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Drivers and Outcomes of Conversational Recommendation Systems in the Online Fashion Industry

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Master in Management

Supervisor:

PhD Inês Vazão Miguel, Invited Assistant Professor,

Iscte - Instituto Universitário de Lisboa

October, 2025

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BUSINESS
SCHOOL

Department of Marketing, Operations and General Management

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Acknowledgments

This dissertation symbolises the end of my academic journey. Throughout my academic journey there were a lot of important people that have helped me throughout my journey. Therefore, I want to dedicate this section to them to express my gratitude. I would like to start off by expressing my gratitude towards my parents. Both of them have sacrificed so much for me. Without their support I would not be in the position where I am today. The next person I would like to thank is my girlfriend. I am so grateful to have you in my life. You honestly make everything in life better, and I love you. Next, I would like to express my gratitude to my supervisor, Dr. Inês Vazão Miguel. I am grateful for your accepting me and guiding me throughout this process. Finally, I would like to thank everybody that I have met at ISCTE, from my friends, peers, professors, and the staff members.

Resumo

Os sistemas de recomendação conversacionais estão prestes a reinventar a descoberta de produtos na indústria da moda online. Estes sistemas envolvem-se em conversas com os consumidores para obter as informações necessárias para captar as suas preferências e oferecer recomendações personalizadas em tempo real. No entanto, esses sistemas são relativamente novos, situando-se entre os primeiros a adotá-los e a maioria inicial. Esta dissertação teve como objetivo explorar os fatores que influenciam a intenção comportamental dos consumidores de moda em adotar esses sistemas, bem como a sua influência nas decisões de compra e na fidelidade dos consumidores de moda online. Através de um questionário online transversal, que incluiu 201 inquiridos válidos, observou-se que a utilidade percebida, a facilidade de utilização percebida e o prazer percebido de um sistema de recomendação conversacional eram determinantes positivos e significativos da intenção comportamental de adoção, sendo o prazer percebido o fator mais significativo. No entanto, observou-se que as preocupações percebidas com a privacidade não influenciaram significativamente a adoção. Além disso, observou-se que a intenção comportamental de adotar sistemas de recomendação conversacionais influenciou positivamente as decisões de compra dos consumidores de moda, o que subsequentemente levou a uma maior probabilidade de eles promoverem a fidelidade do consumidor.

Palavras-chave: Personalização por Inteligência Artificial, Industria de la Moda Online, Sistemas de Recomendación Conversacional, Modelo de Adopción de Tecnología, Recorrido del Consumidor

Sistema de Classificação JEL: M31 – Marketing, L81 - Retail and Wholesale Trade- e-commerce

Abstract

Conversational recommendation systems are set to reinvent product discovery in the online fashion industry. These systems engage in conversations with consumers to elicit information needed to capture consumers' preferences to offer real-time personalised recommendations. However, these systems are relatively new, falling between early adopters and the early majority. This dissertation set out to explore factors that influence fashion consumers' Behavioural Intention towards adopting systems, as well as its influence on online fashion consumers' Purchasing Decisions and Consumer Loyalty. Through a cross-sectional online questionnaire, which included 201 valid respondents, it was observed that the Perceived Usefulness, Perceived Ease of Use, and Perceived Enjoyment of a conversational recommendation system were positive and significant determinants of Behavioural Intention of adoption, with Perceived Enjoyment being the most significant factor. However, it was observed that Perceived Privacy Concerns did not significantly influence adoption. Furthermore, it was observed that the Behavioural Intention of adopting conversational recommendation systems positively influenced fashion consumers' Purchasing Decisions, which subsequently led to an increased likelihood of them fostering Consumer Loyalty.

Keywords: Artificial Intelligence Personalisation, Online Fashion Industry, Conversational Recommendation Systems, Technology Adoption Model, Consumer Journey

JEL classification system:

M31- Marketing, L81- Retail and Wholesale Trade- e-commerce

General Index

Acknowledgments	i
Resumo	iii
Abstract	v
General Index	vii
List of Figures	ix
Glossary of Acronyms.....	xiii
Chapter 1. Introduction	1
1.1. Contextualisation and Relevance	1
1.2. Research Problem and Objectives.....	2
1.3. Dissertation Structure	3
Chapter 2. Literature Review	5
2.1. Artificial Intelligence and Personalised Recommendation Systems.....	5
2.1.1. Defining Artificial Intelligence	5
2.1.2. AI Personalisation	6
2.1.3. Evolution towards Conversational Recommendation Systems.....	7
2.2. The Influence of Conversational Recommendation Systems on the Online Fashion Consumer Journey.....	9
2.2.1. The Online Consumer Journey.....	9
2.2.2. Conversational Recommendation Systems in the Pre-Purchase Stage	9
2.2.3. Conversational Recommendation Systems in the Purchase Stage.....	11
2.2.4. Conversational Recommendation Systems in the Post-Purchase Stage.....	12
2.3. Factors Influencing Consumers Adoption of Conversational Recommendation Systems.....	12
2.4. Ethical and Privacy Concerns	14
Chapter 3. Conceptual Framework and Hypotheses	17
3.1. Conceptual Framework	17
3.2. Hypotheses Formulation	18
3.1.1. Perceived Usefulness and Behavioural Intention.....	18
3.1.2. Perceived Ease of Use and Behavioural Intention	18
3.1.3. Perceived Enjoyment and Behavioural Intention.....	18
3.1.4. Perceived Privacy Concerns and Behavioural Intention	19
3.1.5. Behavioural Intention and Purchasing Decision	19
3.1.6. Purchasing Decision and Consumer Loyalty	20

Chapter 4. Research Methodology	21
4.1. Research Design	21
4.2. Questionnaire Construction.....	22
4.3. Data Procedure	23
Chapter 5. Result and Discussion.....	25
5.1. Sample Characterisation.....	25
5.1.1. Socio-Demographic Characteristics	25
5.1.2. Online Fashion Shopping Behaviour	26
5.1.3. Opinions Towards Static Traditional Recommendation Systems.....	28
5.2. Descriptive Analysis	30
5.3. Reliability and Validity of Core Constructs.....	32
5.4. Simple and Multiple Regression Analysis	33
5.4.1. Multiple Linear Regression: Behavioural Intention.....	34
5.4.2. Simple Linear Regression: Behavioural Intention and Purchasing Decision...36	
5.4.3. Simple Linear Regression: Purchasing Decisions and Consumer Loyalty	38
5.5. Discussion of the Results	39
5.6. Theoretical Contribution	42
5.7. Managerial Implications.....	42
Chapter 6. Conclusion and Recommendations	45
6.1. Conclusion.....	45
6.2. Limitations and Further Research	46
Bibliographical References	47
Appendixes.....	53
Appendix A. Online Questionnaire	53
Appendix B. Additional Graphs Sample Characterisation.....	60
Appendix C. Descriptive Analysis	63
Appendix D. Cronbach's Alpha Coefficient.....	68

List of Figures

Figure 3.1 Conceptual Framework.....	17
Figure 5.1 Distribution of Shopping Frequency.....	27
Figure 5.2 Factors Positively Influencing Online Fashion Shopping.....	27
Figure 5.3 Factors Hindering Online Fashion Shopping.....	28
Figure 5.4 Traditional Static Recommendation Helpfulness.....	29
Figure 5.5 Purchase Frequency Fashion Product Recommendation.....	29
Figure 5.6 Challenges with Traditional Fashion Recommendation Systems.....	29

List of Tables

Table 4.1 Constructs, Number of Items, Scale and Sources.....	23
Table 5.1. Socio-Demographic Characteristics of the Sample.....	26
Table 5.2 Constructs Average Mean, STD and Skewness.....	31
Table 5.3 Cronbach's Alpha.....	33
Table 5.4 KMO and Barlett's Test of Sphericity.....	33
Table 5.5 Multiple Linear Regression Model Summary.....	34
Table 5.6 Multiple Linear Regression Anova Test.....	35
Table 5.7 Multiple Linear Regression Coefficients.....	36
Table 5.8 Simple Linear Regression Model Summary Purchasing Decision.....	36
Table 5.9 Simple Linear Regression Anova Test Purchasing Decision.....	37
Table 5.10 Simple Linear Regression Coefficients Purchasing Decision.....	37
Table 5.11 Simple Linear Regression Model Summary Consumer Loyalty.....	38
Table 5.12 Anova Test Consumer Loyalty.....	38
Table 5.13 Simple Linear Regression Coefficients Consumer Loyalty.....	39

Glossary of Acronyms

AI - Artificial Intelligence

CRS - Conversational Recommendation System.

CV - Computer Vision

DL - Deep Learning

H - Hypothesis

KMO - Kaiser-Meyer-Olkin

LLM - Large Language Model

M - Mean

ML - Machine Learning.

NLP - Natural Language Processing

SD - Standard Deviation

Chapter 1. Introduction

1.1. Contextualisation and Relevance

E-commerce has changed the retail experience for consumers, enabling them to access a global audience without reliance on physical retail space. Online stores have become the virtual marketplaces, fostering innovation and competition (Raji et al., 2024). This shift is reflected in the online fashion industry, with the number of online shops having increased significantly in recent years (Zaman et al., 2025). In 2024, the online fashion industry reached a market valuation of 781.5 billion U.S. dollars and is estimated to reach valuation well over 1.6 trillion U.S. dollars in 2030 (Statista, 2025).

Moreover, consumer's expectations have evolved significantly with the capabilities of e-commerce shops. In the early years of online shopping, consumers were primarily motivated by the convenience of shopping from home, but now, the modern consumer requires more than a mere transactional process, they seek experiences that are engaging, seamless and personalised (Raji et al., 2024). According to Zed et al. (2024), there is a growing emphasis among consumers towards personalised experiences, with over 70% of them expecting some level of personalisation when interacting with a business. Consequently, failing to meet the consumer's expectations can negatively impact the business relevance, encouraging consumers to switch to a competitor that could better fulfill their needs for personalisation. In addition, the competitive landscape of the online fashion industry further amplifies the importance of offering personalised experiences, with consumers always on the lookout for novel and captivating trends (Zaman et al., 2025).

Within personalisation, Artificial Intelligence (AI) is one of the transformative technologies in providing personalised consumer experiences to consumers. Through leveraging machine learning algorithms and predictive analytics AI can analyse vast amounts of consumer data to offer personalised content instantly to consumers, thereby increasing the engagement of consumers which leads to improving consumer loyalty (Ahmed et al., 2025). The most famous example of AI personalisation in online retail is recommendation systems that offer personalised recommendations that match the consumer's preferences (Gopal et al., 2022). Personalised recommendations are set to positively influence consumers purchasing by streamlining the decision-making process among consumers (Raji et al., 2024). As a result, the experience becomes more engaging which results in the consumer fostering a stronger

connection with the business (Zed et al., 2024).

A recent development within AI personalisation is conversational recommendation systems (CRS). These systems, such as chatbots and virtual assistants, leverage machine learning algorithms and advanced Natural Language Processing (NLP) to converse with users to offer personalised services and recommendations (Al-Amin et al., 2024). CRS are 24/7 available and offer relevant and proactive recommendations and product advice to consumers (Singh et al., 2024). In 2025, these systems are set to play a major role in the online fashion industry, with fashion brands such as Zalando and Alibaba investing in them to offer a one-stop shopping experience for product discovery, which provides real-time personalised recommendations and seamless search to fashion consumers (Balchandani et al., 2024).

1.2. Research Problem and Objectives

Conversational systems have existed in e-commerce for a decent time. However, conversational commerce experiencing a void in e-commerce, falling between early adopters and early majority (Sidlauskiene et al., 2023). Prior research has primarily focused on conversational systems in customer service, with limited studies investigating the capabilities of CRS that can assist and sell tailored products to online consumers (Ahmed et al., 2025; Sidlauskiene et al., 2023).

It was not until 2024 that studies began to explore the effects of conversational AI's influence on consumer behaviour and decision-making processes (Bouhlal & Belahcen, 2025). In addition, several studies have indicated some sort of pushback from the consumer side with consumers preferring to interact with human sales people rather than a computer program (Sidlauskiene et al., 2023). Consumers may not trust personalised product recommendations from CRS, since a large amount of personalised data is utilized to respond to their requests (Singh et al., 2024). With these systems using consumer data to offer personalised recommendations to consumers, as such raising privacy concerns among consumers regarding how their personal data is collected, stored and utilised (Agbanu et al., 2024). Ultimately raising the question of whether CRS can positively influence fashion consumer decision-making processes.

Finally, factors that influence consumers' adoption towards CRS are relatively unexplored, with most studies focusing on individual aspects and not providing a comprehensive model that highlights consumers' adoption. (Singh et al., 2024). Hence, a comprehensive model must be

developed that offers a holistic view of factors influencing online fashion consumers' adoption of CRS.

As such, this dissertation aims to address these research gaps through offering a comprehensive model which demonstrates factors influencing online fashion consumers intention to adopt CRS in their online shopping journey, and observe the downstream influence of consumer adoption, in particular, its influence on the online fashion consumer purchasing decisions and consumer loyalty. Therefore, the following research objectives were identified:

RQ1: What factors influence online fashion consumers to adopt conversational recommendation systems?

RQ2: Do conversational recommendation systems positively influence purchasing decisions and consumer loyalty among online fashion consumers?

1.3. Dissertation Structure

This dissertation is composed of several chapters that delve into the various aspects of the research objectives. First, an introduction is given in which the contextualisation and relevance, research problem, objectives, and structure of the research are provided. The section consists of a literature review, which offers a comprehensive analysis of key concepts, theories, and frameworks that lay the foundation for the conceptual model and proposed hypotheses. Following the conceptual model, the research methodology outlines the research design, construction of the empirical research, and data procedure. Afterwards, a result analysis is provided that discusses the findings from the quantitative research and the theoretical and managerial implications. Finally, the conclusions summarises the main findings of the study, while also discussing the limitations of the study.

Chapter 2. Literature Review

2.1. Artificial Intelligence and Personalised Recommendation Systems

2.1.1. Defining Artificial Intelligence

Turing (1950) proposed a thought experiment to test whether a computer could think and act like a human person. The test is carried out by a human interrogator who engages in a conversation with a human and a machine behind a screen. If the human interrogator could not reliably tell which one is human and which one is the machine, the machine won the test. The Turing Test is seen as one of the earlier attempts of evaluating machine intelligence, which is a challenge that occupies scholars to this day (Al-Amin et al., 2024).

In general, there is no accepted definition of AI among scholars (Sheikh et al., 2023). Historically speaking, researchers have categorised AI in different dimensions, with some scholars referring it to the dimension of human performance, whereas others other scholars categorised it to a rational dimension, this is reference to doing the right thing (Russell & Norvig, 2021). From these two dimensions Russell and Norvig (2021) defines the concept of AI. The first dimension emphasise human-like intelligence, highlighting the AI capabilities of thinking and acting like a human. The second dimension refers to rationality, referring to AI's ability to think and act rationally, choosing the optimal outcome with the data available. A more practical definition of AI is provided by Kaplan and Haenlein (2019), who defines AI as the system's ability to analyse data correctly, learn from the data, and apply the findings to achieve specific goals. For clarity and objective sake, this study follows the explanation of Kaplan and Haenlein (2019).

2.1.1.1. Artificial Intelligence Components

AI embraces intelligent technologies at its core, allowing it to emulate human intelligence (Song et al., 2019). AI encompasses a large set of algorithms and models, with advancements in machine learning (ML), deep learning (DL), natural language processing (NLP), and computer vision (CV), allowing AI systems to perceive the environment, analyse and predict information, make rational predictions, and self-develop (Da Silva et al., 2022). ML is a subcategory of AI that involves a set of computer algorithms that, through statistical tools, learn from training data

to capture difficult patterns in data. Moreover, ML algorithms are designed to learn independently with little to no input from human experts (Fedorko et al., 2022; Kaplan & Haenlein, 2019). DL is considered a subdivision of ML, which uses an artificial neural network inspired by the human neural network (Fedorko et al., 2022). DL allows for new information to be decoded in real time (Da Silva et al., 2022). Moreover, it allows machines to comprehend information in various formats, such as text, images, videos, and audio (Al-Amin et al., 2024). The application of ML and DL encompasses NLP and CV, which allows for the system to process, understand, and analyse speech and imagery information (Da Silva et al., 2022). In particular, NLP allows the system to comprehend, process, and respond to human language, which is often observed in conversational AI systems such as chatbots and virtual assistants (Al-Amin et al., 2024; Song et al., 2019). Whereas, CV allows for the system to interpret and process visual data from the world through the use of DL algorithms (Da Silva et al., 2022). Allowing for visual search, in which a consumer can upload an image, which is then recognised by the system and displayed in the search results (Fedorko et al., 2022).

Ultimately, the development of ML, DL, NLP, and CV have led to development of intelligent personalised systems, such as conversational and recommendation systems that encompass AI

2.1.2. AI Personalisation

Given the advancements of AI, businesses now have unprecedented information about consumer behaviour and preferences; this precedence offers online retailers the opportunity to offer marketing methods that are tailored to individual consumers (Zed et al., 2024). AI personalisation refers to using advanced algorithms and ML techniques that analyse vast amounts of data, such as consumer behaviour, preferences and interactions, to predict and offer personalised content tailored to the individual consumer (Raji et al., 2024). At its core, personalisation seeks to establish a deep and meaningful interactions between the consumers. This approach differs from the traditional approach of classifying consumers solely on their demographic characteristics such as their age, gender and location. Instead, it recognises the diversity among consumers and aims to cater to the consumers' individual preferences and needs (Vashishth et al., 2024). Research in cognitive psychology suggests that the effectiveness of personalisation is rooted in the principle of self-reference, this suggest that when information is personally relevant to consumers, they tend to recall more information easier and more

accurately (Aksoy et al., 2021). Personalisation seeks to tailor consumer experiences based on the consumer's personal preferences. This process involves creating a unique digital path for consumers in which recommendations, search results and marketing messages are personalised to match the consumer's taste, behaviour and desire. Thus, simplifying the shopping journey and making it more efficient and enjoyable for the consumers (Choudhary et al., 2023). Resulting in consumer experiences become more engaging and intuitive, therefore, fostering a stronger relationship between consumers and brands (Zed et al., 2024).

2.1.3. Evolution towards Conversational Recommendation Systems

One of the most significant contributions of AI to online shopping is personalised recommendation systems (Raji et al., 2024). These systems have a long history with online shopping. In 1994, Amazon began recommending the most purchased products to consumers through the use of algorithms (Gopal, 2022). However, back then, these systems were limited in their capabilities to understand consumer preferences and needs. The pivotal moment was the inclusion of AI and ML algorithms which allowed recommendation systems to analyse vast amounts of consumer data, learn from patterns in consumer data, which resulted in more personalised recommendations (Choudhary et al., 2023).

The mechanics of personalised recommendations are sophisticated and diverse (Raji et al., 2024). However, recommendation systems typically employ one of three recommendation techniques to provide recommendations, which are collaborative filtering, content-based filtering, and Hybrid filtering (Yassine et al., 2020). With collaborative filtering, the recommendation system build a user-item matrix with preferences, then it matches users with similar interests and preferences, this is referred to as a neighbourhood. Consumers get recommendations based on items he or she never rated, based on positive ratings from users in his or her neighbourhood (Isinkaye et al., 2015). However, a concern associated with collaborative filtering are cold-start problems, which occurs when the recommendation systems cannot recommend products to new users, as they have no ratings (Choudhary et al., 2023; Isinkaye et al., 2015). Content-based filtering emphasises products based on their attributes (e.g., colour, material, style) and examines items the user has previously evaluated (Isinkaye et al., 2015). It determines the user's favourite aspect of an item and recommends the most similar products (Mehta et al., 2022). However, it could limit certain products if the user never consumed a product with a particular set of keywords (Aggarwal, 2016). This is referred to the

filter bubble effect (Choudhary et al., 2023). Finally, hybrid filtering combines both collaborative and content-based filtering algorithms to optimize performance and reduce setbacks (Yassine et al., 2020). However, it is more complex and expensive to build and requires high-quality data that must be sufficient for it to succeed (Salunke & Nichite, 2022).

Although traditional recommendation systems have demonstrated great success, they are unable to capture the current user's preferences. They operate statically, meaning that recommendations are estimated based on past consumer behaviour data and preferences, which prevents it from capturing real-time preferences of consumers (Lei et al., 2020). Conversational recommendation systems (CRS) are a recent evolution that offers an interactive process by engaging in conversation with consumers through NLP to elicit information needed to offer personalised recommendations, product question and consumer support (Lei et al., 2020; Tsagkias et al., 2020).

CRS focus on capturing consumers preferences from conversational context to offer recommendations, moreover, these systems provide answers from consumer questions, such as why this item was recommended (Feng et al., 2023). These systems further enhance the consumer experience in online shopping, with them engaging in complex conversations, understand the situation provide personalised interactions and guide consumers through their shopping journey, improving not only consumer engagement but also leading to higher conversions. (Raji et al., 2024). Recent advancements in Large Language Models (LLM) have allowed for even more powerful CRS, allowing them to perceive, reason, and act (Feng et al., 2023). LLM are considered a subcategory of AI that specializes in generating text or answering questions with text-based responses, they can be trained through a corpus of text, which includes databases, books, and online sources (Corchado et al., 2023). A famous example is Zalando's CRS, which is powered by the LLM ChatGPT, in which consumers can inquire about product recommendations and receive in-real time recommendations (Balchandani et al., 2024).

However, pre-training an LLM requires a significant investment; with popular LLM ChatGPT-3 costing five million dollars alone in computational power (Corchado et al., 2023). Moreover, the effectiveness of personalisation is dependent on the data quality, as businesses continually need to update and analyse consumer data for the AI to make relevant and accurate decisions, which is considered a research-intensive process and requires a substantial investment (Ma, 2023).

2.2.The Influence of Conversational Recommendation Systems on the Online Fashion Consumer Journey

2.2.1. The Online Consumer Journey

According to Gentile et al. (2007), a consumer experience is a set of interactions between a consumer and a product, business, or part of an organization, and the value that the consumer experiences through that set of interactions. Lemon and Verhoef (2016) conceptualize the total consumer experiences as a consumer journey that flows from the prepurchase to purchase to post purchase stage. In each stage the consumer experience touchpoints and incorporates previous experiences. However, with the explosive rise of consumer touchpoints, businesses struggle to manage and control the experience and journey of their consumers (Lemon & Verhoef, 2016; Kaur et al., 2021). Focusing on all possible touchpoints should be avoided since consumers do not experience similar touchpoints and do not assign them equally. Therefore, companies should focus on critical and high-impact touchpoints that resonate the most with their target audience (Rosenbaum et al., 2017).

One way to improve consumer touchpoints is to integrate AI personalisation in the online fashion consumer journey. AI personalisation has changed the landscape of consumer experiences, AI personalisation can be integrated into the pre-purchase, purchasing, and post-purchasing phases, and companies utilizing AI-enabled personalization can create a competitive edge by offering personalised services (Hongfei & Youjiang, 2022; Zaman et al., 2025). Moreover, consumers perceives conversational systems and recommendation as highly valuable tools throughout their consumer journey (Da Silva et al., 2022).

2.2.2. Conversational Recommendation Systems in the Pre-Purchase Stage

The pre-purchase stage highlights all the interactions a consumer conducts before deciding to purchase (Lemon & Verhoef, 2016; Rosenbaum et al., 2017). This phase highlights the consumer's desire/need/impulsive recognition of the consideration of satisfying this goal (Honka et al., 2023). One important consumer touchpoint in the pre-purchase stage for the online fashion industry is product discovery.

Product discovery is performed through the use of searches and recommendations to gather information. The goal is to recreate consumer in-store interactions and experiences that

ultimately lead to purchasing (Tsagkias et al., 2020). In the online fashion industry, 80% of consumers express dissatisfaction with the online search experience, resulting in them abandoning the webshop. Moreover, 74% of fashion consumers walk away from purchasing due to the amount of choice (Balchandani et al., 2024). This phenomenon is referred to as decision paralysis, which occurs when a person experiences cognitive overload and fatigue when trying to decide on a single option, as the human brain cannot process information efficiently, resulting in a mental burden (Adriatico et al., 2022). Decision paralysis can postpone consumers from making decisions (Li & Kang, 2025). Limiting their buying options, as the increase in volume leads to extensive searching, resulting in consumers opting for a more satisfying price strategy (Sanchis et al., 2014).

Offering personalised recommendations and outfit suggestions that are relevant to the consumer can mitigate decision fatigue and simplify the decision-making process, encouraging consumers to complete purchases instead of delaying them or abandoning them (Agbanu et al., 2024; Choudhary et al., 2023; Li & Kang, 2025). In addition, these systems can provide cross-selling by recommending additional items with the original product, thereby persuading the consumer to purchase additional items (Da Silva et al., 2022; Vashishth et al., 2024). Furthermore, recommendations can positively influence new brand discovery in the pre-purchasing stage, as the unfamiliarity of brands may cause one to search for information. That said it could also restrict consumer autonomy by over-relying on algorithmic filtering, leading to a sense of over-curation (Hardcastle et al., 2025).

Another benefit of CRS is offering personalised styling advice to consumers, which can significantly improve the consumer-decision-making process by offering expert-level advice that aligns with the consumer's taste, and consumers are more likely to complete a purchase (Agbanu et al., 2024). This is particularly valuable in the online fashion where consumers face a broader selection of products and are often uncertain which product best fits them (Deldjoo et al., 2025). However, conversations derived from CRS are still not authentic when compared to human interactions, and elements such as trust and friendliness are incomparable to real-life interactions with a salesperson, which these systems can hardly recreate (Bouhlal & Belahcen, 2025; Ma, 2023). In addition, they are less effective in handling complex questions that require emotions intelligence when compared to human consumer service agents (Ma, 2023).

2.2.3. Conversational Recommendation Systems in the Purchase Stage

Once the consumer has decided on a product or service, they must still complete the purchase. There is often a time delay between the intention to purchase and the actual purchase. Therefore, enticing the consumer to pursue their purchase intention is valuable (Stankevich, 2017). In the purchasing stage, consumers act by making their choice, ordering, and paying. Moreover, the emotional experiences shaped in the pre-purchase stage and are closely linked to overall consumer satisfaction, positively influencing decision-making (Yeo et al., 2022). With prior consumer touchpoints, such as decision paralysis, choice overload, and purchase confidence, being relevant to consider, as these factors may hinder purchasing decisions (Lemon & Verhoef, 2016). With consumers that experienced decision paralysis are more likely to postpone or abandon purchasing decisions (Li & Kang, 2025).

Several studies proposes that personalised recommendations can streamline the decision-making process. According to Raji et al. (2024) consumers appreciate the convenience of finding product recommendations that match their taste, streamlining the decision-making process, as well as reducing the cognitive load of navigating the vast amount. Similarly, Li and Kang (2025) observed that Personalised recommendations can mitigate decision fatigue and purchase postponement. Agbanu et al. (2024) observed a significant relationship for consumers that received personalised recommendation and styling advice with purchasing decisions and consumers satisfaction. Furthermore, success stories have emerged, such as Zalando crediting an 18% year-on year increase on their profitability in the second quarter of 2024, largely due to the rollout of their CRS (Balchandani et al., 2024). Bouhlal and Belahcen (2025) offers a more nuanced opinion towards recommendations derived from CRS. While these systems leverage data driven strategies to offer personalised recommendations, it can also create doubt among consumers. For instance, receiving multiple product suggestions before the final purchase, can result in the consumer doubting their original choice, which could lead to hesitation or post-purchase remorse. In contrast, Li and Kang (2025), argue that although the abundance of personalised recommendations could be a criticized for potentially overwhelming consumers, its ability to offer personalised recommendations-based consumer preferences and purchase history is more effective in simplifying the decision-making process.

2.2.4. Conversational Recommendation Systems in the Post-Purchase Stage

In the final stage of the consumer journey, the post-purchase stage, encompasses all the consumer interactions with the business following the actual purchase (Lemon & Verhoef, 2016; Rosenbaum et al., 2017). Managerial research has included the loyalty loop in the post-purchase stage, suggesting that the post-purchase experiences can trigger a consumer to remain loyal or to restart their consumer journey with the brand, i.e., re-entering the pre-purchase stage (Lemon & Verhoef, 2016). Personalised retention is the process whereby companies apply AI to preserve the one-on-one relationship with the consumer and to trigger consumers to restart their consumer journey with their business (Hongfei & Youjiang, 2022).

Empirical research suggests that personalised experiences such as recommendations play a pivotal role in fostering consumer loyalty. Zed et al. (2024) observed in their regression analysis a positive and significant relationship between personalisation strategies such as recommendations with consumer loyalty, suggesting that personalised experiences leads to consumers feeling more appreciated and valued, resulting in an increase in engagement and attachment towards the company, encouraging consumers to repurchase and foster loyalty. Similarly, Raji et al. (2024) claims that personalised experiences such as recommendations develop a stronger connection among consumers towards a business, thereby increasing the likelihood of repurchasing and loyalty.

Another critical touchpoint in the post-purchase stage is offering customer service (Hongfei & Youjiang, 2022). Offering customer service is as important as the quality of the e-commerce website. Customers feel businesses are trying to hide something from them when not offered (Katawetawaraks & Wang, 2013). In e-commerce, conversational systems such as chatbots have been applied for customer support (Da Silva et al., 2022). As these systems effectively interpreting and responding to consumers' questions and recommend products to assist with transactions (Johnpaul et al., 2024).

2.3.Factors Influencing Consumers Adoption of Conversational Recommendation Systems

Since the development of technologies, researchers have been applying different theories to consumer adoption. The Technology Adoption Model (TAM) introduced by Davis (1989) builds upon the Theory of Reasoned Action (Fishbein & Ajzen, 1975) and the Theory of

Planned Behaviour (Ajzen, 1991). This framework is a widely adopted to explain consumer acceptance and technological adoption. Moreover, it is robust and has been employed to explain this phenomenon in various regions, as well as in different technological domains, such as social media, online courses, and e-learning (Dahri et al., 2024).

In the TAM, Davis (1989) proposed two central constructs, which are perceived usefulness and perceived ease of use. These two factors shape a person's attitude toward using the technology which then influences the behavioural intention of using the system, with behavioural intention considered a strong predictor of actual system use (Davis, 1989). The perceived usefulness considers whether the information technology will enable users to perform their jobs more effectively. A system with a high perceived usefulness is a positive use-performance relationship for a user, perceiving the technology as helpful in achieving their objective. Whereas, the perceived ease of use is the personal subjective degree of effort required for a consumer to use the technology.

However, the role of attitude being included is an open discussion among scholars. Even in the original study by Davis (1989), attitude does not fully mediate the effect of the two central constructs on the behavioural intention; notably, the perceived usefulness directly influenced the behavioural intention. Furthermore, in the later model TAM 2, the inclusion of attitude was removed; as the paper highlighted that empirical tests of two central constructs directly influenced behavioural intention towards adopting new technology (Venkatesh & Davis, 2000).

While the original TAM focused on two constructs shaping the behavioural intention subsequent research has modified the TAM to include additional constructs that influence technology adoption. Van Der Heijden (2004) researched consumers acceptance towards pleasure-oriented and productivity-oriented information systems. The author extended the TAM by introducing the construct of perceived enjoyment, which describes the extent to which an activity of using an information system brings enjoyment to the user regardless of performance consequences. Through a cross-sectional survey, the scholar observed that perceived enjoyment and the perceived ease of use were significant predictors of behavioural intention of adopting hedonic information systems, rather than the perceived usefulness of a hedonic system. Hence, why the author theorises that the system's purpose plays a major role in adoption, arguing that a hedonic system prioritise different values of adoption than a utilitarian system

In the context of studies investigated factors influencing the behavioural intention of adopting CRS. Azman et al. (2025) observed that the perceived usefulness of CRS simplifies

the decision-making process and enhances consumers' ability to perform tasks, effectively leading to an increased likelihood of adoption. Likewise, the perceived ease of use such as being user-friendly and intuitive to use, resulted in a higher probability of adoption.

Rese et al. (2020) investigated consumers' adoption of Zalando's conversational system Emma in the pre-purchase stage. The study's empirical results showed that the perceived usefulness and perceived enjoyment were significant factors of user adoption, with perceived usefulness as the most significant factor. In contrast, the perceived ease of use of Emma was determinant to be an insignificant factor of adoption, as according to the authors, was factored with participants perceiving the system to be easy to use, resulting in them putting more importance towards other factors. Furthermore, the study observed a significant negative link between privacy concerns and behavioural intention, negatively impacting consumers' acceptance and usage frequency.

Similarly, Singh et al. (2024) observed that privacy concerns negatively influenced acceptance of online fashion assistants. Conversely, Vimalkumar et al. (2021) observed through a structural equation modelling analysis that privacy concerns had an insignificant effect on the behavioural intention of adopting voice-based digital assistants. However, after a post-hoc analysis, it was observed that the system's perceived performance moderates the relationship between privacy concerns and behavioural intention. High-performance systems observed an insignificant relationship, conversely a low-performance system expectancy resulted in privacy concerns to negatively impact behavioural intention.

2.4.Ethical and Privacy Concerns

The nature of AI personalisation relies on using personalised data, while this improves recommendations, it is dependent on the consumers' willingness to share their personal information, with consumers becoming more aware of their personal data, prompting privacy concerns regarding their personal data being collected, stored, and used by businesses (Raji et al., 2024). This conundrum between balancing personalisation with privacy is referred to as the personalisation-privacy paradox. It emphasises the consumers' desire for personalisation, paralleling their own concerns regarding sharing their personal information (Awad & Krishnan, 2006). There is a trade-off between the value of personalisation and the price of privacy that consumers pay for in this dilemma, in which the consumer is the deciding factor (Aguirre et al., 2014). However, the severity of privacy concerns varies as consumers have different

perceptions of privacy concerns (Laufer & Wolfe, 1977). Positive cognitive appraisals, such as the design and functionality, as well as emotions such as enjoyment, can reduce privacy concerns. For instance, consumers with high privacy concerns are more likely to disclose their personal information when they find entertainment when interacting with the webshop; moreover, the first impression of the cognitive aspects of the website has a big influence on whether the consumers decide to pursue shopping on an unfamiliar website (Li et al., 2017). Furthermore, brands that highlight transparency about data usage and robust privacy concerns principles often showcase higher consumer loyalty, as they showcase how to handle this paradox effectively (Zed et al., 2024). Ultimately, companies that employ AI personalisation must strike a balance between personalisation and privacy concerns, ensuring that data is stored and applied ethically by companies (Ma, 2023).

Another persistent challenge with AI personalisation, in particular with recommendation systems, are algorithmic biases (Raji et al., 2024). AI algorithms learn from historical data, which in turn can result in biased recommendations, it may be unable to distinguish specific attributes that create biases (Davenport et al., 2019). This can result in disproportioning certain demographics. For instance, the AI may offer higher priced product recommendations, based on gender, age and socioeconomic characteristics (Raji et al., 2024).

Finally, privacy concerns extend beyond consumers' concerns. In the early 2010s, discussions about digitalization and concerns regarding sensitive data and privacy, resulted in the European Union designing the General Data Protection Regulation, to improve the protection of personal data (Sheikh et al., 2023). In August 2024, the European Commission's AI ACT was published, laying out the binding regulation categories of AI on their risk levels, including general-purpose AI systems, such as chatbots and generative models, being required to inform consumers they are interacting with a machine as well as labelling AI-generated content. This regulation was designed to address systemic risk and ensure that AI technologies comply with ethical and consumer protection standards (European Commission, 2024).

Chapter 3. Conceptual Framework and Hypotheses

3.1. Conceptual Framework

A conceptual framework is a network of interlinked concepts and ideas that together allow for a comprehensive understanding of a theory or phenomenon (Jabareen, 2009). The aim of this study is to provide a holistic view of online fashion consumers' adoption of CRS and the downstream influences of online fashion consumers' adoption on the purchasing decisions and consumer loyalty. The conceptual framework (see, Figure 3.1) encompasses these elements and provides a visual representation of it. The model draws inspiration from the TAM proposed by Davis (1989), which is framework that explain consumers accepting and using technology, based on the factors of the Perceived Usefulness, and Perceived Ease of Use, and extends it with the inclusion of Perceived Enjoyment and Perceived Privacy Concerns, with studies supporting their significancy in shaping consumers' Behavioural Intention of adopting CRS (Rese et al., 2020; Singh et al., 2024; Vimalkumar et al., 2021). Moreover, the conceptual model depicts the intention of adopting CRS directly with Purchasing Decisions, suggesting that adoption results in facilitating positive Purchasing Decisions, which in turn leads to Consumer Loyalty.

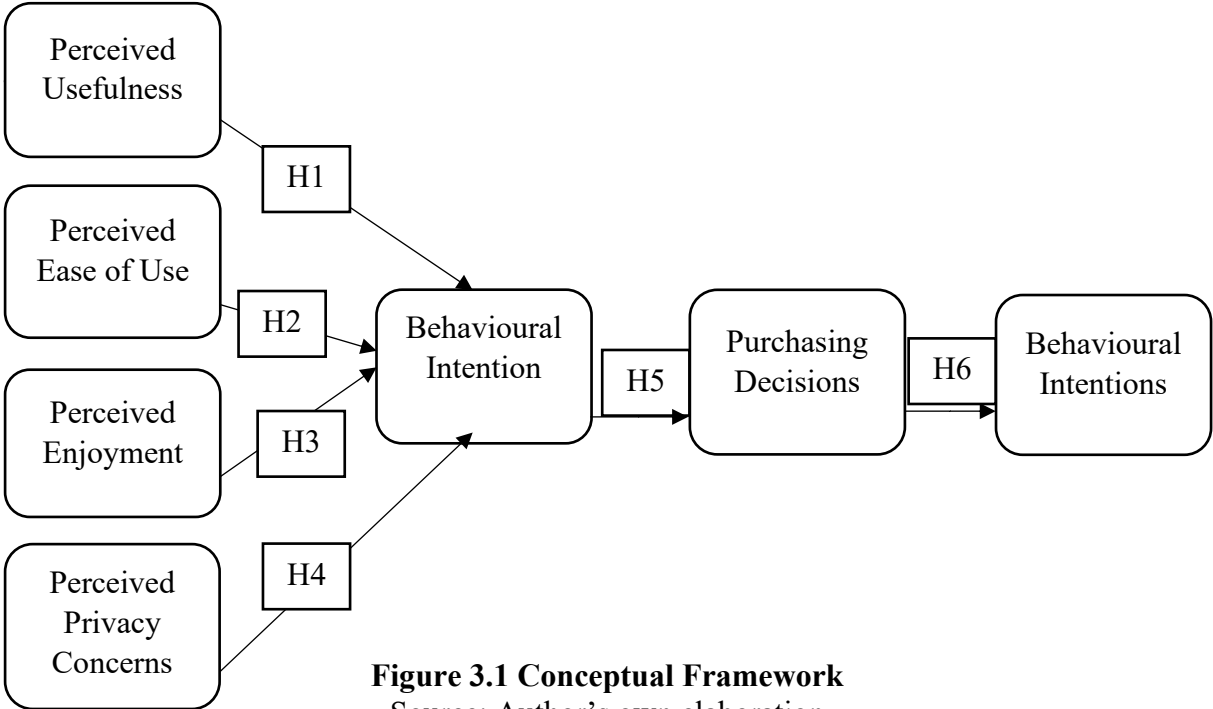


Figure 3.1 Conceptual Framework
Source: Author's own elaboration

3.2. Hypotheses Formulation

3.1.1. Perceived Usefulness and Behavioural Intention

Perceived usefulness refers to the degree in which the technology allows the user to perform their job better (Davis, 1989). In the original TAM, the PU of a system was a positive and significant determinant of Behavioural Intention of usage (Davis, 1989). Similarly, several studies have demonstrated that this construct positively influences the Behavioural Intention of adopting CRS (Azman et al., 2025; Rese et al., 2020; Singh et al., 2024). Suggesting the more useful a CRS is perceived among online fashion consumers, the likelihood of Behavioural Intention to adopt CRS increases. Hence the following hypothesis proposed:

H1: The Perceived Usefulness of conversational recommendation systems positively influence online fashion consumers' Behavioural Intention to adopt.

3.1.2. Perceived Ease of Use and Behavioural Intention

Perceived Ease of Use is the personal subjective degree that using a particular technology would be free of effort (Davis, 1989). The Perceived Ease of Use is an assessment of the amount of mental effort it requires in order to use a system (Van der Heijden, 2004). Previous literature observed inconsistencies regarding its impact on user adoption. Several authors observed Perceived Ease of Use characteristics such user friendliness and intuitive to use, having a positive influence on the Behavioural Intention (Azman et al., 2025; Singh et al., 2024). Conversely, other studies observed the construct to be less influential (Davis, 1989) or to be an insignificant factor of Behavioural Intention (Rese et al., 2020). In this study, the aim is to further investigate its influence on consumer's adoption of CRS. Therefore, the following hypothesis is proposed:

H2: The Perceived Ease of Use of conversational recommendation systems positively influence online fashion consumers' Behavioural Intention to adopt.

3.1.3. Perceived Enjoyment and Behavioural Intention

Perceived Enjoyment is considered an intrinsic motivation that affects the users' perceived attitude and behaviour (Van der Heijden, 2004). Prior studies demonstrated that the construct

significant predicts the Behavioural Intention of using CRS. Singh et al. (2024) observed the construct to be a positive and strong determinant of Behavioural Intention of using conversational shopping assistants. Likewise, Rese et al. (2020) observed hedonic factors such as enjoyment to increase the acceptance of Zalando's CRS. Similarly, Vimalkumar et al. (2021) observed hedonic motivations to be the most significant factor of Behavioural Intention. These observations indicate that CRS that are perceived to be enjoyable, will increase in the likelihood of consumers adopting them. Therefore, the following hypothesis is proposed:

H3: The Perceived Enjoyment of conversational recommendation systems positively influence online fashion consumers' Behavioural Intention to adopt.

3.1.4. Perceived Privacy Concerns and Behavioural Intention

The effectiveness of personalised recommendation systems is dependent on accessing personal information to offer personalised recommendations (Agbanu et al., 2024; Raji et al., 2024), with consumers' demand for personalised recommendations paralleling their own privacy concerns (Awad & Krishnan, 2006). Therefore, striking a balance between offering personalised content and protecting consumer privacy is vital, avoiding situations where consumers feel uncomfortable or watched (Vashishth et al., 2024). Moreover, most prior literature underscore the negative influences of Perceived Privacy Concerns on the Behavioural Intention of adopting CRS (Rese et al., 2020; Singh et al., 2024). However, according to Vimalkumar et al. (2021), this construct was an insignificant, factoring in the system's performance perception moderating privacy concerns. For this study, the aim is to observe whether privacy concerns negatively influence online fashion consumers' intention of adopting CRS. Hence, the following hypotheses is proposed:

H4: Perceived Privacy Concerns of conversational recommendation systems negatively influence online fashion consumers' Behavioural Intention to adopt.

3.1.5. Behavioural Intention and Purchasing Decision

Behavioural Intention is one of the most significant factors that leads to consumers' adoption and usage (Davis, 1989). Several studies observed that CRS can enhance Purchasing Decisions among fashion consumers. Li and Kang (2025) observed that personalised recommendations can reduce decision fatigue and purchase deferment among consumers. Agbanu et al. (2024)

observed a significant relationship among consumers that received personalised recommendations and styling advice with Purchasing Decisions. Brooklyn et al. (2024) suggested that personalised product recommendations significantly increase the likelihood of purchasing. Collectively, these findings suggest that the Behavioural Intention of adopting CRS can play a positive and significant influence in improving consumers' Purchasing Decisions. Therefore, the following hypothesis is proposed:

H5: The online fashion Consumers' Behavioural Intention to adopt conversational recommendation systems positively influences their Purchasing Decisions.

3.1.6. Purchasing Decision and Consumer Loyalty

The post-purchase phase is all the consumers' interactions with the business following the actual purchase (Lemon & Verhoef, 2016; Rosenbaum et al., 2017). Managerial research has included the loyalty loop in this phase, in which a trigger can occur, resulting in consumer loyalty or consumers restarting their consumer journey (Lemon & Verhoef, 2016). Personalized strategies such as personalised recommendations strongly resonate with consumers, with consumers feeling appreciated and valued, resulting in a stronger brand connection and repurchasing intention (Zed et al., 2024). Moreover, AI personalised experiences create a more memorable and unique brand experience for consumers by constantly delivering personalised and relevant experiences, encouraging consumers to develop a stronger connection with the businesses (Raji et al., 2024). In addition, the continuous learning capabilities of machine learning algorithms allow for recommendations to adapt with the consumer's preferences evolving (Raji et al., 2024). This is beneficial as consumers repeatedly receiving spot-on recommendations build a stronger loyalty towards the businesses (Vashishth et al., 2024). Therefore, the following hypothesis suggests the following:

H6: Purchasing Decisions derived from conversational recommendation systems positively influence online fashion Consumer Loyalty.

Chapter 4. Research Methodology

A research methodology is a blueprint that outlines the strategy, reasoning, processes, and application of methods to achieve the desired outcome, encompassing both data collection and data analysis (Given et al., 2023). This chapter outlines the research methodology of the study.

4.1. Research Design

Research designs can be classified into two types based on the type of data collection: qualitative and quantitative research (Thomas, 2021). This study employs a quantitative research design, which involves numerical representation and the manipulation of observations, testing hypotheses, producing empirically validated predictions, and establishing cause-and-effect relationships between constructs (Sukamolson, 2007; Thomas, 2021; Lim, 2024). Moreover, it is deductive, in which established theories, constructs and hypotheses have been established and evidence is gathered to support or refute the hypotheses (Thomas, 2021).

Regarding data collection, a survey-based approach was chosen as its primary data collection method, in which data is collected first hand from the original source (Thomas, 2021). Surveys allow for observing and analyzing data collected from a sample of individuals' responses to questions (Ponto, 2015). Surveys can be categorised into three different categories: attitude surveys, questionnaires, and interviews (Thomas, 2021). Among these, a self-administered online questionnaire was selected and created on Qualtrics, which is an online platform that allows for the creation, distribution and analysis of questionnaires.

Questionnaire designs can be defined in temporal terms, in particular in two ways: cross-sectional or longitudinal design. In a cross-sectional design variables and relationships are captured at a single point in time. Whereas, a longitudinal design captures variables and relationships over time, which offers a more nuanced context into casual relationships, but require more time-investment and are subject to participant attrition and missing data (Lim, 2024). Given the time requirement given to carry out a cross-sectional study it was decided to forgo a longitudinal design and instead opt for a cross-sectional study.

Sampling serves as a critical component in the research design (Ahmed, 2024; Lim, 2024). Sampling involves selecting a subset of individuals from the total population to make generalizations (Ahmed, 2024). For this study, the target population consisted of individuals

aged 18 or older that had prior online fashion shopping experience. There were no limitations regarding the nationality of the participants, since online fashion retail is a global industry and the central focus of the research was on consumer behaviour and attitudes.

The sampling approach for this present study was a non-random convenience sampling method, in which individuals were selected based on their availability and willingness to partake in the study (Lim, 2024).

4.2. Questionnaire Construction

To collect data for this present study a questionnaire was deployed on Qualtrics, which is an online platform that allows for the creation, distribution and analysis of surveys. The questionnaire consisted of 23 questions which were written in English and were mandatory to be completed. The formulation of the questions were inspired from literature studies conducted in the literature review and questionnaires previously published by other scholars that reflect the study's research objective. Table 4.1 offers further insight into the construction of the core constructs.

The questionnaire was composed into two sections with both open and closed questions. Most closed questions applied a five-point Likert scale and were easily coded and provided subsequent analysis for casual relationships among constructs. Open questions were few and primarily explorative. A full overview of the questionnaire is provided in Appendix A.

The first section of the questionnaire focused on the sample characterisation, which included socio-demographic characteristics, online shopping behaviour, and opinions towards traditional recommendation systems. It began with an introduction of the research topic, purpose of the study, and requesting the participants' consent to participate in the study. Following the introduction of the questionnaire, the first set of questions focused on the participant's sociodemographic characteristics, such as age, educational background, and nationality. Afterwards, questions focused on participants' online fashion shopping behaviour, such as shopping frequency and factors that influence and hinder online shopping. Finally, participants were introduced to static traditional recommendation systems in the online fashion industry, where they were asked to assess the helpfulness of prompt recommendations, such as you may also like this product, how frequently they purchase products that were recommended, and the challenges they encountered with recommendation systems.

The second part of the questionnaire focused on the core constructs and proposed

hypotheses highlighted in Chapter 2. First, a brief introduction was given on how CRS operates in the online fashion industry. Afterwards, each of the constructs depicted in the conceptual model were measured through a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). In addition to Likert scale questions, a few explorative questions were asked. A ranking question was deployed in which participants ranked the importance of the Perceived Usefulness, Perceived Easy of Use, Perceived Enjoyment, and Perceived Privacy Concerns, when using a conversational recommendation system, with "1 = most important" to "4 = least important", and an open-ended question in which participants were asked to give their opinion towards what feature or functionality would make a CRS satisfying to use.

Table 4.1 Constructs, Number of Items, Scale and Sources

Construct	Number of Items	Scale	Adapted from
Perceived Usefulness	7	5-point Likert Scale	Azman et al., 2024; Davis, 1989; Rese et al., 2020; Singh et al., 2024
Perceived Ease of Use	5	5-point Likert Scale	Azman et al., 2024; Davis, 1989; Rese et al., 2020; Singh et al., 2024
Perceived Enjoyment	5	5-point Likert Scale	Van Der Heijden, 2004; Rese et al., 2020; Singh et al., 2024; Vimalkumar et al., 2021
Perceived Privacy Concerns	6	5-point Likert Scale	Agbanu et al., 2024; Awad & Krishnan, 2006; Raji et al., 2024; Rese et al., 2020; Singh et al., 2024; Vashishth et al., 2024; Vimalkumar et al., 2021
Behavioural Intention	5	5-point Likert Scale	Davis 1989; Venkatesh & Davis 2000
Purchasing Decisions	5	5-point Likert Scale	Agbanu et al., 2024; Brooklyn et al., 2024; Li & Kang, 2025; Sukharevsky et al., 2024
Consumer Loyalty	4	5-point Likert Scale	Lemon & Verhoef, 2016; Raji et al., 2024; Rosenbaum et al., 2017; Vashishth et al., 2024; Zed et al., 2024

Source: Author's own elaboration

4.3. Data Procedure

The questionnaire launched on April 2025 and remained open until June 14, 2025. Participants were reached out to through several social media platforms, ranging from WhatsApp, Facebook, LinkedIn and Outlook. In addition, the questionnaire was promoted on the platform

Poll-poll, which is a distribution platform for surveys. After closing the questionnaire the sample size consisted of 379 responses. Regarding the data processing, the following responses were removed from the analysis: (1) participants that did not consent to participate, (2) participants that did not finish the questionnaire, (3) participants that filled in incomplete or blank answers, (4) participants that were under the age of 18, (5) participants that did not have online shopping experience. After conducting a two-stage data screening test with the set criteria in Excel and Qualtrics' built-in filtering features, the final filtered sample size was 201 responses. This discrepancy between the initial sample size and the final sample size might be due to a design error in Qualtrics, as participants could abandon the survey at any time; however, it was still recorded in the total response count. The filtered dataset was converted into a SPSS file and analysed in IBM SPSS Statistics 29.

Chapter 5. Result and Discussion

Chapter four offers an analysis of the results derived from the questionnaire, which was primarily analysed through IBM SPSS 29 Statistics. The analysis begins with a characterisation of the sample's socio-demographic characteristics, online shopping behaviour, and views towards recommendation systems. A complete overview of the sample characterisation analysis is provided in Appendix B. Next is a descriptive analysis of the core constructs. Afterwards, the constructs' reliability and validity were analyzed. Then, an analysis of the hypotheses tested through regression is provided. Finally, this chapter discusses the results, the theoretical contribution, and the managerial implications.

5.1. Sample Characterisation

5.1.1. Socio-Demographic Characteristics

As for the socio-demographic attributes of the participants (see Table 5.1.). In relation to gender, most participants identified themselves as female (61.2%), followed by male (38.3%), and other (0.5%). In relation to age, most of the participants were between the ages of 18 and 25 (56.2%), followed by 25 and 35 (27.0%), 36 and 45 (10.4%), 46 and 55 (2.5%), and 56 and above (3.5%). Furthermore, the average age was 28 years, and the median age was 25 years, indicating that 50% of the participants were under the age of 25. With regard to nationality, the study recorded a very diverse population, with approximately 70 different nationalities. The most common nationality was from the Netherlands (15.4%), followed by Germany (10.0%) and Britain (7.0%). Given the diverse nationalities, participants' nationalities were categorized within continents. Most participants originate from Europe (67.7%), followed by Asia (18.9%), North America (7.0%), and Africa (4.0%). In addition, 2.5% identified as having mixed nationality. As for the educational level of the participants. Most participants held a bachelor's degree (44.8%), followed by a master's degree (27.4%), a high school diploma or equivalent (18.9%), a smaller degree held a doctorate or higher (3.5%), an associate degree (3.0%), and 2.5% held less than a high school diploma or equivalent.

Table 5.1. Socio-Demographic Characteristics of the Sample

Variable	Variable classification	Frequency	Percentage
Gender	Male	77	38.3%
	Female	123	61.2%
	Other	1	0.5%
Age	18-25	113	56.2%
	26-35	55	27.4%
	36-45	21	10.4%
	46-55	5	2.5%
	56+	7	3.5%
Regional	Europe	136	67.7%
Nationality	Asia	38	18.9%
	North America	14	7.0%
	Africa	8	4.0%
	Mixed Nationality	5	2.5%
Education	Less than high school	5	2.5%
	High school diploma	38	18.9%
	Associate's degree	6	3.0%
	Bachelor's degree	90	44.8%
	Master's degree	55	27.4%
	Doctorate's degree	7	3.5%

Source: IBM SPSS Statistics 29

5.1.2. Online Fashion Shopping Behaviour

As for the online fashion shopping frequency (see figure 5.2), approximately 51.2% of participants shopped monthly for clothes, 25.0% shopped at least once a year, 16.9% rarely shopped online, and a smaller section shopped weekly (5.0%), and 1.5% shopped daily. Importantly, participants who never shopped online were excluded from the analysis.

Following the online shopping frequency, participants were asked to rank factors that positively influence and hinder online fashion shopping through a 5-point Likert Scale ranging from (strongly disagree) to 5 (strongly agree). As seen in Figure 5.2. most statement were

received positively with mean scores ranging from 4.26 to 3.75 out of 5. With a wide range of clothing options (M = 4.26), convenience of online shopping (M = 4.20), and competitive pricing and discounts (M = 4.05) being the most important.

For factors hindering online fashion shopping among participants (see figure 5.3), the biggest critique was the uncertainty about sizing and fit (M = 3.93), which was further reinforced in an open question where most participants suggested that sizing was their biggest hindrance with online fashion shopping. Further results are provided in Appendix B. The second biggest critique was cart abandonment before purchasing (M = 3.75), purchase-decision-making (M = 3.66), overwhelmed of product options (M = 3.48), frustration with the online search experience (M = 3.26), and lastly participants were more neutral towards the missing element of personalised help and advice often received in brick-and-mortar fashion stores (M = 3.13).

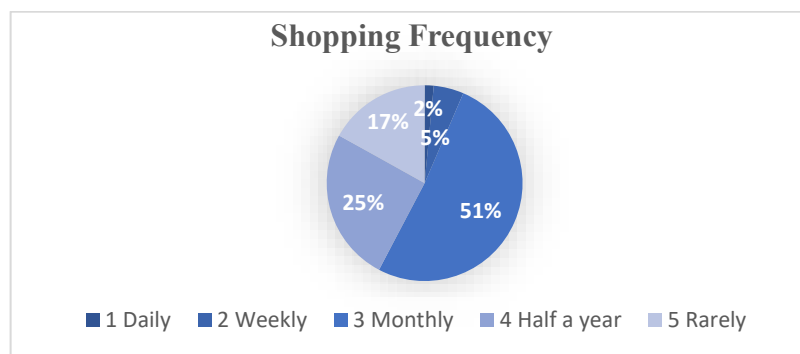


Figure 5.1 Distribution of Shopping Frequency

Source: IBM SPSS Statistics 29



Figure 5.2 Factors Positively Influencing Online Fashion Shopping

Source: Author's own elaboration



Figure 5.3 Factors Hindering Online Fashion Shopping
Source: IBM SPSS Statistics 29

5.1.3. Opinions Towards Static Traditional Recommendation Systems

Next, participants were asked several questions regarding traditional static recommendation system in the online fashion industry. Regarding the helpfulness of product recommendations coming from these systems, most participants perceived them to be helpful (35.8%), followed by moderately helpful (29.4%), slightly helpful (22.9%), extremely helpful (9.0%), and a small percentage found them not helpful at all (3.0%). Overall, participants viewed recommendations to be helpfulness with 74.3% considering them moderately to extremely helpful.

However, when observing purchasing frequency from product recommendations, a largely majority of participants sometimes bough fashion products based on recommendations (45.8%), followed with rarely purchasing fashion products from recommendations (29.4%) and a smaller participant stating to have never purchased fashion items derived from recommendations (6.0%), only 18.9% of participants have either purchased products from recommendations often or very often. Suggesting that participants viewed traditional static recommendations to be helpful, however, few were influenced to buy fashion products that were recommended.

Finally, participants were asked to select challenges with traditional fashion recommendation systems. The most frequent complaint was that many recommendations do not match the participants' interest (27.3%), followed by repeated suggestions of similar items (25.8%), recommendations don't match personal style preferences (25.2%), and recommendations lack diversity (18.3%). A small minority selected other reasons (3.4%) such as "the system gets mixed up if you buy clothes for other persons".

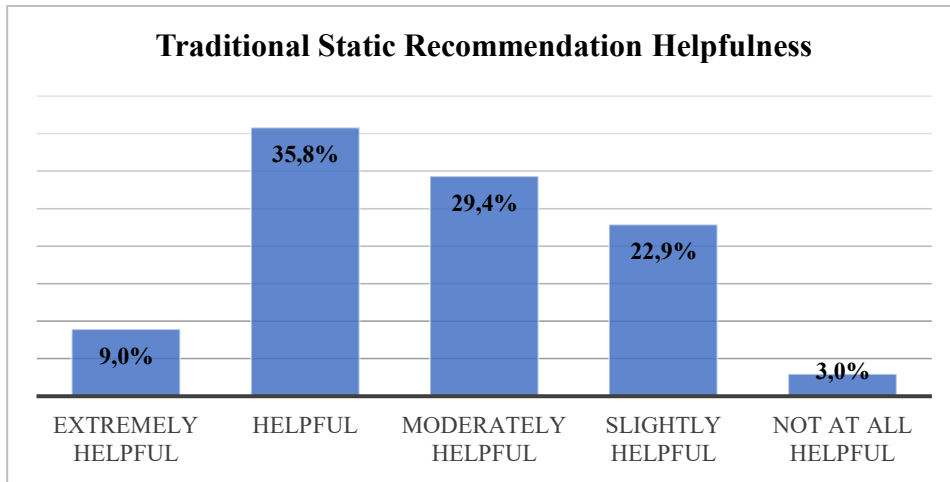


Figure 5.4 Traditional Static Recommendation Helpfulness
Source: IBM SPSS Statistics 29

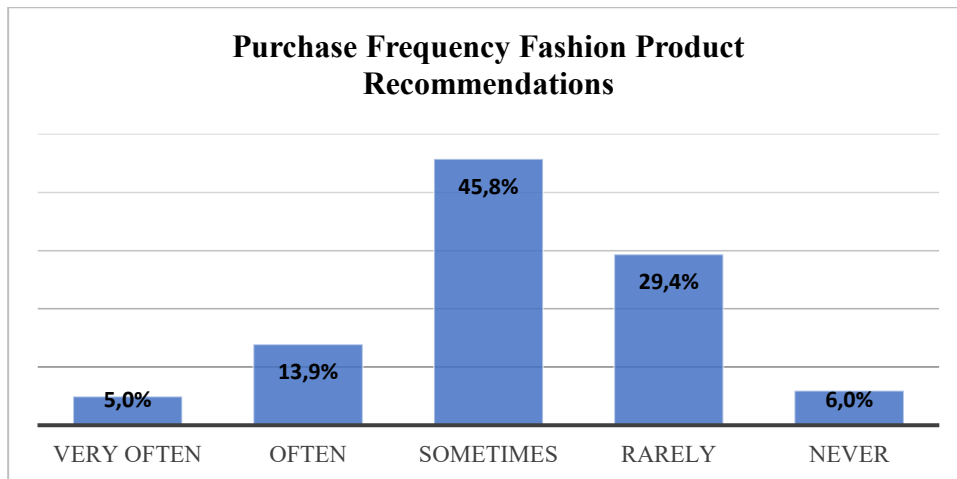


Figure 5.4 Purchase Frequency Fashion Product Recommendation
Source: IBM SPSS Statistics 29

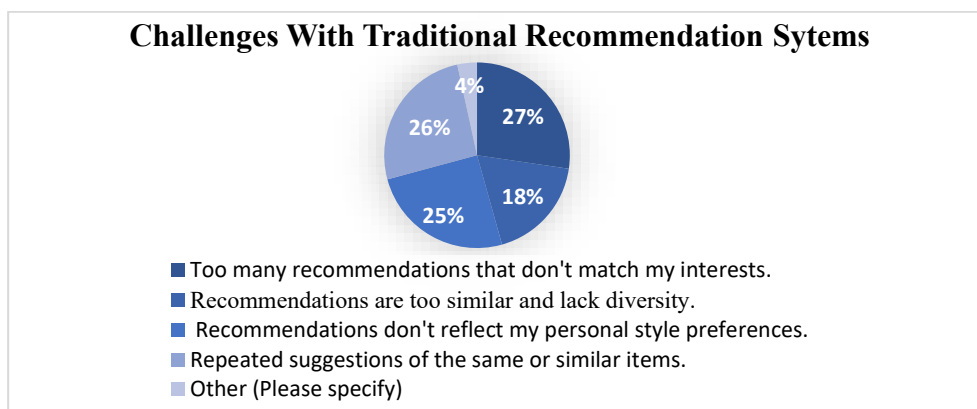


Figure 5.5 Challenges with Traditional Fashion Recommendation Systems
Source: IBM SPSS Statistics 29

5.2. Descriptive Analysis

The descriptive analysis offers an analysis of the constructs depicted in the conceptual model, which were measured through a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). The means, standard deviation (SD), skewness and kurtosis values were calculated to provide insight into the participants' opinion towards CRS in the online fashion industry. A further analysis of each construct's item is presented in Appendix C.

- The construct Perceived Usefulness consisted of seven items. Recording an average mean of 3.71 (SD = 0.66, skewness = -1.41), suggesting that participants positively viewed CRS positively as usefulness, with low variability and distribution skewed to the left. The item with the highest mean score was "when I want answers to specific questions about products" recorded a mean score of 3.94. In contrast, the lowest item score "whether I am looking for everyday styling advice or an outfit for a special event like an interview or wedding" recorded a mean score of 3.54.
- The construct Perceived Ease of Use included five items, recorded the highest mean score of 3.94 (SD = 0.50, skewness = -2.42), suggesting that in general participants viewed CRS as easy to use. Notably among the items, "I believe it would be easy to understand the basic functions of the assistant, based on the description provided" garnered the highest mean of 4.06. In contrast, "I believe the assistant would be easy to integrate into my existing shopping routine" had the lowest mean score of 3.72.
- The construct Perceived Enjoyment included five items. Overall, participants had moderately positive views towards this construct, recording an average mean of 3.46 (SD = 0.89, skewness = -0.97), suggesting that participants viewed it moderately enjoyable with moderate variation among consumers. When observing the individual items, the first two items "using the assistant makes online shopping feel more like a personal experience" and "I would have fun interacting with the assistant", recorded the highest mean of 3.51. Whereas, the last two items, "I would enjoy exploring clothing options from the assistant even when I am planning to buy" and "the assistant would make me feel more inspired and creative with my fashion choice" recorded the lowest mean scores of 3.39.
- Regarding Perceived Privacy Concerns associated with CRS included six items. The average mean was 3.40 (SD = 0.62, skewness = -0.48), suggesting that had moderate privacy concerns towards CRS and distribution was fairly symmetrical. Among the

items, the highest mean score was ‘‘I would prefer to use a fashion assistant that allows me to control and limit what personal information is used’’ with a score of 3.97. In contrast, the lowest mean score was ‘‘For highly relevant and engaging recommendations, I’m willing to compromise on privacy’’, and ‘‘I would feel uncomfortable with a fashion assistant suggesting clothing based on my body type’’, scored a mean score of 3.00.

- The construct Behavioural Intention included five items and registered an average mean of 3.40 (SD = 0.62, skewness of -0.48) and distribution nearly symmetrical. Overall, participants held moderately positive attitude towards this construct. The item with the highest mean score was ‘‘I believe I would utilize the assistant’s recommendations to make informed decisions’’ scoring a mean score of 3.58, with the lowest mean score item of 3.26 being ‘‘I would prefer using the assistant over manually browsing for clothing online’’.
- The construct Purchasing Decision was composed of five items. The construct recorded an average mean score of 3.40 (SD =.0.62, skewness of -0.48), with participants believing that CRS moderately positively could influence their purchasing. The item with the highest mean score was ‘‘the assistant would make my online clothing shopping more efficient, resulting in quicker purchases’’ with a mean score of 3.52. In contrast, the lowest item mean score was ‘‘I would be less likely to purchase impulsively with the assistant’s curated recommendations’’ scoring a score of 3.19.
- The final construct Consumer Loyalty was composed of four items. Participants were moderately positive towards consumer loyalty, with an average mean score of 3.60, (SD = 0.73, skewness of -1.13), with participants tending towards positive agreement. The highest-rated item was ‘‘It is important for a conversational AI assistant to offer customer supports related to my purchases’’ scored the highest mean score of 3.81. Whereas, ‘‘I would switch to a retailer offering a conversational AI fashion assistant with more accurate and personalised recommendations’’ scored the lowest mean score of 3.41.

Table 5.2 Constructs Average Mean, STD and Skewness

	N	Mean	STD Deviation	Skewness Statistic	Skewness Std Error
Perceived Usefulness	201	3.7136	0.66463	-1.410	0.172

Perceived Ease of Use	201	3.9363	0.49872	-0.242	0.172
Perceived Enjoyment	201	3.4557	0.88706	-0.969	0.172
Perceived Privacy Concerns	201	3.3997	0.61781	-0.048	0.172
Behavioural Intention	201	3.4398	0.80025	-1.167	0.172
Purchasing Decisions	201	3.3960	0.73782	-1.082	0.172
Consumer Loyalty	201	3.6032	0.73372	-1.129	0.172

Source: IBM SPSS Statistics 29

5.3. Reliability and Validity of Core Constructs

Before testing the hypotheses through a regression analysis, a reliability and validity test was conducted. To test the reliability, a Cronbach's Alpha analysis was conducted. This internal measurement measures the extent to which items in a scale reliably capture the same underlying construct (Tavakol & Dennick, 2011). Cronbach's Alpha score can range from zero to one, with a generally accepted rule that an Alpha (α) between 0.6 and 0.7 is acceptable, and 0.8 or higher indicating an excellent level (Ursachi et al., 2015). For validity, the sampling adequacy was assessed through the Kaiser-Meyer-Olkin (KMO), which measures whether the items in the dataset are a function of the variance shared by the constructs, with a value of 0.7 being considered desirable (Watkins, 2018). In addition, a Bartlett Spherical Test was conducted to verify the existence of correlation to ensure the correlation matrix is not random, with $P < 0.05$ indicating significance.

As seen in Table 5.3 most constructs showed an excellent level of internal consistency: Perceived Usefulness ($\alpha = 0.819$), Perceived Enjoyment ($\alpha = 0.899$), Behavioural Intention ($\alpha = 0.888$), Purchasing Decision ($\alpha = 0.820$), and Consumer Loyalty ($\alpha = 0.804$). The construct Perceived Ease of Use scored an $\alpha = 0.613$, which is considered an acceptable level of internal consistency. However, item Q16_4 ("having to repeatedly explain my instructions makes me less likely to continue using the assistant") and Q16_5 ("if the assistant is too complex to use, I would be unlikely to use it") had low item-total correlations ($r = 0.220$; $r = 0.223$), which is below the minimum benchmark of 0.30 (Cristobal et al., 2007). Therefore, were excluded from the analysis, resulting in an improved $\alpha = 0.765$.

The construct Perceived Privacy Concerns measured a low reliability level of $\alpha = 0.587$. After reviewing each item, Q18_5 ("For highly relevant and engaging recommendations, I'm willing to compromise on privacy") was removed from the analysis due to its low correlation

($r = 0.013$), resulted in an improve $\alpha = 0.676$ for Perceived Privacy Concerns.

A complete overview of each construct's item, Cronbach's Alpha, and corrected item-total correlation is provided in Appendix D.

Table 5.3 Cronbach's Alpha.

Construct	Cronbach's Alpha	Cronbach's Alpha (after removal)	Item removed
Perceived Usefulness	0.819	-	
Perceived Ease of Use	0.613	0.765	Q16_4, Q16_5
Perceived Enjoyment	0.899	-	
Perceived Privacy Concern	0.587	0.676	Q18_5
Behavioural Intention	0.888	-	
Purchasing Decision	0.820	-	
Consumer Loyalty	0.804	-	

Source: IBM SPSS Statistics 29

As for the validity of the constructs, a KMO measure of sampling adequacy and Bartlett Spherical Test were conducted. Table 5.4 highlights the KMO of 0.925 which is considered to be an excellent level of adequacy, with scores above 0.70 being considered desirable (Watkins, 2018). Furthermore, the Bartlett Spherical test was statistically significant with $p < 0.01$, therefore refuting the null hypothesis of no correlation between the constructs (Rossoni et al., 2016).

Table 5.4 KMO and Barlett's Test of Sphericity

Kaiser-Meyer-Olkin Measure of Sampling Adequacy		0.925
Bartlett's Test of Sphericity	Approx. Chi-Square	3799.536
	Df	561
	Sig	<0.01

Source: IBM SPSS Statistics 29

5.4. Simple and Multiple Regression Analysis

With all the necessary assumptions verified, this section provides a simple and multiple

regression analysis to quantify potential relationships among dependent and independent constructs, and test the proposed hypotheses formulated in Chapter 3.

5.4.1. Multiple Linear Regression: Behavioural Intention

Hypothesis H1 to H4 aimed at observing whether the Perceived Usefulness, Perceived Ease of Use, Perceived Enjoyment, and Perceived Privacy Concerns of Conversational Recommendation systems positively influence online fashion consumers' Behavioural Intention to adopt CRS.

These hypotheses were tested through a multiple linear regression analysis, with Perceived Usefulness, Perceived Ease of Use, Perceived Enjoyment, and Perceived Privacy Concerns as the independent variables, and Behavioural Intention as the dependent variable. With the model equation (5.1) using unstandardized B as the coefficient to measure the linear effect of the independent variable on the dependent variable.

$$\begin{aligned} \text{Behavioural Intention} &= B_0 + B_1 * (\text{Perceived Usefulness} + B_2 * (\text{Perceived Ease of Use}) \\ &+ B_3 * (\text{Perceived Enjoyment}) + B_4 * (\text{Perceived Privacy Concerns} + \epsilon \\ \text{Behavioural Intention} &= B_0 + B_1 * (\text{Perceived Usefulness}) + B_2 * \\ &(\text{Perceived Ease of Use}) + B_3 * (\text{Perceived Enjoyment}) + B_4 * \\ &(\text{Perceived Privacy Concerns}) + \epsilon \end{aligned} \quad (5.1)$$

The Multiple Linear Regression model summary shown in Table 5.5, indicates the model's statistical significance (R square = 0.591; Adjusted R square = 0.583), with the independent constructs explaining 59.1% of the variance in Behavioural Intention. Moreover, the adjusted R square of 0.583, provides a more reliable estimate when generalizing to the target population (Ozili, 2022). These results are acceptable with a R square above 0.5 considered acceptable in social science research (Ozili, 2022).

Table 5.5 Multiple Linear Regression Model Summary

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	0.769 ^a	0.591	0.583	0.51700
a. Predictors: (Constant), Perceived Privacy Concerns, Perceived Usefulness, Perceived Ease of Use, Perceived Enjoyment				
Source IBM SPSS Statistics 29				

Subsequently, an ANOVA test was conducted to test the significance of the regression model. Specifically, it tested whether the independent constructs together significantly predict a variance of the dependent variable. Table 5.6 indicate that the independent constructs together significantly predicts a variance of Behavioural Intention ($F(4, 196) = 70.798, p < 0.001$), with the likelihood of the outcome occurring by random chance being very low.

Table 5.6 Multiple Linear Regression Anova Test

ANOVA^a

Model		Sum of Squares	Df	Mean Square	F	Sig.
1	Regression	75.694	4	18.923	70.798	<.001 ^b
	Residual	52.388	196	0.267		
	Total	128.082	200			

a. Dependent Variable: Behavioural Intention

b. Predictors: (Constant), Perceived Privacy Concerns, Perceived Usefulness, Perceived Ease of Use, Perceived Enjoyment

Source: IBM SPSS Statistics 29

While the ANOVA test and the Model Summary confirm the significance of the regression analysis, it does not reveal the relative contribution of each construct; therefore, the regression coefficients was examined. The regression coefficients depicted in Table 5.7 that the Perceived Usefulness ($\beta = 0.268, t = 4.248, p < 0.001$), Perceived Ease of Use ($\beta = 0.149, t = 2.679, p = 0.008$) and Perceived Enjoyment ($\beta = 0.470, t = 7.478, p < 0.001$), affirming a positive and significant factor of predicting Behavioural Intention to adopt CRS, with the Perceived Enjoyment as the most substantial factor. Consequently, validating hypotheses H1, H2 and H3.

However, Perceived Privacy Concerns was revealed to be an insignificant factor of predicting Behavioural Intention ($\beta = -0.033, t = -0.712, p = 0.477 > 0.05$), suggesting that privacy concerns do not significantly impact the online fashion intention to adopt CRS. Therefore, rejecting H4.

Finally, there was no sign of multicollinearity among the constructs, meaning that constructs are not providing information that is overlapping or redundant when explaining Behavioural Intention. Given that the tolerance for each construct is greater than 0.2 and the VIF is below the threshold of 5 to 10 (Kim, 2019).

Table 5.7 Multiple Linear Regression Coefficients

Coefficients^a

Model	Unstandardized	Coefficients	Standardized	t	Sig.	Collinearity	Statistics
1	B	Std. Error	Coefficients			Tolerance	VIF
			Beta				
(Constant)	0.219	0.296		0.742	0.459		
Perceived Usefulness	0.322	0.076	0.268	4.248	<.001	0.526	1.901
Perceived Ease of Use	0.180	0.067	0.149	2.679	0.008	0.675	1.481
Perceived Enjoyment	0.424	0.057	0.470	7.478	<.001	0.528	1.893
Perceived Privacy Concerns	-0.037	0.052	-0.033	-0.712	0.477	0.995	1.005

a. Dependent Variable: Behavioural Intention

Source: IBM SPSS Statistics 29

5.4.2. Simple Linear Regression: Behavioural Intention and Purchasing Decision

To test hypothesis 5; The consumers’ Behavioural Intention to adopt conversational recommendation systems positively influences Purchasing Decisions. A simple linear regression was calculated, with Purchasing Decisions as the dependent variable and Behavioural Intention as the independent variable. The equation fitted with the regression model (5.2):

$$\text{Purchasing Decisions} = B_0 + B_1 * (\text{Behavioural Intention}) + \epsilon \quad (5.2)$$

First an analysis of the model summary was conducted. Table 5.8 shows the model to be statistically significant, with a R Square value of 0.575 and adjusted R Square of 0.573, indicating that 57.5% of the variance in Purchasing Decision is explained by the Behavioural Intention to adopt CRS.

Table 5.8 Simple Linear Regression Model Summary Purchasing Decision

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	0.758 ^a	0.575	0.573	0.48216

a. Predictors: (Constant), Perceived Behavioural Intention

Source: IBM SPSS Statistics 29

Subsequently an ANOVA test was performed, which is presented in Table 5.9. The result further support the statistically significance of the model ($F(1, 199) = 269.321, sig < .001$), indicating Behavioural Intention to be a reliable predictor of Purchasing Decision, with the likelihood of the outcome being random very low.

Table 5.9 Simple Linear Regression Anova Test Purchasing Decision

ANOVA^a

Model		Sum of Squares	Df	Mean Square	F	Sig.
1	Regression	62.612	1	62.613	269.321	<.001 ^b
	Residual	46.264	199	0.232		
	Total	108.877	200			

a. Dependent Variable: Purchasing Decision

b. Predictors: (Constant), Behavioural Intention

Source: IBM SPSS Statistics 29

Table 5.10. depicts the regression coefficients, which further reinforces that the Behavioural Intention of adopting CRS, is a positive significant predictor of Purchasing Decisions ($\beta = 0.758, t = 16.411, P < 0.001$), indicating that for every unit increase in Behavioural Intention, the Purchasing Decision increase by approximately 0.699 units. These results collectively support H5. Finally, there is no sign of multicollinearity since it is not applicable for a simple linear model.

Table 5.10 Simple Linear Regression Coefficients Purchasing Decision

Coefficients^a

Model	Unstandardized Coefficients	Standardized Coefficients	t	Sig.	Collinearity Statistics
1	B	Beta			Tolerance VIF
(Constant)	0.991		6.587	<.001	
Behavioural Intention	0.699	0.758	16.411	<.001	1.000 1.000

a. Dependent Variable: Purchasing Decisions

Source: IBM SPSS Statistics 29

5.4.3. Simple Linear Regression: Purchasing Decisions and Consumer Loyalty

A simple linear regression analysis was conducted to examine the influence of Purchasing Decisions derived from CRS on Consumer Loyalty, with Purchasing Decisions as the independent construct and Consumer Loyalty as the dependent construct. With the simple regression model equation (5.3):

$$\text{Consumer Loyalty} = B_0 + B_1 * (\text{Purchasing Decisions}) + \epsilon \quad (5.3)$$

The regression model summary displayed in Table 5.11 demonstrates a moderately strong relationship between Purchasing Decisions and Consumer Loyalty with an R-squared of 0.464, indicating 46,4% of the variance in Consumer Loyalty is explained by the Purchasing Decisions, which is considered to be acceptable in social science (Ozili, 2022).

Table 5.11 Simple Linear Regression Model Summary Consumer Loyalty

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	0.681 ^a	0.464	0.461	0.53865
a. Predictors: (Constant), Purchasing Decisions				
Source: IBM SPSS Statistics 29				

Furthermore, The ANOVA test, highlighted in Table 5.12, confirmed the statistical significance of the simple linear regression model with (F(1, 199) = 172.098, p < .001), indicating that Purchasing Decisions is a reliable factor in predicting Consumer Loyalty and is unlikely due to random chance.

Table 5.12 Anova Test Consumer Loyalty

ANOVA^a						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	49.933	1	49.933	172.098	<.001 ^b
	Residual	57.738	199	0.290		
	Total	107.670	200			
a. Dependent Variable: Consumer Loyalty						

b. Predictors: (Constant), Purchasing Decisions

Source: IBM SPSS Statistics 29

Furthermore, the coefficients table presented in Table 5.13, showcases Purchasing Decisions to be reliable predictor of Consumer Loyalty ($\beta = 0.681$, $t = 13.119$, $P < 0.001$), with every unit increasing in Purchasing Decisions, the Consumer loyalty approximately increases with 0.681 units. Therefore, collectively validating hypothesis 6: Purchasing Decisions derived from conversational recommendation systems positively influence Consumer loyalty.

Table 5.13 Simple Linear Regression Coefficients Consumer Loyalty

Coefficients^a

Model	Unstandardized	Coefficients	Standardized	t	Sig.	Collinearity	Statistics
1	B	Std. Error	Coefficients			Tolerance	VIF
			Beta				
(Constant)	1.303	0.179		7.266	<.001		
Purchasing Decisions	0.677	0.052	0.681	13.119	<.001	1.000	1.000

a. Dependent Variable: Consumer loyalty

Source IBM SPSS Statistics 29

5.5. Discussion of the Results

The aim of the study is to investigate factors influencing online fashion consumers' adoption of CRS and its subsequent impact on the fashion consumer Purchasing Decisions and Consumer Loyalty. In order to achieve these research objectives, a conceptual model and proposed hypotheses was proposed, which was tested through quantitative research design, which included an online questionnaire that counted a sample of 201 participants that met the selection criteria.

First, a descriptive analysis was conducted to observe participants opinion towards the seven constructs depicted in the conceptual model, with average mean scores ranging from 3.40 to 3.94, with participants having moderately positive perceptions. The construct with the highest mean score was Perceived Ease of use ($M = 3.94$, $SD = 0.50$), followed by the Perceived Usefulness of the system ($M = 3.71$, $SD = 0.66$), Consumer Loyalty ($M = 3.60$, $SD = 0.73$), Perceived Enjoyment ($M = 3.46$, $SD = 0.89$), Behavioural Intention ($M = 3.44$, $SD = 0.80$),

Perceived Privacy Concerns ($M = 3.40$, $SD = 0.62$) and Purchasing Decisions ($M = 3.40$, $SD = 0.74$).

Before testing the hypotheses, an analysis of the internal consistency and validity of the core constructs were tested. In total two items were removed from the construct Perceived Ease of Use and one item from the construct Perceived Privacy Concerns, due to their low item-total correlations, which after removal led to the research model tested through a regression analysis.

A regression analysis was conducted to test the proposed hypotheses. Hypothesis 1 proposes that the Perceived Usefulness of a CRS positively influences online fashion consumers' Behavioural Intention of adoption. The results from the regression analysis showed the constructs to be a positive and significant factor of predicting Behavioural Intention ($\beta = 0.268$, $t = 4.248$, $p < 0.001$). This finding suggest that CRS that enable fashion consumers to perform their job more efficiently by offering personalised fashion recommendations, finding specific clothing items, receiving personalised styling advice and discovering new brands and style can significantly increase the likelihood of Behavioural Intention. Moreover, this finding aligns with prior studies suggesting its influence on the Behavioural Intention of adopting CRS (Azman et al., 2025; Rese et al., 2020; Singh et al., 2024).

Hypothesis 2 proposes that the Perceived Ease of Use of a CRS positively influences the Behavioural Intention of adopting. The regression analysis observed a moderate but significant predictor of Behavioural Intention ($\beta = 0.149$, $t = 2.679$, $p = 0.008$), suggesting that the system's ease of use plays an important role in shaping online fashion consumers' willingness to adopt it. Similarly, to prior research (Davis, 1989; Venkatesh & Davis, 2000; Singh et al., 2024), the effect of Perceived Ease of Use on Behavioural Intention was significantly weaker than Perceived Usefulness. Finally, this observation contradicts the findings from Rese et al. (2020), who observed the construct to be an insignificant predictor of intention of usage, attributing this factor to participants viewing the CRS as easy to use, with the construct recording the highest mean score, suggesting participants prioritise other constructs more regarding intended usage. With this study observing the highest mean score, indicating a similar pattern but still showing a significant relationship between the Behavioural Intention.

Hypothesis 3 examined whether the Perceived Enjoyment derived from interacting with CRS positively influences Behavioural Intention to adopt. The results from the regression analysis ($\beta = 0.470$ $t = 7.478$, $p < 0.001$), found that this construct was the most significant predictor of Behavioural Intention, suggesting that hedonic aspects such as playfulness, fun and enjoyment were considered more significant than utilitarian aspects. Interestingly, this finding

contrast with the descriptive analysis, with Perceived Usefulness and Perceived Ease of Use scoring higher mean score. This suggest that although participants viewed utilitarian aspects in higher regards, it was the intrinsic aspects that ultimately influenced BI of adopting CRS. Finally, this observation aligns with prior studies observing the construct influence towards the Behavioural Intention of adopting CRS (Rese et al., 2020; Singh et al., 2024; Vimalkumar et al., 2021).

Hypothesis 4 investigated whether Perceived Privacy Concerns associated with CRS negatively influenced Behavioural intention towards adoption. Based on the results derived from the regression analysis ($\beta = -0.33$, $t = -0.712$, $p = 0.477 > 0.05$), this construct was considered as a non significant factor in predicting Behavioural Intention, therefore refuting H4. It is plausible that this is caused by the personalisation-privacy paradox, in which consumers value the personalisation the system offers over privacy concerns. This would align with Vimalkumar et al. (2021) study, who likewise observed no significant effect between Perceived Privacy Concerns and Behavioural Intention, due to consumers forging their privacy concerns due to the fact that the system was considered as high-performance.

Hypothesis 5 proposed that the Behavioural Intention of adopting CRS would result in positive Purchasing Decisions among online fashion consumers. To test this a simple linear regression analysis was conducted. The results observed a positive and significant ($\beta = 0.758$, $t = 16.411$, $P < 0.001$), implying that consumers who adopt CRS are more likely to translate these intentions towards Purchasing Decisions. This finding is consistent with prior studies suggesting that personalised recommendations and personalised advice positively influence consumers' purchasing decision making process (Agbanu et al., 2024; Choudhary et al., 2023; Raji et al., 2024).

The final hypothesis (H6) proposed that Purchasing Decisions derived from CRS result in facilitating Consumer Loyalty. This hypothesis was tested through a simple linear regression model, which observed a positive and significant relationship ($B = 0.677$, $\beta = 0.681$, $t = 13.119$, $P < 0.001$), indicating that fashion consumers who made purchases through CRS, are more likely to foster consumer loyalty with the online fashion retailers. Furthermore, this finding aligns with several other studies that suggest that personalised recommendation systems can positively influence Consumer Loyalty (Raji et al., 2024; Vashishth et al., 2024; Zed et al., 2024).

5.6. Theoretical Contribution

The theoretical contribution of this study is in the area of CRS in the online fashion industry. Prior research on conversational systems primarily focused on the field of customer service, with limited studies investigating the influence of these systems on consumer behaviour. Moreover, factors that influence fashion consumers to adopt these systems were relatively unexplored. This study addresses the research gap by providing a holistic model of factors influencing online fashion consumers' adoption and the downstream influence on the consumers' purchasing decisions and loyalty.

In the current study, a modified TAM was introduced that included the additions of Perceived Enjoyment and Perceived Privacy Concerns directly to the Behavioural Intention of adopting CRS. The results from the empirical study, suggest that intrinsic motivations such as Perceived Enjoyment, was considered more influential than extrinsic motivations, such as Perceived Usefulness and Perceived Easy to Use, in predicting consumers' Behavioural Intention in adopting CRS. However, the inclusion of Perceived Privacy Concerns deemed to be an insignificant factor of Behavioural Intention. Contradicting several prior studies suggesting its negative influence on intended usage (Rese et al., 2020; Singh et al., 2024). It is plausible that this phenomenon could be attributed to the personalisation privacy paradox in which the consumer acts as a rational agent who considers the risks associated with privacy and the benefits of the personalised service (Aguirre et al., 2014).

Additionally, this study investigated the downstream influences of the Behavioural Intention of adopting CRS on the consumers' Purchasing Decisions and Consumer Loyalty. Which is relatively unexplored in academic research, with prior studies investigating static AI personalised recommendation systems. The findings from the regression analysis suggest that the Behavioural Intention of adopting CRS significantly and strongly predict Purchasing Decisions. Thus bridging the gap between consumers' Behavioural Intention and actual action. Furthermore, Purchasing Decisions derived from CRS significantly predict Consumer Loyalty, integrating the extended TAM with the consumer journey, demonstrating that CRS adoption is not an endpoint but a driver in online fashion consumer decisions outcomes.

5.7. Managerial Implications

There are several key takeaways for online fashion managers. Literature studies emphasize the

importance of offering AI personalised services to consumers, with consumers longing for consumer experiences that are tailored to their needs (Raji et al., 2024; Zaman et al., 2025; Zed et al., 2024). Especially, for the online fashion industry, in which online fashion consumers are dissatisfied with the online search experience and volume of choice, resulting in them abandoning their purchasing (Balchandani et al., 2024; Li & Kang, 2025). Prior research towards recommendation systems suggest that personalised product recommendations not only enhance the consumer-decision making process, resulting in higher sales conversions (Agbanu et al., 2024; Ahmed et al., 2025; Choudhary et al., 2023; Da Silva et al., 2022; Li & Kang, 2025), and fostering consumer loyalty (Hongfei & Youjiang, 2022; Raji et al., 2024; Zed et al., 2024). These findings are further supported by the findings from this study, observing a significant relationship between CRS with Purchasing Decisions ($\beta = 0.758$, $t = 16.411$, $P < 0.001$), with every unit increase in Behavioural Intention the Purchasing Decisions increases by 0.758 units. Furthermore, Purchasing Decisions derived from CRS significantly influence Consumer Loyalty, with every unit increase in Purchasing Decisions resulting in an estimated increase of 0.681 units in Consumer Loyalty. From a practical standpoint, implementing CRS in the online fashion industry could have positive outcomes on the bottom line, with likelihood of increased revenue and consumer loyalty.

Regarding the implementation of CRS. The results indicate Perceived Enjoyment to be the biggest factor of adoption, followed by Perceived Usefulness and Perceived Ease of Use, indicating that hedonic aspects were more important than utilitarian aspects, therefore it is important for businesses to emphasize implement hedonic elements in the design. Nevertheless, utilitarian aspects were observed to be a determinant factor and therefore should be reflected in the CRS design.

Finally, Perceived Privacy Concerns was considered an insignificant factor in intended usage. Despite this, businesses should strike a balance between personalisation and privacy concerns, implementing robust privacy rules, which include clear and transparent policies towards data collection and consumer consent. The descriptive analysis showcased participants to have moderate privacy concerns. Moreover, companies must comply with regulatory requirements from governments and regulatory bodies. Therefore, striking a balance between personalisation and privacy concerns is highly recommended.

Chapter 6. Conclusion and Recommendations

6.1. Conclusion

This dissertation set out to investigate the following two research questions: 1) What factors influence online fashion consumers to adopt conversational recommendation systems? 2) Do conversational recommendation systems positively influence purchasing decisions and consumer loyalty among online fashion consumers? To accomplish these research objectives, a detailed literature review was conducted that laid the groundwork for the conceptual framework and proposed hypotheses. Which were tested through a cross-sectional questionnaire, recording a final sample size of 201 responses. These results were then analysed and evaluated in IBM SPSS 29.

The results of the study revealed that Perceived Enjoyment was the most important predictor of Behavioural Intention of adopting CRS. The remaining factors of Perceived Usefulness and Perceived Ease of Use were lesser but still significant predictors of adoption. Suggesting that extrinsic factors such as enjoyment are a more determinant factor of adopting CRS. Conversely, Perceived Privacy Concerns was revealed to be an insignificant predictor of Behavioural Intention, indicating that privacy concerns did not negatively influence online fashion consumers Behavioural Intention, which is in contrary to several literature studies indicating its hinderance towards adoption (Rese et al., 2020; Singh et al., 2024).

Secondly, the empirical results suggest a bridge between Behavioural Intention and Purchasing Decisions, recording a strong significant relationship between the two constructs, therefore, indicating that CRS could facilitate purchasing decisions among online fashion consumers, which aligns with prior research suggesting that recommendation systems can streamline the decision-making process and increase conversions. Furthermore, it was found that Purchasing Decisions derived from CRS significantly predict Consumer Loyalty, thereby, emphasizing its on the online fashion consumer. This is valuable for fashion brands given the industry's high cart abandonment rate (Statista, 2024), and loyalty remaining inherently unstable (Zed et al., 2024).

Drawing from these findings this study offers several recommendations. First and foremost, it is important for the design of the CRS to offer a mix of intrinsic and extrinsic elements to encourage the consumers' likelihood of adopting CRS in their online shopping journey. Secondly, although privacy concerns were deemed insignificant, businesses must comply with regulation, striking a balance between personalised offerings and ethical practices

is recommended, given the contemporary studies emphasizing its importance. Thirdly, given the novelty of these systems and increased advancement of AI technologies, online fashion brands are urged to remain up to date with recent developments and consumer trends within CRS, to remain competitive and relevant.

6.2. Limitations and Further Research

During this investigation, several limitations occurred that should be taken into account. The first consideration is regarding the sample. Most participants were relatively young with an average age of 28 and a median age of 25. Findings were based on this sample, which could influence responses towards constructs such as privacy concerns and usefulness of a CRS. Further research should investigate an older demographic, to observe their responses towards factors influencing CRS adoption and the downstream influences of adoption, given that online fashion industry appeals to all generations. Also, the sample size concluded a wide diversity of nationalities. Therefore, generalizing the findings of the study towards one specific region or country is difficult, given that different countries exhibit different digital habits, cultures and beliefs, which could influence their opinion towards CRS. To address potential cultural differences, future research should investigate specific countries or regions. Secondly, this study employed a cross-sectional research design, where the sample size was analysed in a single period, rather than over a longitudinal period, which measures participants' input over a longer time frame, allowing for the assessment of attitude changes over time. Therefore, further research should measure constructs over a longitudinal period.

A third limitation was with reliability of two items from the Perceived Ease of Use and one item with Perceived Privacy Concerns excluded from the regression analysis, with total-item correlation the below 0.3 benchmark. While excluding them from the analysis did improve internal consistency, it also narrowed the overall scope of the analysis. Furthermore, Perceived Privacy Concerns was considered to be an insignificant factor in Behavioural Intention. This is a divergence from prior studies (Singh et al., 2024; Rese et al., 2021). Therefore, further research should investigate this construct further.

Finally, CRS are relatively new, falling between the early adopters and the early majority, with fashion brands beginning to implement and introduce them to their mass audience. Perspectives, preferences, and habits towards these systems are likely to develop within the next decade. Therefore, the relevance of the findings from this study can change.

Bibliographical References

- Adriatico, J. M., Cruz, A., Tiong, R. C., & Racho-Sabugo, C. R. (2022). An analysis on the impact of choice overload to consumer decision paralysis. *Journal of Economics Finance and Accounting Studies*, 4(1), 55–75. <https://doi.org/10.32996/jefas.2022.4.1.4>
- Agbanu, I. I., Mohammed, A. B., & Inikpi, O. R. (2024). *Effect of AI-driven personalisation on purchasing decisions and customer satisfaction in the fashion industry in Nigeria*. *Global Journal of Research in Business Management*, 4(5), 92–105. <https://doi.org/10.5281/zenodo.13847988>
- Aggarwal, C. C. (2016). Recommender Systems. In *Springer eBooks*. <https://doi.org/10.1007/978-3-319-29659-3>
- Aguirre, E., Mahr, D., Grewal, D., De Ruyter, K., & Wetzels, M. (2014). Unraveling the personalisation paradox: The Effect of Information Collection and Trust-Building strategies on online advertisement effectiveness. *Journal of Retailing*, 91(1), 34–49. <https://doi.org/10.1016/j.jretai.2014.09.005>
- Ahmed, S. K. (2024). Research methodology simplified: how to choose the right sampling technique and determine the appropriate sample size for research. *Oral Oncology Reports*, 12, 100662. <https://doi.org/10.1016/j.oor.2024.100662>
- Ahmed, S. M. M., Owais, M., Raza, M., Nadeem, Q., & Ahmed, B. (2025). The impact of AI-Driven personalisation on consumer engagement and brand loyalty. *Qlantic Journal of Social Sciences.*, 6(1), 311–323. <https://doi.org/10.55737/qjss.v-iv.24313>
- Ajzen, I. (1991). The theory of planned behaviour. *Organizational Behaviour and Human Decision Processes*, 50(2), 179–211. [https://doi.org/10.1016/0749-5978\(91\)90020-t](https://doi.org/10.1016/0749-5978(91)90020-t)
- Aksoy, N. C., Kabadayi, E. T., Yilmaz, C., & Alan, A. K. (2021). A typology of personalisation practices in marketing in the digital age. *Journal of Marketing Management*, 37(11–12), 1091–1122. <https://doi.org/10.1080/0267257x.2020.1866647>
- Al-Amin, M., Ali, M. S., Salam, A., Khan, A., Ali, A., Ullah, A., Alam, M. N., & Chowdhury, S. K. (2024). *History of generative Artificial Intelligence (AI) chatbots: past, present, and future development*. arXiv.org. <https://arxiv.org/abs/2402.05122>
- Awad, N., & Krishnan, N. (2006). The Personalisation Privacy Paradox: an empirical evaluation of information transparency and the willingness to be profiled online for personalisation. *MIS Quarterly*, 30(1), 13. <https://doi.org/10.2307/25148715>
- Azman, H., Keat, T. K., Sufian, A., Aziz, N. a. A., & Azman, A. (2025, February 20). *The influence of machine learning chatbots on consumer purchase intention in the fashion industry*. <https://kwpublications.com/papers/detail/IJARBSS/15570/The-Influence-of-Machine-Learning-Chatbots-on-Consumer-Purchase-Intention-in-the-Fashion-Industry>
- Balchandani, A., Rölkens, F., & D’Auria, G. (2024, November 11). *The State of Fashion 2025: Challenges at every turn*. McKinsey & Company. <https://www.mckinsey.com/industries/retail/our-insights/state-of-fashion>
- Barari, M. & R. M. & S. J. (2020). Negative and positive customer shopping experience in an online context. *ideas.repec.org*. <https://ideas.repec.org/a/eee/joreco/v53y2020ics0969698919307039.html>
- Bouhlal, H., & Belahcen, N. (2025). *The Influence of conversational AI on consumer behaviour and counterfactual Thinking: a Systematic review*. ResearchGate. https://www.researchgate.net/publication/389434053_The_Influence_of_Conversational_AI_on_Consumer_Behaviour_and_Counterfactual_Thinking_A_Systematic_Review
- Brooklyn, P., Olukemi, A., & Bell, C. (2024). AI-Driven personalisation in Digital Marketing:

- Effectiveness and ethical considerations. *SSRN Electronic Journal*. 39. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4906214
- Choudhary, D., Dangi, P., & Saini, D. (2023). AI for Personalisation in E-commerce and Recommendation System. *Tuijin Jishu/Journal of Propulsion Technology*, 44(1), 122–130. <https://doi.org/10.52783/tjpt.v44.i1.2217>
- Corchado, J. M., F, S. L., Núñez, J. M., V., S, R. G., & Chamoso, P. (2023). Generative Artificial Intelligence: Fundamentals. *ADCAIJ ADVANCES IN DISTRIBUTED COMPUTING AND ARTIFICIAL INTELLIGENCE JOURNAL*, 12(1), e31704. <https://doi.org/10.14201/adcaij.31704>
- Cristobal, E., Flavián, C., & Guinaliú, M. (2007). Perceived e-service quality (PeSQ). *Managing Service Quality*, 17(3), 317–340. <https://doi.org/10.1108/09604520710744326>
- Da Silva, R. V., Dias, A., Gonçalves, R., Cavalheiro, I., Da Costa, R. L., & Pereira, L. F. (2022). The influence of artificial intelligence on online behaviour. *International Journal of Services Operations and Informatics*, 12(2), 1. <https://doi.org/10.1504/ijsoi.2022.10050081>
- Dahri, N. A., Yahaya, N., Al-Rahmi, W. M., Aldraiweesh, A., Alturki, U., Almutairy, S., Shutaleva, A., & Soomro, R. B. (2024). Extended TAM based acceptance of AI-Powered ChatGPT for supporting metacognitive self-regulated learning in education: A mixed-methods study. *Heliyon*, 10(8), e29317. <https://doi.org/10.1016/j.heliyon.2024.e29317>
- Davenport, T., Guha, A., Grewal, D., & Bressgott, T. (2019). How artificial intelligence will change the future of marketing. *Journal of the Academy of Marketing Science*, 48(1), 24–42. <https://doi.org/10.1007/s11747-019-00696-0>
- Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 13(3), 319. <https://doi.org/10.2307/249008>
- Deldjoo, Y., Rafiee, N., & Ravanbakhsh, M. (2025, August 4). *Agentic Personalised Fashion Recommendation in the age of Generative AI: Challenges, Opportunities, and Evaluation*. arXiv.org. <https://arxiv.org/abs/2508.02342>
- European Commission. (2024). AI Act enters into force. Retrieved January 15, 2025, from https://commission.europa.eu/news/ai-act-enters-force-2024-08-01_en
- Fedorko, R., Král, Š., & Fedorko, I. (2022). *Artificial intelligence and machine learning in the context of e-commerce: A literature review*. Retrieved from https://www.researchgate.net/publication/362794946_Artificial_Intelligence_and_Machine_Learning_in_the_Context_of_E-commerce_A_Literature_Review
- Feng, Y., Liu, S., Xue, Z., Cai, Q., Hu, L., Jiang, P., Gai, K., & Sun, F. (2023, August 11). *A large language model enhanced conversational recommender system*. arXiv.org. https://arxiv.org/abs/2308.06212?utm_source=chatgpt.com
- Fishbein, M. A., & Ajzen, I. (1975). Belief, attitude, intention and behaviour: An introduction to theory and research. *ResearchGate*. https://www.researchgate.net/publication/233897090_Belief_attitude_intention_and_behaviour_An_introduction_to_theory_and_research
- Gentile, C., Spiller, N., & Noci, G. (2007). How to sustain the customer experience: *European Management Journal*, 25(5), 395–410. <https://doi.org/10.1016/j.emj.2007.08.005>
- Given, L. M., Case, D. O., & Willson, R. (2023). Research design, methodologies, and methods. In *Studies in information* (pp. 179–235). <https://doi.org/10.1108/s2055-53772023005>
- Gopal, B. (2022). *The role of artificial intelligence in transforming retail commerce*. *Educational Administration: Theory and Practice*, 28(4), 8088. https://www.researchgate.net/publication/385097181_The_Role_of_Artificial_Intelligence_in_Transforming_Retail_Commerce
- Hardcastle, K., Vorster, L., & Brown, D. M. (2025). Understanding customer responses to AI-Driven personalised journeys: impacts on the customer experience. *Journal of Advertising*,

- 1–20. <https://doi.org/10.1080/00913367.2025.2460985>
- Hongfei, L., & Youjiang, G. (2022). *Artificial intelligence-enabled personalisation in Interactive Marketing: A Customer Journey perspective*. ResearchGate. https://www.researchgate.net/publication/362087387_Artificial_intelligence-enabled_personalisation_in_interactive_marketing_a_customer_journey_perspective
- Honka, E., Seiler, S., & Ursu, R. (2023). Consumer Search: What Can We Learn from Pre-Purchase Data? *SSRN Electronic Journal*. <https://doi.org/10.2139/ssrn.4623968>
- Isinkaye, F. O., Folajimi, Y. O., & Ojokoh, B. A. (2015). *Recommendation Systems: principles, methods and evaluation*. <https://www.sciencedirect.com/science/article/pii/S1110866515000341>
- Jabareen, Y. (2009). Building a conceptual framework: philosophy, definitions, and procedure. *International Journal of Qualitative Methods*, 8(4), 49–62. <https://doi.org/10.1177/160940690900800406>
- Johnpaul, M., Miryala, R. S. B., Mazurek, M., Jayaprakashnarayana, G., & Miryala, R. K. (2024). Artificial intelligence and machine learning in eCommerce. In *Advances in electronic commerce (AEC) book series/Advances in electronic commerce series* (pp. 31–58). <https://doi.org/10.4018/979-8-3693-5718-7.ch002>
- Kaplan, A., & Haenlein, M. (2018). Siri, Siri, in my hand: Who’s the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence. *Business Horizons*, 62(1), 15–25. <https://doi.org/10.1016/j.bushor.2018.08.004>
- Katawetawaraks, C., & Wang, C. (2013, October 25). *Online Shopper behaviour: Influences of online shopping decision*. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2345198
- Kaur, J., Singh, S., & Singh, R. (2021). AI and Customer Experience in the Fashion Industry. In *Advances in marketing, customer relationship management, and e-services book series* (pp. 127–138). <https://doi.org/10.4018/978-1-7998-7959-6.ch008>
- Kim, J. H. (2019). Multicollinearity and misleading statistical results. *Korean Journal of Anesthesiology*, 72(6), 558–569. <https://doi.org/10.4097/kja.19087>
- Laufer, R. S., & Wolfe, M. (1977). Privacy as a concept and a social issue: a multidimensional developmental theory. *Journal of Social Issues*, 33(3), 22–42. <https://doi.org/10.1111/j.1540-4560.1977.tb01880.x>
- Lei, W., He, X., De Rijke, M., & Chua, T. (2020). Conversational recommendation: formulation, methods, and evaluation. *43rd Annual International ACM SIGIR Conference on Research and Development in Information Retrieval*. <https://doi.org/10.1145/3397271.3401419>
- Lemon, K. N., & Verhoef, P. C. (2016). Understanding customer experience throughout the customer journey. *Journal of Marketing*, 80(6), 69–96. <https://doi.org/10.1509/jm.15.0420>
- Li, H., Luo, X., Zhang, J., & Xu, H. (2017). Resolving the privacy paradox: Toward a cognitive appraisal and emotion approach to online privacy behaviours. *Information & Management*, 54(8), 1012–1022. <https://doi.org/10.1016/j.im.2017.02.005>
- Li, J., & Kang, J. (2025). Less stress, fewer delays: The role of sophisticated AI in mitigating decision fatigue and purchase postponement in luxury retail. *Journal of Retailing and Consumer Services*, 85, 104268. <https://doi.org/10.1016/j.jretconser.2025.104268>
- Lim, W. M. (2024). What is quantitative research? An overview and guidelines. *Australasian Marketing Journal (AMJ)*. <https://doi.org/10.1177/14413582241264622>
- Ma, N. (2023). Analysis of the impact of artificial intelligence on digital marketing. *Highlights in Business Economics and Management*, 19, 625–631. <https://doi.org/10.54097/hbem.v19i.12097>
- Mehta, N. P. P., Dongare, N. O., Tekale, N. R., Umare, N. H., & Wanve, N. R. (2022). An Approach towards Deployable Hybrid Product Recommendation Systems for E-

- commerce. *International Journal of Scientific Research in Computer Science Engineering and Information Technology*, 101–106. <https://doi.org/10.32628/cseit228332>
- Ozili, P. K. (2022). The acceptable R-Square in empirical modelling for social science research. *SSRN Electronic Journal*. <https://doi.org/10.2139/ssrn.4128165>
- Ponto, J. (2015, March 1). *Understanding and evaluating survey research*. <https://pmc.ncbi.nlm.nih.gov/articles/PMC4601897/>
- Raji, N. M. A., Olodo, N. H. B., Oke, N. T. T., Addy, N. W. A., Ofodile, N. O. C., & Oyewole, N. a. T. (2024). E-commerce and consumer behaviour: A review of AI-powered personalisation and market trends. *GSC Advanced Research and Reviews*, 18(3), 066–077. <https://doi.org/10.30574/gscarr.2024.18.3.0090>
- Rese, A., Ganster, L., & Baier, D. (2020). Chatbots in retailers' customer communication: How to measure their acceptance? *Journal of Retailing and Consumer Services*, 56, 102176. <https://doi.org/10.1016/j.jretconser.2020.102176>
- Rosenbaum, M. S., Otolara, M. L., & Ramirez, G. C. (2017). *How to create a realistic customer journey map*. https://econpapers.repec.org/article/eeebushor/v_3a60_3ay_3a2017_3ai_3a1_3ap_3a143-150.htm
- Rossoni, L., Engelbert, R., & Bellegard, N. L. (2016). Normal science and its tools: Reviewing the effects of factor analysis in management. *Revista De Administração*, 198–211. <https://doi.org/10.5700/rausp1234>
- Russell, S., & Norvig, P. (2021). *Artificial Intelligence, Global Edition*. Pearson eLibrary. <https://elibrary.pearson.de/book/99.150005/9781292401171>
- Salunke, T., & Nichite, U. (2022). Recommender systems in e-commerce. *arXiv.org*. <https://doi.org/10.13140/RG.2.2.10194.43202>
- Sanchis, F. Á. & J. R. & R. G. (2014). Choice overload, satisficing behaviour, and price distribution in a time allocation model. *Ideas.repec.org*. <https://ideas.repec.org/a/hin/jnlaaa/569054.html>
- Sheikh, H., Prins, C., & Schrijvers, E. (2023). Artificial intelligence: definition and background. In *Research for policy* (pp. 15–41). https://doi.org/10.1007/978-3-031-21448-6_2
- Sidlauskiene, J., Joye, Y., & Auruskeviciene, V. (2023). AI-based chatbots in conversational commerce and their effects on product and price perceptions. *Electronic Markets*, 33(1). <https://doi.org/10.1007/s12525-023-00633-8>
- Singh, C., Dash, M. K., Sahu, R., & Kumar, A. (2024). Investigating the acceptance intentions of online shopping assistants in E-commerce interactions: Mediating role of trust and effects of consumer demographics. *Heliyon*, 10(3), e25031. <https://doi.org/10.1016/j.heliyon.2024.e25031>
- Song, X., Yang, S., Huang, Z., & Huang, T. (2019). The application of artificial intelligence in electronic commerce. *Journal of Physics Conference Series*, 1302(3), 032030. <https://doi.org/10.1088/1742-6596/1302/3/032030>
- Stankevich, A. (2017). Explaining the Consumer Decision-Making Process: Critical Literature Review. *Journal of International Business Research and Marketing*, 2(6), 7–14. <https://doi.org/10.18775/jibrm.1849-8558.2015.26.3001>
- Statista. (2025, September 3). *Global fashion e-commerce market size 2023-2030*. <https://www.statista.com/statistics/1298198/market-value-fashion-ecommerce-global/>
- Sukamolson, S. (2007). *Fundamentals of Quantitative Research | Request PDF*. ResearchGate. https://www.researchgate.net/publication/242772176_Fundamentals_of_quantitative_research
- Sukharevsky, A., Ess, A., Emelyantsev, D., Reasor, E., & Hürtgen, H. (2024, August 5). *LLM to ROI: How to scale gen AI in retail*. McKinsey & Company.

- <https://www.mckinsey.de/industries/retail/our-insights/llm-to-roi-how-to-scale-gen-ai-in-retail#/>
- Tavakol, M., & Dennick, R. (2011). Making sense of Cronbach's alpha. *International Journal of Medical Education*, 2, 53–55. <https://doi.org/10.5116/ijme.4dfb.8dfd>
- Thomas, C. G. (2021). Research methodology and scientific writing. In *Springer eBooks*. <https://doi.org/10.1007/978-3-030-64865-7>
- Tsagkias, M., King, T. H., Kallumadi, S., Murdock, V., & De Rijke, M. (2020). *Challenges and research opportunities in ecommerce search and recommendations - Amazon Science*. Amazon Science. <https://www.amazon.science/publications/challenges-and-research-opportunities-in-ecommerce-search-and-recommendations>
- Turing, A. M. (1950). I.—COMPUTING MACHINERY AND INTELLIGENCE. *Mind*, LIX(236), 433–460. <https://doi.org/10.1093/mind/lix.236.433>
- Ursachi, G., Horodnic, I. A., & Zait, A. (2015). How Reliable are Measurement Scales? External Factors with Indirect Influence on Reliability Estimators. *Procedia Economics and Finance*, 20, 679–686. [https://doi.org/10.1016/s2212-5671\(15\)00123-9](https://doi.org/10.1016/s2212-5671(15)00123-9)
- Van Der Heijden, H. (2004). *User acceptance of hedonic Information System*. ResearchGate. https://www.researchgate.net/publication/220260355_User_Acceptance_of_Hedonic_Information_System
- Vashishth, T. K., Vikas, N., Sharma, K. K., Kumar, B., Chaudhary, S., & Panwar, R. (2024). Enhancing Customer Experience through AI-Enabled Content Personalisation in E-commerce Marketing. In *CRC Press eBooks* (pp. 7–32). <https://doi.org/10.1201/9781003450443-2>
- Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: four longitudinal field studies. *Management Science*, 46(2), 186–204. <https://www.jstor.org/stable/2634758>
- Vimalkumar, M., Sharma, S. K., Singh, J. B., & Dwivedi, Y. K. (2021). ‘Okay google, what about my privacy?’: User's privacy perceptions and acceptance of voice based digital assistants. *Computers in Human Behaviour*, 120, 106763. <https://doi.org/10.1016/j.chb.2021.106763>
- Watkins, M. W. (2018). Exploratory Factor Analysis: A Guide to Best practice. *Journal of Black Psychology*, 44(3), 219–246. <https://doi.org/10.1177/0095798418771807>
- Yassine, A., Mohamed, L., & Achhab, M. A. (2020). Intelligent recommender system based on unsupervised machine learning and demographic attributes. *Simulation Modelling Practice and Theory*, 107, 102198. <https://doi.org/10.1016/j.simpat.2020.102198>
- Yeo, S. F., Tan, C. L., Kumar, A., Tan, K. H., & Wong, J. K. (2022). Investigating the impact of AI-powered technologies on Instagrammers' purchase decisions in digitalization era—A study of the fashion and apparel industry. *Ideas.repec.org*. <https://ideas.repec.org/a/eee/tefoso/v177y2022ics004016252200083x.html>
- Zaman, M., Jasim, K. M., Hasan, R., Akter, S., & Vrontis, D. (2025). Understanding customers' intentions to use AI-enabled services in online fashion stores – a longitudinal study. *International Marketing Review*. <https://doi.org/10.1108/imr-04-2024-0118>
- Zed, E. Z., Kartini, T. M., & Purnamasari, P. (2024, December 25). *The Power of Personalization : Exploring the impact of AI-Driven marketing strategies on consumer loyalty in E-Commerce*. <https://www.ejournal.seaninstitute.or.id/index.php/Ekonomi/article/view/5694>

Appendixes

Appendix A. Online Questionnaire

Q1

Welcome to my survey on how conversational AI-powered personalized recommendation systems will shape the consumer journey in online fashion retail.

Thank you for taking the time to participate in this study. My name is Ruben Wanders, and I am a master's student at ISCTE University. This survey is part of a research project that examines the impact of conversational AI-powered personalized recommendation systems on the online shopping experience in the fashion industry. Your responses will help me understand the impact of tailored product recommendations on consumer decision-making, trust, and loyalty.

Purpose of this study. This research aims to investigate the role of Conversational AI-Powered Personalized Recommendation Systems in shaping consumer behavior during online shopping. I am interested in learning about your online shopping experiences, perceptions of conversational AI-powered recommendations, and how these factors influence your purchase decisions.

What to Expect:

- The survey will take approximately 5-10 minutes to complete.
- Participation is voluntary, and you may exit the survey anytime.
- All responses are anonymous, and your data will be protected.

Consent:

By proceeding with this survey, you confirm that you are at least 18 years old and have experience with online shopping. Your participation in this study is greatly appreciated and will contribute to a deeper understanding of AI's role in modern retail.

If you have any questions about the survey or the study, please feel free to contact me at rwsnu@iscte-iul.pt

Click " Yes, I consent " to participate in the survey.

Yes I consent

No I do not consent

+ Add page break

Q2

What is your age?

Q3

What is your gender?

Male.

Female.

Other.

Prefer not to say.

Q4

* ...

What is your highest level of education completed?

- Less than high school.
- High school diploma or equivalent.
- Associate's degree.
- Bachelor's degree.
- Master's degree.
- Doctorate or higher.

+ Add page break

Q5

💡 *

What is your nationality?

Q6

*

How often do you shop online for clothes?

- Daily
- Weekly
- Monthly
- Half a year
- Rarely
- Never

Q7

💡 *

How much do you agree with these factors influencing your decision to shop for clothing online?

Please rate on a scale from 1 (Strongly Disagree) to 5 (Strongly Agree).

	1 – Strongly Disagree	2 – Disagree	3 – Neutral	4 – Agree	5 – Strongly Agree
Convenience of shopping online.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Availability of a wide variety of clothing options.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Competitive pricing and discounts.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Customer reviews and ratings.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Ease of navigation and website layout.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Accurate digital sizing and informative product descriptions.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

In your opinion, what is the most significant challenge you face when shopping for clothing online?


Page Break

Q10 | Introduction to AI Personalized Recommendation Systems. What are AI Personalized Recommendation Syst

Introduction to Traditional Recommendation Systems

What are Traditional Recommendation Systems? These are smart tools online fashion retailers use to suggest products that match your tastes and needs. By learning from your browsing history, past purchases, and preferences, these systems can show you items that you're more likely to love. Traditionally, these systems work in the background—passively suggesting items based on past behavior or other users' interactions. For example, you might see prompts like "You May Also Like," "Recommended for You," or "Customers Who Bought This Also Bought."

Home > ASOS DESIGN donut wake me up tee & legging pyjama set



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~~\$35.00~~ **\$28.00** (-20%)

[Free Shipping & Returns*](#)

COLOR: Gray

SIZE: Size Guide

Please select ▼

ADD TO CART 

YOU MIGHT ALSO LIKE

Q11

★ ...

How helpful do you find traditional product recommendation features (such as 'You may also like' or 'Recommended for you' sections) when shopping for clothing online?

- Extremely helpful.
- Helpful.
- Moderately helpful.
- Slightly helpful.
- Not at all helpful.

+ Add page break

Q12

★

How often do you buy products that are recommend by online fashion retailers?

- Very often.
- Often.
- Sometimes.
- Rarely.
- Never.

Q13

★

What challenges do you face with current traditional recommendation systems?" (Select all that apply)

- Too many recommendations that don't match my interests.
- Recommendations are too similar and lack diversity.
- Recommendations don't reflect my personal style preferences.
- Repeated suggestions of the same or similar items.
- Other (Please specify)

Page Break

Q14

Conversational AI-Powered Personalized Recommendation Systems.

While traditional AI personalized recommendation systems passively suggest items based on past behavior, an advancement that integrates Conversational AI-powered personalized Recommendation systems is being used.

Imagine a conversational AI-powered personalized online fashion assistant—an innovative virtual tool that chats with you, learns your style and size preferences, and recommends clothing that suits your needs. This assistant is designed to support you while shopping online by helping you find the right size, discover new styles, and feel more confident in purchasing.

How Do They Enhance Your Experience?

1. Tailored Suggestions: Imagine an online stylist recommending outfits and accessories just for you. For example, Zalando's tool lets you ask, "What should I wear to my dad's 60th birthday in November in Barcelona?" It analyzes weather data, event context, and location-specific fashion trends to provide personalized recommendations.

2. Measurement Guidance: Some systems can help answer questions like, "Would these shoes be available in my size?" by comparing your information with the brand's sizing data. Some systems can also use your device camera to help take measurements.

3. Customer Support: Other advanced systems can also act as virtual assistants, answering your shopping questions in real-time and helping with support like checking product availability, handling sizing concerns, returns, and exchanges.

Q15. 💡 ☆ ...

How useful is a conversational AI fashion assistant with personalized recommendations in these online shopping situations?
Please rate on a scale from 1 (Strongly Disagree) to 5 (Strongly Agree).

	1 - Strongly Disagree	2 - Disagree	3 - Neutral	4 - Agree	5 - Strongly Agree
When I'm looking for a specific clothing item (e.g., a red dress, a leather jacket).	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
When I want help discovering new brands or styles that match my taste.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
When I want answers to specific questions about products.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Whether I'm looking for everyday styling advice or an outfit for a special event like an interview or wedding.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
When I want help to find outfits that fit within a specific budget (e.g., 100 euros).	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Shopping for others (e.g., gifts).	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Color analysis to find clothing that complements my skin tone and hair color.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

+ Add page break

Q16. 💡 ☆

How easy do you think it would be to use a conversational AI fashion assistant with personalized recommendations for online clothing shopping?
Please rate on a scale from 1 (Strongly Disagree) to 5 (Strongly Agree).

	1 - Strongly Disagree	2 - Disagree	3 - Neutral	4 - Agree	5 - Strongly Agree
I believe it would be easy to understand the basic functions of the assistant, based on the description provided.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I believe I could quickly become comfortable using the assistant's features, if it were available.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I believe the assistant would be easy to integrate into my existing online shopping routine.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Having to repeatedly explain my instructions makes me less likely to continue using the assistant.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
If the assistant is too complex to use, I would be unlikely to use it.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Page Break

Q17. 💡 ☆

How much do you agree with these statements about the enjoyment of using a conversational AI fashion assistant with personalized recommendations?
Please rate on a scale from 1 (Strongly Disagree) to 5 (Strongly Agree).

	1 - Strongly Disagree	2 - Disagree	3 - Neutral	4 - Agree	5 - Strongly Agree
Using the assistant would make online shopping feel more like a personal experience.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I would have fun interacting with the assistant.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Interacting with the assistant would add a playful element to my shopping experience.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I would enjoy exploring clothing options from the assistant, even when I'm not planning to buy something.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
The assistant would make me feel more inspired and creative with my fashion choices.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Q18



How strongly do you agree with the following statements about privacy concerns when using a conversational AI fashion assistant with personalized recommendations? Please rate on a scale from 1 (Strongly Disagree) to 5 (Strongly Agree).

	1 - Strongly Disagree	2 - Disagree	3 - Neutral	4 - Agree	5 - Strongly Agree
I would be concerned about the assistant storing and using my personal style preferences and body measurements.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I would feel uncomfortable with a fashion assistant suggesting clothing based on my body type.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I would suspect the assistant's recommendations are driven by sales, not my preferences.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I would prefer to use a fashion assistant that allows me to control and limit what personal information is used.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
For highly relevant and engaging recommendations, I'm willing to compromise on privacy.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I'm more comfortable interacting with AI that uses a humanoid voice, avatar, and conversational style.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

1

Q19



When deciding to use a conversational AI fashion assistant with personalized recommendations, please rank the importance of the following aspects in order of priority (1 - Most Important, 4 - Least Important)

Perceived usefulness (e.g., how helpful it is in finding products, outfits, etc.)	1
Perceived ease of use (e.g., how easy and intuitive it is to interact with)	2
Perceived enjoyment (e.g., how fun, engaging or pleasant the experience is)	3
Privacy concerns (e.g., how the assistant uses or stores your data)	4

+ Add page break

Q20



How strongly do you agree with these statements about your intention to use a conversational AI fashion assistant with personalized recommendations? Please rate on a scale from 1 (Strongly Disagree) to 5 (Strongly Agree).

	1 - Strongly Disagree	2 - Disagree	3 - Neutral	4 - Agree	5 - Strongly Agree
If this assistant was available, I believe I would actively explore its features to enhance my online shopping experience.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I believe I would frequently use the assistant to find clothing items that align with my preferences.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I believe I would utilize the assistant's recommendations to make informed decisions.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I believe I would integrate the assistant into my regular online fashion shopping routine.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I would prefer using the assistant over manually browsing for clothing online.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Q21



To what extent do you agree with these statements about how a conversational AI fashion assistant with personalized recommendations influences your online purchasing decisions?

Please rate on a scale from 1 (Strongly Disagree) to 5 (Strongly Agree).

	1 - Strongly Disagree	2 - Disagree	3 - Neutral	4 - Agree	5 - Strongly Agree
The assistant's recommendations would encourage me to explore and purchase new or different clothing items I wouldn't usually consider.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
The assistant's personalized recommendations would make me more confident in my online clothing purchases.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
The assistant would make my online clothing shopping more efficient, resulting in quicker purchases.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I would be less likely to purchase impulsively with the assistant's curated recommendations.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I believe the assistant's recommendations would lead to higher satisfaction with my online clothing purchases.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Page Break

Q22



In your opinion, what features or functionalities would make a conversational AI fashion assistant with personalized recommendations satisfying for you to use?

Page Break

Q23



To what extent do you agree with the following statements regarding how a conversational AI fashion assistant with personalized recommendations could influence your loyalty as a customer?

Please rate on a scale from 1 (Strongly Disagree) to 5 (Strongly Agree).

	1 - Strongly Disagree	2 - Disagree	3 - Neutral	4 - Agree	5 - Strongly Agree
Helpful and personalized recommendations would increase my loyalty to that online store and increase my purchasing frequency at that store.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
If the online store offered a great conversational AI assistant, I would more likely recommend it to friends and family.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I would switch to a retailer offering a conversational AI fashion assistant with more accurate and personalized recommendations.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
It is important for a conversational AI assistant to offer customer support related to my purchases.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Appendix B. Additional Graphs Sample Characterisation

How often do you shop online for clothing?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1 Daily	3	1.5	1.5	1.5
	2 Weekly	10	5.0	5.0	6.5
	3 Monthly	103	51.2	51.2	57.7
	4 Half a year	51	25.4	25.4	83.1
	5 Rarely	34	16.9	16.9	100.0
	Total	201	100.0	100.0	

Source: IBM SPSS 29

Factors influencing participants' decision to shop for clothing online

	N	Minimum	Maximum	Mean	Std. Deviation
Q7_1 Convenience of shopping online	201	1	5	4.20	0.716
Q7_2 Availability of a wide variety of clothing options	201	1	5	4.26	0.702
Q7_3 Competitive pricing and discounts	201	1	5	4.05	0.814
Q7_4 Customer reviews and ratings	201	1	5	3.84	0.977
Q7_5 Ease of navigation and website layout	201	1	5	3.99	0.914
Q7_6 Accurate digital sizing and informative product descriptions	201	1	5	3.75	1.004

Source: IBM SPSS 29

Factors hindering participants' decision to shop for clothing online

	N	Minimum	Maximum	Mean	Std. Deviation
Q8_1 I often abandon my online shopping cart before completing the purchase	201	1	5	3.75	0.989

Q8_2 I find it difficult to make final decisions about online clothing purchases	201	1	5	3.66	1.066
Q8_3 I often get frustrated or dissatisfied with the online search experience and the website layout, resulting in me leaving the website	201	1	5	3.26	1.056
Q8_4 I get overwhelmed with the amount of options	201	1	5	3.48	1.114
Q8_5 Uncertainty about size and fit prevents me from buying clothes online	201	1	5	3.93	0.990
Q8_6 I miss the personalised help and advice you get when shopping in person	201	1	5	3.13	1.161

Source: IBM SPSS 29

Participants' most significant challenges when shopping online.

Thematic coding	Mentions (estimations)
Sizing	90
Can't Try On	50
Overwhelmed by Options	25
Image vs. Reality	20
Returns	15
Quality	10
Environmental Concerns	5

Source: IBM SPSS 29

Q11 How helpful do you find traditional product recommendation features (such as 'You may also like' or 'Recommended for you' sections) when shopping for clothing online?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1 Extremely helpful	18	9.0	9.0	9.0
	2 Helpful	72	35.8	35.8	44.8
	3 Moderately helpful	59	29.4	29.4	74.1

4 Slightly helpful	46	22.9	22.9	97.0
5 Not at all helpful	6	3.0	3.0	100.0
Total	201	100.0	100.0	

Source: IBM SPSS 29

Q12 How often do you buy products that are recommend by online fashion retailers?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1 Extremely helpful	10	5.0	5.0	5.0
	2 Helpful	28	13.9	13.9	18.9
	3 Moderately helpful	92	45.8	45.8	64.7
	4 Slightly helpful	59	29.4	29.4	94.0
	5 Not at all helpful	12	6.0	6.0	100/0
	Total	201	100.0	100.0	

Source: IBM SPSS 29

Q13 Challenges in traditional recommendation systems

	Responses	
	N	Percent
Q13_1 Too many recommendations that don't match my interests	88	27.3%
Q13_2 Selected Choice Recommendations are too similar and lack diversity	59	18.3%
Q13_3 Selected Choice Recommendations don't reflect my personal style preferences	81	25.2%
Q13_4 Selected Choice Repeated suggestions of the same or similar items	83	25.8%
Q13_5 Selected Choice Other (Please specify)	11	3.4%
Total	322	100.0%
a. Dichotomy group tabulated at value 1		

Source: IBM SPSS 29

Appendix C. Descriptive Analysis

Perceived Usefulness (PU) Descriptive Statistics

	N	Mean	STD. Deviation	Skewness	Skewness
	Statistic	Statistic	Statistic	Statistic	Std. Error
PU_1: When I'm looking for a specific clothing item (e.g., a red dress, a leather jacket)	201	3.82	0.932	-1.135	0.172
PU_2: When I want help discovering new brands or styles that match my taste	201	3.72	0.912	-1.015	0.172
PU_3: When I want answers to specific questions about products	201	3.94	0.870	-0.989	0.172
PU_4: Whether I'm looking for everyday styling advice or an outfit for a special event like an interview or wedding	201	3.54	1.000	-0.770	0.172
PU_5: When I want help to find outfits that fit within a specific budget (e.g., 100 euros)	201	3.84	0.897	-1.066	0.172
PU_6: Shopping for others (e.g., gifts)	201	3.58	1.046	-0.763	0.172
PU_7: Color analysis to find clothing that complements my skin tone and hair color	201	3.55	1.048	-0.613	0.172
Perceived Usefulness Average	201	3.7136	0.66463	-1.410	0.172

Source: IBM SPSS Statistics 29

Perceived Ease of Use (PEU) Descriptive Statistics

	N	Mean	STD. Deviation	Skewness	Skewness
	Statistic	Statistic	Statistic	Statistic	Std. Error
PEU_1: I believe it would be easy to understand the basic functions of the assistant, based on the description provided	201	3.96	0.723	-0.653	0.172
PEU_2: I believe I could quickly become comfortable using the assistant's features, if it were available	201	3.83	0.803	-0.904	0.172
PEU_3: I believe the assistant would be easy to integrate into my existing online shopping routine	201	3.72	0.880	-0.924	0.172
PEU_4: Having to repeatedly explain my instructions makes me less likely to continue using the assistant	201	4.06	0.791	-0.657	0.172
PEU_5: If the assistant is too complex to use, I would be unlikely to use it	201	3.84	0.897	-1.002	0.172
Perceived Ease of Use Average	201	3.9363	0.49872	-0.242	0.172

Source: IBM SPSS Statistics 29

Perceived Enjoyment (PE) Descriptive Statistics

	N	Mean	STD. Deviation	Skewness	Skewness
	Statistic	Statistic	Statistic	Statistic	Std. Error
PE_1: Using the assistant would make online shopping feel more like a personal experience	201	3.51	1.064	-0.839	0.172
Pe_2: I would have fun interacting with the assistant	201	3.51	1.011	-0.740	0.172
PE_3: Interacting with the assistant would add a playful element to my shopping experience	201	3.47	1.025	-0.742	0.172
PE_4: I would enjoy exploring clothing options from the assistant, even when I'm not planning to buy something	201	3.39	1.095	-0.761	0.172
PE_5: The assistant would make me feel more inspired and creative with my fashion choices	201	3.39	1.058	-0.636	0.172
Perceived Enjoyment Average	201	3.4557	0.88706	-0.969	0.172

Source: IBM SPSS Statistics 29

Perceived Privacy Concerns (PPC) Descriptive Statistics

	N	Mean	STD. Deviation	Skewness	Skewness
	Statistic	Statistic	Statistic	Statistic	Std. Error
PPC_1: I would be concerned about the assistant storing and using my personal style preferences and body measurements	201	3.41	1.150	-0.362	0.172
PPC_2: I would feel uncomfortable with a fashion assistant suggesting clothing based on my body type	201	3.00	1.202	-0.095	0.172
PPC_3: I would suspect the assistant's recommendations are driven by sales, not my preferences	201	3.73	0.922	-0.744	0.172
PPC_4: I would prefer to use a fashion assistant that allows me to control and limit what personal information is used	201	3.97	0.916	-0.926	0.172
PPC_5: For highly relevant and engaging recommendations, I'm willing to compromise on privacy	201	3.00	1.181	-0.249	0.172
PPC_6: I'm more comfortable interacting with AI that uses a humanoid voice, avatar, and conversational style	201	3.28	1.078	-0.357	0.172
Perceived Privacy Concerns Average	201	3.3997	0.61781	-0.048	0.172

Source: IBM SPSS Statistics 29

Behavioural Intentions (BI) Descriptive Statistics

	N	Mean	STD.	Skewness	Skewness
	Statistic	Statistic	Deviation	Statistic	Std.
			Statistic		Error
BI_1: If this assistant was available, I believe I would actively explore its features to enhance my online shopping experience	201	3.58	0.962	-1.141	0.172
BI_2: I believe I would frequently use the assistant to find clothing items that align with my preferences	201	3.39	0.979	-0.877	0.172
BI_3: I believe I would utilize the assistant's recommendations to make informed decisions	201	3.63	0.857	-1.140	0.172
BI_4: I believe I would integrate the assistant into my regular online fashion shopping routine	201	3.34	0.998	-0.885	0.172
BI_5: I would prefer using the assistant over manually browsing for clothing online	201	3.26	1.011	-0.626	0.172
Behavioural Intention Average	201	3.4298	0.80025	-1.167	0.172

Source: IBM SPSS Statistics 29

Purchasing Decision Descriptive Statistics

	N	Mean	STD.	Skewness	Skewness
	Statistic	Statistic	Deviation	Statistic	Std.
			Statistic		Error
PD_1: The assistant's recommendations would encourage me to explore and purchase new or different clothing items I wouldn't usually consider	201	3.43	0.920	-0.954	0.172
PD_2: The assistant's personalized recommendations would make me more confident in my online clothing purchases	201	3.33	0.976	-0.776	0.172
PD_3: The assistant would make my online clothing shopping more efficient, resulting in quicker purchases	201	3.52	0.944	-1.024	0.172
PD_4: I would be less likely to purchase impulsively with the assistant's curated recommendations	201	3.19	1.093	-0.522	0.172
PD_5: I believe the assistant's recommendations would lead to higher satisfaction with my online clothing purchases	201	3.51	0.895	-0.904	0.172
Purchasing Decisions Average	201	3.3960	0.73782	-1.082	0.172

Source: IBM SPSS Statistics 29

Consumer Loyalty Descriptive Statistics

	N	Mean	STD.	Skewness	Skewness
	Statistic	Statistic	Deviation	Statistic	Std. Error
CL_1: Helpful and personalized recommendations would increase my loyalty to that online store and increase my purchasing frequency at that store	201	3.66	0.858	-1.240	0.172
CL_2: If the online store offered a great conversational AI assistant, I would more likely recommend it to friends and family	201	3.54	0.943	-1.083	0.172
CL_3: I would switch to a retailer offering a conversational AI fashion assistant with more accurate and personalized recommendations	201	3.41	1.017	-0.640	0.172
CL_4: It is important for a conversational AI assistant to offer customer support related to my purchases	201	3.81	0.870	-1.038	0.172
Consumer Loyalty Average	201	3.60	0.73372	-1.13	0.172

Source: IBM SPSS Statistics 29

Ranking Question: When deciding to use a CRS, rank the following aspects in order of priority (1 = most important, 4 = least important)

	N	Minimum	Maximum	Mean	STD. Deviation
Perceived Usefulness	201	1	4	1.67	0.757
Perceived Ease of Use	201	1	4	2.30	0.831
Perceived Enjoyment	201	1	4	3.46	0.781
Perceived Privacy Concerns	201	1	4	2.58	1.219

Source: IBM SPSS Statistics 29

Features for a satisfying Conversational AI Fashion Assistant

Theme	Example Responses	Count	% of Total
Ease of Use & Efficiency	“Easy to use”, “Quick and relevant advice”, “Helps me find products faster”, “Simple to navigate”	42	20.9%
Personalization & Style Understanding	“Understands my style and preferences”, “Learns from my feedback”, “Personalized recommendations based on my taste”	38	18.9%
Size, Fit & Body Type Accuracy	“Accurate sizing”, “Body measurements input”, “Find clothes that fit my shape”	28	13.9%
Visual & Virtual Features	“Virtual try-on”, “Visual previews of outfits”, “Find clothing from a picture”	20	10.0%
Privacy & Data Protection	“Strong privacy rules”, “Deletes data after a week”, “Doesn’t use cookies”	16	8.0%
Budget & Discounts	“Show discounts”, “Filter by budget”, “Save money when buying online”	14	7.0%
Occasion & Context-Aware Recommendations	“Outfits for specific events”, “Weather-based recommendations”, “Outfits for business meetings or dates”	13	6.5%
Trust, Transparency & Reliability	“Trustworthy”, “Honest and accurate responses”, “Doesn’t encourage unnecessary purchases”	11	5.5%
Human-Like Interaction	“Natural conversation”, “Human-like responses”, “Nice tone of voice”	9	4.5%
Trend Awareness & Inspiration	“Keeps up with fashion trends”, “Offers new styles or ideas”	8	4.0%
Other / Neutral / Unsure	“Don’t know”, “Not sure”, “I wouldn’t use it”	2	1.0%
Total		201	100%

Source: IBM SPSS Statistics 29.

Appendix D. Cronbach's Alpha Coefficient

Dimension	Cronbach's Alpha Coefficient	Items	Correlated Item-Total Correlation	Cronbach's Alpha if Item deleted
Perceived Usefulness (PU)	0.819	PU 1.1	0.559	0.795
		PU 1.2	0.596	0.789
		PU 1.3	0.547	0.797
		PU 1.4	0.607	0.786
		PU 1.5	0.548	0.797
		PU 1.6	0.513	0.804
		PU 1.7	0.556	0.796
Perceived Ease of Use (PEU)	0.613	PEU 2.1	0.516	0,488
		PEU 2.2	0.485	0.495
		PEU 2.3	0.426	0.526
		PEU 2.4	0.220	0.631
		PEU 2.5	0.223	0.628
Perceived Enjoyment (PE)	0.899	PE 3.1	0.738	0,879
		PE 3.2	0.816	0.863
		PE 3.3	0.794	0.867
		PE 3.4	0.703	0.888
		PE 3.5	0.704	0.887
Perceived Privacy Concerns (PPC)	0.587	PPC 4.1	0,446	0.485
		PPC 4.2	0,465	0.472
		PPC 4.3	0,367	0.529
		PPC 4.4	0,337	0.540
		PPC 4.5	0,013	0.676
		PPC 4.6	0.387	0.514
Behavioural Intention (BI)	0.888	BI 5.1	0.675	0.876
		BI 5.2	0.777	0.852
		BI 5.3	0.708	0.869
		BI 5.4	0.817	0.842
		BI 5.5	0.674	0.877

Purchasing	0.820	PD 6.1	0.547	0.802
Decisions (PD)		PD 6.2	0.653	0.772
		PD 6.3	0.676	0.765
		PD 6.4	0.523	0.815
		PD 6.5	0.682	0.765
		Consumer	0.804	CL 7.1
Loyalty (CL)		CL 7.2	0.698	0.715
		CL 7.3	0.642	0.746
		CL 7.4	0.536	0.793

IBM SPSS 29 Statistics