pre-tested with three individuals to ensure its reliability and quality. Feedback led to several modifications, such as updating images and rephrasing sentences, thereby increasing the survey's clarity and inclusivity. The expected moderate to large effect size (Guadagnoli & Velicer, 1988) suggests that the sample size would provide sufficient statistical power to detect relationships between variables.

The five-part survey began with a brief introduction and an illustrative statement to familiarize respondents with the Likert scale format. Part 1 evaluated respondents' AI knowledge and exposure through a visual example of personalized product recommendations and related multiple-choice questions. Part 2 investigated respondents' online shopping habits classifying respondents as active or passive shoppers. Following this, statements addressing the “cognitive elaboration” construct assess respondents' cognitive processing without preconceived ideas or expectations about the case (Ball, 2019). Part 3 introduced a fictional case involving ABC Retail, an online clothing store, with related statements examining constructs like “personalization effectiveness” (Ho & Badoff, 2014) and “trust” (Hsiao et al., 2010). This sequence is adopted to emphasize the importance of starting with the effectiveness of recommended products before considering the credibility and trustworthiness of the recommendations. The visual shoe example is then revisited, with statements on “customer satisfaction” (Vasić et al., 2019) and “purchase intention” (Pappas et al., 2017). This arrangement is deemed logical, as it initiates with satisfaction concerning the recommendations and proceeds to examine future purchase intentions. Indeed, the conceptual model positions purchase intention as a consequence of satisfaction, rendering it more suitable as the concluding element. Part 4 collected demographics via multiple-choice questions to provide a detailed research context. Part 5, included evaluative statements assessing the survey's understandability (Presser et al., 2004). Finally, the case of ABC Retail, while fictional, aimed to provoke realistic responses without the influence of real-world brands.

3.4 Measurements

The measurement scales for this study were carefully selected based on their definitions and items. The chosen measurement items were deemed most appropriate for examining the effectiveness of personalized marketing on customer relationships. Construct items are selected from various articles and fields. All scales have a confidence alpha greater than 0.90 confirming the reliability of the measurement model used in this thesis (Shevlin et al., 2000). The first construct, level of cognitive elaboration, was adapted from Zhang et al. (2013) which explored the quality aspect of wiki use in a team context. The original items have been modified from “during wiki use” to “shopping online” to suit this study's focus. The second construct, personalization effectiveness, derives from Ho and Bodoff (2014) with “book” changed to the example shown product, for relevancy purposes. The constructs for customer relationship marketing outcomes were chosen from Vasić et al. (2019); Hsiao et al. (2010); and Pappas et al. (2017). Each article provides clear definitions and measurement items that align with the objectives of this study to enhance marketing relationships with customers. Minor modifications were made for relevance, like adjusting “virtual community” to “ABC retail website” for the trust in recommendation construct (Hsiao et al., 2010). Measurement items are found in *Appendix A*.

3.5 Validity & Reliability

The assessment of reliability and validity is crucial to ensure the integrity and quality of the study. Reliability refers to the consistency and repeatability of the measurement process, while validity indicates the degree to which the instrument measures what it is intended to measure (Brace et al., 2012). This thesis includes respondents aged 18 or over to ensure accurate self-reported shopping behaviors. Furthermore, reliability is ensured by employing well-established scales that have been previously validated and have demonstrated high internal consistency, as evidenced by Cronbach's alpha coefficients greater than 0.90 (Shevlin et al., 2000). Pre-test and feedback further refine survey reliability. The online platform "Qualtrics" provides standardized question presentation, minimizing potential measurement errors. The survey evaluation showed high effectiveness and reliability, with a mean of 5.86 out of 7 for ease, understanding, and answering questions.

Validity in this study is established by careful item selection from credible sources, ensuring content validity. Construct validity is also strengthened through the use of scales that have been previously validated in the literature. Utilization of a 7-point Likert scale improves the measurement validity of the data (Joshi et al., 2015). Furthermore, the use of a clear and structured online survey minimizes possible interviewer bias, thereby bolstering the survey's validity. Assumptions of regression analysis are verified and the common method variance is evaluated using Harman’s single-factor test. This emphasis on validity and reliability across the stages of research design, data collecting, and analysis increases the study's credibility and robustness, contributing to the overall quality of the thesis.

3.6 Analysis Method and Strategy

Survey data is analyzed using SPSS Statistics 28, with multiple regression being deemed the most suitable method for hypothesis testing due to the model's three dependent variables. Hayes' PROCESS Macro Model 6 is used for distinct mediation analyses on each variable. This added a layer of depth to the analysis, enhancing its overall robustness. A bootstrap sample of 10000 and a confidence interval of 95% is utilized to ensure precision and reliability of the indirect effects in the analysis (Preacher et al., 2007).

3.7 Research Ethics

This study prioritizes ethical considerations, focusing on openness, informed consent, privacy, and confidentiality. The survey begins by detailing its purpose and duration, thereby encouraging voluntary participation (McNeill & Chapman, 2005). To maintain anonymity, the study did not collect any personal information like names or phone numbers from respondents, restricting the data collected to demographic information only. This approach is highlighted in both the survey introduction and distribution emails. The study ensured equal and respectful treatment, maintaining accuracy and honesty throughout data collection, analysis, and reporting, adhering to ethical guidelines.

4. RESULTS

This chapter outlines the data analysis results, including the validity and reliability analyses. Next, univariate and bivariate analyses are discussed, as well as regression analysis assumptions. Then, Process Macro Model 6 is utilized for multiple regression analysis to assess hypotheses. This model is the most appropriate due to the presence of multiple mediators - namely personalization effectiveness, trust, and customer satisfaction - within the conceptual model. The chapter ends with further findings.

4.1 Sample Statistics

To facilitate an effective examination of the data, the dataset was meticulously cleaned, focusing on addressing missing values from 174 survey respondents. Although 42 respondents (24%) partially completed the survey, their responses were excluded due to the lack of data on personalized recommendations, crucial for this study. Additional criteria also impacted the final sample size. Exclusions included respondents under 18 years and preference was given to those with previous online shopping experience. Consequently, two responses were removed due to the lack of online shopping experience or a neutral stance on all statement items. The final sample, used for analysis, comprised 130 completed responses, which is an adequate size for conducting multiple regression analyses as the model contains five or fewer constructs each with more than 3 items (Hair et al., 2018, p. 280; Guadagnoli & Velicer, 1988). This sample included 49 males, 79 females, and 2 respondents who preferred not to say. See *Table 1* for further demographic information.

Table 1 - Demographics of the sample

GENDER	**N**	**% of total**
Male	49	37.69
Female	79	60.77
Non-binary / third gender	0	0
Prefer not to say	2	1.54
AGE	**N**	**% of total**
Under 18 years	0	0
18 to 29 years	104	80.00
39 to 44 years	10	7.69
45 to 64 years	12	9.23
Older than 65 years	4	3.08
EDUCATIONAL LEVEL	**N**	**% of total**
Primary education (vmbo/havo/vwo)	20	15.38
Mbo	18	13.85
Hbo-bachelor	40	30.77
Wo-bachelor/master, doctor	47	36.15
Other	5	3.85
INCOME LEVEL	**N**	**% of total**
Low	50	38.46
Average	75	57.69
High	5	3.85

The data in *Table 2* summarizes respondents' online shopping habits and preferences. Most respondents shop online occasionally (41.54%) or monthly (33.08%), or weekly (23.85%) with only 1.54% shopping daily. In terms of product preference, clothing, and fashion accessories were the most commonly purchased items (33.53%), followed by electronics and gadgets (23.24%). Regarding exposure to personalized product recommendations, a majority of respondents (73.85%) have experienced personalized product recommendations, while 26.15% have not. These statistics provide a base for analyzing the impact of personalized product recommendations on marketing relationships.

Table 2 - Characteristics of shopping online

FREQUENCY OF ONLINE SHOPPING	**N**	**% of total**
Daily	2	1.54
Weekly	31	23.85
Monthly	43	33.08
Occasionally	54	41.54
Never	0	0
PRODUCTS TYPICALLY BOUGHT ONLINE	**N**	**% of total**
Clothing and fashion accessories	114	33.53
Electronics and gadgets	79	23.24
Beauty and personal care products	49	14.41
Groceries and household supplies	27	7.94
Sports and outdoor equipment	37	10.88
Toys and games	25	7.35
Other	9	2.65
EXPOSURE TO PERSONALIZED PRODUCT RECOMMENDATIONS	**N**	**% of total**
Yes	96	73.85
No	34	26.15

4.2 Data Preparation

This study employs multiple regression analysis to investigate variable relationships, ensuring they are metrically expressed (Preacher & Kelley, 2011). Harman's single-factor analysis was used to check for common method bias, a common risk in questionnaire-based research (Tehseen et al., 2017). Harman's single-Factor test identifies common method variance concerns if the first factor in an exploratory factor analysis explains over 50% of the variable variance (Podsakoff & Organ, 1986). The results from *Table 1 in Appendix C* showed a common variance of 36.8%, well below the critical 50%, suggesting the bias is unlikely to significantly impact the dataset analysis.

Validity and reliability analyses were also conducted to evaluate how effectively the items measure their constructs and their internal consistency. This method is crucial as it aids the integrity of the data, enabling the required statistical analysis and deepening the understanding of the data and derived insights.

Validity Analysis

Factor analysis using Principal Axis Factoring with oblique rotation was conducted to analyze construct structure. Oblique rotation is an approach that enables the examination of potential correlations among factors, thereby illustrating the theoretical linkage among the constructs under consideration (Harris & Kaiser, 1964). All KMO values exceeded the 0.50 limit and Bartlett's test of Sphericity achieved a p-value less than .001, indicating dataset suitability for Factor analysis (Shrestha, 2021; Tobias & Carlson, 1969). A threshold of .32 was applied, serving as a practical guideline for the minimum loading of an item, to determine the significance of factor loadings (Costello & Osborne, 2005). The detailed pattern matrix in addition to KMO and Bartlett's test of Sphericity can be found in *Appendix D*.

The Factor analysis brought to light an issue with item PE3 (*personalization effectiveness, item 3*). PE3 was loading onto a different factor compared to other items within the same construct and displayed a lower loading on its designated factor. Despite various attempts to rectify this misalignment through rotation and other techniques, the inconsistency persisted. Thus, the decision was made to remove PE3 from the analysis. Another issue was the cross-loading of items PE2 and PI1 (*purchase intention, item 1*), which seemed to load onto multiple factors. In order to ensure clarity in the factor structure cross-loadings are often removed (Hair et al., 2018, p. 154). However, for items PE2 and PI1, a difference of at least 0.20 between primary and secondary factor loadings were observed, indicating these items as satisfactory (Costello & Osborne, 2005).

The examination of the commonalities and factor loadings unveiled a considerable shared variance among the items and their corresponding constructs, supporting their role in explaining the variance in the measured constructs (Hair et al., 2018, p. 140). All items exhibited commonalities above the 0.32 threshold, signifying robust factor loadings. This indicates their high convergent validity, implying that they have strong correlations with their assigned constructs. Furthermore, the pattern matrix suggested reasonable discriminant validity as items heavily loaded onto their assigned factors with minimal cross-loadings, suggesting that these constructs are suitably distinct (Bian & Forsythe, 2012; Costello & Osborne, 2005).

Reliability Analysis

This study used multiple measurement items to assess the five constructs. Aggregating these items allows the evaluation of each construct in terms of reliability. A reliability analysis, conducted using Cronbach's alpha, measured the internal consistency of the constructs used in this study to verify whether the items of each corresponding construct can be combined into a single variable (Hair et al., 2018, p. 761). The Cronbach's alpha values for the different items are illustrated in *Table 3* and *in Appendix D*. According to Hair et al. (2013), a Cronbach's alpha value above 0.7 is deemed acceptable, suggesting that the scales for each of the constructs are reliable (p. 161). The analysis affirmed that all constructs had an alpha value exceeding 0.7, suggesting high internal consistency (see *Table 3*).

Table 3 - Cronbach's alpha

Construct	Original number of items	Cronbach's Alpha	Number of items deleted	Cronbach's alpha after deletion
Cognitive Elaboration	3	.727	0	
Personalization Effectiveness	5	.782	1	.727
Customer Satisfaction	5	.840	0	
Trust	3	.892	0	
Purchase Intention	3	.911	0	

4.3 Descriptive Statistics

This section includes a descriptive analysis, outlining the mean values, standard deviations, and Pearson correlation coefficients for the study's variables. *Tables 1 and 2 in Appendix E* reveal the correlations between variables. The correlation coefficient, signified as 'r', measures the strength and direction of a linear relationship between two variables. The value of 'r' can range from -1 to +1. For instance, when 'r' is close to +1, it signifies a strong positive correlation between the two variables. This suggests that an increase in one variable is generally accompanied by an increase in the other

(Hair et al., 2018, p. 261). The matrix shows significant positive correlations: cognitive elaboration correlates with personalization effectiveness ($r = 0.232$, $p<0.01$) and moderately with purchase intention ($r = 0.182$, $p<0.05$). As cognitive elaboration increases, so do the perceived personalization effectiveness and purchase intention. Personalization effectiveness strongly correlates with customer satisfaction ($r = 0.370$, $p<0.01$) and trust ($r = 0.576$, $p<0.01$), and substantially with purchase intention ($r = 0.469$, $p<0.01$). Trust has a strong positive correlation with customer satisfaction ($r = 0.381$, $p<0.01$) and purchase intention ($r = 0.512$, $p<0.01$), illustrating its vital role in influencing purchase decisions. Lastly, a remarkably high correlation exists between customer satisfaction and purchase intention ($r = 0.594$, $p<0.01$).

Furthermore, only age and shopping frequency among the control variables correlated significantly with the dependent variable, purchase intention. Age displayed a negative correlation of ($r = -0.199$, $p<0.023$), indicating that younger respondents were more likely to exhibit purchase intentions. Similarly, shopping frequency also showed a negative correlation of ($r = -0.226$, $p<0.010$), suggesting that a higher frequency of shopping corresponds with increased purchase intention (*Table 2 in Appendix E*).

4.4 Assumptions of Regression Analysis

Before proceeding to hypothesis testing via multiple regression analysis, it is critical to verify the fundamental assumptions underlying regression analysis. These include normality, linearity, homoscedasticity, the interdependence of error terms, and the absence of multicollinearity. Violating any of these standards could risk undermining the credibility and reliability of the research outcomes (Hair et al., 2018, p. 287).

The normality assumption assumes that the distribution of the dependent variable follows a normal pattern (Hair et al., 2018, p. 291). To verify this assumption, an examination of the frequency table was conducted, confirming that all values fall within the -3 to 3 range for Skewness and Kurtosis, indicative of a normal distribution (*Table 1 in Appendix F*). Additionally, no missing values were detected in the dataset. Histograms and Q-Q plots are used for visual inspection of normality. Histograms, a sort of frequency distribution plot, are used to show the distribution of the dependent variables graphically. A histogram of the residuals was created (see *Figure 1 in Appendix F*), and it presented a pattern relatively similar to a normal distribution, showing a bell shape with tails on both sides (Hair et al., 2018, p. 291). The Q-Q plots (quantile-quantile plots) compare the observed quantiles of a variable with the expected quantiles of a normal distribution. If the data is normally distributed, the points on the Q-Q plot will fall along the 45-degree reference line (Mach et al., 2006). In this case, the Q-Q plot of residuals (see *Figure 2 in Appendix F*) shows that the points are reasonably close to the reference line, again indicating a relatively normal distribution. Given that both the histogram and Q-Q plots suggest a relatively normal distribution of the residuals and that the residuals fall within the -3 to 3 range for Skewness and Kurtosis, it can be concluded that the assumption of normality is met for this dataset.

The linearity assumption investigates the correspondence between independent and dependent variables in the model. To validate linearity, examine the graph that compares the standardized residuals to the regression's standardized predicted value. If there is no obvious pattern in the scatterplots and the residuals are spread around the zero line, this indicates that the regression model meets the linearity condition (Hair et al., 2018, p. 332). In *Figure 3 in Appendix F*, careful observation of the plot indicates a lack of systematic patterns, and the data is uniformly scattered across the plot. Thus, it can be confidently affirmed that the data meets the linearity assumption.

The homoscedasticity assumption, meaning the residuals have constant variance at different levels of the predicted values, is also a prerequisite for valid regression analysis. This is verified by examining the plot of standardized residuals against the standardized predicted values (Hair et al., 2018, p. 332). The absence of a pattern and a uniform spread of residuals around the zero line suggests that the assumption of homoscedasticity was met.

The fourth assumption of regression analysis is the independence of error terms, which states that the predicted values should not be systematically related to each other (Hair et al., 2018, p. 291). Violation of this assumption can lead to biased results and inaccurate hypothesis testing. Therefore, it is important to ensure the independence of error terms when conducting regression analysis. The expected value of the residuals should indeed be zero, indicating that predictions align with observed values on average. Additionally, the standard deviation of these residuals should ideally be one after standardization for easy identification of outliers (Hair et al., 2018, p. 88). The residual statistics' standardized predicted value reveals that the mean equals zero and the standard deviation equals one (*Table 2 in Appendix F*). This indicates that there is no correlation of the errors with the independent variables (Hair et al., 2018, p. 304). Therefore, the assumption can be met.

Lastly, multicollinearity assesses the level of correlation among independent variables. Multicollinearity can complicate the interpretation of individual relationships and effects between independent and dependent variables. It can be identified by examining correlation coefficients and tolerance/VIF values. The VIF values should ideally be above 1.0 but not exceed 10, while tolerance values should be greater than 0.10 to meet this assumption (Hair et al., 2018, p. 316). Results from *Table 3 in Appendix F* indicated that all variables showed VIF ranging from 1.071 to 1.582 providing evidence of the absence of multicollinearity. The tolerance values of all variables were greater than 0.10, ranging from .631 to .934. Thus there is no indication of multicollinearity and the assumption can be met.

Having satisfied all the necessary assumptions for a valid regression analysis, the regression analysis can be confidently conducted.

4.5 Hypotheses Testing

To validate the research hypotheses, a regression analysis using the PROCESS Macro Model 6 in SPSS was conducted to verify the research hypotheses. This process checked the assumptions for regression, confirming data reliability. This statistical approach evaluated the influence of the independent variable and multiple mediators on the dependent variable (Hair et al., 2018, p. 409). Covariates, age and shopping frequency, were also used as they had a significant correlation with purchase intention (*Table 2 in Appendix E*). A summary of direct relationships is provided in *Table 4*. The full output can be found in *Appendix G*.

Table 4 - Summary of hypotheses testing

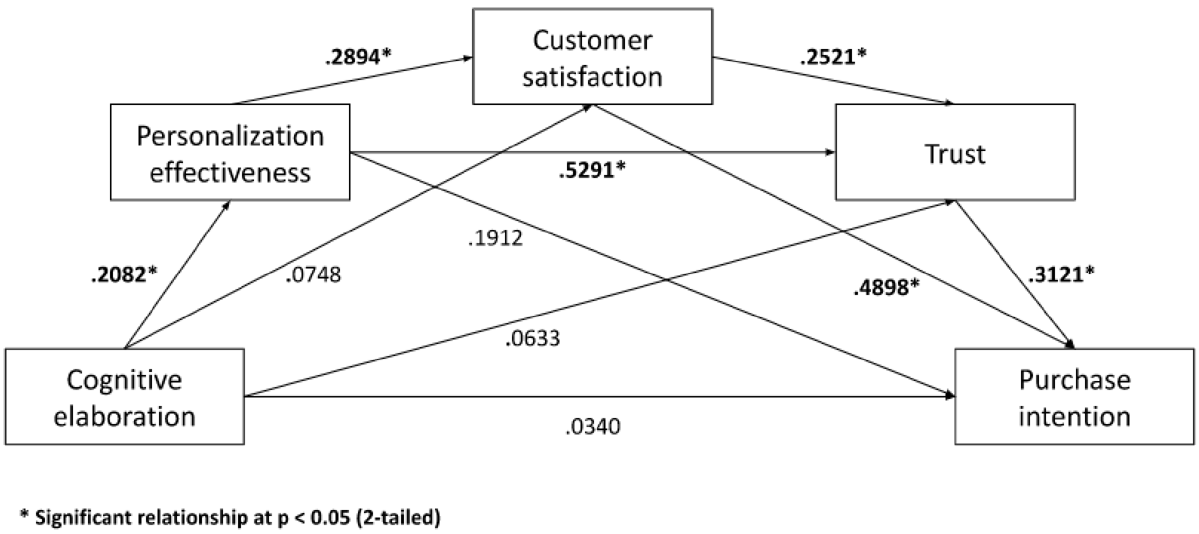
Relationship	**B**	**SE**	**T**	**P**	**Hypothesis**
Customer satisfaction → trust	.2521	.0836	3.0160	.0031*	H1 : accepted
Trust → Purchase intention	.3121	.0971	3.2127	.0017	H2 : accepted
Cognitive elaboration → personalization effectiveness	.2082	.0823	2.5299	.0126*	H3 : accepted
Personalization effectiveness → customer satisfaction	.2894	.0858	3.3736	.0010*	H4 : accepted
Personalization effectiveness → trust	.5291	.0837	6.3186	.0000*	H5 : accepted
Personalization effectiveness → purchase intention	.1912	.1042	1.8361	.0688	H6 : rejected
Customer satisfaction → purchase intention	.4898	.0937	5.2280	.0000*	NOT TESTED

The analysis brought to light the significant effect of customer satisfaction on trust, with a coefficient of .2521 ($p < .0031$). Therefore, hypothesis H1: "*There is a positive relationship between customer* *satisfaction and trust*" is accepted. Further, the coefficients for trust on purchase intention (.3121, p = .0017) suggest that hypothesis H2: "*There is a positive relationship between trust and purchase intention*" is also accepted.

Key insights include the influence of cognitive elaboration on personalization effectiveness (coefficient .2082, p = .0126), confirming hypothesis H3: "*There is a positive relationship between the level of cognitive elaboration and personalization effectiveness".* Further, personalization effectiveness contributes significantly to customer satisfaction by a coefficient of .2894 (p = .0010) accepting hypothesis H4: "*There is a positive relationship between personalization effectiveness and customer satisfaction*". The relationship between personalization effectiveness and trust was also statistically significant, as shown by a coefficient of .5291 (p < .0001). This affirms hypothesis H5: "*There is a positive relationship between personalization effectiveness and trust*" respectively. However, hypothesis H6: "*There is a positive relationship between personalization effectiveness and purchase intention*", was not statistically significant (coefficient .1912, p = .0688) and was rejected. Notably, there was a strong direct relationship between customer satisfaction and purchase intention (coefficient .4898, p < .0001), not previously hypothesized. These interactions are shown in *Figure 3.*

Despite age and shopping frequency showing non significant correlations with purchase intention, their impact is noticeable on different variables. Lower age positively influenced personalization effectiveness (coefficient -.2635, p = .0190) and customer satisfaction (coefficient -.2682, p = .0154). Less frequent shopping negatively affected customer satisfaction (coefficient -.3338, p = .0008) and positively affected trust (coefficient .2355, p = .0144).

Figure 3 - Regression model



Analysis of indirect effects reveals significant paths linking cognitive elaboration to purchase intention, all mediated via personalization effectiveness (see *Table 5*).

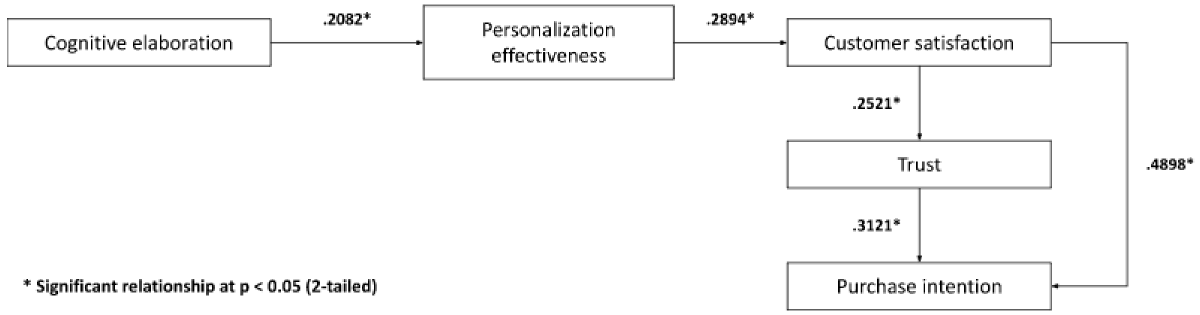
Table 5 - Indirect effects of cognitive elaboration on purchase intention

Indirect effect(s) of X on Y	B	SE	LLCI	ULCI
Total	.1707	.0726	.0358	.3207
Ind1: CE → PE_N → PI	.0398	.0355	-.0099	.1274
Ind2: CE → CS → PI	.0367	.0399	-.0360	.1225
Ind3: CE → TR → PI	.0198	.0331	-.0393	.0963
Ind4: CE → PE_N → CS → PI	.0295	.0157	.0050	.0664
Ind5: CE → PE_N → TR → PI	.0344	.0224	.0024	.0886
Ind6: CE → CS → TR → PI	.0059	.0077	-.0068	.0237
Ind7: CE → PE_N → CS → TR → PI	.0047	.0039	.0002	.0149

CE = *cognitive elaboration*		**PE_N** = *personalization effectiveness*
CS = *customer satisfaction*	**TR** = *trust*	**PI** = *purchase intention*

The significant pathways for the indirect effect of cognitive elaboration on purchase intention are from cognitive elaboration through personalization effectiveness to customer satisfaction, another through personalization effectiveness to trust, and the last one passing through personalization effectiveness, then customer satisfaction, and finally trust. The results highlight the crucial role of personalization effectiveness, customer satisfaction, and trust as mediators and suggest that cognitive elaboration only influences other variables through personalization effectiveness, signifying full mediation (Hair et al., 2018, p. 419). This illustrates how customer decisions are influenced by the complex interplay of various variables. An updated conceptual model showing these relationships is depicted in *Figure 4*.

Figure 4 - Adjusted meditation model



5. CONCLUSION & DISCUSSION

This chapter discusses the results derived from the hypotheses testing in light of the existing body of knowledge and the theoretical framework proposed in the introductory chapters. Conclusions alongside theoretical and practical implications, as well as proposing recommendations for future research are presented as well.

5.1 Conclusion

This master's thesis sought to explore how AI personalization effectiveness influences relationship marketing outcomes in the retail industry. From a theoretical perspective, personalization effectiveness was hypothesized to impact three key marketing relationship constructs: customer satisfaction, trust, and purchase intention. However, after data collection and analysis, it was found that while AI personalization effectiveness greatly impacts customer satisfaction and trust, its direct influence on purchase intention was not significant. Instead, customer satisfaction has a direct impact on purchase intention. Consequently, while AI personalization plays a significant role in determining relationship marketing outcomes in the retail sector, its function is more complex and indirect. It is noteworthy that the role of personalization effectiveness as a mediator, particularly between cognitive elaboration and purchase intention, was strongly emphasized.

5.2 Findings

The first findings of this study are the significant and positive relationship between customer satisfaction and trust. This aligns with previous research which demonstrates that high levels of customer satisfaction often yield increased trust in a given retail environment, meaning satisfaction is a prerequisite for trust (Chu & Zhang, 2016; Leninkumar, 2017). The satisfaction-trust relationship observed in this study also underscores the foundational role that satisfaction plays in the trust-building process within the retail sector. The positive relationship between trust and purchase intention concurs with existing studies where trust has been demonstrated as a significant predictor of purchase intention (Gao, 2011; Azizan & Yusr, 2019). These findings suggest that businesses that can effectively build and maintain customer trust are likely to see an improvement in customers' intention to purchase. The trust-purchase intention relationship found in this study provides further empirical support for the pivotal role trust plays in the decision-making processes of customers. Regarding cognitive elaboration, the findings of this study indicate a significant relationship with personalization effectiveness. This aligns with the assertions of Tam and Ho (2006) who suggest that a higher level of cognitive elaboration may enhance the perceived effectiveness of personalized messages, resulting in greater customer engagement and conversion.

In addition, this study provides empirical support by demonstrating that personalization effectiveness has a positive relationship with customer satisfaction and trust. In the context of customer satisfaction and trust, Thirumalai and Sinha's (2011) and Chen et al. (2021) studies highlight that personalization significantly contributes to customer satisfaction in online purchasing behavior. Interestingly, however, the expected relationship between personalization effectiveness and purchase intention did not materialize. This contradicts earlier findings (Hirsh et al., 2012; Panigrahi & Karuna, 2021) where they emphasize the significant role of personalization in enhancing customers' shopping experience and influencing their purchase intentions. Based on the mediation output, it appears that personalization effectiveness indirectly impacts purchase intention through its substantial effects on customer satisfaction and trust. This suggests that the role of personalization in influencing purchasing behavior may be more multifaceted and indirect than initially presumed. In fact, one of the key findings of this research is the robust direct relationship between customer satisfaction and purchase intention, which was not explicitly discussed in earlier literature. This reinforces the notion that satisfied customers are more likely to make purchase decisions, a fact that retailers must prioritize in their strategies.

The examination of the control variables, age and shopping frequency, revealed further significant relationships. The negative coefficient for age suggests an inverse relationship between age and the associated variables. Essentially, as age decreases, the value of the associated variables tends to increase. The significant negative effect of age on personalization effectiveness indicates that younger customers are more likely to perceive personalization as effective. Simultaneously, age had a significant negative effect on customer satisfaction implying younger customers tend to report higher levels of satisfaction. Similarly, the variable shopping frequency, indicated by a negative coefficient, suggests that as the frequency of shopping decreases, the value of associated variables tends to increase. Notably, shopping frequency exhibited a significant negative effect on customer satisfaction. This suggests that customers who shop more frequently report higher satisfaction levels. In contrast, shopping frequency had a substantial positive influence on trust, showing that customers who shop less frequently had higher levels of trust. This could be because less frequent shoppers, who are more selective about their interactions, may develop higher trust in retailers when their selective shopping experiences meet or exceed expectations. These insights reveal the nuanced influence of demographic and behavioral variables on key aspects of the customer's experience and decision-making process (*Appendix G*).

5.3 Theoretical Implication

The findings from this study contribute to the existing knowledge in relationship marketing and the emerging field of AI-enabled personalization. By empirically demonstrating the influence of personalization effectiveness on customer satisfaction and trust, this research extends the understanding of relationship marketing variables within the context of the retail industry (Chu & Zhang, 2016; Gao, 2011). Additionally, it lends empirical support to the argument that customer satisfaction is a prerequisite for trust, adding nuance to the understanding of the dynamics between these two constructs (Leninkumar, 2017). This study also uncovers a robust direct relationship between customer satisfaction and purchase intention, which has not been studied previously. This emphasizes that customer satisfaction is a potent driver of purchase decisions, thereby highlighting its strategic importance in customer relationship marketing. Furthermore, this study highlights the noteworthy role of cognitive elaboration in influencing the effectiveness of personalization, which has been less explored in prior research (Tam & Ho, 2006). By showing that the cognitive processes customers employ when interacting with personalized offerings are crucial in shaping the outcomes of personalization efforts, this research illuminates a new avenue for exploring how customer cognition interplays with AI personalization. This unexpected finding nudges to rethink and further explore the mechanisms through which personalization influences key relationship marketing outcomes. It opens up the possibility of a more complex interplay of factors driving purchase decisions, suggesting that personalization's role might be more multifaceted and indirect than conventionally assumed. Moreover, the study reveals an interesting correlation between shopping frequency and trust, which deviates from existing research (Styvén et al., 2017). Less frequent shoppers display higher levels of trust, an insight that can stimulate research for understanding customer behavior in the online retail sector.

5.4 Practical Implications

The insights derived from this study provide a valuable guide for businesses and retailers. By emphasizing the significant impact of personalization effectiveness on customer satisfaction and trust, it encourages businesses to invest in personalized marketing strategies. However, it also advises a nuanced approach, suggesting that a direct focus on increasing customer satisfaction and trust may have a stronger influence on purchase intention. Moreover, the study's findings on the role of cognitive elaboration in personalization effectiveness are particularly beneficial for businesses aiming to enhance customer engagement and retention (Arora et al., 2021). Findings suggest that to maximize the impact of personalization, retailers should focus on designing content and information that encourages cognitive elaboration. This could mean providing more detailed product descriptions or/and engaging narratives to engage the customer's cognitive processes (Morgan, 2021). Consequently, this enhances the effectiveness of personalized marketing efforts which, in turn, positively influences customer marketing relationships. Further, the control variables, age and shopping frequency, provide additional insights for retailers. Younger customers respond more positively to personalization and report higher satisfaction, implying a need for retailers to focus on advanced personalization strategies tailored to this demographic. Interestingly, more frequent shoppers report higher satisfaction levels, prompting retailers to analyze factors that contribute to this relationship to enhance the shopping experience.

5.5 Limitations and Future Research

The limitations in this study, including the low response rate to the survey, potential under-reporting of personalized product recommendations exposure, the use of a potentially recognizable fictional retailer (Zalando), and potential interpretation differences due to back translation of survey items, may have influenced the results and interpretations. Additionally, the sample consisted mostly of young individuals (18-29 years old) from the researcher's circle, limiting the findings' generalizability to larger age groups and geographical locations. Future research could address these limitations by using wider and more representative sampling and a unique fictional retailer to avoid potential bias. Addressing these issues will enhance the validity of findings and offer more comprehensive insights into personalization effectiveness in marketing (Charter, 1999). Additional limitations may include methodological challenges, such as potential measurement biases and the potential need for construct refinement. Future research could address these limitations by employing more robust measurement techniques and refining the survey items to ensure their validity and reliability (Malhotra et al., 1996). Moreover, there may be theoretical implications that arise from the findings, such as the need for further exploration of the underlying mechanisms and processes involved in the relationship between personalization effectiveness and key marketing outcomes. Future studies could delve deeper into these theoretical aspects to provide a more comprehensive understanding of the phenomenon.

The results of this study, while insightful, bring further questions for exploration. A key area for exploration is why AI personalization does not directly affect purchase intentions, despite its significant role in business strategies (Hirsh et al., 2012). Investigating this could lead to more strategic resource use and more effective personalization strategies. Additionally, delving deeper into the potential moderating factors such as customer experience or the quality of personalized recommendations, as well as the role of cognitive elaboration in personalization effectiveness, could provide more nuanced insights. Given the varying results depending on the product category, future research could also examine these differences in more detail, potentially leading to industry-specific insights. Furthermore, given the rapid improvements in AI and machine learning technologies, it would be beneficial to investigate these dynamics longitudinally to understand how they evolve over time (McKendrick, 2021). A longitudinal analysis will track the evolution of these dynamics over time and will provide insights into how businesses need to adapt their AI personalization strategies as technology evolves. Understanding this will not only provide a broader perspective but can also lead to more targeted and effective business strategies, improving customer satisfaction and potentially enhancing business profitability over time (Azizan & Yusr, 2019).

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APPENDICES

Appendix A - Operationalization: Constructs and Scales

Construct	*Definition*	*Scale Name*	*Items*	*Reference*
Level of cognitive elaboration	the mental efforts that people spend in processing relevant information (Zhang et al., 2013)	Cognitive elaboration during wiki use (a=0,91)	1. I tried to take into consideration all possible perspectives when shopping online. 2. I tried to make judgments and decisions as thorough as possible when shopping online. 3. I thought deeply before making a decision when shopping online.	Adjusted from (Zhang et al., 2013)
Personalization effectiveness	the degree to which a person believes that using the personalization system would enhance his/her performance in product selection (Ho & Bodoff, 2014)	Perceived usefulness (a= 0.94)	1. I could decide more quickly which X I wanted to select than in the past. 2. I could better decide which X I wanted to select than in the past. 3. I was better informed about new X's. 4. I could decide more quickly whether I wanted to explore a particular X or not. 5. I could better decide whether I wanted to select a particular X or not.	Adjusted from (Ho & Bodoff, 2014)
Customer satisfaction	satisfied consumers are those whose expectations related to online commerce are fulfilled or exceeded (Vasić et al., 2019)	Customer satisfaction (a=0.96)	1. I am satisfied that websites offer online purchasing options. 2. Internet shopping makes the purchasing process interesting. 3. I would recommend online shopping to other consumers. 4. I enjoy online shopping. 5. It is my opinion that online shopping is excellent.	Vasić et al. (2019)
Trust	the willingness of a consumer to trust the product	Trust in recommendation	1. I think that the product recommendations of this website are credible.	Adjusted from (Hsiao et al., 2010)

	recommendations of shoppers (Hsiao et al., 2010)	(a=0,93)	2. I trust the product recommendations of this website. 3. I believe the product recommendations of this website are trustworthy.	
Purchase intention	customer's intention to shop online based on personalized services (Pappas et al., 2017)	Intention to purchase (a=0,90)	1. In the future, I intend to continue shopping online based on personalized services. 2. My general intention to buy online based on personalized services is very high. 3. I will shop online in the future based on personalized services.	Pappas et al. (2017)

Appendix B - Example of the Questionnaire

Dear respondents,

I am conducting a survey as part of my Master's thesis research, and I would greatly appreciate your participation. The survey is aimed at understanding personalized product recommendations in online retail industries.The survey is anonymous and will only take approximately 5 minutes to complete. Your participation in this survey is entirely voluntary. The responses will be used solely for research purposes. Please answer all questions as honestly as possible, from your personal perspective and try to answer even if you are uncertain.

If you have any questions or concerns about the survey or my research, please do not hesitate to contact me at ohanes.muradian@ru.nl. I will be happy to address any queries you may have.

Thank you in advance for your time and valuable input. Your participation will greatly contribute to the success of my research and help me in fulfilling my academic requirements.

Sincerely,
Ohanes Muradian

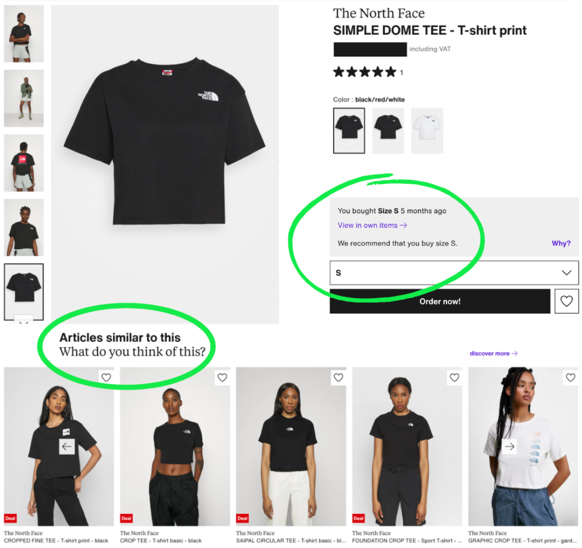
Introduction

This master's thesis study uses a questionnaire that includes a combination of multiple-choice questions and statement-based questions. Towards the end, there are a few extra questions that inquire about your background and feedback on the survey. The questionnaire explores various constructs and includes visual examples. Please take your time to review it carefully. You will see statements and you can initiate how much you agree with these statements using the answers ranging from strongly disagree (1) to strongly agree (7). An example question is presented below. Thank you for your participation!

	Strongly disagree						Strongly agree
I love to shop online.	1	2	3	4	5	6	7

Part 1

Personalized product recommendations are product recommendations that you encounter while browsing or shopping online that are tailored specifically to you based on your past shopping behavior, search history, and preferences. For example, a shopper who previously bought a black t-shirt may receive a personalized recommendation for a similar t-shirt in their own size (see example below).



Q1: Are you familiar with AI (artificial intelligence) technologies in the online retail industries?

- Yes
- No

Q2: Have you been exposed to personalized product recommendations before?

- Yes; if so, where?
- No

Part 2

The following questions and statements are about how you approach online shopping when making purchasing decisions.

Q3: How often do you shop online?

- Daily
- Weekly
- Monthly
- Occasionally
- Never

Q4: What types of products do you typically purchase online? (*multiple answers possible*).

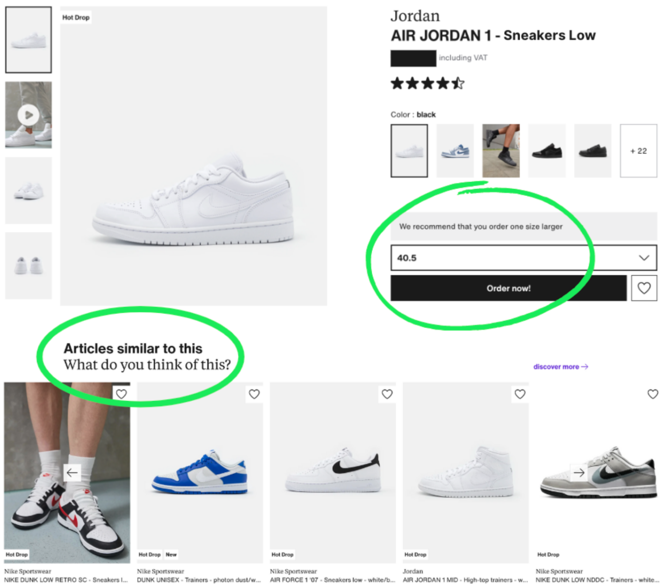
- Clothing and fashion accessories
- Electronics and gadgets
- Beauty and personal care products
- Groceries and household supplies
- Sports and outdoor equipment
- Toys and games
- Other (please specify)

Please indicate to what extent you agree/disagree with each of the statements on a 7-point scale ranging from strongly disagree (1) to strongly agree (7).

	Strongly disagree						Strongly agree
I try to take into consideration all possible perspectives when shopping online.	1	2	3	4	5	6	7
I try to make judgments and decisions as thoroughly as possible when shopping online.	1	2	3	4	5	6	7
I think deeply before making a decision when shopping online.	1	2	3	4	5	6	7

Part 3

ABC retail uses an AI-powered personalized product recommendation system to assist customers in finding products that best suit their needs. Imagine that you are browsing ABC retail's website looking for shoes. On the product page of a selected pair of shoes, you see a recommendation tailored to your size and a couple of additional product recommendations (see example). What do you think of these recommendations?

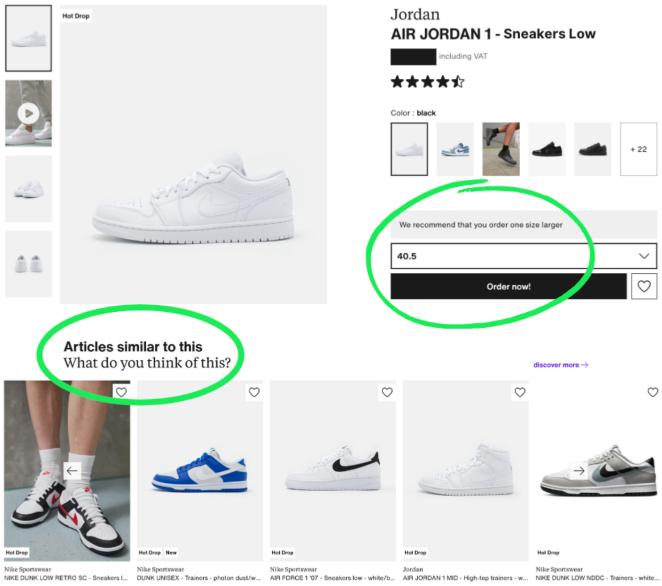


Please indicate to what extent you agree/disagree with each of the statements on a 7-point scale ranging from strongly disagree (1) to strongly agree (7), taking the example of shoes into consideration.

	Strongly disagree						Strongly agree
The recommended products help me decide more quickly which product I want to select than in the past.	1	2	3	4	5	6	7
The recommended products help me better decide which product I want to select than in the past.	1	2	3	4	5	6	7
The recommended products make me feel better informed about new products.	1	2	3	4	5	6	7
The recommended products help me decide more quickly whether I want to explore a particular product or not.	1	2	3	4	5	6	7
The recommended products help me better decide whether I want to select a particular product or	1	2	3	4	5	6	7

not.							
I think that the product recommendations of ABC retail are credible.	1	2	3	4	5	6	7
I trust the product recommendations of ABC retail website.	1	2	3	4	5	6	7
I believe the product recommendations of ABC retail are trustworthy.	1	2	3	4	5	6	7

The following statements also relate to ABC retail. What do you think of ABC retail?



Please indicate to what extent you agree/disagree with each of the statements on a 7-point scale ranging from strongly disagree (1) to strongly agree (7), taking the example of shoes into consideration.

	Strongly disagree						Strongly agree
I am satisfied that ABC retail offers online purchasing options.	1	2	3	4	5	6	7
Internet shopping makes the purchasing process interesting.	1	2	3	4	5	6	7
I would recommend online shopping to other consumers.	1	2	3	4	5	6	7
I enjoy online shopping.	1	2	3	4	5	6	7
It is my opinion that online shopping is excellent.	1	2	3	4	5	6	7
In the future, I intend to continue shopping online at ABC retail based on personalized services.	1	2	3	4	5	6	7
My general intention to buy online based on personalized services from ABC retail is very high.	1	2	3	4	5	6	7
I will shop online at ABC retail in the future based on personalized services.	1	2	3	4	5	6	7

Part 4
Please answer the following additional questions regarding your demographic information.

Q5: What is your gender?
- Male
- Female
- Non-binary / third gender
- Prefer not to say

Q5: What is your age?
- Under 18 years
- 18 to 29 years
- 30 to 44 years
- 45 to 64 years
- Older than 65 years

Q6: What is your highest completed educational level?
- Primary education (vmbo/havo/vwo)
- Mbo
- Hbo-bachelor
- Wo-bachelor/master, doctor
- Other (please specify)

Q7: How would you describe your income level?
- Low
- Average
- High

Part 5 - Evaluation
Please rate the following statements regarding this survey.

	Strongly disagree						Strongly agree
I understood all the questions in this research.	1	2	3	4	5	6	7
The language used in this research was not difficult.	1	2	3	4	5	6	7
It was easy to answer the questions in this research to other consumers.	1	2	3	4	5	6	7

Thank you
Please note that ABC retail was a fictional case that has been created solely for the purpose of this research.

You arrived at the end of the questionnaire. Thank you for participating! If you have further questions, comments, or would like to be informed about the results don't hesitate to contact me: Ohanes.muradian@ru.nl!

Appendix C - Harman's Single Factor Analysis

Table 1 - Harman's single factor analysis

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	6.998	36.831	36.831	6.998	36.831	36.831
2	2.274	11.970	48.801			
3	1.759	9.260	58.062			
4	1.359	7.151	65.213			
5	1.096	5.770	70.983			
6	.885	4.657	75.640			
7	.797	4.194	79.835			
8	.641	3.373	83.208			
9	.497	2.618	85.826			
10	.466	2.455	88.281			
11	.452	2.381	90.661			
12	.331	1.744	92.405			
13	.300	1.580	93.986			
14	.269	1.413	95.399			
15	.241	1.267	96.666			
16	.222	1.170	97.835			
17	.167	.878	98.713			
18	.132	.697	99.409			
19	.112	.591	100.000			

Extraction Method: Principal Component Analysis.

Appendix D - Validity & Reliability Analysis

Table 1 - Principal factor analysis

Pattern Matrix[a]

	Factor 1	2	3	4	5
CE1 – I try to take into consideration all possible perspectives when shopping online.			.708		
CE2– I try to make judgments and decisions as thoroughly as possible when shopping online.			.931		
CE3– I think deeply before making a decision when shopping online.			.498		
PE1 – The recommended products help me decide more quickly which product I want to select than in the past.					.452
PE2 – The recommended products help me better decide which product I want to select than in the past.				-.339	.588
PE4 – The recommended products help me decide more quickly whether I want to explore a particular product or not.					.680
PE5 – The recommended products help me better decide whether I want to select a particular product or not.					.662
CS1– I am satisfied that ABC retail offers online purchasing options.		-.347			
CS2 – Internet shopping makes the purchasing process interesting.		-.623			
CS3 – I would recommend online shopping to other consumers.		-.867			
CS4 – I enjoy online shopping.		-.830			
CS5– It is my opinion that online shopping is excellent.		-.751			
TR1 – I think that the product recommendations of ABC retail are credible.	.717				
TR2 – I trust the product recommendations of ABC retail website.	1.021				
TR3 – I believe the product recommendations of ABC retail are trustworthy.	.763				
PI1– In the future, I intend to continue shopping online at ABC retail based on personalized services.		-.330		-.601	
PI2– My general intention to buy online based on personalized services from ABC retail is very high.				-.625	
PI3 – I will shop online at ABC retail in the future based on personalized services.				-.725	

Extraction Method: Principal Axis Factoring.
Rotation Method: Oblimin with Kaiser Normalization.

a. Rotation converged in 17 iterations.

Table 2 - Extended PFA with KMO and Barlett's test - Cognitive elaboration

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.621
Bartlett's Test of Sphericity	Approx. Chi-Square	99.674
	df	3
	Sig.	<.001

Table 3 - Extended PFA with KMO and Barlett's test - Personalization effectiveness

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.686
Bartlett's Test of Sphericity	Approx. Chi-Square	153.448
	df	6
	Sig.	<.001

Table 4 - Extended PFA with KMO and Barlett's test - Customer satisfaction

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.806
Bartlett's Test of Sphericity	Approx. Chi-Square	281.987
	df	10
	Sig.	<.001

Table 5 - Extended PFA with KMO and Barlett's test - Trust

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.700
Bartlett's Test of Sphericity	Approx. Chi-Square	241.716
	df	3
	Sig.	<.001

Table 6 - Extended PFA with KMO and Barlett's test - Purchase intention

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.739
Bartlett's Test of Sphericity	Approx. Chi-Square	271.494
	df	3
	Sig.	<.001

Table 7 - Reliability analysis - Cognitive elaboration

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.727	.737	3

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
I try to take into consideration all possible perspectives when shopping online.	10.27	5.020	.570	.426	.618
I try to make judgments and decisions as thoroughly as possible when shopping online.	9.98	4.581	.661	.482	.508
I think deeply before making a decision when shopping online.	10.09	4.782	.440	.209	.788

The Cronbach's Alpha for level of cognitive elaboration is .727, indicating that the items underlying this construct are internally consistent. The removal of the item CE3 'I think deeply before making a decision when shopping online' would result in a minor improvement of Cronbach's Alpha. However, due to the small impact of this change, the item will be retained in the analysis.

Table 8 - Reliability analysis - Personalization effectiveness

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.772	.772	4

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
PE1 – The recommended products help me decide more quickly which product I want to select than in the past.	14.27	9.826	.535	.386	.738
PE2 – The recommended products help me better decide which product I want to select than in the past.	14.34	9.450	.615	.436	.696
PE4 – The recommended products help me decide more quickly whether I want to explore a particular product or not.	14.04	10.053	.546	.395	.732
PE5 – The recommended products help me better decide whether I want to select a particular product or not.	14.12	9.427	.602	.431	.703

The Cronbach's Alpha for this construct is .772, signifying a high level of internal consistency among the indicators for personalization effectiveness. There are no potential improvements to the Cronbach's Alpha value that could result from the removal of any items.

Table 9 - Reliability analysis - Customer satisfaction

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.840	.833	5

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
I am satisfied that ABC retail offers online purchasing options.	19.76	23.454	.396	.186	.863
Internet shopping makes the purchasing process interesting.	20.05	19.028	.594	.377	.821
I would recommend online shopping to other consumers.	19.88	17.535	.760	.580	.775
Click to write the question text - I enjoy online shopping.	20.05	15.927	.770	.648	.770
It is my opinion that online shopping is excellent.	20.28	17.213	.716	.620	.787

The Cronbach's Alpha for customer satisfaction is .840, indicating that the items underlying this construct are internally consistent. The removal of the item CS1 'I am satisfied that ABC retail offers online purchasing options' would result in a minor improvement of Cronbach's Alpha. However, due to the small impact of this change, the item will be retained in the analysis.

Table 10 - Reliability analysis - Trust

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.892	.892	3

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
I think that the product recommendations of ABC retail are credible.	8.96	5.464	.733	.572	.893
I trust the product recommendations of ABC retail website.	9.29	4.550	.863	.748	.778
I believe the product recommendations of ABC retail are trustworthy.	9.08	4.962	.776	.653	.858

The Cronbach's Alpha for trust is .892, indicating that the items underlying this construct are internally consistent. The removal of the item TR1 'I think that the product recommendations of ABC retail are credible' would result in a small improvement of Cronbach's Alpha. However, due to the small impact of this change, the item will be retained in the analysis.

Table 11 - Reliability analysis - Purchase intention

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.911	.912	3

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
In the future, I intend to continue shopping online at ABC retail based on personalized services.	8.46	7.243	.789	.636	.901
My general intention to buy online based on personalized services from ABC retail is very high.	8.99	6.147	.819	.690	.878
I will shop online at ABC retail in the future based on personalized services.	8.72	6.236	.868	.753	.833

The Cronbach's Alpha for this construct is .911, signifying a high level of internal consistency among the indicators for purchase intention. There are no potential improvements to the Cronbach's Alpha value that could result from the removal of any items.

Appendix E - Descriptive Statistics and Correlation Matrix

Table 1 - Descriptive statistics

Descriptive Statistics

	N	Range	Mean	Std. Deviation	Variance
Cognitive Elaboration	130	4.67	5.0564	1.02689	1.055
Personalization Effectiveness	130	4.75	4.7308	1.00030	1.001
Customer Satisfaction	130	4.80	5.0015	1.05815	1.120
Trust	130	5.33	4.5564	1.08818	1.184
Purchase Intention	130	6.00	4.3615	1.25138	1.566
AGE	130	3	2.35	.776	.603
Gender	130	3	1.65	.567	.321
Education_level	130	4	2.99	1.131	1.279
Income_level	130	4	2.31	1.106	1.222
AI_familiarity	130	1	1.25	.437	.191
PPR_expostion	130	1	1.26	.441	.195
Shop_cat_clothing	130	1	.88	.330	.109
Shop_cat_electronics	130	1	.61	.490	.240
Shop_cat_beauty	130	1	.38	.488	.239
Shop_cat_groceries	130	1	.21	.407	.166
Shop_cat_sport	130	1	.28	.453	.205
Shop_categ_toys	130	1	.19	.396	.157
Valid N (listwise)	130				

Table 2 - Correlation matrix

Correlations

		CE	PE_N	CS	TR	PI	AGE	Gender	Education_level	Income_level	AI_familiarity	PPR_expostion	Shoping_frequency	Shop_cat_cloth	Shop_cat_elect	Shop_cat_beauty	Shop_cat_groc	Shop_cat_sport	Shop_categ_toys
Cognitive Elaboration	Pearson Correlation	--																	
	N	130																	
Personalization Effectiveness	Pearson Correlation	.232**	--																
	Sig. (2-tailed)	.008																	
	N	130	130																
Customer Satisfaction	Pearson Correlation	.154	.370**	--															
	Sig. (2-tailed)	.079	<.001																
	N	130	130	130															
Trust	Pearson Correlation	.212*	.576**	.381**	--														
	Sig. (2-tailed)	.015	<.001	<.001															
	N	130	130	130	130														
Purchase Intention	Pearson Correlation	.182*	.469**	.594**	.512**	--													
	Sig. (2-tailed)	.039	<.001	<.001	<.001														
	N	130	130	130	130	130													
AGE	Pearson Correlation	-.087	-.238**	-.320**	-.195*	-.199*	--												
	Sig. (2-tailed)	.326	.006	<.001	.026	.023													
	N	130	130	130	130	130	130												
Gender	Pearson Correlation	-.175*	-.176*	-.084	-.117	-.150	.069	--											
	Sig. (2-tailed)	.047	.045	.340	.186	.088	.434												
	N	130	130	130	130	130	130	130											
Education_level	Pearson Correlation	.141	.133	.235**	.228**	.154	-.288**	.044	--										
	Sig. (2-tailed)	.111	.130	.007	.009	.081	<.001	.618											
	N	130	130	130	130	130	130	130	130										
Income_level	Pearson Correlation	.085	.012	.141	-.030	.081	.197*	-.089	-.017	--									
	Sig. (2-tailed)	.338	.889	.109	.738	.357	.024	.317	.850										
	N	130	130	130	130	130	130	130	130	130									
AI_familiarity	Pearson Correlation	-.084	-.086	-.118	-.104	-.056	.282**	-.049	-.373**	-.019	--								
	Sig. (2-tailed)	.342	.329	.180	.240	.529	.001	.577	<.001	.834									
	N	130	130	130	130	130	130	130	130	130	130								
PPR_expostion	Pearson Correlation	.013	-.019	-.237**	-.009	.029	.384**	-.100	-.369**	.088	.417**	--							
	Sig. (2-tailed)	.885	.828	.007	.915	.746	<.001	.257	<.001	.319	<.001								
	N	130	130	130	130	130	130	130	130	130	130	130							
Shoping_frequency	Pearson Correlation	-.005	-.120	-.340**	.037	-.226**	.191*	-.120	-.192*	-.205*	.207*	.264**	--						
	Sig. (2-tailed)	.955	.175	<.001	.676	.010	.029	.175	.029	.019	.018	.002							
	N	130	130	130	130	130	130	130	130	130	130	130	130						
Shop_cat_clothing	Pearson Correlation	-.094	.093	.267**	.012	.140	-.283**	-.105	.081	-.023	-.158	-.310**	-.083	--					
	Sig. (2-tailed)	.289	.295	.002	.890	.112	.001	.233	.362	.796	.072	<.001	.345						
	N	130	130	130	130	130	130	130	130	130	130	130	130	130					
Shop_cat_electronics	Pearson Correlation	-.038	.214*	.121	.131	.149	-.142	-.353**	.120	-.076	-.038	-.060	.135	.131	--				
	Sig. (2-tailed)	.669	.015	.171	.136	.091	.108	<.001	.173	.391	.667	.501	.126	.139					
	N	130	130	130	130	130	130	130	130	130	130	130	130	130	130				
Shop_cat_beauty	Pearson Correlation	-.136	.043	.152	-.012	.092	.006	.289**	.033	-.049	-.025	-.147	-.300**	.007	.052	--			
	Sig. (2-tailed)	.122	.627	.085	.892	.298	.943	<.001	.705	.583	.776	.096	<.001	.933	.554				
	N	130	130	130	130	130	130	130	130	130	130	130	130	130	130	130			
Shop_cat_groceries	Pearson Correlation	.089	.057	.039	.029	.059	.134	.045	.088	.046	-.037	.040	-.052	-.155	-.016	-.015	--		
	Sig. (2-tailed)	.313	.516	.661	.745	.502	.130	.609	.321	.600	.674	.647	.558	.079	.858	.866			
	N	130	130	130	130	130	130	130	130	130	130	130	130	130	130	130	130		
Shop_cat_sport	Pearson Correlation	-.190*	.106	-.014	-.051	-.014	-.156	-.157	.004	-.192*	-.015	-.104	-.252**	.184*	.332**	.167	-.029	--	
	Sig. (2-tailed)	.030	.229	.876	.563	.872	.076	.075	.961	.029	.862	.240	.004	.036	<.001	.057	.745		
	N	130	130	130	130	130	130	130	130	130	130	130	130	130	130	130	130	130	
Shop_categ_toys	Pearson Correlation	-.021	.142	-.001	.146	.036	-.021	-.116	.055	.023	-.150	.020	.044	.123	.352**	.056	.279**	.211*	--
	Sig. (2-tailed)	.817	.108	.994	.098	.685	.809	.190	.532	.794	.088	.817	.618	.162	<.001	.530	.001	.016	
	N	130	130	130	130	130	130	130	130	130	130	130	130	130	130	130	130	130	130

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

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

Appendix F - Assumptions of Regression Analysis

Table 1 - Frequency table

Statistics

		Cognitive Elaboration	Personalization Effectiveness	Customer Satisfaction	Trust	Purchase Intention
N	Valid	130	130	130	130	130
	Missing	0	0	0	0	0
Mean		5.0564	4.7308	5.0015	4.5564	4.3615
Median		5.3333	5.0000	5.2000	4.5000	4.5000
Mode		5.67	5.25[a]	5.40[a]	4.00	4.00
Std. Deviation		1.02689	1.00030	1.05815	1.08818	1.25138
Skewness		-.391	-.763	-.512	-.220	-.304
Std. Error of Skewness		.212	.212	.212	.212	.212
Kurtosis		-.322	.296	-.226	-.169	-.551
Std. Error of Kurtosis		.422	.422	.422	.422	.422

a. Multiple modes exist. The smallest value is shown

Figure 1 - Histogram

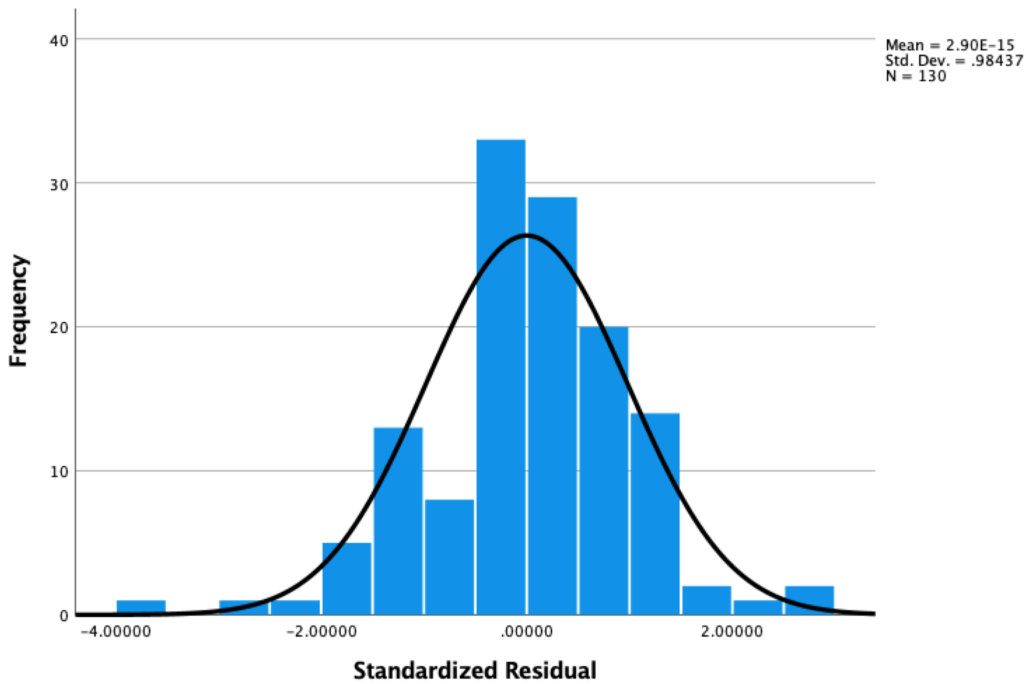


Figure 2 - Quantile plot

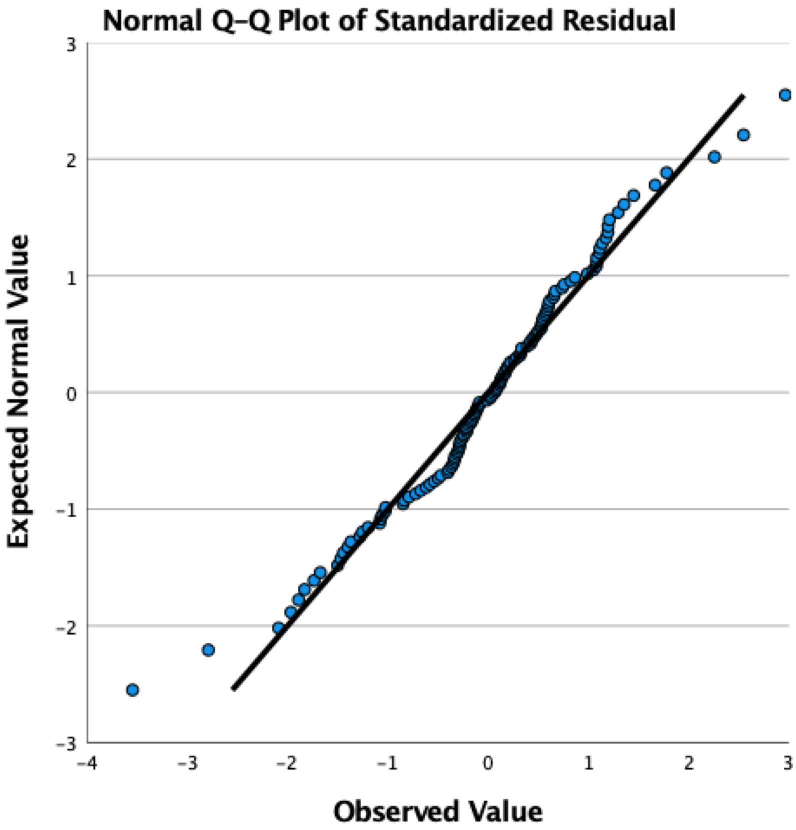


Figure 3 - Scatterplot DV purchase intention

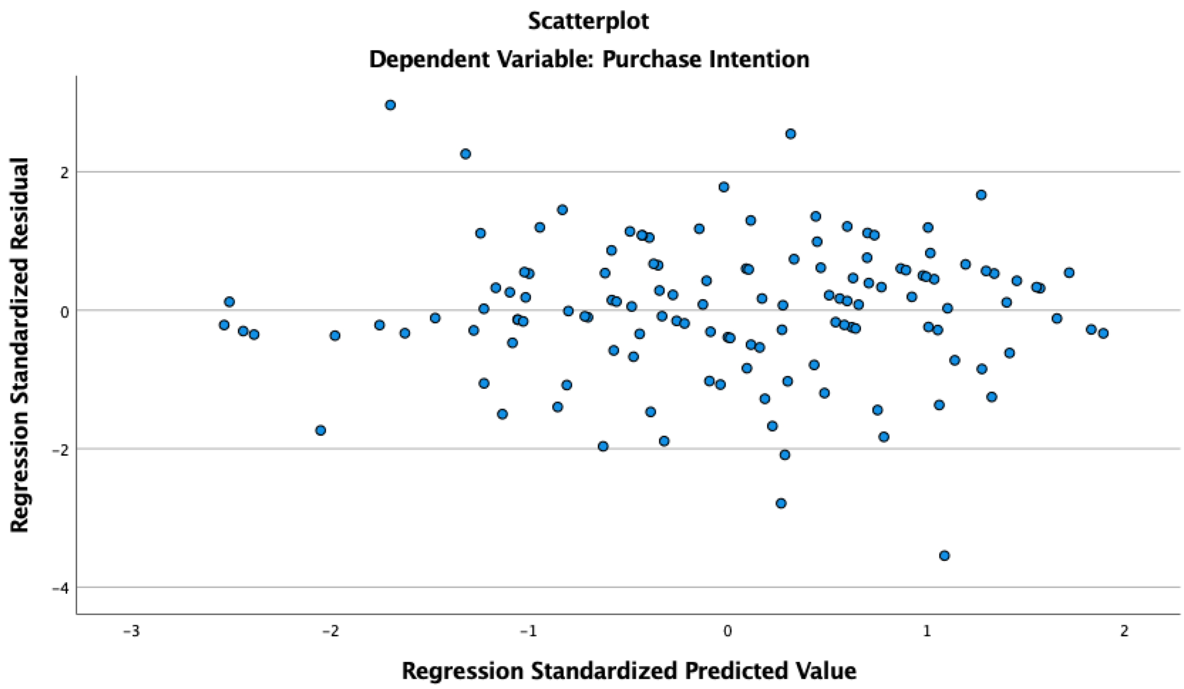


Table 2 - Residuals statistics

Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	2.1974	5.9760	4.3615	.85402	130
Residual	-3.29346	2.75481	.00000	.91466	130
Std. Predicted Value	-2.534	1.890	.000	1.000	130
Std. Residual	-3.544	2.965	.000	.984	130

a. Dependent Variable: Purchase Intention

Table 3 - Coefficients

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	-.616	.567		-1.088	.279		
	PE_N	.198	.103	.158	1.926	.056	.632	1.582
	CE	.030	.082	.025	.365	.716	.934	1.071
	TR	.287	.095	.249	3.027	.003	.631	1.585
	CS	.516	.085	.437	6.043	<.001	.818	1.222

a. Dependent Variable: Purchase Intention

Appendix G - PROCESS Macro Model 6 Output

```
Run MATRIX procedure:

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

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

**************************************************************************
Model  : 6
    Y  : PI
    X  : CE
   M1  : PE_N
   M2  : CS
   M3  : TR

Covariates:
 Age      ShopFreq

Sample
Size:  130

**************************************************************************
OUTCOME VARIABLE:
 PE_N

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .3283      .1078      .9140     5.0751     3.0000   126.0000      .0024

Model
              coeff         se          t          p       LLCI       ULCI
constant     4.5897      .5756     7.9743      .0000     3.4507     5.7287
CE            .2082      .0823     2.5299      .0126      .0453      .3710
Age          -.2635      .1109    -2.3763      .0190     -.4830     -.0441
ShopFreq     -.0932      .1004     -.9283      .3550     -.2920      .1055

Standardized coefficients
              coeff
CE            .2137
Age          -.2045
ShopFreq     -.0796

**************************************************************************
OUTCOME VARIABLE:
 CS

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .5165      .2667      .8473    11.3683     4.0000   125.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     4.9278      .6798     7.2492      .0000     3.5824     6.2731
CE            .0748      .0812      .9215      .3586     -.0859      .2356
PE_N          .2894      .0858     3.3736      .0010      .1196      .4591
Age          -.2682      .1091    -2.4571      .0154     -.4842     -.0522
ShopFreq     -.3338      .0970    -3.4392      .0008     -.5258     -.1417

Standardized coefficients
              coeff
```

```
CE              .0726
PE_N            .2736
Age            -.1967
ShopFreq       -.2693

**************************************************************************
OUTCOME VARIABLE:
 TR

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .6318      .3992      .7401    16.4787     5.0000   124.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     -.1612      .7572     -.2129      .8318    -1.6599     1.3375
CE            .0633      .0762      .8317      .4072     -.0874      .2141
PE_N          .5291      .0837     6.3186      .0000      .3634      .6948
CS            .2521      .0836     3.0160      .0031      .0867      .4176
Age          -.0435      .1044     -.4161      .6781     -.2502      .1633
ShopFreq      .2355      .0949     2.4821      .0144      .0477      .4233

Standardized coefficients
              coeff
CE            .0598
PE_N          .4864
CS            .2452
Age          -.0310
ShopFreq      .1848

**************************************************************************
OUTCOME VARIABLE:
 PI

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .6875      .4726      .8661    18.3723     6.0000   123.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     -.3563      .8193     -.4349      .6644    -1.9780     1.2654
CE            .0340      .0826      .4110      .6818     -.1296      .1975
PE_N          .1912      .1042     1.8361      .0688     -.0149      .3974
CS            .4898      .0937     5.2280      .0000      .3044      .6753
TR            .3121      .0971     3.2127      .0017      .1198      .5044
Age           .0663      .1131      .5861      .5589     -.1575      .2901
ShopFreq     -.1237      .1052    -1.1763      .2417     -.3319      .0845

Standardized coefficients
              coeff
CE            .0279
PE_N          .1529
CS            .4142
TR            .2714
Age           .0411
ShopFreq     -.0844

************************** TOTAL EFFECT MODEL ****************************
OUTCOME VARIABLE:
 PI
```

Model Summary

R	R-sq	MSE	F	df1	df2	p
.3229	.1043	1.4361	4.8888	3.0000	126.0000	.0030

Model

	coeff	se	t	p	LLCI	ULCI
constant	4.7854	.7215	6.6330	.0000	3.3577	6.2132
CE	.2047	.1031	1.9846	.0494	.0006	.4088
Age	-.2370	.1390	-1.7051	.0906	-.5121	.0381
ShopFreq	-.2885	.1259	-2.2914	.0236	-.5377	-.0393

Standardized coefficients

	coeff
CE	.1680
Age	-.1470
ShopFreq	-.1968

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

Total effect of X on Y

Effect	se	t	p	LLCI	ULCI	c_cs
.2047	.1031	1.9846	.0494	.0006	.4088	.1680

Direct effect of X on Y

Effect	se	t	p	LLCI	ULCI	c'_cs
.0340	.0826	.4110	.6818	-.1296	.1975	.0279

Indirect effect(s) of X on Y:

	Effect	BootSE	BootLLCI	BootULCI
TOTAL	.1707	.0726	.0358	.3207
Ind1	.0398	.0355	-.0099	.1274
Ind2	.0367	.0399	-.0360	.1225
Ind3	.0198	.0331	-.0393	.0963
Ind4	.0295	.0157	.0050	.0664
Ind5	.0344	.0224	.0024	.0886
Ind6	.0059	.0077	-.0068	.0237
Ind7	.0047	.0039	.0002	.0149

Completely standardized indirect effect(s) of X on Y:

	Effect	BootSE	BootLLCI	BootULCI
TOTAL	.1401	.0575	.0301	.2559
Ind1	.0327	.0284	-.0084	.1015
Ind2	.0301	.0326	-.0294	.0999
Ind3	.0162	.0272	-.0322	.0791
Ind4	.0242	.0125	.0043	.0526
Ind5	.0282	.0180	.0020	.0720
Ind6	.0048	.0063	-.0056	.0198
Ind7	.0039	.0032	.0002	.0120

Indirect effect key:

Ind1	CE	->	PE_N	->	PI				
Ind2	CE	->	CS	->	PI				
Ind3	CE	->	TR	->	PI				
Ind4	CE	->	PE_N	->	CS	->	PI		
Ind5	CE	->	PE_N	->	TR	->	PI		
Ind6	CE	->	CS	->	TR	->	PI		
Ind7	CE	->	PE_N	->	CS	->	TR	->	PI

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

Level of confidence for all confidence intervals in output:
  95.0000

Number of bootstrap samples for percentile bootstrap confidence intervals:
  10000

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