T.C.

ISTANBUL TICARET UNIVERSITY
GRADUATE SCHOOL OF SOCIAL SCIENCES
DEPARTMENT OF DIGITAL ECONOMY AND MARKETING
MASTER'S PROGRAM OF DIGITAL ECONOMY AND MARKETING

AI-ENHANCED PERSONALIZATION IN THE TURKISH E-COMMERCE MARKET: A SURVEY ON CONSUMER BEHAVIOR AND DECISION-MAKING

Master's Thesis

Aya KHALIL

ISTANBUL, 2024

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Declaration

I declare that all the required information in this title “AI-Enhanced Personalization in the Turkish E-Commerce Market: A Survey on Consumer Behavior and Decision-Making” has been written in accordance with the academic manners and ethical commitment. I would clarify that all the materials, sources, data and all extra inputs have been benefited well throughout the writing procedure of this thesis. All matters contained in this thesis are my personal opinion and do not reflect the official view of Istanbul Ticaret University.

Aya, Khalil

ABSTRACT

This study explores the applications of artificial intelligence tools and features in e-commerce, focusing on platforms and consumer behavior and decision-making in Türkiye. The main purpose of this research is to investigate the impact of AI-driven tools and features integrated into e-commerce platforms on Turkish consumers' engagement. The study examines the effects of users' perceived efficiency of AI-driven tools, namely chatbots, visual search, recommender systems, and automated after-sales services, on their psychological and behavioral engagement levels by employing a user survey and a quantitative research methodology. The findings of this research demonstrate that effectively integrating efficient AI-driven tools into e-commerce platforms positively affects users' interaction with those platforms and leads to the development of psychological and behavioral engagement attitudes from those users towards the platforms in Türkiye, which highlights the crucial role of technological tools in enhancing user experience and satisfaction. This research has significant implications for marketers, e-commerce professionals, and policymakers, as it provides evidence-based insights that can guide them through developing a more interactive and engaging e-commerce environment for consumers in Türkiye. Future research could explore other AI applications or e-commerce platform features that would contribute to higher user engagement levels and further enhance the Turkish e-commerce sector.

Keywords: *Artificial Intelligence, E-Commerce, E-Commerce Platforms, Consumer Behavior, Consumer Engagement.*

ÖZET

Bu çalışma, yapay zeka araçlarının ve özelliklerinin e-ticaretteki uygulamalarını incelemekte, özellikle Türkiye'deki platformlar ve tüketici davranışları ile karar alma süreçlerine odaklanmaktadır. Araştırmanın temel amacı, e-ticaret platformlarına entegre edilen yapay zeka destekli araç ve özelliklerin Türk tüketicilerin etkileşim düzeylerine olan etkisini incelemektir. Çalışma, kullanıcıların algıladığı yapay zeka destekli araçların verimliliği, yani sohbet robotları, görsel arama, öneri sistemleri ve otomatikleştirilmiş satış sonrası hizmetlerin, psikolojik ve davranışsal etkileşim düzeylerine olan etkilerini, bir kullanıcı anketi ve nicel araştırma metodolojisi kullanarak inceler. Bu araştırmanın bulguları, etkili bir şekilde entegre edilen yapay zeka destekli araçların e-ticaret platformlarıyla kullanıcıların etkileşimini olumlu yönde etkilediğini ve Türkiye'deki platformlara karşı kullanıcıların psikolojik ve davranışsal bağlılık tutumlarının gelişimine yol açtığını göstermektedir. Bu sonuçlar, kullanıcı deneyimini ve memnuniyetini artırma konusunda teknolojik araçların hayati rolünü vurgulamaktadır. Bu araştırmanın pazarlamacılar, e-ticaret profesyonelleri ve politika yapıcılar için önemli sonuçları bulunmaktadır; çünkü Türkiye'de tüketiciler için daha etkileşimli ve çekici bir e-ticaret ortamı geliştirmelerine rehberlik edecek kanıta dayalı içgörüler sağlamaktadır. Gelecek araştırmalar, kullanıcı etkileşim düzeylerini daha da artırabilecek diğer yapay zeka uygulamalarını veya e-ticaret platformu özelliklerini inceleyebilir ve Türk e-ticaret sektörünü daha da geliştirebilir.

Anahtar Kelimeler: *Yapay Zeka, E-Ticaret, E-Ticaret Platformları, Tüketici Davranışı, Tüketici Etkileşimi.*

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This thesis stands as a milestone in my academic career and as a testament to the collective effort of all those mentioned above.

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LIST OF ABBREVIATIONS

AI : Artificial Intelligence
ANN : Artificial Neural Networks
AR : Augmented Reality
AS : Automated After-Sales Service Efficiency
ASC : Attention to Social Comparison Level
B2B : Business-to-Business
B2C : Business-to-Consumer
BE : Behavioral Engagement Level
C2C : Consumer-to-Consumer
CAGR: Compounded Annual Growth Rate
CB : Chatbot Efficiency
CRM : Customer Relationship Management
EDI : Electronic Data Interchange
EFA : Exploratory Factor Analysis
EFT : Electronic Fund Transfer
EKB : Engel-Kollat-Blackwell
ICT : Information and Communication Technology
NLP : Natural Language Processing
PE : Psychological Engagement Level
RS : Recommender System Efficiency
SDG : Sustainable Development Goals
SOR : Stimulus-Organism-Response
VAT : Value-added Tax
VIF : Variance Inflation Factor
VR : Virtual Reality
VS : Visual Search Efficiency

INTRODUCTION

The application and integration of artificial intelligence (AI) in this era of rapid technological growth and advancements has revolutionized various industries and their operations and offered them unprecedented opportunities. This integration has been particularly transformative in reshaping the relationship between businesses and their consumers and consumer experiences, where AI's influence is evident across multiple touchpoints. Among these industries, e-commerce stands out as a dynamic and transformative domain. E-commerce has been at the forefront of leveraging AI technologies to streamline operations, enhance user experiences, and create more personalized and efficient shopping journeys. This study aims to delve into the intricate relationship between AI, e-commerce, and consumer behavior, exploring how AI is not just a tool but a revolutionary force transforming the way businesses interact with their customers and influence their behavior.

Having experienced a rapid expansion in recent years due to the rising consumerism led by the ever-evolving demands and needs and the circumstances brought on by the global COVID-19 pandemic, the e-commerce market worldwide is anticipated to continue growing at unprecedented rates. The first touchpoint that businesses have with their customers nowadays happens online. According to Baluch, author of the Forbes Advisor 2023 article on "E-Commerce Statistics of 2023," 20.8% of retail purchases worldwide were expected to occur online and reach 24% by 2026. With more customers departing physical stores by the day and favoring online platforms for making their purchases from the comfort of their homes, it is no surprise that e-commerce sales are also expected to surge. According to the same article, global e-commerce sales were expected to grow by 10.4% in the year 2023, bringing this market to a total of 6.3 trillion USD, and are further expected to expand 28.6% by the year 2026, bringing the market to a whopping total of 8.1 trillion USD (Baluch, 2023).

Just like in many other industries, the unprecedented boom in the e-commerce market is also attributed to the substantial digital transformation driven by the Internet, with over five billion users worldwide capable of enjoying the benefits of making purchases online, according to Van Gelder, author of the 2023 Statista article, "E-Commerce Worldwide - Statistics & Facts." AI is undoubtedly one of the most prominent of those advancements. In the McKinsey & Company 2024 research on AI adoption, authors Singla et al. report that while 50% of respondents' organizations reported implementing AI usage in 2023, this figure has increased by 72% in this past year alone. 58% of those respondents reported witnessing an increase in revenue and 35% reported a cost reduction post-adoption by incorporating AI into their services and operations (Singla et al., 2024). In another 2023 Statista article, "E-Commerce Areas Where AI is Useful According to Executives 2021," author Chevalier revealed that 70% of the executives surveyed believed that AI would help in the personalization of their customers' experiences in their e-commerce platforms. Additionally, 34% saw AI as a tool for enhancing customer service, while 54% anticipated that AI would improve the efficiency of site searches for their customers (Chevalier, 2023).

With the unprecedented disruption led by the COVID-19 pandemic and the price consciousness of consumers driven by ever-increasing inflation, the Turkish e-commerce sector has emerged as one of the fastest-growing markets in the world. As reported by the Turkish Ministry of Trade (T.C. Ticaret Bakanlığı) in their 2024 annual e-commerce data report, Türkiye's e-commerce market reached a total value of 1.85 trillion TL in 2023 (equivalent to about 78 billion dollars at that time), which reflected a substantial growth of 115.15% from its 2022 size, and witnessed a 22.25% increase in transactions number. The retail e-commerce sector contributed to 54.19% of the general Turkish retail market value in 2023 (T.C. Ticaret Bakanlığı, 2024), and according to Dierks, author of the 2024 Statista article, "E-Commerce in Turkey - Statistics & Facts," around 64% of Türkiye's population reported shopping online in 2022. The Turkish Ministry of Trade revealed in their semi-annual e-commerce data report on the first half of 2023 that the retail e-commerce sector recorded an astounding 119% volume increase compared to the same timeframe of 2022, with its contribution to the Turkish e-commerce market value reaching 59.75%, and orders rising by 20%.

The remarkable high-paced growth and expansion of Türkiye's e-commerce market, which witnessed 559,412 active businesses in 2023, with around 540 thousand of them serving their customers through e-commerce marketplace platforms (T.C. Ticaret Bakanlığı, 2024), demonstrate its significance as a valuable market to study. Furthermore, according to Bilik, author of the 2023 İzmir İktisat Dergisi article, "Analyzing Challenges and Opportunities in the E-Commerce Industry of Turkey," the Turkish government demonstrates a commitment to further nurturing the e-commerce market growth by launching various incentives and initiatives to improve the overall digital economy, like the Digital Türkiye Platform and the National E-Commerce Strategy. Many of those initiatives aim to promote and facilitate the adoption of digital technologies, of which AI stands at the forefront. This governmental support fosters a conducive environment for technological innovation and positions AI as a potential driver in advancing the Turkish e-commerce market and reshaping its customers' journeys. Such an e-commerce landscape offers a unique opportunity to research the integration of AI into its platforms and investigate the impact of that integration in enhancing its customer experiences.

Integrating AI tools and features into e-commerce platforms and its impact on consumer behavior, especially in the Turkish market, is a topic that has not been fully explored by previous literature. However, the key issue lies in the efficiency of AI applications on e-commerce platforms in improving consumer experience and satisfying their needs. It is evident from the literature, which will be explored in the literature review chapter of this study, that e-commerce platforms, or what is known as "Platformization," build a competitive edge for businesses, especially with the utilization of AI tools and features. Most studies and reports on AI applications in e-commerce have also focused on the adoption and the application technicalities, with less attention to the interaction between those applications and consumers. Consumer end-users expect a satisfactory experience from interactions with new technological applications on e-commerce platforms.

The primary purpose of this study is to explore and understand the impact of AI on e-commerce, focusing on consumer behavior within the Turkish market. This study aims to fill the gap in the existing literature by examining, from the viewpoint of Turkish consumers, how advanced technologies within e-commerce platforms, particularly AI tools and features, contribute to fostering positive engagement and attitudes among consumers. It builds upon existing literature to assess these AI elements in the context of their impact on consumer interaction.

This research aims to evaluate and dissect how AI-driven tools, specifically chatbots, visual search, recommender systems, and automated after-sales services, are revolutionizing the online shopping experience and how well they influence consumers' psychological and behavioral engagement. This study attempts to answer the question:

How does integrating AI tools and features into e-commerce platforms influence the development of positive engagement attitudes among users?

The importance of this research question lies in its relevance to the current technological era, where AI integration is a critical factor in the success of e-commerce platforms and, thus, their businesses. Understanding these dynamics in an emerging digital market like Türkiye is crucial, as it can provide insights into consumer behavior patterns, technological adaptation, and business strategy optimization inf similar global markets. The focus on AI in e-commerce platforms indicates a progressive approach that highlights the potential for Türkiye to serve as a model for emerging digital economies globally.

The introduction of this thesis lays the foundation for the research by providing context and relevance and sets the stage for the subsequent chapters of this research. The background, purpose, research question, and importance of the study are also presented. The subsequent chapters of this thesis are structured as follows:

The first chapter, titled "Literature on E-Commerce Market," provides a comprehensive review of existing research and literature on the e-commerce market, focusing on its evolution and technological advancements. It will also explore various AI technologies, their historical advancements, and their applications in e-commerce and other industries.

The second chapter, "Consumer Behavior and Decision-Making," provides a theoretical foundation on consumer behavior and decision-making, introduces various consumer behavior models, and explores the multiple factors influencing consumers. It will also explore established consumer behavior models and their applicability in the context of this study.

The third chapter, titled "Research on AI-Enhanced Personalization in the Turkish E-Commerce Market: A Survey on Consumer Behavior and Decision-Making," builds upon the previous chapters to introduce this study's hypotheses and research methodology and design, including the sampling and data collection processes, and the rationale behind the chosen methods. The chapter also presents the statistical techniques used for data analysis and the results of the data analysis, including the hypotheses testing. The last section in this chapter will be the culmination of this thesis. It interprets the results of the data analysis and summarizes the key findings of the research, discussing them in the context of the existing literature and the hypotheses developed and will explore the implications of the findings for both theory and practice.

The conclusion of this thesis will summarize the study's results, address the study's limitations, and suggest recommendations for future research.

CHAPTER 1: LITERATURE ON E-COMMERCE MARKET

This chapter of the study provides a comprehensive overview and introduction of the existing literature on the e-commerce market, both globally and in Türkiye, and AI in e-commerce, focusing on definitions, historical evolution, and technological advancements in both fields and their application within the broader context of this study. It introduces a theoretical background to examine the Turkish e-commerce market specifically. It lays the foundation, especially for the second chapter on consumer behavior and decision-making, to explore the importance and role of AI in transforming this sector and consumer interaction and support the development of the hypotheses of this research.

1.1. E-Commerce:

E-commerce has transformed how businesses and consumers interact on multiple levels, which was made possible thanks to the increasing global internet penetration and the technological advancements it accelerated. From online shopping to electronic payments, e-commerce encompasses various activities. This section of the literature review provides a comprehensive introduction and overview of e-commerce, its definition, evolution, types, and technological advancements that facilitate its growth, lays the foundation for the following chapters, and highlights its importance as a subject area of study.

1.1.1. Introduction To E-Commerce:

Various pieces of literature emphasized the significant role that e-commerce plays as a dominant force in the global economy and, perhaps, one of the strongest in reshaping traditional business models. A. Dhanalakshmi et al. (2020) highlight this significant role as evidenced by the focus on the advancements in e-commerce and their impact on customer relationship management, which underscores its importance and influence in modern business practices. Al Hamli and Sobaih (2023) discuss the implications of e-commerce and emphasize its important role in reshaping consumer behavior. Baluch (2023) provides various statistics about e-commerce, underlining its significant role and impact on the global economy. Bilik (2023) analyzes the challenges and opportunities in the e-commerce industry in Türkiye, highlighting its economic significance. The following subsections, however, focus on providing an introduction and an overview of research and literature that defined e-commerce, traced its historical evolution, presented its types, and highlighted its significance in the business landscape to provide a background on the subject area.

1.1.1.1. Definition and Evolution of E-Commerce:

In their 2021 article “An Overview of Electronic Commerce (E-Commerce)”, published in the Journal of Contemporary Issues in Business and Government, the authors Jain et al. provide an in-depth overview and analysis of e-commerce and its many facets, including the benefits, potentials, facilitators and technological impacts in the modern market (Jain et al., 2021).

Electronic commerce, more popularly known as e-commerce, refers to the utilization of electronic media and the Internet for conducting business transactions, which includes but is not limited to, the purchase and sale of goods and services (Jain et al., 2021). E-commerce utilizes technological tools, like electronic data interchange (EDI) and Internet platforms, to facilitate trading goods, services, and monetary transactions between companies and their customers (Jain et al., 2021). This digital commerce model has even allowed businesses to set up virtual shops or websites for direct sales of their offerings to consumers and also provided the convenience for shoppers to buy items online through different payment options, including credit cards, debit cards, or electronic fund transfers (EFT) (Jain et al., 2021).

Overall, Jain et al. (2021) present e-commerce as a tool that leverages digital communication and information systems to evolve, transform, and enhance how businesses interact and create value with individuals and other organizations.

While Jain et al. provide insights and contributions into understanding e-commerce and its significance, especially regarding technological advancements and the Internet, covered in later sections in this research, their article does not present a detailed historical account of the evolution of e-commerce from its inception to the present day. However, authors of the 2017 article “E-Commerce: A Short History Follow-up on Possible Trends”, published in the International Journal of Business Administration, Santos et al. examine the evolution that e-commerce undergoes, especially since the 1990s, with the development and advancement of information technology (Santos et al., 2017).

Santos et al. (2017) lay out a timeline that is composed of four phases for the evolution of e-commerce. The first stage, which started in the 1970s, saw e-commerce limited to large corporations that used private networks and EFT systems to conduct their financial dealings and dealings as well as facilitate document exchanges. These entities also started utilizing the Internet to promote and market their products and services, which laid the foundation for e-commerce (Santos et al., 2017). The second stage of e-commerce evolution witnessed a shift towards handling orders, disseminating product and service usage information, and coordinating logistics, which then began drawing attention and influencing companies (Santos et al., 2017). The third stage was marked by products and services distribution through Information Technology, including the digital sale of items like music and software through digital platforms (Santos et al., 2017). Finally, the fourth stage represented the maturation of e-commerce, which was a stage characterized by interactive relationships between sellers and buyers. This phase went beyond mere data exchange or product delivery, driven by information technology advancements and the widespread use of the Internet, which expanded the potential consumer base (Santos et al., 2017).

By providing this brief history and evolution of e-commerce, Santos et al. (2017) fill the gaps and provide a historical perspective that complements and lays the foundation for the more contemporary analysis provided by Jain et al. (2021). The combination of historical and modern analyses offers a more comprehensive understanding of e-commerce.

1.1.1.2. Types and Advantages of E-Commerce:

Santos et al. (2017) argue that one of the greatest advantages of e-commerce is that it facilitates the realization of large amounts of transactions as those transactions can all be conducted electronically, whether between companies, between companies and consumers, or even between those two entities and government organs. Santos et al. (2017) present and detail the types of transactions possible in e-commerce which lays the groundwork for a better understanding of the e-commerce market key players and its landscape.

Table 1. Types of E-Commerce Transactions

Type	Acronym	Description
Business-to-business	B2B	Transactions between companies
Business-to-consumer	B2C	Transactions between companies and consumers
Consumer-to-business	C2B	Transactions between consumers and companies
Consumer-to-consumer	C2C	Transactions between consumers
Government-to-consumer	G2C	Transactions between the government and consumers
Consumer-to-government	C2G	Transactions between consumers and the government
Business-to-government	B2G	Transactions between companies and the government
Government-to-business	G2B	Transactions between the government and companies
Government-to-government	G2G	Transactions between the government departments

Santos et al. (2017) claim that the highest volume of e-commerce transactions occurs between business-to-business (B2B), business-to-consumer (B2C), and consumer-to-consumer (C2C), with the main highlight going for B2Cs, which has the greatest number of transactions and is the main focus of this research.

Jain et al. (2021) argue that consumers obtain the highest and most distinct advantage from this type of e-commerce due to the openness of the market. Consumers can easily compare prices, evaluate different offerings, and easily switch to a substitute or competitor because of their awareness of all the alternatives, giving them a significant edge. This e-commerce type has witnessed unprecedented growth with the rise of the Internet, leading to an expansion in online stores offering products like electronics, books, accessories, food, vehicles, and even financial resources. Through digital stores, consumers can access more information, make lower-cost purchases, and receive their products more conveniently without compromising on a personalized customer experience. Jain et al. (2021) stress that the best advantage that consumers benefit from thanks to e-commerce is in terms of time-saving and convenience as consumers can make purchases at any time and any place with no physical contact with the sellers, but further list other key advantages like lower trading rates, higher flexibility, easy access, enhanced comfort, more range of options, and finally, the ability to provide feedback on a product and make purchase assessments and decisions based on other consumers' feedback.

While Jain et al. (2021) focus on the consumer advantages of e-commerce and its advancements, they also present and highlight the numerous benefits from the viewpoint of businesses. E-commerce has allowed businesses to generate more revenues and cut running and sustaining costs like operations, maintenance, procurement, and transportation. E-commerce has also enhanced the relationship between those businesses and their customers and suppliers, assisted in promoting their companies' image and brand, and in building customer loyalty and retention (Jain et al., 2021).

Santos et al. (2017), on the other hand, focus more on the business benefits of e-commerce and its advancements, and while it is not the main focus of this research, it provides a comprehensive understanding of the advantages of e-commerce, specifically B2C, for all its key players. Those advantages can be categorized into five main types. The first is competitive advantages. Those advantages are realized in terms of cost reduction, increased precision, and faster online transactions. These also represent benefits to consumers and not only businesses. The second type is marketing and supply chain optimization, which is achieved by utilizing data mining for targeting consumers, higher adaptability to changing market conditions, enhanced supply chain optimization, and improved leveraging of partners' skills. The third type is transaction efficiency, which is realized in terms of processing time reduction, leading to less storage and management costs and faster adjustment to market conditions, leading to better customizability of promotions to consumers. These advantages also represent benefits to consumers and not only businesses. The fifth and last type is delivery and cost advantages, specifically for products and services like software, music, news, consultancy, reservations, and banking services, that is in terms of reduced delivery costs and constant availability of the products and services, which also represent benefits to consumers as well.

1.1.2. Technological Advancements in E-Commerce:

According to various pieces of literature, technological advancements have significantly shaped the current e-commerce landscape globally. A. Dhanalakshmi et al. (2020) focused on the technological advancements in e-commerce and their impact on customer relationship management like the use of data analytics for enhancing customer insights, the implementation of automated customer service systems, the advancements in payment processing technologies, and the use of machine learning algorithms for personalizing customer experiences. Cheng et al. (2023), on the other hand, focused on technologies like recommendation systems for enhancing personalization, chatbots for facilitating customer service, machine learning for inventory management, and other technologies for price optimization and fraud detection. Other pieces of literature discussed technologies like visual search, supply chain optimization tools, predictive analytics (Nimbalkar & Berad, 2021), price prediction, and advanced interfaces (Sudarsan et al., 2022). Those technological advancements have played the role of facilitators that enabled businesses worldwide to operate more efficiently while simultaneously enhancing customer experience. Multiple other innovations in e-commerce have also contributed to its rapid and unprecedented growth. The following subsections provide an overview of the most notable facilitators of e-commerce and innovations in the field, as emphasized by previous research.

1.1.2.1. Facilitators of E-Commerce:

Jain et al. (2021) claim in their article that the transformation that the e-commerce market has undergone is being facilitated by many technologies and innovations, like the adoption of the Internet, the integration of payment gateways, the utilization of data analytics, the deployment of social media platforms, and the vast potential of the use of autonomous vehicles and 3D printing. While multiple other literature lists a similar or additional set of facilitators, Jain et al. (2021) provide a comprehensive and concise account of some of the most important ones.

Internet: The widespread use of the Internet, with over 5.3 billion users worldwide (Petrosyan, 2023), and smartphones, with an estimated 4.6 billion users worldwide (Degenhard, 2023), has been significantly contributing to the expansion of e-commerce as those tools have become an integral part of people's daily lives. The digitalization of the supply chain from businesses to customers has been made more efficient and rapid. This information and communication technology (ICT) revolution has been of transformative power, opening up new markets and boosting economies worldwide (Jain et al., 2021).

Payment Gateways: Payment transfers have been enabling the boom of the e-commerce market by transforming and facilitating transactions for both online and physical stores alike. Payment services like credit and debit cards, online banking, and EFTs have significantly eased the conduction of transactions, and with the shift towards digital currencies in e-commerce, payment gateways continue supporting customers' demands and need for more reliable and efficient payment methods (A. Dhanalakshmi et al., 2020; Jain et al., 2021).

Analytics: It has been serving as a methodical approach to transform e-commerce data into actionable insights for decision-making. By utilizing data analytics, e-commerce businesses have been able to gather, organize, analyze, and interpret their customer data, which made it a valuable and essential tool for understanding their customers' behavior. Customer preferences, order sizes, and shopping cart values are all data that e-commerce businesses have insight into and can use for their analytical strategies. Through data analytics, retailers have also been able to evaluate the profitability of their online investments in e-commerce and e-commerce platforms and assess the effectiveness of their channels (A. Dhanalakshmi et al., 2020; Cheng et al., 2023; Jain et al., 2021; Nimbalkar & Berad, 2021).

Social Media: Out of 5.3 billion internet users worldwide, 4.95 billion are social media users (Petrosyan, 2023). E-commerce businesses have been effectively deploying social media platforms, blogs, and applications to facilitate interaction and information exchange with their customers, whether those using computers or smartphones. Social media has been playing a pivotal role in disseminating information to customers and developing products as customers have been able to provide their insights and feedback on products and services through these platforms. It has also transformed into a valuable tool for brand development and the establishment of a reliable and loyal consumer base (Hajli, 2014; Hollebeek et al., 2014; Jain et al., 2023; Phua et al., 2017).

1.1.2.2. Innovations in E-Commerce:

In her 2023 article “A Conceptual Framework for the Technological Advancements of E-Commerce Applications”, published in the Businesses journal, author Sulova presents and discusses several technological advancements and innovations that the e-commerce field has witnessed over the past couple of years. Sulova (2023) focuses on innovations with the most significant impact on customer segmentation and user interactions and the importance of deploying those technologies to guide marketing strategies and enhance user experience.

Big Data Analytics: E-commerce platforms collect and generate crucial data that can be analyzed and then utilized to optimize logistics, segment customers, and assess customer satisfaction. The analysis of these sets of data can have a significant impact on personalizing the quality of products and services that the e-commerce platforms provide and thus improving customer engagement. These analytical processes rely heavily on the use and integration of AI and machine learning and can provide comprehensive and accurate insights for decision-makers in e-commerce businesses and the field as a whole. Furthermore, data analytics can aid in conducting risk research, guiding users, understanding customers' usage, and identifying user’s interests, thereby supporting market analysis and segmentation (Sulova, 2023). In addition to what Sulova (2023) presented in her research, A. Dhanalakshmi et al. (2020) discussed the integration of various technological advancements, including the use of big data analytics, to enhance customer relationship management in e-commerce, further supporting its significance in this industry.

AI: The application of AI in e-commerce through tools like recommender systems, virtual reality (VR) systems, augmented reality (AR) systems, and even automated customer support systems and chatbots has been on the rise in the past couple of years (Sulova, 2023). AI has been integrated into many e-commerce technologies. Many e-commerce professionals and researchers advocate for this integration and the utilization of this tool to create personalized suggestions and user services based on their previous feedback. AI is also deployed in e-commerce to analyze customer engagement levels and lead to increased sales and customer satisfaction (Sulova, 2023). Supporting Sulova (2023) are various pieces of literature that discussed innovation in AI integration in e-commerce and its increasing importance. Adam et al. (2021) explored the role of AI-based chatbots in customer service and their impact on user compliance in the context of e-commerce. Aktepe and Karakulle (2023) discussed the use of artificial intelligence to gain a competitive advantage in businesses, particularly focusing on mobile applications of e-commerce sites. Asante et al. (2023) argued on the optimization of consumer engagement using AI elements on e-commerce platforms, highlighting the significance of AI technologies integration. Cheng et al. (2023) and Nimbalkar and Berad (2021) explored AI-enabled technology innovations in e-commerce, emphasizing its transformative impact on the industry. The applications of AI in e-commerce will be explored further in the proceeding subchapter.

Chatbots: Research indicates that chatbots are well-received by e-commerce platform users, with 71% of those users stating that they turn to chatbots for assistance with their purchase-related issues. Chatbots and other AI-powered automated software programs provide users with fast and instant support through machine-powered conversations, which are used to address customers' questions and respond to their queries. Some of those chatbots have a range of features that enhance user experience and interaction with the platform, and some are even capable of learning and adapting. E-commerce businesses also benefit significantly from those tools for decision-support systems, which offer instant interactions with staff and customers (Sulova, 2023). Adam et al. (2021) also explored the role of chatbots in customer service and their impact on user compliance within e-commerce settings. According to Mori (2021), virtual assistance, which are the equivalent of chatbots, have a great impact on improving customer interactions and service efficiency. Tran et al. (2021) also examined the impact of chatbots in e-commerce, focusing on their important role in enhancing consumer sentiment and expectations in the retail sector.

Social Commerce: This practice can be defined as the integration of direct sales of e-commerce businesses' products and services through social media platforms. This practice has had a significant impact on the advancement of e-commerce and has been a growing trend in recent years. Social commerce has proven to be a valuable online sales channel for many businesses (Sulova, 2023). E-commerce platforms are also integrating features like reviews and recommendations that enable user interaction and sharing of information about their products and services, which facilitates information management for users and businesses and allows businesses to enhance customer engagement (Busalim et al., 2021; Hajli, 2014; Sulova, 2023). Phua et al. (2017) highlighted the role that social media platforms and integrating their use in marketing have on consumer motivations and behaviors, and emphasized their significance in creating brand engagement and loyalty.

The previous pieces of literature focus on and discuss the broader concepts of the technological advancements in e-commerce, which provides a strategic overview of those innovations, the authors A. Dhanalakshmi et al., in their 2020 Journal of Engineering and Management Research article "Technological Advancements in E-Commerce and Customer Relationship Management", delve into specific technological innovations that are transforming the e-commerce sector and the relationship between e-commerce businesses and their customers. A. Dhanalakshmi et al. (2020) provide detailed insights into specific tools enhancing e-commerce and customer interactions. Some of the most important ones cited are summarized below.

Unbxd: A new e-commerce tool that uses context-aware technology to help marketers enhance site search and personalize recommendations (A. Dhanalakshmi et al., 2020). This tool uses the same technology utilized by chatbots and virtual assistants as discussed by Adam et al. (2021), Mori (2021), and Tran et al. (2021), and by recommender systems as discussed by Asante et al. (2023), Cheng et al. (2023), and Nimbalkar and Berad (2021).

Google AdWords: A tool that uses Google search targeted ads to help boost an e-commerce site's visibility (A. Dhanalakshmi et al., 2020). Cheng et al. (2023) and Nimbalkar and Berad (2021) emphasize the importance of innovation in e-commerce technologies that enhance user experience and personalization, which are foundational aspects of targeted advertising in e-commerce.

Optimizely: A premium A/B testing tool that allows e-commerce sites to test and determine the most effective design elements (A. Dhanalakshmi et al., 2020). Busalim et al. (2021), support the importance of such a technology as they discussed how the design of an e-commerce platform influences customers behavior. Bhagyasree and Venugopal (2021) also highlighted the impact of e-commerce platform design on consumer buying behavior, emphasizing user interface and experience.

SearchSpring: A site navigation tool used by major brands to improve search and navigation by connecting online shoppers with relevant products (A. Dhanalakshmi et al., 2020). This technology strikes a resemblance with recommender systems, the importance of which in e-commerce sites and platforms is highlighted by Asante et al. (2023), Cheng et al. (2023), and Maslowska et al. (2022).

1.1.3. E-Commerce in the Turkish Market:

As highlighted in the introduction of this research and evidenced by the figures and literature presented, the Turkish e-commerce market has witnessed a substantial transformation and growth over the past years. Various players and facilitators drove this transformation and development, and these were underscored in multiple pieces of literature. The following subsections provide an overview of the e-commerce market in Türkiye including its facilitators and key players, and present the various factors contributing to its expansion discussed in previous research.

1.1.3.1. Facilitators of E-Commerce in Türkiye:

The e-commerce market in Türkiye has witnessed a substantial expansion and significant transformation over the past decade. According to the Turkish Competition Authority report of 2024 on Turkish e-commerce platforms, this unprecedented growth in the e-commerce sector can be attributed to two main factors, the developments in Internet access and technologies and the level and speed of Turkish consumers' adaptation to these developments being a young and dynamic population (T.C. Ticaret Bakanlığı, 2024). According DataReportal, the percentage of households with internet access in Türkiye increased dramatically to 83.4% in the year 2023, with 95.4% of the total population having access to mobile internet (Kemp, 2023). Moreover, Türkiye is considered to have a younger and larger population base than the European average, with 38.23% of Türkiye's population under the age of 24, further contributing to the population's adaptation ability to the advancements of this market (Sarıçiçek et al., 2022).

In an article published by the Izmir Journal of Economics in 2023, titled "Analyzing Challenges and Opportunities in the E-Commerce Industry of Turkey," the author Bilik describes the Turkish population as young and tech-savvy, demonstrating a high degree of comfort and familiarity with digital technologies. Bilik's claims further support the demographic statistics and attributes of the Turkish population presented by Sarıçiçek et al. (2022). These two factors have opened up a vast digital marketplace and laid the groundwork for the expansion and transformation of the e-commerce sector. Bilik (2023) further attributes this growth to the rising disposable incomes in Türkiye, which he claims has created a fertile ground for e-commerce as more consumers have the means and technological literacy to engage in online shopping.

He argues that the e-commerce landscape in Türkiye has been further diversified through the integration of social media platforms into the e-commerce marketplace, more commonly known as social commerce, which has been introduced in the preceding subchapter of this research. Social media platforms in Türkiye have become a hub for commercial activities, allowing customers to make purchases directly through these platforms and blend social interactions with online shopping (Bilik, 2023).

Another factor that played a significant role in shaping the e-commerce sector in Türkiye according to Bilik (2023) is the COVID-19 pandemic, which is a factor cited and supported in numerous other literature (A. Dhanalakshmi et al., 2020; Asante et al., 2023; Cheng et al., 2023; Chui et al., 2021; Dierks, 2024; Khrais, 2020; Sarıçiçek et al., 2022; Sulova, 2023). The worldwide health crisis and its resulting lockdown and social distancing measures, which lead consumers to seek safe and convenient ways to purchase goods and services, have contributed to the acceleration of the shift towards online shopping. This substantial shift led to an unmatched increase in e-commerce sales, especially in the food, groceries, health, and beauty sectors (Bilik 2023). Sarıçiçek et al. (2022) supported these claims by reporting that the food and supermarket sector witnessed a 196% increase in sales post-pandemic. Moreover, multi-category e-marketplaces witnessed increased growth rates and substantially increased their product and service portfolios during the pandemic (T.C. Ticaret Bakanlığı, 2024). Consumers' e-commerce shopping frequencies and average spending also increased; weekly shopping frequency increased by 1%, bi-weekly shopping frequency increased by 3%, and monthly shopping frequency increased by 3% (Sarıçiçek et al., 2022).

Remarkably, the Turkish government has also played a crucial role in expanding the e-commerce sector by implementing multiple incentives that support e-commerce businesses. In 2017, the Turkish government offered a tax exemption for small businesses that generated annual revenues below a certain threshold to support them in sustaining their businesses (Bilik, 2023). In addition, the Turkish Ministry of Trade also launched the Electronic Commerce Information System in that same year to follow the direction of e-commerce and meet the new data requirements that arise due to its dynamic structure in order to develop further targeted policies (T.C. Ticaret Bakanlığı, 2024). In 2020, law no: 7256 was officially introduced, which exempted all e-commerce sellers that generated less than 240,000TL in annual sales from paying income tax and VAT, in an attempt to promote economic growth and development. In addition to tax exemptions, the Turkish government offered investment support, which included financial incentives like grants and loans and non-financial incentives like company registration and licensing support, through its investment promotion agency. Moreover, The Turkish government has heavily invested in improving infrastructure for logistics and delivery to support e-commerce businesses in enhancing their operations. The establishment of the national postal and courier service (PTT) and the implementation of digital address services are two of the most notable infrastructure improvements (Deloitte Digital, 2022). Furthermore, the Turkish government launched many digital transformation initiatives, like the Digital Türkiye Platform, which promoted digital technology use in various sectors, and the National E-Commerce Strategy, which aimed at expanding the e-commerce sector and promoting competitiveness amongst this market's players (Bilik, 2023).

1.1.3.2. Key E-Commerce Players in Türkiye:

"Platformization," as the author Melih Yeşilbağ argues in his article titled "New Geographies of Platform Capitalism: The Case of Digital Monopolization in Turkey," which was published in the Big Data & Society journal in 2022, is reshaping the e-commerce landscape in Türkiye. Yeşilbağ (2022) states that it is difficult to imagine a sector that has not been transformed and impacted by the adoption of digital platforms. The Turkish e-commerce sector is one of the most prominent ones. E-commerce platforms represent a competitive edge to their businesses through their unique capabilities (Asante et al., 2019). Most firms with an online presence nowadays have been migrating to e-commerce platforms to strengthen this presence (Asante et al., 2023). The importance of e-commerce platforms is also evident in the fact that the top five ranking companies on the S&P 500 index are digital platforms (Yeşilbağ, 2022).

As evident by the statistics on e-commerce in Türkiye that are presented in the introductory chapter of this research (Bilik, 2023; Dierks, 2024; T.C. Ticaret Bakanlığı, 2023; T.C. Ticaret Bakanlığı, 2024), this sector is expanding widely and quickly. This expansion has led to the rise of many local Turkish platforms which are further developing in a way that mimics and supersedes the global trends and growth patterns in the e-commerce sector (Yeşilbağ, 2022). According to the Statista Research Department's country report on e-commerce in Türkiye in 2021, the compounded annual growth rate (CAGR) of the retail e-commerce market was 14.6%, while the global average was 6.3%, making Türkiye the fastest-growing market in the world (Statista Research Department, 2021). Despite this market's growth and the relatively large number of e-marketplaces operating in Türkiye, though, the e-commerce sector is dominated by a few e-commerce platforms, which has been an intensifying phenomenon over the past few years (Yeşilbağ, 2022).

Trendyol has been Türkiye's e-commerce market leader since 2018, rising to this position due to its aggressive growth strategy. Trendyol, founded in 2009 by Demet Mutlu, started its journey in the Turkish e-commerce market with an initial capital of 300,000 USD as a fashion online shopping platform. Despite receiving many venture capital investments between the years 2010 and 2012, Trendyol was still a slow-growing e-marketplace until it achieved its breakthrough in 2018 when Alibaba Group, the Chinese giant, acquired 75% of its stakes for 728 million USD thereby transforming Trendyol into Türkiye's first "unicorn." With many additional investments following its great success in grabbing market share, Alibaba's share increased to 86.5%, and in 2021, Trendyol reached a valuation of 16.5 billion USD, making it Türkiye's first "decacorn" (Yeşilbağ, 2022). After this acquisition, and since 2020, Trendyol has emerged as Türkiye's e-commerce market leader with a share of 50.7% of the market's net sales (Statista Research Department, 2021). According to the Turkish Competition Authority's final report of 2021 on Turkish e-commerce platforms, Trendyol served 30 million customers and delivered 347 million packages during the year 2020 alone (İnce et al., 2021). Trendyol has been extensively diversifying over the past couple of years and is currently seeking to "achieve the super-app status" according to Yeşilbağ (2022), which is an app that combines all functions in one app, from retail e-commerce to grocery and food delivery, to payments, etc.

Hepsiburada is Türkiye's second e-commerce market leader, which had taken the lead since its inception and up until 2018 when Trendyol rose as the new market leader (Yeşilbağ, 2022). In 2020, Hepsiburada and Trendyol alone dominated 70.1% of the Turkish e-commerce market share (Statista Research Department, 2021). Hepsiburada, founded in 2000 by Hanzade Doğan, started its journey in the Turkish e-commerce market as a direct sales marketplace. It later introduced a merchant's marketplace in 2015, transitioning to a hybrid model. As a result, Abraaj Capital acquired 25% of Hepsiburada's stake in 2015, which led to its enlistment on the NASDAQ index in mid-2021, thus becoming Türkiye's first company to be listed and allowing it to raise over 680 million USD and get valued at 3.9 billion USD (Yeşilbağ, 2022). From 2018 to 2021, Hepsiburada's customer base grew at a CAGR of 38%, reaching 10.7 million active customers, which expanded its merchant base from 12,000 to 67,000 (Hepsiburada, 2021). Despite its growing sales, though, Hepsiburada suffered losses due to its substantial increases in advertising expenses, which has cost it its market leadership to its second-in-line rival (Yeşilbağ, 2022).

N11 is another prominent Turkish e-commerce platform, which caters to different market segments and needs like fashion, automotive, supermarket, wholesale trading, and even cloud and professional services. In 2012, N11 got established by Doğuş Group, a Turkish company, and SK Group, one of South Korea's biggest companies, which holds 50-50 of its shares, and in 2014 part of N11's shares were acquired by Getir, which marked a shift in N11's strategic direction. N11 was amongst Türkiye's top five frequently used e-commerce platforms in 2022, coming forth after Trendyol (49.6%), Hepsiburada (26.1%), and Gittigidiyor (8.4%), with 7.8% of Turkish consumers reporting that N11 is their preferred platform. N11 also came forth in 2022 amongst Türkiye's most downloaded mobile e-commerce platforms, after Trendyol (61.9%), Hepsiburada (39.9%), and Gittigidiyor (19.8%), with 19.6% of Turkish consumers reporting they have its application on their mobile phones (Sarıçiçek et al., 2022).

Getir is Türkiye's highest-valued e-commerce player, with a valuation of 12 billion USD that soared significantly in 2022 after multiple venture capital investments (Sezer, 2022). It was founded by Nazim Salur in 2015 and has achieved substantial growth in a relatively short period (Sarıçiçek et al., 2022), making it one of the most successful startups in the Turkish e-commerce sector. Getir's business model focuses on ultrafast delivery of groceries and other essentials with a price markup and a delivery fee, which turned out to be a successful business model. To run its operations, Getir utilizes what is called "dark stores," which are warehouses located strategically, ensuring its promise of "delivery times under 10 minutes". These stores are operated on a franchise model in which Getir is responsible for product quality and franchisees managing shipping. By December 2021, Getir was operating in 81 cities around Türkiye, boasting 3.5 million active users, and handling more than 75,000 deliveries daily. Getir was able to expand its services locally and aggressively expand internationally, successfully reaching 29 cities across eight countries worldwide (Yeşilbağ, 2022).

1.2. Artificial Intelligence:

AI has transformed various industries as evidenced by multiple previous literature like Bonada et al. (2020), Bughin et al. (2017), Cheng et al. (2023), and many more. As supported and suggested by other pieces of literature, like Asante et al. (2023), Chen et al. (2023), Nimbalkar and Berad (2021), Khrais (2020), and many others, the e-commerce industry has been a primary beneficiary of AI's transformation. This section provides a comprehensive introduction and overview of AI, its definition, evolution, applications in various industries, and impact on those industries to highlight its growing significance as a transformative force in the current business landscape. The section will primarily focus on AI in the e-commerce market to establish the importance of AI in this field and its influence on consumers in this market.

1.2.1. Introduction To AI:

AI has become a cornerstone of modern technological advancements and has a pivotal role in driving contemporary technological progress and innovation (Bughin et al., 2017). To comprehend it, its evolution, and its significance in today’s world, it is crucial to understand its essence. This subsection focuses on providing a general introduction to AI, its definitions, historical evolution, and growing significance in various industries.

1.2.1.1. Definition of AI:

In their article titled “AI-Enabled Technology Innovation in E-Commerce,” published in the Journal of Electronic Commerce Research in 2023, the authors Cheng et al. present AI as a general term that encompasses a set of software systems and applications specially designed to perform traditional tasks that require human intelligence. In another article titled “The Increasing Importance of AI Applications in E-Commerce,” published in the Vidyabharati International Interdisciplinary Research Journal in 2021, the authors Nimbalkar and Berad provide a very similar definition, echoing that of Cheng et al. (2023), by introducing AI as a broad field of computer science that aims to build “smart” machines capable of overtaking tasks that require human intelligence to perform. These two definitions are perhaps the most easily comprehensible of the term AI, as it has been described and defined differently by multiple sources since its inception, which leads to a certain level of ambiguity.

Reviewing several pieces of literature (Cheng 2023; Du-Harpur, 2020; Grewal, 2014; Nimbalkar & Berad, 2021), the complexity and dynamism of the definition and description of AI are further highlighted. In the 2020 article titled “What is AI? Applications of Artificial Intelligence to Dermatology,” published in the British Journal of Dermatology, the authors Du-Harpur et al. support this claim by discussing how AI is a term that is difficult to accurately define and describe it as the capability of machines to resemble human behavior through communication, reasoning, and autonomous functioning in both familiar and unfamiliar situations. They note, however, that most references and definitions of AI nowadays are used interchangeably with the terms “Deep Learning” and “Machine Learning,” which indicates a shift in the term’s usage.

In another article titled “A Critical Conceptual Analysis of Definitions of Artificial Intelligence as Applicable to Computer Engineering,” published in the IOSR Journal of Computer Engineering in 2014, the author Grewal argues that AI’s definitions have been changed and updated over time depending on the need, usage, and context and that these changes have limited AI’s scope. The author conducted a comprehensive review and a critical examination of AI’s historical and modern definitions, evolution, scope, and limitations to propose a definition of AI as a mechanical simulation system that gathers, processes, and disseminates knowledge in the form of actionable intelligence.

1.2.1.2. Evolution of AI:

The historical trajectory of the conception and evolution of AI is outlined by authors Haenlein and Kaplan in their article titled “A Brief History of Artificial Intelligence: On the Past, Present, and Future of Artificial Intelligence,” published in the California Management Review in 2019, which has been marked by significant milestones, as well as challenges. Although it is difficult to pinpoint, the concept of “Artificial Intelligence” was first introduced in the 1940s, which represented a simple theory of machines exhibiting human intelligence and inspired scientists in the robotics field. Since the conception of AI, its development has gone through different phases of growth, optimism, setback, and regrowth, which Haenlein and Kaplan (2019) metaphorically divided into seasons.

The “AI spring” began in 1950, when the Turing test was developed by Alan Turing, a British Mathematician widely known as the “father of modern computing.” The Turing test is considered one of the first and most significant milestones in AI history. Turing (1950) described how to create an intelligent machine and designed a test to determine a machine’s level of intelligence and distinguish it from that of humans. This test primarily attempted to assess if a machine could demonstrate intelligent behavior that closely resembled humans' intelligent behavior. Participants were set to interact with another human and a machine, and machines that were indistinguishable from humans by participants were deemed intelligent Turing (1950).

Six years later, the term “Artificial Intelligence” was officially coined by Marvin Minsky and John McCarthy during the Dartmouth Summer Research Project on Artificial Intelligence, which is recognized as the beginning of AI Spring according to Haenlein and Kaplan (2019). This conference brought together key figures who are now recognized as the founding fathers of AI, including Nathaniel Rochester, the designer of the first commercial scientific computer, and Claude Shannon, the founder of information theory (Moor, 2006). The Dartmouth Conference marked the initiation of a new research area with the primary goal of developing machines that mimic human intelligence (Moor, 2006).

The second and third seasons are AI summer and winter, which witnessed the ups and downs of AI. Following the Dartmouth Conference, the AI field was marked by several significant achievements and developments, starting with the ELIZA computer program. Created by Joseph Weizenbaum between the years 1964 and 1966, ELIZA was a natural language processing (NLP) tool that could simulate a human conversation and was one of the first programs capable of passing the Turing test (Switzky, 2020). ELIZA was followed by the General Problem Solver program, developed by Nobel Prize winner Herbert Simon, which could solve simple problems automatically. ELIZA and General Problem Solver represent just two examples of success stories in the AI field, which eventually led to a significant increase in funding and as a result more project advancements. Optimism in the field reached a level where Marvin Minsky stated in an interview in 1970 that people would be witnessing the development of a machine that has the intelligence of a human within three to eight years Haenlein and Kaplan (2019).

Unfortunately, Minsky’s prediction did not see the light as only three years later, in 1973, the US government as well as the British government ended their support for AI research by cutting off funding, marking the beginning of the AI winter (Yang, 2006). The decision came following US Congress’s strong criticism over the high spending being allocated to that research and a British Science Research Council report that questioned what was viewed as unrealistic optimism in the field. James Lighthill, a British mathematician who published the British Science Research Council report, stated that machines would never be able to go beyond common-sense reasoning and would only be able to reach an amateur’s experience level in chess at best (Yang, 2006). Despite the US increasing funding again in the 1980s in response to the Japanese government’s heavy investment in AI research, no further advances were achieved (Haenlein & Kaplan, 2019).

The fourth season is AI fall, which witnessed the harvest of AI. Haenlein and Kaplan (2019) argue that another reason for the lack of progress in AI research and development is how scientists tried to simulate human intelligence. Expert Systems, like ELIZA and the General Problem Solver, was a collection of rules developed following the assumption that human intelligence could be deconstructed and replicated by a series of "if-then" statements (Switzky, 2020; Turing, 1950). This approach was effectively applicable for performing some tasks but was reductive and insufficient in others as it failed to capture the complexity of human intelligence. An Expert System like IBM's Deep Blue chess-playing program demonstrated the effectiveness of the "if-then" logic in performing a structured task (Campbell et al., 2002). Deep Blue beat the world champion in 1997 with its ability to process hundreds of millions of possible moves per second and employ a "tree search" method to anticipate 20 steps ahead (Campbell et al., 2002), proving Lighthill's statement wrong. However, Expert Systems cannot as successfully perform tasks where deeper understanding and interpretation of input is needed, like facial recognition and distinguishing objects in a picture, as they would require information beyond the "if-then" logic. In performing such tasks, a system should have access to external data, correctly interpret and learn from them, and use that learning to perform other tasks through flexible adaptation, making Expert Systems an untrue AI (Haenlein & Kaplan, 2019).

The concept of true AI has been discussed since the 1940s, following the development of the Hebbian Learning theory. This theory, proposed by the Canadian psychologist Donald Hebb, explains the learning process on the brain neurons and neural networks level, thereby inspiring AI research and leading to the initiation of research on Artificial Neural Networks (ANN) (Kuriscak et al., 2015). That research, however, stagnated in 1969 as computers at that time did not have the capability or processing power to handle the work required by such artificial networks (Haenlein & Kaplan, 2019).

In 2015, ANN resurfaced through Deep Learning when Google launched its AlphaGo program that beat the world champion of the Go game, known to be more complex than chess, as it opens with 361 possible moves (Wang et al., 2016). Nowadays, Deep Learning and ANN are the foundation of most applications and tools that fall under the AI label, like image search and recognition algorithms utilized by social media platforms, speech recognition algorithms that run smart sound systems, and object recognition algorithms used in automated driving (Haenlein & Kaplan, 2019).

As evident through its historical journey from conceptual inception to practical application, AI has undergone significant developments, and with further advancements in this field and its applicability over the past couple of years, AI has been increasingly adopted and integrated across various industries.

1.2.2. AI in Various Industries:

Exploring multiple pieces of literature on AI's adoption and integration across various industries reveals its impact and significant transformation (Bughin et al., 2017; Espina-Romero et al., 2023). In their 2023 article titled "Which Industrial Sectors Are Affected by Artificial Intelligence? A Bibliometric Analysis of Trends and Perspectives," published in the Sustainability journal, the authors Espina-Romero et al. analyze various industrial sectors that have been employing AI technologies from 2018 to 2022 and discuss their results that showcase AI's growing impact in the finance, healthcare, environment, and construction industries.

In a report published by the McKinsey Global Institute in 2017, titled "Artificial Intelligence The Next Digital Frontier," the authors Bughin et al. further identify sectors that are leading in utilizing AI technologies and growing their investments through AI applications, including manufacturing, energy and resources, transportation and logistics, education, and travel and tourism. Multiple other pieces of literature discuss sector-specific applications, impacts, and benefits of AI, further highlighting its role in reshaping industries.

1.2.2.1. AI in the Financial Services Industry:

In a chapter of the "Virtual Assistant" book published in 2021 by IntechOpen, titled "AI-Powered Virtual Assistants in the Realms of Banking and Financial Services," the author Mori discusses the application and integration of AI technologies in the banking and financial services sector, and highlights how this application and integration have had a significant positive impact on customer service and operational efficiency.

The Statista Research Department's survey in 2024 on the "Main Benefits of Artificial Intelligence (AI) in the Financial Services Sector Globally in 2022 and 2023," supports Mori's study as it was concluded in that survey that operational efficiencies were one of the main reported benefits of AI integration in the financial services sector, with other benefits reported by financial services professionals being improved customer experience, competitive advantage, better models, as well as cost reductions, which were also highlighted in Mori's chapter. Mori (2021) emphasizes the utilization of two main AI-powered tools, virtual assistants and chatbots, and their role in providing 24/7 customer support, streamlining banking processes, and introducing new financial products.

1.2.2.2. AI in the Healthcare Industry:

In an article published by the Journal of Medical and Health Studies in 2023, titled "Strategic Applications of Artificial Intelligence in Healthcare and Medicine," the authors Chan and Petrikat discuss the strategic application and integration of AI technologies in the healthcare and medical fields and highlight how this application and integration have revolutionized the delivery of healthcare services. The authors focus on AI technologies like predictive analytics, NLP, and machine learning, and how those technologies are being utilized for facilitating the early detection of diseases, personalizing patients' treatment plans, and improving operational efficiency in health institutions.

Other benefits highlighted were enhancing the accuracy of diagnostics, improving treatment outcomes and patient satisfaction, streamlining healthcare operations, and automating administrative tasks (Chan & Petrikat, 2023). In a survey published by Statista in 2023 on "Artificial Intelligence (AI) in Healthcare Market Size Worldwide from 2021 to 2030," the author Conor Stewart reported that around one in five healthcare institutions around the world were in an early stage of adopting AI technologies in 2021. Stewart (2023) highlights that with the adoption of AI technologies in the healthcare field, physicians would be able to reduce 20% of their time spent on administrative tasks and allocate it to caring for patients.

1.2.2.3. AI in the Environmental Industry:

In an article titled "Environmental Sustainability: Can Artificial Intelligence be an Enabler for SDGs?," published in the Nature Environment and Pollution Technology journal in 2023, the author Chaudhary explores AI's application and integration in addressing environmental challenges and achieving advances in Sustainable Development Goals (SDG). Chaudhary (2023) highlights the significant role and positive impact of implementing AI technologies, like machine learning models, remote sensing technology, predictive analytics, and NLP, in facilitating environmental sustainability by emphasizing its contribution to enhancing energy management and efficiency, improving water resource management, reducing waste and pollution, improving agricultural productivity, monitoring and controlling climate change, and conserving forests and biodiversity. Espina-Romero et al. (2023) further explore AI technologies that facilitate the analysis of large environmental data sets thereby enhancing precision and enabling the prediction of risks and trends, which helps specialists in the environmental field, as well as governments and decision-makers, in taking actions and making informed decisions for sustainable practices and policies that protect the world's natural resources and preserve the environment for future generations.

1.2.2.4. AI in the Construction Industry:

In an article titled "Application of AI in Construction," published in the Applied and Computational Engineering journal in 2023, the author Wu discusses the applications and benefits of AI tools and technologies in the construction sector and its impact on each of this sector's processes and phases, from design to physical construction, which leads to enhanced efficiency and quality, and lower labor, energy, and operational costs. Wu (2023) explores how AI is being used in this industry to automate various tasks, like design and risk management by utilizing AI-driven insights, which also help in monitoring safety compliance and improving construction management.

Pan and Zhang (2021), on the other hand, focus on specific AI applications, like integration with BIM, building construction, and operation and maintenance management, to emphasize its significant role in the industry. Through integration with BIM, AI helps construction designers fill their component libraries, generate 3D models, and plan layouts, which enhances design accuracy and efficiency (Pan & Zhang, 2021). AI has also been enhancing on-site construction management, as well as safety and quality, through safety standards and progress monitoring. Additionally, AI algorithms are being utilized to analyze sensor data to optimize operations and management by monitoring energy usage and predicting maintenance needs (Wu, 2023).

1.2.2.5. AI in the Manufacturing Industry:

In a chapter of the "New Trends in the Use of Artificial Intelligence for the Industry 4.0" book published in 2020 by IntechOpen, titled "AI for Improving the Overall Equipment Efficiency in Manufacturing Industry," the authors Bonada et al. discuss how AI tools and applications are used to optimize manufacturing operations and improving equipment efficiency. The authors highlight the importance and benefits of integrating AI for enhancing processes like monitoring, optimization, and control by utilizing systems data (Bonada et al., 2020).

Bonada et al. (2020) emphasize the role of multiple AI tools and technologies that are being utilized in the manufacturing industry nowadays to leverage data analysis, machine learning algorithms, and AI-driven insights to improve operations. Predictive maintenance systems help businesses in the manufacturing field lower their maintenance and downtime costs by predicting equipment failures through the use of AI algorithms. According to Espina-Romero et al. (2023) machine learning models also aid those businesses in enhancing their operational efficiency and reducing waste by optimizing processes through the use of data pattern analysis. Quality control AI systems, on the other hand, allow businesses to minimize errors and improve their customers' satisfaction by ensuring product quality and detecting defects through visual inspection systems (Espina-Romero et al., 2023).

1.2.2.6. AI in the Energy and Resources Industry:

In Bughin et al.'s (2017) report, the authors report many AI tools and applications utilized in the energy and resources industry and their impact on increasing operational efficiency, reducing costs, facilitating the integration of renewable energy sources, and improving customer service, thereby revolutionizing this industry. These AI tools and technologies include machine learning, deep learning, predictive analytics, and AI-enabled devices, which have been crucial players in transforming the energy and resources sector (Bughin et al., 2017).

Chaudhary (2023) also emphasizes the significant role of those AI tools and technologies in this sector through their contribution to environmental sustainability, focusing on pollution control, resource management, and supporting the achievement of Sustainable Development Goals. Additionally, AI tools and technologies reduce transmission loss and help in combating energy theft, which cuts costs and losses in the sector. Espina-Romero et al. (2023), highlights how AI is being used to improve efficiency and sustainability in resource management and energy consumption. Furthermore, AI is used in implementing dynamic pricing and encouraging efficient energy use, which represents an advantage for both suppliers and users (Bughin et al., 2017).

1.2.2.7. AI in the Transportation and Logistics Industry:

In an article titled "Applications of Smart Technologies in Logistics and Transport: A Review," published in the Transportation Research Part E: Logistics and Transportation Review journal in 2021, the author Sai-Ho Chung discusses how "smart" technologies, including AI, induce a significant transformation in the transportation and logistics sector. Chung (2021) states that AI applications can be observed in many areas in this industry and that those applications mainly assist in routing optimization and scheduling.

In warehouse automation, AI algorithms are utilized for autonomous path planning and motion coordination, which eliminates deadlocks that were reported to cause a 20% delay in transaction processing (Pandian, 2019). Additionally, genetic AI algorithms are being used in the public transport sector through autonomous vehicles, which are still in early adoption but were proven to enhance the mobility and flexibility of transportation systems using point-to-point and ride-sharing features Chung (2021). Moreover, algorithms are also utilized in autonomous vehicles to reduce travel costs and energy consumption through routing models in the logistics sector. Furthermore, autonomous robots and drones, which are also still in early adoption, have proven to optimize deliveries and enhance efficiency and customer satisfaction (Pandian, 2019).

1.2.2.8. AI in the Educational Services Industry:

In their article titled "AI Technologies for Education: Recent Research & Future Directions," published in the Computers and Education: Artificial Intelligence journal in 2021, the authors Ke

Zhang and Ayşe Begum Aslan report on the applications of AI tools and technologies in education and the proven benefits of these applications on the sector. Zhang and Aslan (2021) present various AI tools and technologies like chatbots, expert systems, intelligent tutors, machine learning, personalized learning systems, and virtual learning environments, which are widely used and represent the most significant advances in education.

According to Holmes and Toumi (2022), those AI applications present many benefits to learners, like facilitating their interactions, enhancing their engagement levels, generating adaptive study materials that better fit their capabilities, creating engaging learning environments, and improving their learning outcomes, and also present many benefits to educators and administrators, like aiding them in monitoring learning progress, personalizing learning materials, drafting assessments, providing feedback, and analyzing data for better evaluation of learners and identification of at-risk learners.

1.2.2.9. AI in the Travel and Tourism Industry:

In their article titled "When Artificial Intelligence Meets the Hospitality and Tourism Industry: An Assessment Framework to Inform Theory and Management," published in the Journal of Hospitality and Tourism Insights in 2022, the authors Huang et al. report on the applications of AI tools and technologies in the travel, hospitality, and tourism industry and the benefits of these applications on the sector. Huang et al. (2022) present various AI tools and technologies like search and booking engines, virtual agents and chatbots, robots and autonomous vehicles, kiosks and self-service screens, and AR and VR devices.

According to the authors, those AI applications present many benefits to the industry. By providing customized services, personalized recommendations, and round-the-clock support and assistance, businesses in this sector improve their customer service and create better experiences for their customers. AR and VR experiences create a competitive edge for businesses. According to Gupta et al. (2022), AI applications in the travel and tourism industry can also provide customers with a unique experience. Through routine task automation and dedicating more time to customer services, businesses significantly improve their processes and operations' efficiency (Gupta et al., 2022). Additionally, AI applications assist in decision-making through data analysis, in ensuring safety and security through recognition technologies, and in reducing costs through resource optimization (Huang et al., 2022).

1.2.3. AI in E-Commerce:

AI's transformational impact has had a significant effect on e-commerce, as highlighted and supported by evidence and figures from multiple sources in the introduction of this research. According to various literature (Asante et al., 2023; Cheng et al., 2023; Khrais, 2020; Nimbalkar & Berad, 2021), AI is reshaping the relationship and interactions between businesses in the e-commerce sector and their customers. The following subsections focus on presenting and introducing the literature on AI applications in e-commerce and their impact on companies and customers.

1.2.3.1. Introduction to AI in E-Commerce:

Asante et al. (2023) emphasize the significance of AI applications in enhancing the performance of e-commerce businesses and its growing importance as a technological priority for those businesses. Cheng et al. (2023) highlight that AI-driven technologies represent a competitive advantage to e-commerce businesses and contribute to their digital transformation. Nimbalkar and Berad (2021) stress the positive effect of AI technologies on the productivity and operational efficacy of e-commerce businesses, which are increasingly centering their customer engagement strategies around AI and heavily investing in AI technologies to maintain their competitive edge. Khrais, in his 2020 article "Role of Artificial Intelligence in Shaping Consumer Demand in e-commerce, published in the Future Internet journal, underscores the importance of AI further by describing it as an essential innovative tool in the e-commerce sector for personalizing customer experiences and customizing products to meet their demands.

By examining both the applications of AI in e-commerce and the impact of these applications, this section aims to provide a comprehensive overview of the role of AI in e-commerce and lay the foundation for investigating its effect on consumer behavior and decision-making.

1.2.3.2. AI Applications in E-Commerce:

AI integration and applications in e-commerce are utilized in a wide range of systems, tools, and features, which affect all stages of operations and customer interactions, from initial contact with customers through purchase and payment to after-sale support and operations. Those systems, tools, and features have been progressively optimizing transactions and operations in this field according to multiple studies and literature (Asante et al., 2023; Cheng et al. 2023; Khrais, 2020; Nimbalkar & Berad, 2021).

Visual and Audio Search Functionalities: AI is utilized in these functionalities to simplify the product search process (Dagan et al., 2023) and allow users of e-commerce sites and platforms to search for products using images (Asante et al., 2023) or voice commands (Cheng et al., 2023).

Recommender Systems: These systems utilize AI big data collected by e-commerce sites and platforms on customers' search history and habits, as well as previous purchases (Nimbalkar & Berad, 2021). Recommender systems provide customers with personalized product recommendations that are tailored to their needs and preferences (Asante et al., 2023; Cheng et al. 2023; Nimbalkar & Berad, 2021) and offer them a personalized shopping experience (Nimbalkar & Berad, 2021) that saves them the hassle of wasting time searching for products (Asante et al., 2023).

Chatbots and Virtual Customer Service Assistants: These tools utilize AI technologies like self-learning capabilities and NLP to interact with customers (Tran et al., 2021), offer them insights (Nimbalkar & Berad, 2021), answer their inquiries instantly (Cheng et al., 2023), as well as provide them with human-like conversations that comply with service feedback (Asante et al., 2023).

CRM Systems: AI enhances CRM systems by automating repetitive and monotonous tasks like data entry and customer segmentation, which enables e-commerce businesses to personalize their marketing strategies and initiatives (Cheng et al., 2023).

Dynamic Pricing Models: AI-driven tools assist e-commerce businesses in organizing product data and building optimal pricing models for adjusting to market conditions and clearing inventory (Bughin et al., 2017; Cheng et al., 2023).

Forecasting Tools: AI-supported forecasting systems enable e-commerce businesses to project demand and automate ordering and restocking processes, which allows them to optimize their stock levels (Cheng et al., 2023).

Automated Warehousing and Inventory Management Systems: AI is deployed in these systems to automate warehouse operations like stocking and shelving (Cheng et al., 2023) and to utilize data on sales and demand trends (Nimbalkar & Berad, 2021). Automated warehousing and inventory management systems also enable e-commerce businesses to maintain optimal inventory meeting market demands (Nimbalkar & Berad, 2021).

Risk Management Systems: AI is used to support these systems to help e-commerce businesses in identify and manage potential risks in their operations and contribute to safer and more reliable online transactions (Cheng et al., 2023).

Automated After-Sales Services: AI is deployed by e-commerce sites and platforms to automate feedback, facilitate product exchange requests, resolve post-purchase issues, and provide transaction notifications (Asante et al., 2023; Nasir, 2023).

1.2.3.3. Impact of AI Applications on E-Commerce:

As evident through recent studies and literature (Asante et al., 2023; Cheng et al., 2023; Khrais, 2020; Nimbalkar & Berad, 2021), AI tools and applications have a significant role in enhancing various aspects of e-commerce, from customer experience and operational efficiency to securing transactions and optimizing prices.

Enhancing Personalization and User Experience: Through AI personalization tools, e-commerce businesses provide customers with tailored offers and suggestions, and a consistent user experience across their devices (Nimbalkar & Berad, 2021). Visual and audio search functionalities facilitate the search process for customers, making it more intuitive and user-friendly (Cheng et al., 2023), which helps them save time on browsing and improves their search result satisfaction (Asante et al., 2023). Recommender systems also provide customers with personalized shopping experiences (Nimbalkar & Berad, 2021) and increase customer conversion (Nimbalkar & Berad, 2021), retention (Asante et al., 2023), and sales (Cheng et al., 2023) by facilitating their browsing activities (Asante et al., 2023) and suggesting relevant products (Nimbalkar & Berad, 2021), which impacts their experience positively.

Improving Customer Service: Chatbots and virtual customer service assistants provide customers with constant (Nimbalkar & Berad, 2021) and instant support with their issues and inquiries (Cheng et al., 2023) round the clock, which enhances their user experience (Asante et al., 2023; Nimbalkar & Berad, 2021) and improve their satisfaction levels (Cheng et al., 2023). They also help improve e-commerce businesses' services while reducing the need for service agents (Cheng et al., 2023). Automated after-sales services also enhance customer service by providing automated feedback and notifications and facilitating product exchange and return (Asante et al., 2023). They also contribute to boosting the e-commerce business's perceived value and customer conversion rates (Asante et al., 2023).

Guiding Marketing Strategies: AI-powered CRM systems allow e-commerce businesses to automate their customer segmentation process more accurately and efficiently, which enables them to personalize their marketing strategies and initiatives more effectively (Cheng et al., 2023). Recommender systems utilize big data collected by e-commerce sites and platforms on customers' previous purchases, search history, purchasing habits, and browsing habits (Nimbalkar & Berad, 2021), which represents valuable input and insights for guiding marketing strategies.

Boosting Operational Efficiency: Automated warehousing and inventory management systems enable e-commerce businesses to improve their warehouse and inventory-related operations through automation, reduce human error, and lower operational costs (Cheng et al., 2023). Those systems also enable businesses to optimize their inventory levels and avoid shortages and surpluses (Nimbalkar & Berad, 2021), leading to a more efficient management of stock that meets market demand (Nimbalkar & Berad, 2021). CRM systems also contribute to boosting operational efficiency by automating repetitive and monotonous tasks (Cheng et al., 2023), which allows for a more efficient allocation of human power. Moreover, automated after-sales services improve operational efficiency by taking over the exchange and return processes (Asante et al., 2023), and dynamic pricing models optimize and adapt prices to changes in the market to clear inventory faster (Cheng et al., 2023).

Optimizing Supply Chain: AI forecasting tools allow e-commerce businesses to estimate their demand level and automate ordering and restocking processes, which helps them optimize their stock levels and improve the efficiency of their supply chain operations (Cheng et al., 2023). Automated warehousing and inventory management systems also assist e-commerce businesses in enhancing their supply chain optimization through efficient stock management (Cheng et al., 2023) and maintaining optimal inventory levels to meet market demand (Nimbalkar & Berad, 2021). By helping e-commerce businesses optimize their prices based on market demand and inventory levels (Cheng et al., 2023), dynamic pricing models contribute to enhancing the supply chain.

Despite the extensive applications of AI in e-commerce and their significant impact on various aspects in this market, this research will only further examine those directly relevant to interactions with customers as the study is focused on the impact of AI applications on consumer behavior and decision-making. AI elements that will therefore be explored are chatbots, visual search, recommender systems, and automated after-sales services.

CHAPTER 2: CONSUMER BEHAVIOR AND DECISION-MAKING

This chapter builds on the literature reviewed in the previous chapter and provides a theoretical foundation on various prominent consumer behavior models and factors influencing consumers' actions and decisions. The chapter begins by laying the foundation for the subject by introducing the concept of consumer behavior and the factors that influence it according to multiple research and literature in this field and then explores well-established consumer behavior models like the Nicosia Model, Howard-Sheth Model, and Engel-Kollat-Blackwell Model, and how they can be applied within the context of e-commerce, focusing on and highlighting the impact of the AI integration. The chapter then highlights the dimensions of consumer behavior to be investigated in this study within e-commerce platforms and underscores the importance of the Stimulus-Organism-Response (SOR) Model and how it will be utilized in this research to explain how AI-driven tools influence consumer decision-making processes.

2.1. Theoretical Foundations of Consumer Behavior:

Theories on consumer behavior and decision-making have evolved throughout history to understand and explain how individuals make decisions about purchasing goods and services and what factors play a role in shaping and guiding those decisions. This interest in the subject has led researchers and experts in the field to establish what is now known as consumer behavior models. This section provides an introduction to consumer behavior, factors influencing it, and models that attempt to explain it within the context of existing literature.

2.1.1. Introduction to Consumer Behavior:

In their article titled "Theoretical Models of Consumer Behaviours: A Literature Review," published in the International Journal of Education Humanities and Social Science in 2022, the authors Manuere et al. define consumer behavior as the study of consumers and how they "select, buy, use and dispose of goods, services, ideas, or experiences that meet their needs and desires." According to the authors, consumer behavior is a complex and multifaceted concept that has been significantly influenced by social, psychological, economic, demographic, and cultural factors (Manuere et al., 2022). In another article titled "Consumer Behavior Models: An Overview," published in the Sai Om Journal of Commerce & Management in 2014, the author Jisana explores those factors and highlights their impact on the purchasing behavior of consumers.

Cultural Factors: According to the author, the cultural factors that influence the behavior of consumers consist of their culture itself, their subculture, and their social class (Jisana, 2014). Those factors have a significant impact on the needs, interests, preferences, lifestyles, activities, and consumption patterns of consumers, which in turn affect their purchasing behavior (Jisana, 2014). Bhagyasree et al. (2021) also discuss the various factors that impact consumer behavior, especially in the context of online shopping, including cultural factors, and highlight their significant role in shaping purchasing decisions and preferences.

Social Factors: Some of the most important social factors that impact the behavior of consumers consist of their reference groups, their family, and their roles and status, as per the author (Jisana, 2014). Those factors significantly impact personal beliefs, attitudes, lifestyle, behavior, and purchasing decisions, which in turn affect their behavior (Jisana, 2014). Phua et al. (2017) examine the role of social factors such as social comparison, trust, and tie strength and emphasize their strong impact on consumers' engagement, commitment, and membership intentions. Busalim et al. (2021), on the other hand, highlight the importance of social factors like peer influence and social interactions in influencing customer behavior.

Personal Factors: The most notable personal factors cited by the author, which shape consumers' behavior, consist of age, occupation, economic situation, lifestyle, and personality (Jisana, 2014). Those factors have a significant impact on consumers' needs, interests, preferences, lifestyles, attitudes, opinions, and price sensitivity, which in turn affects their behavior (Jisana, 2014). Mittal (2013) support these claims by underscoring the role of various personal factors like individual preferences, personal attitudes, and lifestyle choices in influencing and shaping consumer behavior. Furthermore, Islam et al. (2020) highlight the role of personal factors like individual motivations and perceptions and how they impact customers' behavior.

Psychological Factors: Four important psychological factors affect consumers' behavior, which are perception, motivation, learning, and beliefs and attitudes (Jisana, 2014). The author explains how different consumers have different needs, and how those needs turn into motives directing them to seek satisfaction as they become more pressing (Jisana, 2014). Perception, according to the author, is what a consumer thinks about a product or service, and is composed of three processes, selective attention, distortion, and retention (Jisana, 2014). Consumers' beliefs and attitudes, on the other hand, are those directed toward products and are what shape their image in the consumers' minds (Jisana, 2014). Other literature like Hajli (2014) examines how psychological factors like trust, perceived usefulness, and satisfaction affect consumer behavior. Jacoby (2002) explored the impact of other psychological factors like perception, motivation, and attitudes and how they influence consumers behavior.

The authors of "Consumer Behavior Analysis," published in the International Journal of Research and Applied Technology in 2022, Sundareswaran et al. underscore the importance of studying consumer behavior for better-understanding consumers buying behavior, the factors that underlie and influence it, and the resulting decisions and actions towards the business. According to the authors, businesses understanding consumer behavior is crucial to predicting customers' reactions, tailoring their products and services to their needs and expectations, and guiding their activities and strategies (Sundareswaran et al., 2022), thereby creating value for the consumers and profits for the businesses (Jisana, 2014).

2.1.2. Introduction to Consumer Behavior Models:

According to Rau and Samiee, the authors of "Models of Consumer Behavior: The State of the Art," published in 1981 in the Journal of the Academy of Marketing Science, the development of consumer behavior models is the by-product of the intense interest of theorists in the marketing field in exploring and understanding consumer behavior, since the 1960s. These models were advanced to understand and explain the behavior of consumers in decision-making situations, define the variables involved in making these decisions, and recognize the factors influencing them (Rau & Samiee, 1981). In the 2023 article titled "Main Theoretical Consumer Behavioural Models. A Review from 1935 to 2021," published in the Heliyon journal, the authors Paz and Rodríguez-Vargas outline the evolution of consumer behavior models over the past 50 years. According to the authors, early consumer behavior models were focused on the psychological underpinnings of consumer behavior, with significant contributions through the Nicosia Model, Howard-Sheth Model, and Engel-Kollat-Blackwell (EKB) Model (Paz & Rodriquez-Vargas, 2023).

Several consumer behavior models can offer insights into consumer behavior and decision-making in digital environments like e-commerce sites and platforms. The Nicosia Model, Howard-Sheth Model, and EBM Model, which were referred to by multiple literature as the most complete and exhaustive behavioral models (Paz & Rodriquez-Vargas, 2023; Rau & Samiee, 1981), can contribute to identifying and understanding the factors influencing consumers' behavior and decisions in e-commerce. In an article titled "Comparative Analysis of Customer Behavior Models," published in the Proceedings of the 2016 International Conference on Economic Science for Rural Development, the authors Viksne et al. analyze and compare those models along others, and emphasize that while those models can attempt to explain consumers' behavior, can be utilized inappropriately. Consumers behave differently in different markets, and consumer behavior models vary, which might lead to incorrectly employing a model in a practical application (Viksne et al., 2016).

Consumer behavior models can provide a valuable framework for understanding consumer behavior in the e-commerce market and are crucial for examining the impact of AI technologies integrated into e-commerce platforms -namely chatbots, visual search, recommender systems, and automated after-sales services- on the decision-making process. However, the e-commerce market, specifically e-commerce platforms, presents new and unique factors and complex interactions that influence consumer behavior and decision-making due to its rapidly evolving nature and the inherent lack of physical interaction between the consumer and the business. As a result, consumer behavior in this context might not be explained clearly or appropriately by traditional consumer behavior models. Therefore, consumer behavior in the e-commerce context will be explored, and the contributions of the Nicosia Model, the Howard-Sheth Model, and the EBM Model will be assessed.

2.2. Consumer Behavior in E-Commerce:

Technological and digital advancements in the e-commerce sector have had a transformative impact on consumer behavior and decision-making processes due to changing and evolving consumer shopping patterns and the new forms of interaction with businesses through e-commerce platform tools that altered how consumers discover, search, and purchase products. Multiple pieces of literature (Al Hamli & Sobaih, 2023; Bhagyasree & Venugopal, 2021; Fuentes & Svingstedt, 2017; Hajli, 2014; Mittal, 2013; Senecal et al., 2005; Wolfinbarger & Gilly, 2000) have investigated this transformative impact to understand the changing dynamics of consumer behavior in online and digital environments and how e-commerce platforms have reshaped purchasing habits.

Convenience: The main distinctive feature of e-commerce is that it enables consumers to overcome the constraints of physical stores, whether in terms of time or location, which provides them with a high level of convenience. In his study on the impact of e-commerce on consumer behavior, Mittal (2013) emphasizes convenience as the first motivation behind the choice of online shopping over traditional retail shopping. Through e-commerce platforms, consumers can browse and purchase products anytime, anywhere. In a research on the factors influencing consumer behavior towards online shopping, authors Al Hamli and Sobaih (2023) highlight the significant role of convenience in shaping consumer purchasing habits and facilitating their switch from physical to online stores.

Product Variety: Another distinctive feature of e-commerce is that e-commerce platforms provide consumers with a vast product selection, usually coupled with advanced search and filtering capabilities, presenting them with an unprecedented level of choice they have not previously enjoyed through traditional retail stores. Al Hamli and Sobaih (2023) also highlight product variety and diversity as a factor that impacts e-commerce consumers' shopping behavior, as this variety and diversity increase their chances of finding a product that matches their needs and preferences.

Accessibility: A result of this increased convenience and choice, e-commerce sites and platforms also provide consumers with a high level of accessibility, especially as consumers can now use any internet-enabled device, including their mobile phones, to access online stores. In a study on the attributes that facilitate online shopping, Wolfinbarger and Gilly (2000) emphasize the role of accessibility in motivating consumers to resort to e-commerce sites and platforms. The authors also highlight selection and information availability as other attributes shaping the online shopping behavior of consumers (Wolfinbarger & Gilly, 2000).

Cost-effectiveness: The wide variety of products on e-commerce platforms and the ease of accessing these product selections from multiple online stores allows consumers to assess and compare prices of the same or similar products and thus get better deals. In their research on the impact of online shopping on consumer behavior, Bhagyasree and Venugopal (2021) state that price comparison and the ability to purchase products at a lower price are the main advantages of e-commerce. Mittal (2013) also highlights this cost advantage as a main functional motive impacting the purchase decisions of e-commerce consumers.

Information-driven: The research by Senecal et al. (2005) on consumers' online behavior underscores a shift towards information-driven decision-making as consumers utilize online sources and research to gather information on products and brands that they are interested in and to seek relevant recommendations from other people before making a purchase decision. This pre-purchase behavioral trend has also been supported further by the increased use of mobile phones to shop online. According to Fuentes and Svingstedt (2017), mobile phones allow consumers to collect information, search for products, and compare prices easily, simultaneously, and on the go, which supports their online shopping and decision-making process.

Moreover, the transformative impact of e-commerce extends beyond convenience and choice. The new features and interactivity of e-commerce platforms lead to enhanced consumer engagement throughout the online shopping process. According to Hajli (2014), consumers nowadays contribute actively to online communities, generating content about their shopping experiences, networking with other consumers about products and recommendations, and seeking validation about purchase decisions through social media platforms. This social influence has become a significant driver of consumers' purchase decisions and building trust in businesses (Hajli, 2014). As consumers navigate digital marketplaces, two factors emerge as determinants of their behavior and decisions: consumer engagement and social comparison.

2.2.1. Consumer Engagement in E-Commerce:

Consumer engagement is a multilayered and dynamic concept and phenomenon that emerged and rapidly gained the interest of academicians in multiple fields. However, it has been defined and conceptualized differently across various pieces of literature. In their study on the nature and scope of consumer engagement, Vivek et al. (2012) highlight the diversity in the definitions and dimensionalities of consumer engagement while emphasizing its contribution to building value, trust, and commitment.

In the context of e-commerce, the definition of consumer engagement takes on added significance due to the importance of interaction in its platforms. In research on enhancing consumer engagement in e-commerce, authors Hu and Chaudhry (2020) define consumer engagement as the level of connection and participation that a consumer has with the business, its product, or its activities and emphasize its role in garnering lasting relationships and fostering loyalty. Brodie et al. (2011) stress the importance of consumer engagement in a highly dynamic and interactive business environment, like e-commerce, in creating positive customer experiences, business value, and competitive advantage.

The complexity of consumer engagement is explored widely in literature due to its significant implications for businesses and their customers. In e-commerce, and within the context of this study, consumer engagement is multifaceted, represents the dynamic interaction between consumers and online shopping platforms, and encompasses psychological and behavioral dimensions, taking inspiration from the work of Asante et al. (2023). AI-driven tools and features in Turkish e-commerce platforms play a pivotal role in shaping this engagement by personalizing consumers' online shopping experience and facilitating their interactions with the platform (Hollebeek et al., 2014).

2.2.2. Psychological Engagement in E-Commerce:

In her conceptual framework study on customer engagement, Bowden (2009) proposed that consumer engagement is a sequential psychological process that consumers move through in developing loyalty, commitment, and attachment to a service brand that leads to repeat purchases or use of a service brand if maintained. In her research for demystifying the concept of engagement, Hollebeek (2011) expanded on the work of Bowden (2009) and defined consumer engagement in a psychological context as the level of cognitive absorption, emotional resonance, and affective attachment towards a brand, which reflects the depth of the consumer-brand relationship. Building upon these insights and multiple themes identified in previous literature on consumer engagement and its multidimensionality, Brodie et al. (2013) developed a working definition for investigating engagement in a virtual brand community, defining it as a fluctuating psychological state that involves interactive experiences comprising cognitive and emotional aspects occurring within dynamic environments.

In e-commerce, and within the context of this study, psychological engagement can be defined as the positive cognitive and emotional connection that consumers develop towards an e-commerce platform through interactions with its features, which encompasses their positive subjective experiences, perceptions, and attitudes that influence their behavior. Inspired by the work of Asante et al. (2023), AI-enhanced personalization through chatbots, visual search, recommender systems, and automated after-sales services can significantly impact the psychological engagement of e-commerce platform users by facilitating their online shopping experience and their interactions with these platforms. Additionally, according to Utami et al. (2022), interactivity in e-commerce platforms positively impacts all forms of consumer engagement, emphasizing the importance of psychological engagement in driving other forms of engagement behaviors in e-commerce.

2.2.3. Behavioral Engagement in E-Commerce:

Behavioral engagement, or engagement behaviors as defined by Van Doorn et al. (2010), is the behavioral manifestation of the motivational drivers of consumers toward a brand or firm, which extend beyond purchase or usage. Those behaviors include writing reviews, recommending products or firms to others, helping other consumers, and engaging in word-of-mouth communication (Van Doorn et al., 2010). These activities reflect the extent of participation and contribution of consumers to brand-related activities.

Multiple pieces of literature define or describe behavioral engagement as a dimension or manifestation of consumer engagement (Asante et al., 2023; Bowden, 2009; Brodie et al., 2011; Brodie et al., 2013; Busalim et al., 2021; Hollebeek, 2011; Hu & Chaudhry, 2020; Van Doorn et al., 2010; Vivek et al., 2012), which emphasizes its importance in understanding consumer interactions with brands and firms. Brodie et al. (2011) highlight that behavioral outcomes of consumer engagement are generated by consumers interactive experiences and, as demonstrated by authors Busalim et al. (2021) in their research on customer engagement behavior in social commerce platforms, are influenced strongly by social, motivational, and technological factors.

In the context of e-commerce platforms, based on the literature and inspired by the work of Asante et al. (2023), behavioral engagement can be defined as e-commerce platform users continued use and interaction with the platform as a result of their experience with AI-driven features and their psychological engagement influenced by these features. AI-enhanced personalization through chatbots, visual search, recommender systems, and automated after-sales services can significantly impact the behavioral engagement of users by facilitating their interactions with the platforms. Busalim et al. (2021) and Utami et al. (2022) emphasize the importance of interactivity and technological factors, like AI-driven features, in positively impacting users' behavioral engagement and their purchase and repurchase intentions.

2.2.4. Attention to Social Comparison in E-Commerce:

Lennox and Wolfe (1984) define attention to social comparison as the awareness and sensitivity of consumers to other consumers' opinions or reactions to their consumption choices and habits. This concept proposes that consumers who are highly sensitive to negative evaluations of their consumption choices and habits -by other consumers- present a higher level of adherence to social cues and norms and that consumers with lower self-esteem present a higher level of conformity to social pressure and norms (Lennox & Wolfe, 1984).

Multiple pieces of literature investigated the impact of consumers' attention to social comparison on their behavior and highlighted the significant role of social factors in influencing consumer engagement (Busalim et al., 2021). In their research on consumers' role in e-commerce success, Asante et al. (2019) emphasize that consumers' attention to social comparison moderates their engagement with e-services in e-commerce. Consumers who pay more attention to social comparison demonstrate a lower level of engagement when purchasing products socially considered less prestigious, even if they experience a quality e-service, and a higher level of engagement when considering those socially considered more prestigious, even if they do not experience a quality e-service (Asante et al., 2019). Phua, Jin, and Kim (2017) highlight the significant role of attention to social comparison by investigating its impact on influencing consumer purchases and participation in brand-related activities. Their findings stated that consumers' attention to social comparison negatively moderates the relationship between their level of online participation in brand-related activities and their identification with the brand (Phua et al., 2017), which aligns with the findings of Asante et al. (2019).

Based on the literature, within the context of this study, and inspired by the work of Asante et al. (2023), attention to social comparison can be defined as the degree of e-commerce platform users' responsiveness to the opinions and reactions of other consumers regarding their consumption choices and habits on those platforms. Attention to social comparison influences and moderates the psychological and behavioral engagement of e-commerce platform users resulting from their interaction with AI-driven features like chatbots, visual search, recommender systems, and automated after-sales services, highlighting its heightened role in impacting those users' preferences and behaviors.

2.3. Consumer Behavior Models in E-Commerce:

This section provides an overview of the applications of traditional consumer behavior models in the context of e-commerce to provide insights into how consumers interact with e-commerce platforms and make purchasing decisions. This section will also provide an overview of how different AI-driven tools can influence consumer behavior within the context of these models.

2.3.1. The Nicosia Model:

The Nicosia Model is a psychological consumer behavior model developed by Francesco Nicosia, an expert in consumer motivation and behavior, in 1966 (Jisana, 2014) and focuses on the relationship between the company and its customers (Khegay & Aubakirov, 2021). According to Viksne et al. (2016), this model aims to understand and explain shopping behaviors and decision-making processes and is considered one of the oldest and earliest models to be recognized by marketing experts in the field. Jisana (2014) explains that the Nicosia Model proposes that firms influence consumers' predisposition towards their products or services through direct messages, thus impacting their attitude towards those products or services. This attitude might result in an active search or evaluation by consumers for those products and services and their attributes, which might lead to a response of either purchasing those products or searching for other products (Jisana, 2014). The Nicosia model also proposes that this final response represents an input that impacts and influences consumers' attitudes, intentions, and behavior in a circular flow (Paz & Rodriquez-Vargas, 2023). The most distinct aspect of this consumer behavior model is that it presents consumer purchasing behavior as a response to the information that a consumer receives and observes about a product or a service and views the act of purchase as a separate stage in the process (Paz & Rodriquez-Vargas, 2023).

The four primary fields of the Nicosia Model that summarize those activities are customer attitude formation, search and evaluation, act of purchase, and feedback (Nicosia, 1966).

Field 1: This field is recognized as the customer attitude formation field and consists of two subfields: firm attributes and customer attributes (Nicosia, 1966). In this field, companies expose consumers to messages about their products and services, which serves as a stimulus that influences the attitudes of those consumers (Jisana, 2014). Those messages include product advertisements, marketing messages, and recommendations.

Field 2: This field is recognized as the search and evaluation field or pre-action field (Nicosia, 1966). The first component represents the actions of consumers in seeking relevant information about products or services from various sources (Nicosia, 1966). Those actions involve conducting online research, reading product reviews, and asking friends, family, and other consumers for advice. The second component represents the actions of consumers in evaluating the information gathered to form their opinions on the product or service, which ultimately shapes their motivation toward the purchase (Nicosia, 1966). Those actions include comparing similar and alternative products, assessing pros and cons, and considering personal preferences.

Field 3: This field is recognized as the act of purchase field (Nicosia, 1966). In this field, consumers decide whether to purchase the product or service based on their attitudes and motivations formed throughout the previous stages (Viksne et al., 2016).

Field 4: This field is recognized as the feedback field (Nicosia, 1966) and represents an output of the third field of the act of purchasing and as an input influencing the first field of customer attitude formation. In this field, customers consume or use the product or service, an action that shapes their experience and impacts their attributes, and forms their feedback that can affect the firm's attributes and is the final stage of the model (Jisana, 2014).

The Nicosia Model can be applied in the context of this study to understand consumer behavior throughout the online shopping journey and how AI-driven tools utilized in e-commerce platforms can influence consumer behavior and decision-making processes.

Chatbots: Chatbots can enhance and facilitate the search stage by providing consumers with instant responses to their inquiries on specific products and services (Tran et al., 2021), which assists in product selection. Chatbots can also guide online consumers through the evaluation stage through personalized interactions based on their previous interactions and preferences (Asante et al., 2023).

Visual Search: Visual search can streamline and simplify the search stage by allowing consumers to find products visually (Dagan et al., 2023), which is most helpful when consumers cannot articulate their needs and preferences or are searching for specific products seen somewhere else. By reducing search time and effort (Asante et al., 2023), visual search can enhance the general user experience and facilitate the decision-making of consumers.

Recommender Systems: Recommender systems can have a significant influence on the customer attitude formation stage of the online shopping behavior of consumers by providing them with personalized product recommendations (Maslowska et al., 2021) based on their demographics, preferences, browsing habits, and previous purchases. Recommender systems can also enhance and facilitate the search and evaluation stage of the online shopping behavior of consumers by narrowing options to relevant products and services (Asante et al., 2023) and reducing their decision-making efforts.

Automated After-Sales Services: After-sales services like order-tracking, customer support, and easy return and exchange can have a positive impact on the attitudes and purchase intentions of consumers (Asante et al., 2023), which impacts their feedback stage and serves as a factor that can influence their customer attitude formation stage post the previous output. The positive experience of consumers can foster trust and loyalty, leading to repeat purchases and providing recommendations to others (Nasir, 2023).

2.3.2. The Howard-Sheth Model:

Developed by Jagdish Sheth and Howard Ritchie in the 1960s, the Howard-Sheth Model is considered the earliest, most famous, and one of the most comprehensive consumer behavior models (Jisana, 2014). Through this model, Howard and Sheth attempted to holistically reflect the consumer decision-making process (Khegay & Aubakirov, 2021) by identifying many of the variables that influence consumer behavior and how they interact and distinguishing three levels of consumer knowledge that determine their decision-making process (Paz & Rodriquez-Vargas, 2023).

Extensive Problem Solving: The first level, or state, is the initial stage of decision-making where the buyer is new to the market. At this level, the consumer lacks knowledge about a product, service, or brand or has limited knowledge; they do not have specific preferences and are actively searching for information about the product, service, or brand and its alternatives (Howard, 1969). This state entails activities from gathering information about the product, service, or brand to checking different alternative products, services, and brands available in the market before making a purchase decision (Khegay & Aubakirov, 2021).

Limited Problem Solving: The second level, or state, is when a consumer's knowledge about a product, service, or brand is inadequate or incomplete, the consumer is confused among the various alternatives, and their preferences are partially determined (Howard, 1969). This state entails a limited set of activities, from gathering information about alternative products, services, or brands to comparing them and establishing the criteria for deciding on a purchase (Khegay & Aubakirov, 2021).

Routinized Response Behavior: The third level, or state, is the habitual response behavior stage when a consumer's knowledge and preferences about a product, service, or brand are adequate (Howard, 1969). At this stage, the consumer has a determined set of criteria for selecting a product, service, or brand and strong-set preferences, which leaves little doubt when making a purchase decision (Paz & Rodriquez-Vargas, 2023).

The Howard-Sheth model also offers a structured framework for studying and understanding consumer behavior by focusing on the role of four key variables: inputs, hypothetical constructs, outputs, and exogenous variables (Howard, 1969), the four major components of their model.

Input Variables: Inputs, according to Howard (1969), represent external stimuli that impact consumer behavior and decision-making, including marketing efforts, social factors, cultural influences, and personal experiences.

Hypothetical Constructs: Jisana (2014) explains that the hypothetical constructs introduced by the Howard-Sheth Model are perceptual and learning constructs. According to Howard (1969), perceptual constructs deal with how consumers perceive and respond to the information they receive and formulate from the inputs about the products, services, or brands.

On the other hand, the learning constructs of this model deal with the stages from consumer motives formation to needs satisfaction through purchase (Howard, 1969). Jisana (2014) explains that a consumer’s purchase intention is the product of the interaction of their motives, selection criteria, brand understanding, brand attitude, and confidence in their purchase decision.

Output Variables: Outputs, according to Howard (1969), represent observable actions and behaviors displayed by consumers as a result of their interaction with the inputs, such as brand loyalty, purchasing decisions, and recommendations to others.

Exogenous Variables: Jisana (2014) explains that the exogenous variables introduced by the Howard-Sheth Model are those taken as a constant but not defined. According to Howard (1969), purchase significance, consumer personality variables, social class, and culture are some exogenous variables introduced in his model.

The Howard-Sheth Model, just like the Nicosia Model, can be applied in the context of this study as it provides a structured approach for understanding consumer behavior in a digital marketplace, their interaction with AI-driven tools in e-commerce platforms, and how that interaction can influence their behavior and decision-making processes.

Chatbots: Chatbots engage consumers in instant personalized conversations, address their inquiries, and provide support along their shopping journey (Tran et al., 2021), thus contributing to consumer learning and motive formation. Chatbots can also influence consumer perceptions and attitudes by understanding their preferences and motivations, leading to positive outputs like satisfaction and repeated platform usage (Asante et al., 2023).

Visual Search: Visual search allows users to search for products visually and reduces their need to use text queries (Dagan et al., 2023), which can enhance the inputs of consumers and support their perceptual stage. By simplifying the search process and improving user experience (Asante et al., 2023), visual search can also influence outputs like customer retention and conversion rates.

Recommender Systems: Recommender systems can significantly impact consumer inputs through personalized suggestions based on their preferences and past searches and purchases (Asante et al., 2023; Maslowska et al., 2021). They also align with the learning stage of the Howard-Sheth Model. By helping consumers navigate through their choices and options of products, recommender systems facilitate the decision-making process, enhance their perception, and impact outputs like their purchase behavior and brand loyalty.

Automated After-Sales Services: After-sales services can shape consumer perceptions of the reliability and commitment of a brand to customer satisfaction (Nasir, 2023). E-commerce platforms can enhance consumer attitudes and their relationship with the brand by addressing post-purchase concerns and promptly resolving issues. That can lead to positive outputs like recommending the brand to others and repeat purchases (Asante et al., 2023; Nasir, 2023).

2.3.3. The Engel-Kollat-Blackwell Model:

Developed by Engel, Kollat, and Blackwell in 1973, the EKB Model is a prominent consumer behavior model focusing on the learning and problem-solving aspects of consumers' purchase behavior (Jisana, 2014). According to Blackwell, Miniard, and Engel (2006), this model represents a guideline for managers and marketers that can assist them in directing communication, strategies, and product mix. The EKB model stands as a groundbreaking consumer behavior model as it introduced consumer decision-making as a process rather than a single act of purchase, and according to Paz and Rodriquez-Vargas (2023), it is one of the most illustrative representations of consumer behavior.

The EKB Model encompasses five main components representing the stages of the consumer decision-making process: problem recognition/need recognition, information search, evaluation of alternatives, choice, and outcome (Engel et al., 1973).

Problem Recognition/Need Recognition: According to the EKB Model, the first stage of a decision-making process involves the need or problem that arises and the recognition of that need or problem. Internal or external factors trigger recognition and prompt consumers to search for products or services to resolve those problems or satisfy those needs (Engel et al., 1973).

Information Search: The second stage of the decision-making process starts with consumers actively seeking information on products or services that can satisfy their needs or resolve their problems (Engel et al., 1973). Throughout this stage, consumers gather information from multiple sources (Engel et al., 1973), like friends, family, advertisements, or online research.

Evaluation of Alternatives: During this stage of the decision-making process, consumers assess, compare, and contrast the different options available to them, which they found during the information search stage, based on criteria like features, quality, and price to make an informed decision (Engel et al., 1973).

Choice: At this stage, consumers decide on which product or service to purchase based on the evaluation stage (Engel et al., 1973). Consumer choice also depends on attitude and intention (Jisana, 2014) and can be influenced by factors like past experiences, personal preferences, and others' recommendations (Engel et al., 1973).

Outcome: The fifth and final stage of the decision-making process, according to the EKB model, is the outcome stage, which is the post-purchase stage, when a consumer evaluates their satisfaction with a product or service (Engel et al., 1973). The outcome of their decision might ultimately be positive or negative (Jisana, 2014).

Just like the two previous consumer behavior models, the Nicosia Model and the Howard-Sheth Model, the EKB model can be applied in the context of this study as it provides a valuable framework for understanding how consumers behave and navigate the e-commerce environment and make purchasing decisions as a result of their interaction with AI-driven tools in e-commerce platforms.

Chatbots: Chatbots assist consumers throughout the decision-making process by offering them information, answering their inquiries, and providing them with prompt support (Asante et al., 2023; Tran et al., 2021), which can help them make informed decisions and navigate the options available. As a result, chatbots can contribute to the information stage of the evaluation of alternatives stage.

Visual Search: Visual search can contribute to the information search stage by allowing consumers to search for products and navigate the alternative options (Asante et al., 2023; Dagan et al., 2023). As a result, a visual search in an e-commerce platform can also facilitate the problem recognition stage and the evaluation of alternatives stage.

Recommender Systems: Recommender systems provide consumers with personalized suggestions based on their preferences, previous purchases, and search histories (Maslowska et al., 2021), which can contribute to the information search stage of the EKB model by facilitating the product search process. By helping consumers navigate their options and relevant products (Asante et al., 2023), recommender systems can also assist in the problem recognition stage and evaluation of alternatives stage.

Automated After-Sales Services: After-sales services can contribute to the outcome stage by influencing consumer satisfaction and post-purchase experience (Nasir, 2023). Effective after-sales services like prompt and responsive customer support and easy exchange and return services can have a positive outcome that would enhance consumer satisfaction and promote repeat purchases and positive recommendations to others (Asante et al., 2023).

2.4. The Stimulus-Organism-Response Model:

Introduced in 1974 by Mehrabian and Russel, the Stimulus-Organism-Response (SOR) Model represented a significant development in psychology and consumer research as it offered a more sophisticated understanding of the role and importance of internal factors and their impact on the individual (Jacoby, 2002). The SOR Model was derived from the black-box decision-making approach, which focuses on the cognitive aspects of decision-making (Hochreiter et al., 2023). According to Hochreiter et al. (2023), this model is a guiding principle in the field of environmental psychology due to its valuable contribution to the understanding and analysis of human behavior, the origin and formation of decisions specifically, which lead to its application in the fields of consumer and organizational behavior. This framework evolved from the earlier Stimulus-Response (S-R) Model, which focused on the direct link between environmental stimuli and human behavior, disregarding the role of an individual's internal state and processes (Jacoby, 2002).

2.4.1. Overview of the Stimulus-Organism-Response Model:

The SOR Model suggests that when an individual gets exposed to an external factor in their environment, a stimulus (S), a trigger in their inner state takes place, the organism (O), which leads to a resulting behavior, the response (R) (Mehrabian & Russel, 1974).

Stimulus (S): According to Mehrabian and Russel (1974), a stimulus (S) is a factor that can impact an individual's internal state. Jornales (2023) explains that many aspects or factors in an external environment can act as a stimulus and influence an individual's internal state. To a consumer, things like logos, ads, pricing, packaging, recommendations, and multiple other factors interact and compete as stimuli (Jacoby, 2002). Hochreiter et al. (2023) clarify further that those factors can be external or internal, like motives, experiences, and interests, and stimulate consumers to purchase a product or a service.

Organism (O): According to Mehrabian and Russel (1974), an organism (O) is an individual's internal state that mediates the relationship between the stimuli and their response. Jornales (2023) explains that this organism refers to the individual's internal experience of cognition, both cognitive and emotional. According to Hochreiter et al. (2023), cognitive components are consumers' perceptions, thinking, and learning, while emotional components are their feelings, motivations, values, and attitudes. A consumer's previous experiences, attitudes, knowledge, beliefs, motives, expectations, and various other cognitive and emotional factors involving brands or companies represent an organism (Jacoby, 2002).

Response (R): According to Mehrabian and Russel (1974), a response (R) is an individual's behavior resulting from the processing of the stimulus through their organism, which can be a physical action, a decision, or an emotional reaction. Jacoby (2002) explains that a response can be internal, which is nonvisible, or external, which can be detected, whether verbal or behavioral. A consumer's purchase, usage, and disposal of a product or service represent a response (Jacoby, 2002). Hochreiter et al. (2023) clarify that this phase begins with a conscious processing of information, which initiates a consumer's decision-making process.

2.4.2. The Stimulus-Organism-Response Model in E-Commerce:

According to existing literature, the SOR Model presents a well-accepted and valuable framework for studying and investigating consumer behavior and decision-making (Asante et al., 2019; Asante et al., 2023; Hochreiter et al., 2023; Jacoby, 2002; Jornales, 2023). Various other pieces of literature utilized this model to analyze and understand consumer behavior in fields like retail (Jornales, 2023), electronic services (Asante et al., 2023), banking (Islam et al., 2020), tourism (Chen et al., 2021), healthcare (Suess & Mody, 2018), social commerce (Wu & Li, 2018), and most importantly, e-commerce (Asante et al., 2023; Guo et al., 2021; Li, 2023; Wei, 2023).

Multiple studies that utilized the SOR Model in the context of e-commerce have shown that websites and other online shopping platforms' features that consumers interact with throughout their purchase experience represent important stimuli that impact their behavior and decision-making process (Asante et al., 2023; Guo et al., 2021; Li, 2023; Wei, 2023). Guo et al. (2021) focused on the role of streaming features as stimuli and showed how they impact consumers' purchase intention. Li (2023) highlighted the impact of multimedia visual features as stimuli on consumers' online purchasing behavior. Wei (2023) underscored the importance of recommendations features in e-commerce platforms as stimuli and its influence over consumers' purchasing aspirations.

In the context of this study, the application of AI in Turkish e-commerce platforms, inspired by the work of Asante et al. (2023), stimuli include consumers' interaction with AI-driven tools like chatbots, visual search, recommender systems, and automated after-sales service, which are external to the consumers. The SOR Model is employed to explain how those features (S) impact the formation of consumer engagement, which is composed of two dimensions: psychological engagement (O) and behavioral engagement (R).

CHAPTER 3: RESEARCH ON AI-ENHANCED PERSONALIZATION IN THE TURKISH E-COMMERCE MARKET: A SURVEY ON CONSUMER BEHAVIOR AND DECISION-MAKING

Building upon the literature presented and discussed in the previous chapters, the arguments and relationships between consumer behavior dimensions and AI tools and features utilized in e-commerce platforms, and within the framework of hypothesis development, this chapter outlines the research methodology and design adopted to investigate the impact of those AI-driven tools and features on consumer engagement, introduces the hypotheses development and theoretical framework of the study, and presents the statistical tools and techniques utilized to collect data on and investigate the relationships between the variables.

This chapter also details the research strategy chosen, the methods adopted for data collection, and introduces the data sampling techniques utilized, including a discussion of the sample size collected and the rationale behind the sample selection. A description of the measures and instruments used for variables operationalization is also presented and an overview of the analytical techniques and statistical tools used to examine the data.

The chapter continues to delve into the dynamics of consumer interaction with AI tools and features within the context of the Turkish e-commerce market by exploring the data collected on the impact of chatbots, visual search, recommender systems, and automated after-sales services on consumer engagement, and discussing the findings of the study.

3.1. AI-Enhanced Personalization in The Turkish E-Commerce Market:

AI applications and integration initiated a rapid transformation in the Turkish e-commerce sector, providing consumers with an enhanced level of personalization through a multichannel approach (Güven & Güven, 2023), which includes, but is not limited to, the use of chatbots, recommendation systems, dynamic pricing, personalized marketing, and many more. AI applications in this sector not only helps businesses increase their profits and returns and improve their decision-making and operational efficiency (Tuncalı, 2020), but also helps them understand and target their customer more effectively and improve their customer satisfaction by utilizing these applications to analyze customer behavior and offer them a personalized online shopping experience (Güven & Güven, 2023).

AI-driven personalization is arguably a crucial tool for increasing consumer engagement and loyalty, and according to Tuncalı (2020), personalization can boost interaction with consumers by over 40%. Güven and Güven (2023) highlight that AI helps e-commerce sites predict what customers want to buy, enhancing the customer shopping experience and increasing conversions.

Building upon the literature presented in the two previous chapters, this study aims to explore and investigate the impact of prominent AI-driven tools and features integrated in e-commerce platforms, namely chatbots, visual search, recommender systems, and automated after-sales service, on consumer engagement, to highlight the importance of technological advancements in shaping consumer behavior and business strategies in the Turkish e-commerce market.

3.2. Research Methodology:

This study employs a quantitative research methodology to investigate the impact of AI-driven tools and features integrated into Turkish e-commerce platforms, namely chatbots, visual search, recommender systems, and automated after-sales services, on consumer behavior. This research methodology was deemed appropriate for this study as it is the most suitable for hypothesis testing, allows for precise measurement of variable relationships, and facilitates quantifying the influence of AI-driven tools on user behavior.

The primary data for this research were collected from users of e-commerce platforms in Türkiye through a structured online survey. This approach was chosen as it allows for a representative and comprehensive analysis of consumer interactions and responses to AI-driven tools and features and how they impact their psychological and behavioral engagement.

3.3. Research Design:

The research design adopted in this study is cross-sectional as the primary data used for testing the theoretical framework developed were collected from a sample of e-commerce platform users at this point in time, which also allows generalizability of the findings to the broader population of e-commerce platform users in Türkiye.

The quantitative data was collected through the online survey, which included 27 closed-ended 7-point Likert scale questions to allow for statistical analysis, and a typical demographic questionnaire comprised of 16 questions to allow for a descriptive analysis of the participants' demographics. This method was chosen to quantify the impact of AI-driven tools and features on consumers' psychological and behavioral engagement levels.

In addition to the primary data, secondary data played a crucial role in this study. Multiple official and governmental reports, industry statistics, and academic articles were reviewed to support the findings of this research and provide context to e-commerce platform users' and consumers' behavior in Türkiye.

This research design was mapped out to ensure a solid methodology by collecting data from multiple sources. It provides a comprehensive overview and understanding of AI in e-commerce and its effect on Turkish consumers and enhances the validity and reliability of the research results for analysis and discussion.

3.4. Hypothesis Development:

This section of the study builds upon the literature introduced in the previous chapters on AI applications in e-commerce and their impact on consumer behavior and decision-making to establish the hypotheses theorized and to be tested through the primary data collected from the participants in an attempt to answer the research question. The hypotheses are theorized on the impact of efficient AI-driven tools in e-commerce platforms, namely chatbots, visual search, recommender systems, and automated after-sales services, on consumer engagement, psychological and behavioral, and the relationship between consumers’ psychological and behavioral engagement.

3.4.1. Chatbots and Consumer Engagement:

Tran, Pallant, and Johnson (2021) define chatbots as artificial intelligence software that mimics conversations with human users over the internet. They provide users with fast and instant support through machine-powered conversations used to address customers questions (Sulova, 2023), offer them insights (Nimbalkar & Berad, 2021), and answer their inquiries (Cheng et al., 2023). Chatbots in multiple Turkish e-commerce platforms appear as chat box prompts that provide users with turn-by-turn conversations to address questions, inquiries, concerns, and issues. Their ability to handle user inquiries effectively and promptly is valuable in retail and consumer services and contributes to positive consumer sentiment (Tran et al., 2021), an enhanced experience (Asante et al., 2023; Nimbalkar & Berad, 2021), and an improved satisfaction level (Cheng et al., 2023). As discussed in the literature, chatbots are well-received by e-commerce platform users, with 71% stating they turn to them for assistance with purchase-related issues (Sulova, 2023).

According to the SOR Model, the exposure of an individual to an external factor in their environment, or stimulus (S), triggers a change in their inner state, referred to as the organism (O), which leads to a resulting behavior, referred to as the response (R) (Mehrabian & Russel, 1974). In the context of this study, the characteristics of chatbots (S) used in Turkish e-commerce platforms are examined to understand their impact on the psychological (O) and behavioral engagement (R) of consumers towards those platforms.

As evident through the literature, chatbots can engage consumers further with the e-commerce platform and provide a positive and enhanced experience that influences their perception of and attitude towards that platform. That leads to positive outputs like satisfaction, repeated usage, writing reviews, and providing favorable recommendations to friends and family. Therefore, this study hypothesizes that:

Hypothesis 1a: Chatbot's efficiency in an e-commerce platform positively affects Turkish consumers' psychological engagement level.

Hypothesis 1b: Chatbot's efficiency in an e-commerce platform positively affects Turkish consumers' behavioral engagement level.

Hypothesis 1c: Turkish consumers' psychological engagement level mediates the relationship between the chatbot's efficiency in an e-commerce platform and their behavioral engagement level positively.

3.4.2. Visual Search and Consumer Engagement:

Dagan, Guy, and Novgorodov (2023) define visual search as a function that allows users to utilize images as search input queries to retrieve a list of results similar to the item the user is searching for. The authors argue that visual search, or search by image, is fast and intuitive and allows user search to transcend linguistic or expressive restrictions (Dagan et al., 2023). According to Asante et al. (2023), AI is utilized in these functionalities to simplify the product search process. Various literature emphasizes that visual search enhances personalization and user experience (Cheng et al., 2023) and helps users save time on browsing by improving their search result satisfaction (Asante et al., 2023). Visual search functions implemented in Turkish e-commerce sites and platforms are most helpful when consumers cannot articulate their needs and preferences or when searching for products they have seen elsewhere. By reducing search time and effort, visual search can enhance the general user experience, which can also influence outputs like customer retention and conversion rates.

According to the SOR Model, the exposure of an individual to an external factor in their environment, or stimulus (S), triggers a change in their inner state, referred to as the organism (O), which leads to a resulting behavior, referred to as the response (R) (Mehrabian & Russel, 1974). In the context of this study, the characteristics of visual search (S) used in Turkish e-commerce platforms are examined to understand their impact on the psychological (O) and behavioral engagement (R) of consumers towards those platforms.

As evident through the literature, visual search can engage consumers further with the e-commerce platform and provide a positive and enhanced experience that influences their perception of and attitude towards that platform. That leads to positive outputs like satisfaction, repeated usage, writing reviews, and providing favorable recommendations to friends and family. Therefore, this study hypothesizes that:

Hypothesis 2a: Visual search efficiency in an e-commerce platform positively affects Turkish consumers' psychological engagement level.

Hypothesis 2b: Visual search efficiency in an e-commerce platform positively affects Turkish consumers' behavioral engagement level.

Hypothesis 2c: Turkish consumers' psychological engagement level mediates the relationship between the visual search efficiency in an e-commerce platform and their behavioral engagement level positively.

3.4.3. Recommender Systems and Consumer Engagement:

Maslowska, Malthouse, and Hollebeek (2022) define recommender systems as tools that provide users with suggestions of relevant items to their interests and preferences. In e-commerce, these systems utilize AI big data collected by e-commerce sites and platforms on customers' search history and habits, as well as previous purchases (Nimbalkar & Berad, 2021), which allows businesses to improve their customer service and provide their customers with a better shopping experience through personalization (Huang et al., 2022). Recommender systems can also increase customer conversion (Nimbalkar & Berad, 2021), retention (Asante et al., 2023), and sales (Cheng et al., 2023) by facilitating their browsing activities (Asante et al., 2023) and suggesting relevant products (Nimbalkar & Berad, 2021), which impacts their experience positively. According to Maslowska et al. (2022), these systems' effectiveness has a significant impact on users' interaction and engagement with the platform. Asante et al. (2023) also argue on the influential role of recommender systems in shaping customer engagement.

According to the SOR Model, the exposure of an individual to an external factor in their environment, or stimulus (S), triggers a change in their inner state, referred to as the organism (O), which leads to a resulting behavior, referred to as the response (R) (Mehrabian & Russel, 1974). In the context of this study, the characteristics of recommender systems (S) used in Turkish e-commerce platforms are examined to understand their impact on the psychological (O) and behavioral engagement (R) of consumers towards those platforms.

As evident through the literature, recommender systems can engage consumers further with the e-commerce platform and provide a positive and enhanced experience that influences their perception of and attitude towards that platform. That leads to positive outputs like satisfaction, repeated usage, writing reviews, and providing favorable recommendations to friends and family. Therefore, this study hypothesizes that:

Hypothesis 3a: Recommender system's efficiency in an e-commerce platform positively affects Turkish consumers' psychological engagement level.

Hypothesis 3b: Recommender system's efficiency in an e-commerce platform positively affects Turkish consumers' behavioral engagement level.

Hypothesis 3c: Turkish consumers' psychological engagement level mediates the relationship between the recommender system's efficiency in an e-commerce platform and their behavioral engagement level positively.

3.4.4. Automated After-Sales Services and Consumer Engagement:

Nasir, Adil, and Dhamija (2021) define after-sales services as an integral part of a business's customer support system and highlight its role in garnering customer loyalty and satisfaction. According to Asante et al. (2023), an automated after-sales service is the AI element in an e-commerce platform that automates all after-sales support, from handling customer feedback to tackling product replacement and return issues. Automated after-sales services can enhance customer service by facilitating all their post-sale requests, boosting an e-commerce business's perceived value and conversion rates, and offering customers a personalized experience (Asante et al., 2023). Nasir et al. (2021) emphasize the significant role of after-sales services in engaging customers, enhancing their shopping experience, generating positive word-of-mouth, and driving their repurchase intentions.

According to the SOR Model, the exposure of an individual to an external factor in their environment, or stimulus (S), triggers a change in their inner state, referred to as the organism (O), which leads to a resulting behavior, referred to as the response (R) (Mehrabian & Russel, 1974). In the context of this study, the characteristics of automated after-sales services (S) used in Turkish e-commerce platforms are examined to understand their impact on the psychological (O) and behavioral engagement (R) of consumers towards those platforms.

As evident through the literature, automated after-sales services can engage consumers further with the e-commerce platform and provide a positive and enhanced experience that influences their perception of and attitude towards that platform. That leads to positive outputs like satisfaction, repeated usage, writing reviews, and providing favorable recommendations to friends and family. Therefore, this study hypothesizes that:

Hypothesis 4a: Automated after-sales services efficiency in an e-commerce platform positively affects Turkish consumers’ psychological engagement level.

Hypothesis 4b: Automated after-sales services efficiency in an e-commerce platform positively affects Turkish consumers’ behavioral engagement level.

Hypothesis 4c: Turkish consumers’ psychological engagement level mediates the relationship between the automated after-sales service’s efficiency in an e-commerce platform and their behavioral engagement level positively.

3.4.5. Psychological Engagement and Behavioral Engagement:

Asante et al. (2023) define consumer engagement as an “attitude formation process represented by consumers’ psychological and behavioral engagement attitudes driven by their satisfaction with the AI elements experienced on an e-commerce platform” (p. 13). As discussed in the previous chapter of this research, multiple pieces of literature describe behavioral engagement as a dimension or manifestation of consumer engagement (Asante et al., 2023; Bowden, 2009; Brodie et al., 2011; Brodie et al., 2013; Busalim et al., 2021; Hollebeek, 2011; Hu & Chaudhry, 2020; Van Doorn et al., 2010; Vivek et al., 2012), which is defined in other pieces of literature as a psychological state that involves interactive experiences comprising cognitive and emotional aspects occurring within dynamic environments. As such, this study defines behavioral engagement as a manifestation and a direct result of a customer’s psychological engagement with AI-driven tools in an e-commerce platform.

As evident through the literature, and building upon the conceptual link between psychological and behavioral dimensions of consumer engagement, this study hypothesizes that:

Hypothesis 5: Turkish consumers’ psychological engagement level affects their behavioral engagement level positively.

3.4.6. The Moderating Role of Attention to Social Comparison:

Attention to social comparison, as discussed in the literature review, is defined as people' attention and sensitivity to the judgement and evaluation of other individuals of their purchase and consumption habits and choices (Asante et al., 2019: Asante et al., 2023: Lennox & Wolfe, 1984). Lennox and Wolfe (1984) emphasize in their study that consumers who are highly sensitive to negative evaluations of their consumption choices and habits -by other consumers- present a higher level of adherence to social cues and norms and that consumers with lower self-esteem present a higher level of conformity to social pressure and norms (Lennox & Wolfe, 1984). In the context of this study, and as hypothesized that consumers' psychological engagement level influences their behavioral engagement level, this study also hypothesizes that:

Hypothesis 6: Turkish consumers' attention to social comparison moderates the effect of their psychological engagement level on their behavioral engagement level negatively.

3.5. Theoretical Framework:

This section of the study builds upon the hypothesis developed in the previous section and the SOR Model introduced in the literature chapter to present the theoretical framework established on the relationships between AI-driven tools and consumer engagement, which will be tested through the primary data collected from the participants in an attempt to answer the research question. This framework was adapted from the work of Asante et l. (2023), who investigated similar relationships in the Chinese e-commerce market. The hypotheses are theorized on the impact of efficient AI-driven tools in e-commerce platforms, namely chatbots, visual search, recommender systems, and automated after-sales services, on consumer engagement, psychological and behavioral, and the relationship between consumers' psychological and behavioral engagement.

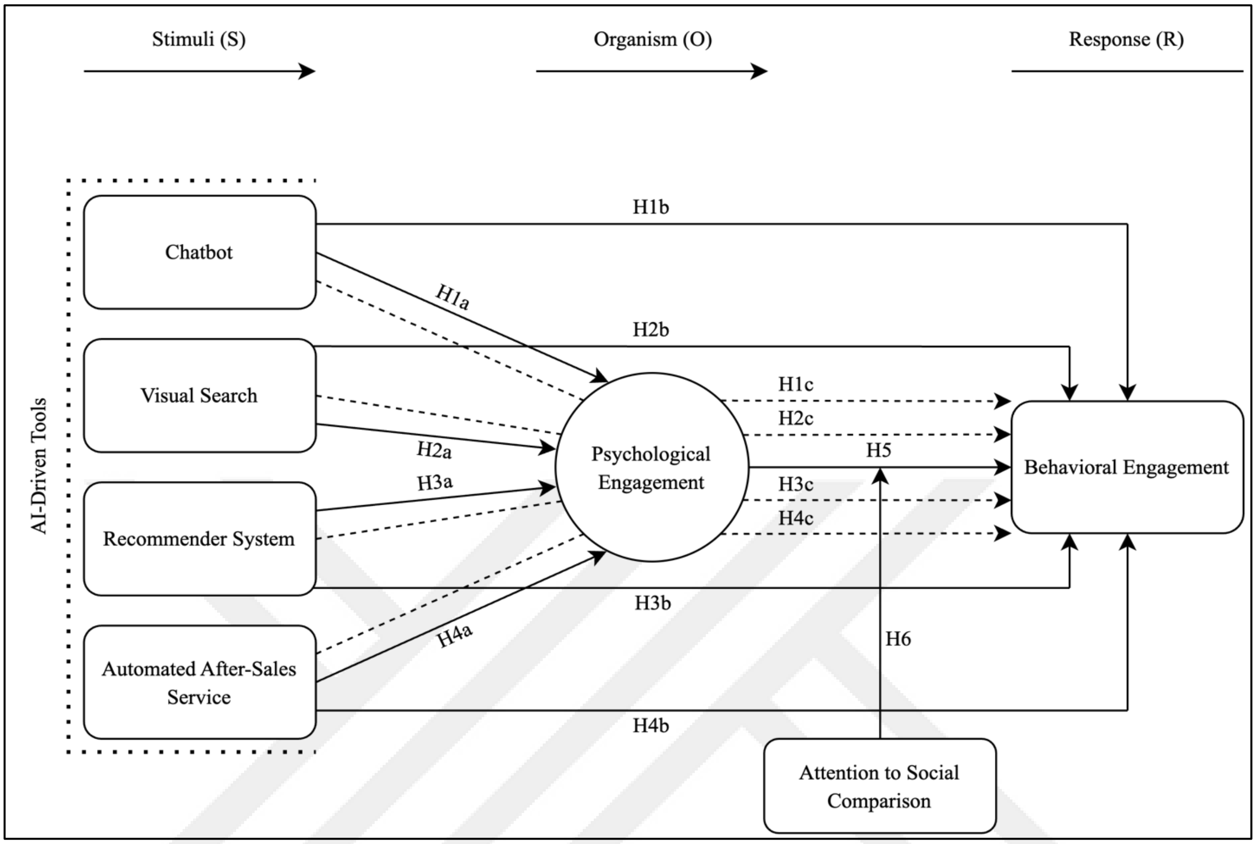

Figure 1. Theoretical Framework

Figure 1 displays a summary of the hypothesized relationships in this chapter of the study. This theoretical framework aids in visually understanding how various AI-driven tools impact consumer behavior on e-commerce platforms directly and indirectly, through their psychological engagement with those tools, and how attention to social comparison potentially moderates the relationship between consumers' psychological and behavioral engagement.

3.6. Sampling Method:

This section outlines the methodology adopted for sampling in the study, detailing the logic and rationale for defining the population and selecting the sample size, and the sampling techniques utilized. The first subsection describes the target population, the second introduces the sample size determination process.

3.6.1. Population:

A population is the set of all objects, items, or people who possess the attributes and characteristics the researcher intends to study (Bhattacherjee, 2012). According to the literature, a target population, which is different from the population, is generally more difficult to define but is widely known as the group of all objects, items, or people that meet a pre-determined set of criteria identified by the researcher to conduct their study and to whom they aim to generalize the findings (Bhattacherjee, 2012).

Due to geographic, logistic, or institutional limitations, researchers might not be able to access the whole target population. As a result, a subset of this target population was selected for data collection and generalization of conclusions (Bhattacherjee, 2012).

In the context of this study, the target population identified are users of e-commerce platforms and sites in Türkiye. According to the most recent data report published by Data Reportal on Türkiye's digital trends and stats, internet penetration in Türkiye at the beginning of 2023 was 83.4%, with 71.38 million internet users (Kemp, 2023). Authors of the Turkish Competition Authority’s e-marketplace sector review state that 75% of internet users in Türkiye shop online and that 68.5% of those users shop via e-commerce sites and platforms (Sarıçiçek et al., 2022). As such, the estimated target population of this study is 36.7 million users of e-commerce platforms and sites in Türkiye.

3.6.2. Sampling:

Sampling is selecting a subset of objects, items, or people of a target population or population of interest to observe, draw statistical inferences from, and generalize them to the target population (Bhattacherjee, 2012). As stated in the previous section, the target population in this study is users of e-commerce platforms and sites in Türkiye. With an estimated total of 36.7 million users, a confidence level of 95%, and a margin of error of 8%, the sample size was set at 151 users. This sample size was calculated following the below formulas (Bhattacherjee, 2012):

$$n = \frac{Z^2 \times p \times (1-p)}{\epsilon^2}$$

$$n' = \frac{n}{1 + \frac{Z^2 \times p \times (1-p)}{\epsilon^2 \times N}}$$

Due to data privacy and resource restrictions, this study could not define a sampling frame since it would have required compiling a list of all e-commerce platform users in Türkiye. As a result, this alternative approach of estimating the population of users, upon which a sample size was calculated, was adopted to gather representative data of the target group. Given these constraints, this study adopted a non-probabilistic convenience sampling technique, which is a sampling method that is deemed the least expensive and time-consuming as the subset drawn is easily accessible, close to hand, readily available, or convenient (Bhattacherjee, 2012).

3.7. Data Collection Method:

Data collection is the systematic process of gathering data from the target population and measuring that information using various tools and sources (Bhattacherjee, 2012). This study's data collection entailed a methodological approach to collecting data from its target audience: users of Turkish e-commerce platforms. The research utilized data collected from these voluntary participants to address the research question, test the hypotheses, and evaluate the research outcomes.

3.7.1. Primary Data:

Primary data for this study was collected using Google Forms as an online survey tool. This approach was chosen to reach a wider audience, strengthen the response rate, and ensure the data's representativeness. The survey specifically targeted 151 participants in Türkiye who shop online and use e-commerce platforms and sites. The survey was disseminated through contacts and social media platforms, and participants were recruited accordingly. To ensure anonymity and encourage participation, respondents were instructed to fill out the survey anonymously, which also helped minimize response bias. The online survey was available for response collection from January 7, 2024, to February 25, 2024.

Upon concluding data collection and closing the online survey form, 151 responses were recorded, reflecting a response rate of 100%. None of the recorded responses were disqualified throughout the process, resulting in a response validity ratio of 100%. All 151 responses collected were utilized to test the research model.

3.7.2. Secondary Data:

In addition to the primary data, secondary data was crucial for this study. Secondary data included multiple official and governmental reports from sources such as the Turkish Ministry of Trade, industry statistics from credible sources like McKinsey & Company, Forbes Advisor, and Statista, as well as academic articles. These sources were reviewed to provide a broader context regarding e-commerce platform users' and consumers' behavior globally and in Türkiye. Specifically, secondary data from reputable Turkish governmental organizations were analyzed to complement and contextualize the findings from the consumer survey.

3.8. Operationalization of Variables:

Table 2. Variables Operationalization

Variable	Conceptualization	Operationalization
Independent Variables		
Chatbot Efficiency (CB)	The efficiency of the software that mimics conversations with human users over the internet (Tran et al., 2021)	Asante et al.'s four items measurement scale (2023) adapted from Adam et al. (2021)
Visual Search Efficiency (VS)	The efficiency of the function that allows users to use images as search queries to retrieve a list of visually similar results (Dagan et al., 2023)	Asante et al.'s four items measurement scale (2023) adapted from Sudarsan et al. (2022)
Recommender System Efficiency (RS)	The efficiency of the tool that provides users with suggestions of items relevant to their interests and preferences (Maslowska et al., 2022)	Asante et al.'s four items measurement scale (2023) adapted from Chinchanachokchai et al. (2021)
Automated After-Sales Service Efficiency (AS)	The efficiency of the feature that automates after-sales support, from handling customer feedback to product replacement and return (Asante et al., 2023)	Asante et al.'s four items measurement scale (2023) adapted from Daqar and Smoudy (2019)
Dependent and Mediating Variable		
Psychological Engagement Level (PE)	The level of positive and fulfilling state of mind experienced by e-commerce platform users as a result of their interaction with AI-driven tools on the platform (Asante et al., 2023)	Asante et al.'s three items measurement scale (2023) adapted from Fang et al. (2017)

Dependent Variable		
Behavioral Engagement Level (BE)	The level of continued interaction displayed by e-commerce platform users as a result of their interaction with AI-driven tools on the platform and its resulting positive state of mind (Asante et al., 2023)	Asante et al.'s four items measurement scale (2023) adapted from Fang et al. (2017)
Moderating Variable		
Attention to Social Comparison Level (ASC)	The level of attention and sensitivity of e-commerce platform users to society's judgement of their purchase choices (Asante et al., 2023)	Asante et al.'s four items measurement scale (2023) adapted from Asante et al. (2019)

Based on the literature presented in the second chapter, this research adopts the conceptual definitions and measurement tools listed in Table 2.

Chatbot Efficiency (CB): Asante et al.'s (2023) four-item scale for measuring users' perceived chatbot efficiency on an e-commerce platform assesses the chatbot's availability, the presence of pop-up notifications, the effectiveness of interaction with the chatbot in returning beneficial results, and the ease of communication with the chatbot.

Visual Search Efficiency (VS): Asante et al.'s (2023) four-item scale for measuring users' perceived visual search efficiency on an e-commerce platform assesses the function's ease of use, its ability to utilize the camera feature or saved images, its match result quality, and its ability to minimize users' need for text searches.

Recommender System Efficiency (RS): Asante et al.'s (2023) four-item scale for measuring users' perceived recommender system efficiency on an e-commerce platform assesses its ability to generate recommendations based on previous searches, purchase history, the relevance of the products recommended, and its effectiveness in minimizing search time.

Automated After-Sales Service Efficiency (AS): Asante et al.'s (2023) four-item scale for measuring users' perceived automated after-sales service efficiency on an e-commerce platform assesses the automation of feedback requests, the handling of product ambiguity, the automation of refund and replacement processes, and the availability of guidance throughout the shopping journey.

Psychological Engagement Level (PE): Asante et al.'s (2023) three-item scale for measuring users' psychological engagement as a result of their interaction with AI-driven tools and features on an e-commerce platform assesses their feelings of shopping-related stress, enthusiasm and inspiration, and immersion and time perception.

Behavioral Engagement Level (BE): Asante et al.’s (2023) four-item scale for measuring users’ behavioral engagement as a result of their interaction with AI-driven tools and features on an e-commerce platform assesses their self-reported intention to continue using the platform, referral of friends and family to the platform, providing positive word-of-mouth about the platform, and writing reviews about their experience with the platform.

Attention to Social Comparison Level (ASC): Asante et al.’s (2023) four-item scale for measuring users’ attention to social comparison assesses their tendency towards consuming reputable brands, the significance of famous brands, their reliance on other’s opinions when deciding what to buy, and their attention to societal consumption trends.

3.9. Data Analysis Techniques:

A comprehensive set of data analysis techniques was utilized to thoroughly explore the impact of AI-driven tools on Turkish e-commerce platforms and their effects on consumer engagement, as well as to test the theoretical framework developed in the study. These techniques provided both descriptive and inferential insights into the data collected from 151 participants.

An analysis of the demographic data provided detailed profiles of the participants and helped to understand the characteristics of the user base of Turkish e-commerce platforms. Simple averages were generated using Microsoft Excel to analyze demographic information, including participants' ages, gender, marital status, education level, work experience, online shopping experience, shopping preferences, and more.

To further interpret the data, a descriptive analysis was conducted using SPSS. This analysis summarized the main features of the collected data, including ranges, means, standard deviations, and variances for all variables such as chatbot efficiency, visual search efficiency, recommender system efficiency, automated after-sales service efficiency, psychological engagement, behavioral engagement, and attention to social comparison.

Next, Pearson's correlation coefficients were calculated to determine the strength and direction of relationships between the different variables measured in this study. This analysis was critical for identifying associations between various AI-driven tools and participants' engagement levels. The correlation matrix was generated using SPSS.

Multiple regression analysis was employed to test the proposed hypotheses, particularly those related to the direct effects of AI-driven tools on psychological and behavioral engagement and the moderating role of attention to social comparison. Regression analysis was chosen because it allows for the assessment of how much variance in engagement outcomes can be explained by AI-driven tools, while also controlling for the impact of other variables. SPSS was used to conduct the regression analysis, providing insight into the individual contribution of each predictor variable.

For hypotheses concerning the indirect effects of AI-driven tools on behavioral engagement and the mediating role of psychological engagement, a bootstrap procedure was utilized through the PROCESS add-on in SPSS to generate the relevant statistics. This approach helped confirm the mediation effects, offering more robust insights into the causal pathways between variables.

Statistical significance in this study was evaluated using p-values and t-statistics, with a significance level set at $p < 0.05$ to determine whether observed relationships were statistically significant or could be attributed to chance.

3.10. Validity And Reliability:

Constructs from previously published academic studies were adopted to ensure the construct validity of the measurement scales used in this research. Specifically, the constructs and measurement scales were adapted from Asante et al.'s study (2023), which examined similar relationships in the Chinese e-commerce market. To further enhance validity, an Exploratory Factor Analysis (EFA) was conducted to verify the underlying factor structure and ensure that the adapted constructs were suitable for the context of this study. The EFA ensured that the measurement items loaded appropriately onto the intended factors, confirming their relevance and suitability for measuring the constructs.

This approach ensured both theoretical and empirical validity. Asante et al.'s (2023) measurement scales were also adapted from prior studies that validated them (Adam et al., 2020; Asante et al., 2019; Chinchanachokchai et al., 2021; Daqar & Smoudy, 2019; Fang et al., 2017; Sudarsan et al., 2022), providing additional empirical support. Together with the factor structure validated through EFA, these constructs effectively reflected the intended variables, as demonstrated in previous research.

Additionally, and in order to ensure the reliability of the constructs, internal consistency tests were conducted for each measurement scale. Cronbach's alpha was used to assess the internal consistency of the scales, ensuring that each construct reliably measured the intended variable. Additionally, a collinearity test was performed to ensure the independence of all variables, preventing potential multicollinearity that could distort the results. These tests supported the reliability of the regression coefficients obtained for testing the study's theoretical framework, ensuring the robustness of the findings.

3.11. Ethical Considerations:

This study adhered by ethical guidelines to ensure protecting the rights of the participants and adhering to integrity standards during the research process.

Participants of the study were informed that their involvement in this research was voluntary and that they had the option to withdraw at any point. The online survey form included a detailed consent form outlining the purpose of the study and how the data collected would be used. The consent form also included an anonymity and confidentiality clause that pledged to protect the data and privacy of the participants.

The survey design questions were reviewed and approved by Istanbul Commerce University's ethics committee to ensure that they meet all the institutional standards for ethical research.

3.12. Limitations of the Study:

To ensure transparency, it is important to acknowledge that despite the potential contributions and implications of this study, it has several limitations.

First, the findings primarily reflect the perspectives of Turkish consumers who use e-commerce platforms. This geographic and cultural focus may limit the broader applicability of the results, as they may not fully account for variations in other regions or cultural contexts. Additionally, the reliance on secondary data from official and governmental sources introduces potential limitations regarding the scope and coverage of the data.

Another limitation pertains to the size and geographic diversity of the participant pool within Türkiye. The study's sample size of 151 participants, constrained by time and resource limitations, may affect the representativeness of the findings. Despite efforts to target e-commerce platform users across Türkiye, the online survey's visibility on social platforms might have been influenced by algorithms that prioritize content based on location. Consequently, the survey may have predominantly reached participants residing in Istanbul, where social media usage and proximity are higher. This disproportionality could impact the generalizability of the data and the representativeness of the findings across different regions of Türkiye.

The research design also presents limitations. The study employed a cross-sectional design, which captures a “snapshot” of consumer engagement with AI-driven tools at a single point in time. This approach does not account for temporal changes, which are significant given the rapid evolution of AI technologies, their adoption, and their acceptance by businesses and consumers. Additionally, while the study utilized a quantitative methodology to quantify relationships between observed variables, it does not capture the qualitative depth of users’ attitudes and perceptions.

Moreover, the focus on the Turkish e-commerce market may not fully reflect behaviors applicable to other regions with differing cultural, economic, and technological contexts. Even within Türkiye, findings that are representative of an Istanbul-based majority may not accurately reflect trends and behaviors in other cities, considering the diverse nature of the Turkish population.

Furthermore, although EFA was conducted to verify the factor structure and ensure the suitability of the measurement scales, Confirmatory Factor Analysis, which is typically used in Structural Equation Modeling (SEM), was not feasible due to sample size constraints. SEM generally requires a larger sample size to provide reliable estimates and validate the theoretical framework with high confidence. Given the sample size of 151 participants, which is relatively small for SEM standards, regression analysis was selected as the more appropriate method for hypothesis testing. While SEM could have offered a more comprehensive examination of the relationships between latent variables, the small sample size limited the feasibility of such complex analysis. Consequently, the validation of the measurement model may be less rigorous than if SEM had been employed. Nonetheless, regression analysis provided a straightforward approach to examining direct effects and moderation relationships without the complexity of SEM's requirements for model fit indices and latent variable analysis. The combination of EFA, Cronbach’s alpha for internal consistency, and collinearity tests to assess multicollinearity offered sufficient validity and reliability for the regression analysis conducted.

Finally, while the sample size was adequate for regression analysis, it does limit the generalizability of the results. Larger sample sizes could provide more robust insights and enable the use of more advanced techniques for a deeper analysis.

3.13. Data Analysis Results:

This section of the chapter focuses on presenting and analyzing this study’s data collected using the online survey form from 151 Turkish consumers who use e-commerce platforms to purchase products online and voluntarily participated in this study. The results of the data analysis are presented systematically in an attempt to form conclusive and informed deductions about the impact of Turkish consumers’ interaction with AI-driven tools in e-commerce platforms on their psychological and behavioral engagement. Additionally, this section presents the associations between the independent and dependent variables and interprets the results so that the hypotheses formulated about those relationships can be accepted or rejected.

3.13.1. Demographics Analysis:

Demographic analysis of the socio-economic characteristics, as well as other characteristics of the participants of this study, can provide a comprehensive view of the user base of e-commerce platform users in Türkiye, which includes insights into their age, gender, marital, parental, education, work details, and income. Those insights represent a valuable resource that can help marketers tailor e-commerce strategies to align with their platform users' demographics and characteristics.

Table 3. Socio-Demographic Characteristics of Participants

Characteristics	Category	Frequency	Percentage (%)
Age Group	18-24	49	32.5%
	25-34	65	43.0%
	35-44	22	14.6%
	45-54	13	8.6%
	55-64	2	1.3%
	65 or Older	0	0.0%
Gender	Female	77	51.0%
	Male	74	49.0%
Marital Status	Single	96	63.6%
	Married	53	35.1%
	Divored	1	0.7%
	Widowed	1	0.7%
Parental Status	Have Children	38	25.2%
	Do not Have Children	113	74.8%
Education Level	Primary School	5	3.3%
	Middle School	2	1.3%
	High School	35	23.2%
	Technical Degree	8	5.3%
	Associate Degree	2	1.3%
	Bachelor's Degree	70	46.4%
	Master's Degree	26	17.2%
	Doctoral Degree	3	2.0%
Work Status	Working	117	83.6%
	Not Working	23	16.4%
Work Experience	Less than 1 Year	38	25.2%
	1 - 5 years	43	28.5%
	5 - 10 years	38	25.2%
	11 Years or More	32	21.2%
Work Arrangment	Fully at the Office	74	63.2%
	Fully Remote	19	16.2%
	Hybrid	24	20.5%
Preferred Work Arrangment	Fully at the Office	48	31.8%
	Fully Remote	41	27.2%
	Hybrid	62	41.1%
Daily Work Hours	Less than 4 Hours	5	4.3%
	4 - 6 Hours	10	8.5%
	6 - 8 Hours	39	33.3%
	8 - 10 Hours	55	47.0%
	11 Hours or More	8	6.8%
Work Sector	Private	97	82.9%
	Public	20	17.1%
Monthly Income	0 - 11400TL	29	19.2%
	11401 - 30400TL	51	33.8%
	30401 - 50400TL	36	23.8%
	50401 - 70400TL	17	11.3%
	70401TL or More	18	11.9%

Presented in Table 3 is a summary of the socio-demographic information of the participants.

As per the demographic data presented in Table 3, most of the participants of this study, who are users of e-commerce platforms in Türkiye, fall within the age group of 25-34 years old (43%), followed by those who fall within the age group of 18-24 years old (32.5%). These statistics suggest that online shopping in Türkiye and the use of e-commerce platforms are most popular among younger adults. This aligns with the information reported by the Turkish competition authority in their 2022 sector review on the age group distribution of e-marketplace users (Sarıçiçek et al., 2022) and may indicate a higher tech-savviness and inclination towards online shopping in younger age groups.

This study aimed for a balanced representation of both male and female users of e-commerce platforms in Türkiye. With the actual participants' distribution of 49% male users and 51% female users, there is an indication that these platforms appeal to both genders equally.

The demographic data collected on the marital and parental status of participants indicate that most of the user base is single (63.6%), which aligns with the age group statistics, indicating a predominantly younger user base of e-commerce platforms in Türkiye. Furthermore, most participants do not have children (74.8%), which is consistent with this younger demographic.

The data collected on the education level of participants reveal that the user base of e-commerce platforms in Türkiye can be deemed well-educated. A significant portion, 46.4% of participants, hold a Bachelor's degree, 17.2% a Master's degree, and 2% a Doctoral degree, totaling 65.6% of the participants with higher education degrees. These statistics could imply greater tech-savviness and comfort with using digital platforms.

The data collected from participants on their work status and experience indicate that a large portion of e-commerce platform users in Türkiye are employed (83.6%) and possess a diverse range of work experience, spanning from less than one year to 11 years or more. This suggests a broad range of professional stages among participants and a fair level of representativeness.

The data collected on current and preferred work arrangements indicate that most participants work fully at the office (63.2%), with a substantial preference for hybrid work arrangements (41.1%). This suggests that e-commerce platform users in Türkiye value work flexibility.

The demographic data on daily work hours and the work sector of participants show that a majority of e-commerce platform users in Türkiye work between 8 to 10 hours a day (47%), primarily in the private sector (82.9%). This may suggest a busy lifestyle, making online shopping a convenient option.

Finally, the data collected on the monthly income levels of participants reveal that income levels among platform users in Türkiye vary, with the majority earning between 11,401 TL and 30,400 TL (33.8%). The distribution of income levels reflects a diverse economic demographic.

3.13.2. Online Shopping Preferences and Behavior Analysis:

In addition to the demographic data of the participants, other data on their online shopping experience and preferences were collected and analyzed to provide a comprehensive view of their online shopping patterns and behavior, which can also provide valuable insight to marketers on how to tailor strategies to align with their platform users' online shopping characteristics.

Table 4. Online Shopping Preferences and Behavior of Participants

Online Shopping Experience	Yes	151	100.0%
	No	0	0.0%
Preferred Shopping Channel	Online	116	76.8%
	Offline	35	23.2%
Most Used Platforms	Amazon	2	1.3%
	Çiçeksepeti	1	0.7%
	Cimri	1	0.7%
	Getir	19	12.6%
	Hepsiburada	20	13.2%
	N11	3	2.0%
	Trendyol	101	66.9%
	Yemeksepeti	4	2.6%
Most Purchased Product Category	Beauty and Personal Care	11	7.3%
	Electronics	25	16.6%
	Fashion and Apparel	62	41.1%
	Groceries	28	18.5%
	Home and Living	25	16.6%

Presented in Table 4 is a summary of the online shopping preferences and behavior of the participants of this study.

As per the data presented in Table 4, all participants have experience in online shopping and using Turkish e-commerce platforms (100%), which was the main criterion for classifying a valid response. Additionally, 76.8% of the user base reported preferring online shopping over offline traditional shopping, highlighting a level of digital nativity or preference.

Most of the participants in this study, who are users of e-commerce platforms in Türkiye, reported Trendyol as their most used platform (66.9%), followed by Hepsiburada (13.2%). These statistics suggest that Trendyol is a user favorite and dominates the retail e-commerce market in Türkiye, which aligns with the information the Turkish competition authority reported in their 2022 sector review (Sarıçiçek et al., 2022).

According to the data collected on the most purchased product category, fashion and apparel is the most purchased category (41.1%) by e-commerce platform users in Türkiye, which also aligns with the information the Turkish competition authority reported in their 2022 sector review (Sarıçiçek et al., 2022). Groceries (18.5%) and electronics (16.6%) followed that category, which could indicate an inclination towards lifestyle and daily needs products.

3.13.3. Validity Analysis:

Before proceeding with further data analysis, it was essential to ensure that the constructs used in this study were valid and accurately measured the intended theoretical concepts introduced in section 3.8. The validity analysis serves to confirm that the measurement scales effectively capture the underlying dimensions of the conceptual constructs of the study's variables as proposed by the literature.

To achieve this, an EFA was conducted to examine the factor structure of the variables and assess construct validity. EFA helps identify the latent factors that explain the correlations among the observed variables and ensures that the measurement scales are both valid and reliable.

In this study, the variables were divided into two groups for factor analysis: (1) AI Tools Efficiency, as perceived by platform users, comprising Chatbot Efficiency (CB), Visual Search Efficiency (VS), Recommender System Efficiency (RS), and Automated After-Sales Service Efficiency (AS); and (2) Consumer Behavior, consisting of Psychological Engagement (PE), Behavioral Engagement (BE), and Attention to Social Comparison (ASC). This division allowed for a more focused analysis of the constructs within their respective categories.

The results of the EFA guided the validity of these constructs, ensuring that the subsequent analyses, such as reliability analysis, correlation analysis, and regression analysis, are built on sound measurement foundations.

Table 5. AI Tools Efficiency Scales Factor Analysis Results

Factor	Dimensions	Loadings	Explained Variance
Chatbot Efficiency	CB1	0.774	38.664%
	CB2	0.702	
	CB3	0.743	
	CB4	0.657	
Visual Search Efficiency	VS1	0.805	14.295%
	VS2	0.871	
	VS3	0.895	
	VS4	0.827	
Recommender System Efficiency	RS1	0.849	9.059%
	RS2	0.899	
	RS3	0.718	
	RS4	0.580	
Automated After-Sale Service Efficiency	AS1	0.612	7.416%
	AS2	0.771	
	AS3	0.844	
	AS4	0.702	
Total Variance Explained			69.434%
Kaiser-Meyer-Olkin Measure of Sampling Adequacy			0.856
Bartlett's Test of Sphericity	Approx. Chi-Square		1335.506
	Sig.		0.000

Table 5 presents the factor analysis results for four key constructs of AI Tools Efficiency in the context of consumer engagement: Chatbot Efficiency (CB), Visual Search Efficiency (VS), Recommender System Efficiency (RS), and Automated After-Sales Service Efficiency (AS).

Chatbot Efficiency (CB): The measurement scale items CB1 to CB4 show factor loadings ranging from 0.657 to 0.774, with all items loading onto their intended factors. These loadings are above the commonly accepted threshold of 0.40, suggesting that each item has a significant relationship with the chatbot efficiency construct (Hair et al., 2010).

This factor explains 38.664% of the variance, indicating that chatbot efficiency plays a significant role within the AI Tools Efficiency constructs. The substantial variance explained highlights the importance of this factor in understanding AI tool's efficiency (Field, 2009).

Visual Search Efficiency (VS): The loadings for VS1 to VS4 range from 0.805 to 0.895, indicating very strong correlations with the visual search efficiency construct, with all items loading onto their intended factors. Loadings above 0.70 are considered very strong (Hair et al., 2010), suggesting that these items are very good indicators of this construct.

This factor explains 14.295% of the total variance. While this percentage is lower compared to chatbot efficiency, the strong loadings confirm that visual search efficiency is a well-defined construct (Field, 2009).

Recommender System Efficiency (RS): The loadings for measurement scale items RS1 to RS4 range from 0.680 to 0.899, with all items loading onto their intended factors. All loadings were also above the acceptable threshold of 0.40, indicating a good representation of the recommender system efficiency construct (Hair et al., 2010).

This dimension explains 9.059% of the variance. Although this is a smaller percentage compared to the first two factors, it still represents a significant part of the model (Field, 2009).

Automated After-Sale Service Efficiency (AS): The items AS1 to AS4 have loadings ranging from 0.612 to 0.844, with all items loading onto their intended factors. All items exceed the 0.40 threshold, indicating that they are good indicators of automated after-sale service efficiency (Hair et al., 2010).

This factor explains 7.416% of the variance. Although it contributes less compared to the other dimensions, the factor loadings suggest that this construct is adequately represented in the model (Field, 2009).

In total, 69.434% of the variance in AI Tools Efficiency is explained by the four factors analyzed, which is a robust result indicating that these four factors identified in the model account for a substantial proportion of the variance in the data (Kaiser, 1974). In addition, the KMO score of 0.856 suggests that the sample size is adequate for factor analysis, as values above 0.80 are considered very good (Kaiser, 1974), confirming that the correlations between the variables are suitable for EFA. Bartlett's Test of Sphericity, with a significant p-value of 0.000 (with a chi-square value of 1335.506), indicates that there are significant correlations between these variables, further validating the use of factor analysis (Bartlett, 1954).

Table 6. Consumer Behavior Scales Factor Analysis Results

Factor	Dimensions	Loadings	Explained Variance
Psychological Engagement	PE1	0.531	43.860%
	PE2	0.664	
	PE3	0.773	
Behavioral Engagement	BE1	0.589	15.418%
	BE2	0.912	
	BE3	0.802	
	BE4	0.541	
Attention to Social Comparison	ASC1	0.832	8.841%
	ASC2	0.737	
	ASC3	0.704	
	ASC4	0.672	
Total Variance Explained			68.119%
Kaiser-Meyer-Olkin Measure of Sampling Adequacy			0.847
Bartlett's Test of Sphericity	Approx. Chi-Square		734.653
	Sig.		0.000

Table 6 presents the factor analysis results for three key constructs of consumer behavior: Psychological Engagement (PE), Behavioral Engagement (BE), and Attention to Social Comparison (ASC).

Psychological Engagement (PE): The measurement scale items PE1 to PE3 have loadings ranging from 0.531 to 0.773. These loadings are above the commonly accepted threshold of 0.50, indicating that the items are good indicators of the psychological engagement construct (Hair et al., 2010). All items loaded onto their intended factors except for PE1, which also loaded on the behavioral engagement factor, which was expected as both constructs are defined by the literature as dimensions of the consumer engagement construct (Van Doorn et al., 2010). As such, no adjustments to this construct were made.

This construct explains 43.860% of the variance, indicating that psychological engagement is a major factor in the Consumer Behavior group of constructs. This high percentage suggests that this factor is well-represented and crucial in the context of consumer behavior (Field, 2009).

Behavioral Engagement (BE): The loadings for BE1 to BE4 range from 0.541 to 0.912, with all items loading onto their intended factors. All items exceed the acceptable threshold of 0.50, with the highest loading (BE2) at 0.912, suggesting that behavioral engagement is well-represented by these items (Hair et al., 2010).

This factor explains 15.418% of the variance. Although this percentage is lower compared to psychological engagement, the high loadings confirm that this dimension is well-defined and important (Field, 2009).

Attention to Social Comparison (ASC): The loadings for measurement scale items are 0.672 to 0.832, with all items loading onto their intended factors. All loadings were also above the acceptable threshold of 0.50, indicating that the items are strong indicators of the attention to social comparison construct (Hair et al., 2010).

This dimension explains 8.841% of the variance. While it explains a smaller portion of the variance compared to the other constructs, the high loadings suggest that this dimension is adequately represented in the model (Field, 2009).

In total, 68.119% of the variance in Consumer Behavior is explained by the three factors analyzed, which is also a robust result indicating that these three factors identified in the model account for a substantial proportion of the variance in the data (Kaiser, 1974). In addition, the KMO score of 0.847 suggests that the sample size is adequate for factor analysis, as values above 0.80 are considered very good (Kaiser, 1974), confirming that the correlations between the variables are suitable for EFA. Bartlett's Test of Sphericity, with a significant p-value of 0.000 (with a chi-square value of 734.653), indicates that there are significant correlations between these variables, further validating the use of factor analysis (Bartlett, 1954).

The factor analysis results revealed and confirmed that all the constructs identified in this study's theoretical framework are represented by items with strong loadings and explain a meaningful proportion of variance, which further supports the literature (Adam et al., 2021; Asante et al., 2019, 2023; Chinchanachokchai et al., 2021; Daqar & Smoudy, 2019; Fang et al., 2017; Sudarsan et al., 2022). The total variance explained by both sets of constructs was also substantial, indicating a good fit for the model, and the KMO and Bartlett's test results further supported the adequacy of the factor analysis. Based on these results, all constructs and their factors were retained as initially intended for further analysis.

3.13.4. Reliability Analysis:

In addition to the validity analysis, a reliability analysis was employed in this study to assess the internal consistency of the scales used to measure the conceptual constructs of the theoretical framework, including the efficiency of AI-driven tools integrated into e-commerce platforms in Türkiye, as well as users' psychological and behavioral engagement levels, and their attention to social comparison. The reliability of these measurement scales was evaluated using Cronbach's alpha coefficients. Generally, a Cronbach's alpha coefficient of 0.7 or above is considered acceptable for research purposes (Bhattacherjee, 2012).

Table 7. Reliability Analysis Results

Variable	Number of Scale Items	Cronbach's Alpha Coefficient
CB	4	0.808
VS	4	0.936
RS	4	0.875
AS	4	0.848
PE	3	0.710
BE	4	0.787
ASC	4	0.826

Presented in Table 7 is a summary of the study's variables, the number of scale items used to measure each variable, and their corresponding Cronbach's alpha coefficients.

The Cronbach's alpha coefficient for Chatbot Efficiency (CB) is 0.808, indicating a good level of reliability and internal consistency among the four scale items used to measure this variable. The coefficient for Visual Search Efficiency (VS) is 0.936, reflecting very high reliability and internal consistency among the four scale items. The coefficient for Recommender System Efficiency (RS) is 0.875, which also indicates a high level of reliability and consistency. The Automated After-Sales Service Efficiency (AS) scale has an alpha value of 0.848, demonstrating a high level of reliability and internal consistency.

For the measurement scales of Psychological Engagement (PE), Behavioral Engagement (BE), and Attention to Social Comparison (ASC), the Cronbach's alpha coefficients are 0.710, 0.787, and 0.826, respectively. These values indicate good reliability and internal consistency for the measurement items of these variables.

3.13.5. Descriptive Analysis:

Descriptive statistics are utilized in this study to summarize the efficiency metrics of the AI-driven tools and features integrated into Turkish e-commerce platforms, in addition to the measures of psychological and behavioral engagement levels of consumers.

Table 8. Variables Descriptive Statistics

Variable	N	Range	Min.	Max.	Mean	St. Error	St. Dev.	Variance
CB	151	6	1	7	4.4983	0.11238	1.38097	1.907
VS	151	6	1	7	4.2798	0.13834	1.69998	2.89
RS	151	5.5	1.5	7	5.2169	0.10182	1.25122	1.566
AS	151	5.5	1.5	7	4.9768	0.10549	1.29626	1.68
PE	151	6	1	7	5.0068	0.11147	1.36981	1.876
BE	151	5.25	1.75	7	4.957	0.10426	1.2812	1.641
ASC	151	5.75	1.25	7	4.8907	0.10843	1.33247	1.775

Presented in Table 8 are the descriptive statistics of this study’s variables. The sample size (N) of all variables (151) measured, indicates that the data collected from the participants of this study (e-commerce platform users in Türkiye) are complete across all scale items, which allows for the comparison of variables without adjusting for different sample sizes or missing values.

The range statistic, as per Table 8, exhibits the spread between the lowest and highest responses of the participants for each variable measured. Since all variables have a minimum score ranging from 1 to 1.75 and a maximum score of 7, this indicates that all scale items were rated using the 7-point Likert scale and that the data collected are uniform. As the range values of the scores of each measure vary from 5.25 to 6, this suggests a relatively wide range, which indicates a diversity in perceptions amongst e-commerce platform users in Türkiye on the efficiency of different AI-driven tools and features and a diversity in their engagement levels.

The means reflect the average score for each variable measured and rated by the participants. As per Table 8, the mean statistic ranges from 4.2798 for visual search efficiency to 5.2169 for recommender system efficiency, as perceived by users of the platforms. These values indicate that users of e-commerce platforms in Türkiye perceive recommender systems as the most efficient AI-driven tool and visual search as the least efficient one. However, since all mean values are above 3.5, which is the mid score, this indicates an overall positive perception of the efficiency of all tools (chatbots, visual search, recommender systems, and automated after-sales services). The mean values of psychological engagement and behavioral engagement are 5.0068 and 4.957, respectively, which indicate a positive level of consumer engagement with the platforms and their AI features.

The standard deviation and variance statistics reflect the level of variability and dispersion of each variable measured and rated by the participants in this study. As per Table 8, the visual search score has the highest variance, 2.89, and the highest standard deviation, 1.69998, indicating that e-commerce platform users in Türkiye have a wide range of opinions on its efficiency. On the other hand, recommender systems have the lowest variance, 1.566, and the lowest standard deviation, 1.25122, indicating that users' opinions of its efficiency are more uniform and consistent.

The descriptive statistics presented in Table 8 suggest a generally positive perception of AI-driven tools and features' efficiency amongst e-commerce platform users in Türkiye, with recommender systems rated highest by those users, which is evident through the analysis of the mean scores. The perceived efficiency of recommender systems possesses the highest level of consensus amongst users. In contrast, the perceived efficiency of visual search reflects more divided opinions, which is evident through the analysis of the standard deviations and variances.

Psychological and Behavioral engagement levels received score higher than 4.9, which indicates that e-commerce platform users in Türkiye are engaged psychologically and behaviorally by those platforms. Psychological engagement scored lowered than behavioral engagement, which could indicate a higher level of consistency in users' internal engagement than it is reflected by their behavior. Attention to social comparison also scored relatively high (4.8907) which indicates that users of these platforms are sensitive to society's evaluation and judgement of their purchasing and consumption choices within the e-commerce environment.

3.13.6. Correlation Analysis:

A Pearson correlation test measures the strength (through the value) and direction (through the sign) of linear relationships between the different variables observed through the correlation coefficient values, indicating a more substantial relationship when closer to 1 or -1 (Cohen, 1988). The Pearson correlation analysis is utilized in this study to gain insight into the relationships between the AI-driven tools variables and the consumer engagement variables measured, providing valuable practical implications for understanding consumer engagement. The direction of the relationship between the variables is determined through the sign of the value. Additionally, a correlation matrix indicates the significance of the relationships between the variables at the 0.01 level (2-tailed).

Table 9. Correlation Analysis Results

		CB	VS	RS	AS	PE	BE	ASC
CB	Pearson Correlation	1	.446**	.537**	.531**	.524**	.556**	.330**
	Sig. (2-tailed)		0	0	0	0	0	0
	N	151	151	151	151	151	151	151
VS	Pearson Correlation	.446**	1	.569**	.457**	.538**	.518**	.444**
	Sig. (2-tailed)	0		0	0	0	0	0
	N	151	151	151	151	151	151	151
RS	Pearson Correlation	.537**	.569**	1	.680**	.588**	.666**	.470**
	Sig. (2-tailed)	0	0		0	0	0	0
	N	151	151	151	151	151	151	151
AS	Pearson Correlation	.531**	.457**	.680**	1	.559**	.665**	.299**
	Sig. (2-tailed)	0	0	0		0	0	0
	N	151	151	151	151	151	151	151
PE	Pearson Correlation	.524**	.538**	.588**	.559**	1	.713**	.429**
	Sig. (2-tailed)	0	0	0	0		0	0
	N	151	151	151	151	151	151	151
BE	Pearson Correlation	.556**	.518**	.666**	.665**	.713**	1	.441**
	Sig. (2-tailed)	0	0	0	0	0		0
	N	151	151	151	151	151	151	151
ASC	Pearson Correlation	.330**	.444**	.470**	.299**	.429**	.441**	1
	Sig. (2-tailed)	0	0	0	0	0	0	
	N	151	151	151	151	151	151	151

Presented in Table 9 is the correlation test matrix generated for the cross-relationships between this study's variables.

3.13.6.1. Chatbot Efficiency and Consumer Engagement:

As per the correlation test matrix in Table 9, the relationship coefficient between perceived chatbot efficiency and psychological engagement level with the platform (0.524) indicates a significantly positive and moderate correlation. This statistic means that the perceived chatbot efficiency of e-commerce platform users in Türkiye is associated with higher psychological engagement.

This study draws an exact inference about the relationship between their perceived chatbot efficiency and behavioral engagement level. With a correlation coefficient of 0.556, which indicates a significantly positive and moderate relationship, perceived chatbot efficiency is associated with a higher behavioral engagement level.

Analysis of the correlations between the perceived chatbot efficiency of e-commerce platform users in Türkiye and their engagement levels, psychological and behavioral, suggest that improvements in this feature might enhance their engagement with the platform.

3.13.6.2. Visual Search Efficiency and Consumer Engagement:

As per the correlation test matrix in Table 9, the relationship coefficient between perceived visual search efficiency and psychological engagement level with the platform (0.538) also indicates a significantly positive and moderate correlation between those variables. This statistic means that the perceived visual search efficiency of e-commerce platform users in Türkiye is associated with higher psychological engagement.

This study draws an exact inference about the relationship between their perceived visual search efficiency and behavioral engagement level. With a correlation coefficient of 0.518, which indicates a significantly positive and moderate relationship, perceived visual search efficiency is associated with a higher behavioral engagement level.

Analysis of the correlations between the perceived visual search efficiency of e-commerce platform users in Türkiye and their engagement levels, psychological and behavioral, suggest that improvements in this feature might enhance their engagement with the platform.

3.13.6.3. Recommender System Efficiency and Consumer Engagement:

As per the correlation test matrix in Table 9, the relationship coefficient between perceived recommender system efficiency and psychological engagement level with the platform (0.588) indicates a significantly positive and moderate correlation. This statistic means that the perceived recommender system efficiency of e-commerce platform users in Türkiye is associated with higher psychological engagement. This association is slightly higher than those between the psychological engagement level of users and their perceived chatbot and visual search efficiency.

This study draws the exact inference about the relationship between their perceived recommender system efficiency and behavioral engagement level. With a correlation coefficient of 0.666, which indicates a significantly positive and moderate relationship, it is evident that users' perceived recommender system efficiency is associated with a higher behavioral engagement level. This association is also slightly stronger than those between the behavioral engagement level of users and their perceived chatbot and visual search efficiency.

Analysis of the correlations between the perceived recommender system efficiency of e-commerce platform users in Türkiye and their engagement levels, psychological and behavioral, suggest that improvements in this feature might enhance their engagement with the platform.

3.13.6.4. Automated After-Sales Service Efficiency and Consumer Engagement:

As per the correlation test matrix in Table 9, the relationship coefficient between perceived automated after-sales service efficiency and psychological engagement level with the platform (0.559) indicates a significantly positive and moderate correlation. This statistic means that the perceived automated after-sales service efficiency of e-commerce platform users in Türkiye is associated with higher psychological engagement. This association is slightly higher than those between the psychological engagement level of users and their perceived chatbot and visual search efficiency.

This study draws the exact inference about the relationship between their perceived automated after-sales service efficiency and behavioral engagement level. With a correlation coefficient of 0.665, which indicates a significantly positive and moderate relationship, it is evident that users' perceived automated after-sales service efficiency is associated with a higher behavioral engagement level. This association is also slightly stronger than those between the behavioral engagement level of users and their perceived chatbot and visual search efficiency.

Analysis of the correlations between the perceived automated after-sales service efficiency of e-commerce platform users in Türkiye and their engagement levels, psychological and behavioral, suggest that improvements in this feature might enhance their engagement with the platform.

3.13.6.5. Psychological Engagement and Behavioral Engagement:

As per the correlation test matrix in Table 9, the strongest relationship observed in this study is between the psychological and behavioral engagement levels of e-commerce platform users in Türkiye, with a correlation coefficient of 0.713, indicating a significantly positive and high degree of correlation. This result was expected as more emotionally engaged consumers are likely to engage in behaviors that reflect this engagement, as the literature supports.

3.13.6.6. Attention to Social Comparison and Consumer Engagement:

As per the correlation test matrix in Table 9, the relationship observed between attention to social comparison and the psychological and behavioral engagement levels of e-commerce platform users in Türkiye is weak, with correlation coefficients of 0.429 and 0.441, respectively, which indicates a significant but low degree of correlation.

3.13.7. Regression Analysis:

To provide a comprehensive understanding of the factors influencing e-commerce platform users' Behavioral Engagement, a comprehensive regression model was utilized, which integrates all the predictors, mediators, and moderators. This model includes Chatbot Efficiency (CB), Visual Search Efficiency (VS), Recommender System Efficiency (RS), and Automated After-Sales Service Efficiency (AS), Psychological Engagement (PE), Attention to Social Comparison (ASC), and their interaction. The aim was to capture the combined effects of these variables on Behavioral Engagement and to assess the overall model fit.

Table 10. Regression Analysis Results

Model Summary				R			.808[a]
				R Square			0.653
				Adjusted R Square			0.636
				Std. Error of the Estimate			0.773
ANOVA				Sum of Squares			160.864
				df			7
				Mean Square			22.981
				F			38.500
				Sig.			<.001[b]
Predictor	B	Std. Error	Beta	t	Sig.	Tolerance	VIF
Constant	-0.588	0.789	-	-0.745	0.457	-	-
CB	0.092	0.059	0.099	1.566	0.012	0.610	1.641
VS	0.013	0.049	0.017	0.256	0.049	0.575	1.739
RS	0.168	0.080	0.165	2.108	0.037	0.396	2.523
AS	0.259	0.071	0.262	3.635	0.000	0.466	2.147
PE	0.504	0.160	0.539	3.158	0.002	0.083	12.020
ASC	0.251	0.169	0.261	1.482	0.140	0.078	12.797
Moderating Effect of ASC	-0.033	0.031	-0.294	-1.075	0.284	0.032	30.965

The regression analysis results in Table 10 indicate that this model demonstrates a strong fit with an R^2 value of 0.653, signifying that approximately 65.33% of the variance in e-commerce platform users' Behavioral Engagement in the Turkish market is explained by the model. The adjusted R^2 of 0.636 adjusts for the number of predictors and confirms the model's robustness. Additionally, the F-test result ($F = 38.5004$, $p < .001$) shows that the overall model is statistically significant.

Chatbot Efficiency ($B = 0.0916$, $p = 0.012$): The effect of Chatbot Efficiency on Behavioral Engagement is positive and statistically significant.

Visual Search Efficiency ($B = 0.0125$, $p = 0.049$): This predictor has a very small positive effect on Behavioral Engagement but is also statistically significant.

Recommender System Efficiency ($B = 0.1681$, $p = 0.0368$): This predictor has a positive and significant effect on Behavioral Engagement.

Automated After-Sales Service Efficiency ($B = 0.2592$, $p = 0.0004$): This predictor positively and significantly contributes to Behavioral Engagement.

Psychological Engagement Level (B = 0.5042, p = 0.0019): This variable has a strong positive effect on Behavioral Engagement and is highly significant.

Attention to Social Comparison (B = 0.2510, p = 0.1404): While this effect is positive, it is not statistically significant.

Moderating Effect of Attention to Social Comparison (B = -0.0333, p = 0.2844): The interaction term does not significantly moderate the effect of Psychological Engagement on Behavioral Engagement.

In Summary, this model provides a comprehensive overview of the predictors influencing Behavioral Engagement. Significant positive effects are observed for Chatbot Efficiency, Visual Search Efficiency, Recommender System Efficiency, Automated After-Sales Service Efficiency, and Psychological Engagement. This analysis facilitated the generation of the model’s regression equation:

$$BE = -0.588 + 0.092 \cdot CB + 0.013 \cdot VS + 0.168 \cdot RS + 0.259 \cdot AS + 0.504 \cdot PE + 0.251 \cdot ASC + (-0.033 \cdot ASC \times PE)$$

Moreover, it demonstrates that other predictors like Attention to Social Comparison do not show significant effects. The lack of significant moderation by Attention to Social Comparison indicates that its interaction with Psychological Engagement does not meaningfully alter the relationship with Behavioral Engagement. This integrated approach allows for a holistic understanding of the dynamics influencing Behavioral Engagement in the context of AI-driven tools and psychological engagement.

3.14. Hypothesis Testing Results:

Before commencing testing of the hypotheses of this study, a collinearity test was conducted to ensure no collinearity or multicollinearity issues among the variables tested. The variance inflation factor (VIF) assesses the increase in the variance value of an estimated regression coefficient if the variables are correlated; a VIF above 10 indicates a high level of collinearity (Bhattacherjee, 2012). Tolerance, on the other hand, is the inverse of VIF and suggests the presence of multicollinearity as it measures the change in the variance value of an independent variable explained by other independent variables in the model; a tolerance value lower than 0.1 indicates the presence of multicollinearity (Bhattacherjee, 2012).

Table 11. Collinearity Analysis Results

Variable	VIF	Tolerance	Collinearity Presence
CB	1.64200	0.60900	No
VS	1.71800	0.58200	No
RS	2.51200	0.39800	No
AS	2.11600	0.47300	No
PE	1.92800	0.51900	No
ASC	1.41400	0.70700	No

The collinearity test results in Table 11 indicate that no significant collinearity affects any of this study's variables, with VIF values of all variables below three and all tolerance values above 0.1. The results of this test assure reliable interpretation and inferences from the estimated regression coefficients, as the independence of variables is supported.

A regression analysis on the different sets of effects was conducted to test the hypotheses of this study on the direct effects of chatbot efficiency (CB), visual search efficiency (VS), recommender system efficiency (RS), and automated after-sales service efficiency (AS), which are AI-driven tools and features integrated into e-commerce platforms in Türkiye, on the psychological (PE) and behavioral engagement level (BE) of users of those platforms, the indirect effects of those tools and features on the behavioral engagement level (BE) of those users through the mediating impact of their psychological engagement level (PE), and test the moderating effect of those users' attention to social comparison (ASC) on their engagement level.

3.14.1. Direct Effects:

The analysis on the hypothesized direct effects reveals significant positive relationships between the perceived efficiencies of chatbots, visual search functions, recommender systems, and automated after-sales services with both psychological and behavioral engagement. Each hypothesis is tested through regression analysis, with path coefficients, t-statistics, and significance levels provided. The findings confirm that these AI-driven features significantly enhance user engagement on e-commerce platforms, indicating their crucial role in improving the overall user experience.

Table 12. Results of Hypothesized Direct Effects

Hypothesis	Relationship	Path Coefficient	t-statistic	Significance	Result
H1a	CB -> PE	0.1980	2.6280	0.0100	Supported
H2a	VS -> PE	0.2390	3.1760	0.0020	Supported
H3a	RS -> PE	0.2070	2.2660	0.0250	Supported
H4a	AS -> PE	0.2030	2.3730	0.0190	Supported
H1b	CB -> BE	0.1760	2.5750	0.0110	Supported
H2b	VS -> BE	0.1360	1.9970	0.0480	Supported
H3b	RS -> BE	0.2760	3.3380	0.0010	Supported
H4b	AS -> BE	0.3220	4.1650	0.0000	Supported
H5	PE -> BE	0.7130	12.4150	0.0000	Supported

Table 12 presents the results of the regression analysis conducted to test the hypotheses on the direct effects of all AI-driven tools and features on the psychological and behavioral engagement of users.

H1a: As per the results presented in Table 12, for a t-statistic of 2.6280 and a p-value of $0.0100<0.05$, there is a significant positive direct effect of the perceived chatbot efficiency of e-commerce platform users in Türkiye on their psychological engagement level with the platform.

This significant impact suggests that chatbots that provide platform users with constant support, push pop-up notifications, beneficial results to queries, and are easy to communicate with enhance their psychological engagement by fostering a continuous sense of support and reliability throughout their online shopping experience.

H2a: As per the results presented in Table 12, for a t-statistic of 3.1760 and a p-value of $0.0020<0.05$, there is a significant positive direct effect of the perceived visual search efficiency of e-commerce platform users in Türkiye on their psychological engagement level with the platform.

This significant impact suggests that visual search functions that are easy to use, allow users to use their camera or saved files, return quality search results, and minimize users' dependency on keywords enhance their psychological engagement by providing a more enjoyable and stress-free online shopping experience.

H3a: As per the results presented in Table 12, for a t-statistic of 2.2660 and a p-value of $0.0250<0.05$, there is a significant positive direct effect of the perceived recommender system efficiency of e-commerce platform users in Türkiye on their psychological engagement level with the platform.

This significant impact suggests that recommender systems that provide users with suggestions relevant to their needs and preferences, recommendations based on their previous searches and purchases, and expedite their search process enhance their psychological engagement by personalizing their online shopping experience.

H4a: As per the results presented in Table 12, for a t-statistic of 2.3730 and a p-value of 0.0190<0.05, there is a significant positive direct effect of the perceived automated after-sales service efficiency of e-commerce platform users in Türkiye on their psychological engagement level with the platform.

This significant impact suggests that automated after-sales services that provide users with automatic feedback requests, clarify any product ambiguity, facilitate replacement and refund processes, and guide them throughout their shopping journey enhance their psychological engagement by maintaining ongoing engagement.

H1b: As per the results presented in Table 12, for a t-statistic of 2.5750 and a p-value of 0.0110<0.05, there is a significant positive direct effect of the perceived chatbot efficiency of e-commerce platform users in Türkiye on their behavioral engagement level with the platform.

This significant impact suggests that chatbots that provide platform users with constant support, push pop-up notifications, beneficial results to queries, and are easy to communicate with drive active behavioral engagement responses of users, such as continued usage, providing referrals, engaging in positive word-of-mouth, and writing reviews.

H2b: As per the results presented in Table 12, for a t-statistic of 1.9970 and a p-value of 0.0480<0.05, there is a significant positive direct effect of the perceived visual search efficiency of e-commerce platform users in Türkiye on their behavioral engagement level with the platform.

This significant impact suggests that visual search functions that are easy to use, allow users to use their camera or saved files, return quality search results, and minimize user dependency on keywords drive active behavioral engagement responses of users, such as continued usage, providing referrals, engaging in positive word-of-mouth, and writing reviews.

H3b: As per the results presented in Table 12, for a t-statistic of 3.3380 and a p-value of $0.0010<0.05$, there is a significant positive direct effect of the perceived recommender system efficiency of e-commerce platform users in Türkiye on their behavioral engagement level with the platform.

This significant impact suggests that recommender systems that provide users with suggestions relevant to their needs and preferences, recommendations based on their previous searches and purchases, and expedite their search process drive active behavioral engagement responses of users, such as continued usage, providing referrals, engaging in positive word-of-mouth, and writing reviews.

H4b: As per the results presented in Table 12, for a t-statistic of 4.1650 and a p-value of $0.0000<0.05$, there is a significant positive direct effect of the perceived automated after-sales service efficiency of e-commerce platform users in Türkiye on their behavioral engagement level with the platform.

This significant impact suggests that automated after-sales services that provide users with automatic feedback requests, help clarify product ambiguity, facilitate replacement and refund processes, and guide them throughout their shopping journey drive active behavioral engagement responses of users, such as continued usage, providing referrals, engaging in positive word-of-mouth, and writing reviews.

H5: As per the results presented in Table 12, for a t-statistic of 12.4150 and a p-value of $0.0000<0.05$, there is a significant positive direct effect of the psychological engagement level of e-commerce platform users in Türkiye on their behavioral engagement level with the platform.

The results indicate that all AI-driven tools positively influence both psychological and behavioral engagement, thereby rejecting all null hypotheses and confirming the effectiveness of these tools in enhancing user engagement on e-commerce platforms in Türkiye. The results also indicate that psychological engagement with the e-commerce platform and its AI-driven tools positively influences users' behavioral engagement responses.

3.14.2. Mediating Effects:

The analysis on the hypothesized mediating effects reveals that psychological engagement significantly mediates the relationship between the perceived efficiencies of chatbots, visual search functions, recommender systems, and automated after-sales services, and users' behavioral engagement. These results suggest that enhancing psychological engagement with the platform can effectively increase overall user engagement.

Table 13. Results of Hypothesized Mediating Effects

Hypothesis	Relationship	Path Coefficient	BootSE	BootLLCI	BootULCI	Result
H1c	CB -> PE -> BE	0.2829	0.5040	0.1909	0.3903	Supported
H2c	VS -> PE -> BE	0.2479	0.0408	0.1705	0.3317	Supported
H3c	RS -> PE -> BE	0.2956	0.5600	0.1906	0.4082	Supported
H4c	AS -> PE -> BE	0.2742	0.0525	0.1786	0.3840	Supported

Table 13 presents the results of the analysis conducted to test the hypotheses on the mediating role of psychological engagement in the relationship between all AI-driven tools and features and user behavioral engagement.

Since the PROCESS tool was employed to conduct this analysis instead of regression analysis, the assessment of the significance of the mediating relationships depended on the BootLLCI and BootULCI values. The relationship is deemed significant if the value 0 does not fall within their range.

The results of the PROCESS tool analysis supported the hypothesis that psychological engagement significantly mediates the relationship between the efficiency of all AI-driven tools and features and users' behavioral engagement, indicating that increasing users' psychological engagement with the platform is a viable strategy for enhancing overall user engagement.

3.14.3. Moderating Effect:

The analysis on the hypothesized moderating role of attention to social comparison in the relationship between the psychological and behavioral engagement levels of users reveal that attention to social comparison does not significantly affect this relationship.

Table 14. Result of Hypothesized Moderating Effect

Hypothesis	Relationship	Interaction Effect	t-statistic	Significance	Result
H6	Moderated PE -> BE	-0.0450	-0.7970	0.4270	Not Supported

Table 14 presents the results of the analysis conducted to test the hypothesis on the moderating role of attention to social comparison in the relationship between the psychological and behavioral engagement levels of users.

H6: With a t-statistic of -0.7970 and a p-value of 0.4270>0.05, the analysis did not support the moderating effect of attention to social comparison, suggesting that the influence of psychological engagement on behavioral engagement as a result of users' interaction with AI-driven tools does not vary significantly based on their level of attention to social comparison. The sign of the t-statistic does indicate a negative effect despite being non-significant, which aligns with the findings of Asante et el. (2023).

3.15. Discussion:

The preceding sections provided a comprehensive analysis of the data collected in this study, focusing on the impacts of AI-driven tools on consumer engagement within the Turkish e-commerce sector. This chapter interprets the results of the data analysis and discusses the theoretical and practical implications of these findings. The discussion is structured around the interpretation of the study's results, highlighting the significant role of AI in enhancing user experience and satisfaction in the Turkish e-commerce sector.

3.15.1. Interpretation of Results:

The results of the data analysis reveal that AI-driven tools on e-commerce platforms in Türkiye have a positive and significant effect on consumer engagement. This study's main aim was to answer the research question, "How does integrating AI tools and features into e-commerce platforms influence the development of positive engagement attitudes among users?" The findings demonstrate that chatbot efficiency, visual search efficiency, recommender systems efficiency, and automated after-sales services efficiency are all essential AI-driven technological tools for garnering positive psychological and behavioral engagement user attitudes in the Turkish e-commerce sector.

As hypothesized, consumers' perceived chatbot efficiency is strongly associated with their psychological (0.1980) and behavioral (0.1760) engagement levels with the platform in use, demonstrating the crucial role of a chatbot's ability to provide users with prompt and beneficial answers to their queries, and a sense of constant availability and ease while interacting with them, in attracting positive user engagement attitudes.

Additionally, consumers' perceived visual search efficiency's strong and positive association with their psychological (0.2390) and behavioral (0.1360) engagement levels with the platform in use exhibits the importance of a visual search's ability to save users search time, minimize their need for text search, and provide them with good match results, in motivating consumer's engagement with the platform.

Moreover, the results of this study also demonstrate the strong and positive association between consumers' perceived recommender system efficiency and their psychological (0.2070) and behavioral (0.2760) engagement levels with the platform in use, which emphasizes their critical role of providing users with relevant product suggestions based on their interests, searches, and purchases in creating a positive, personalized experience that keeps them engaged.

Furthermore, consumers' perceived automated after-sales service efficiency is strongly associated with their psychological (0.2030) and behavioral (0.3220) engagement levels with the platform in use, highlighting the critical role of automating feedback requests and user guidance, the handling of product ambiguity, and refund and replacement processes in user satisfaction.

These results align with the findings of Asante et al. (2023), who found a significant relationship between AI-driven tools on Chinese e-commerce platforms and users' engagement with those platforms. In addition, the results also align with some of the findings and claims of other previous studies. Tran et al. (2021) found that chatbots, and AI tools in general, can lead to enhanced consumer sentiment and involvement (engagement) and that involved consumers express more interest in engaging with the service provider (platform). Dagan et al. (2023) emphasized the role of visual search and how integrating it as a feature in e-retail platforms can increase customer engagement levels and enhance their experience. Maslowska et al. (2022) revealed that recommender systems, effective ones specifically, can create more robust consumer engagement on platforms and are a precursor to long-term platform engagement. Nasir (2023) showed that after-sales services positively impact customer satisfaction and that satisfied customers are more likely to be loyal and willing to display engagement behaviors like positive word-of-mouth and repurchasing.

Besides the findings on the direct effects of AI-driven tools on consumer engagement, the results also demonstrate a very strong positive relationship between users' psychological engagement level (0.7130) due to their interaction with those tools and their behavioral engagement, aligning with the findings of Asante et al. (2023). These findings indicate that users who develop a positive and engaging state of mind (PE), characterized by enthusiasm, inspiration, immersion, and lower stress and time perception (Fang et al., 2017), as a result of their interaction with AI-driven tools on an e-commerce platform, are more likely to display active engagement behaviors towards the platform like continued usage, providing referrals, engaging in positive word-of-mouth, and writing reviews about their experience (Fang et al., 2017).

Likewise, the findings on the indirect effects of AI-driven tools on consumer engagement support the mediating effect that users' psychological engagement has on the association between the AI-driven tools and those users' behavioral engagement, also aligning with the findings of Asante et al. (2023). These results suggest that users' active and observable engagement behaviors towards the platform, characterized by continued usage, providing referrals, engaging in positive word-of-mouth, and writing reviews about their experience (Fang et al., 2017), can be enhanced and are partly explained by their psychological engagement with the platform and its AI-driven tools.

On the contrary, the results do not support the moderating effect of users' attention to social comparison on the association between their psychological engagement with AI-driven tools and those users' behavioral engagement. However, those findings still align with those of Asante et al. (2023) and suggest that consumers' attention to social comparison level is not likely to influence their willingness to engage, or not, in observable actions as a result of their psychological engagement with the platform.

3.15.2. Theoretical Implications:

This study contributes to e-commerce, AI technologies, and consumer engagement research and literature. First and foremost, this research expands the knowledge in the field of e-commerce in

Türkiye by examining the integration and applications of AI tools and features and their impact on consumer engagement within a vibrant and growing environment. While most of the literature mainly focuses on the technicalities of AI technologies, their adoption, and their impact on businesses (Bonada et al., 2020; Bughin et al., 2017; Chan & Petrikat, 2023; Chaudhary, 2023; Cheng et al., 2023; Du-Harpur et al., 2020; Espina-Romero, 2023; Haenlein & Kaplan, 2019; Huang et al., 2022; Khrais, 2020; Mori, 2021; Nimbalkar & Berad, 2021; Wu, 2023; Zhang & Aslan, 2021), this study focuses on its significance within the context of consumer behavior, specifically Turkish consumers' behavior, by exploring their interaction with AI technologies utilized by leading e-commerce platforms.

In addition, this study contributes to the research and literature on consumer engagement and its formation over two dimensions, psychological and behavioral as a result of consumer interaction with AI technologies in the Turkish context. Inspired by the work of Asante et al. (2019) and Asante et al. (2023), this study contributes to the understanding of the process of consumer engagement formation from unobservable attitudes and state of mind (psychological engagement), as a result of the interactions with external factors (AI-driven tools on e-commerce platforms), to observable actions and behaviors (behavioral engagement) by utilizing the SOR Model of consumer behavior and expanding its context. The findings further support the validity and effectiveness of this consumer behavior model in developing theoretical frameworks in the digital environment.

3.15.3. Practical Implications:

The findings of this study can provide practical and actionable insights for marketers, e-commerce professionals, e-commerce businesses, and policymakers, who are all stakeholders in the Turkish e-commerce landscape, as the results supported the crucial role of integrating AI efficiently into e-commerce platforms to foster user psychological engagement and ascertain their behavioral engagement of continued use of the platform, providing referrals and good word-of-mouth, as well as writing reviews about their experiences.

First of all, the results of this study suggest that automated after-sales service efficiency and recommender system efficiency have the most significant impact on users' behavioral engagement level, which emphasizes the importance of enhancing and tailoring those tools to the needs and preferences of consumers in the Turkish e-commerce market to attract more observable engagement behaviors from them. E-commerce platforms can improve the efficiency of their after-sales service by enhancing the automation of feedback requests and the replacement and refund processes. They can also develop product handling and guidance prompts that better aid users throughout their shopping journey, providing users with a satisfying and stress-free experience on the platform that encourages them to continue using the platform and engage in positive word-of-mouth on their experience with the platforms. E-commerce platforms can also improve the predictive capability and relevance of their recommender systems by better utilizing user data on search and purchase history to provide them with more personalized suggestions that are tailored to their needs, interests, and preferences, which would significantly enhance those users' experience on the platform and allow them to save time searching for products.

Secondly, the results of this study suggest that users' psychological engagement with the platform mediates the impact of AI tools on their behavioral engagement, indicating that chatbot efficiency, visual search efficiency, recommender system efficiency, and automated after-sales service efficiency can all attract more observable engagement behaviors from users through their positive interaction with the platform and its resulting state of mind. E-commerce platforms can improve the interactive capability of their AI tools by better tailoring them to provide users with a stress-free and more enjoyable shopping experience that keeps them satisfied, enthused, and at ease while on the platform. As suggested by the study's findings, garnering this positive, unobservable state of mind from users would also directly lead to more positive, observable behaviors.

In addition to the practical implications suggested by the results of the hypotheses testing, this study's demographic, descriptive, and correlation analysis also provide various actionable insights that serve as practical implications for e-commerce stakeholders in Türkiye.

Given the younger, educated, and predominantly single profile of e-commerce platform users in the Turkish market, marketing strategies of those e-commerce businesses can better cater to their needs, interests, and preferences by tailoring their efforts and messages to focus on elements like trendiness, convenience, and technology use. The popularity of platforms like Trendyol, as evident from the findings of this study, suggests that a strong brand presence is crucial for an e-commerce platform's success in this market. E-commerce businesses can also follow a product-focused strategy regarding promotions and center them around fashion and electronics, as those are users' most popular product categories. Additionally, e-commerce platforms can enhance user experience by tailoring their features to cater to their users' tech-savvy and busy lifestyles through enhanced interfaces and faster checkout processing, which can further boost their engagement levels. Effectively reaching their major user demographic can be achieved by utilizing social media and online marketing, given their users' preference for online shopping and their evidently high digital fluency.

Furthermore, the findings of this study can provide valuable information for policymakers in Türkiye about the importance of encouraging and facilitating the integration of AI in the e-commerce sector. Developing and implementing supportive guidelines, policies, and regulations that promote ethical innovation in AI and ensure the protection of consumer rights can have a pivotal role in developing this sector and the overall economic development in Türkiye, as shaping strategies can promote the growth of the digital economy. Policymakers can also facilitate this adoption by establishing clear standards and certifications that reassure users of its safety and reliability. Moreover, policymakers can provide incentives to small and medium businesses to adopt AI technologies, which can help further economic development and foster fair competition in the e-commerce sector.

This study fills a gap in academic research while also providing tangible, actionable insights for businesses and policymakers. It bridges theoretical knowledge with practical applications, contributing to the broader understanding and effective utilization of AI in the evolving landscape of e-commerce in Türkiye.

CONCLUSION

The research conducted in this study not only provides strong and clear evidence but also highlights the critical role that AI-driven tools and features and their efficient integration play in enhancing consumer engagement, psychological and behavioral, on e-commerce platforms in Türkiye. One of the main goals of this study was to answer the research question, “How does integrating AI tools and features into e-commerce platforms influence the development of positive engagement attitudes among users?” The various analytical tools utilized to explore the primary data collected, going hand in hand with secondary data from credible and reputable Turkish sources, proved successful in addressing it. The findings, which are of significant importance for all stakeholders in the Turkish e-commerce sector, suggest that by creating and facilitating a more personalized, satisfying, and efficient shopping experience, AI-driven tools and features integrated into e-commerce platforms not only meet consumers' immediate needs but also attract and foster users’ psychological and behavioral engagement towards those platforms. This not only supports the business's objectives of increased and enhanced consumer interaction and sales but also contributes to a more enjoyable and satisfying shopping experience for consumers in Türkiye.

Significance of AI-Driven Tools in Consumer Engagement:

The applications and integration of AI-driven tools and features in e-commerce have revolutionized how businesses interact with their consumers at all touch-points. The findings from this study emphasize and underscore the transformative potential of AI applications and integration in creating a more engaging and personalized shopping experience. For instance, chatbots, as discussed in the study, provide users with instant support and handle their inquiries efficiently, leading to enhanced customer satisfaction and a positive attitude towards the platform. This immediate and personalized interaction is crucial in retaining customers, fostering loyalty, and acquiring new customers through referrals and positive word-of-mouth. Moreover, visual search functions simplify the product search process, making it a more enjoyable, intuitive, and less time-consuming experience, which directly impacts user satisfaction and engagement with the platform.

Recommender systems, another AI-driven tool examined in this study, were proven to significantly contribute to consumer engagement by personalizing the user experience and suggesting products that align with their needs, preferences, and previous behaviors. This not only enhances users' engagement and shopping experience but also increases the likelihood of purchasing and retaining customers, which boosts sales. Automated after-sales services were also proven to significantly enhance customer experience and satisfaction by efficiently handling post-purchase issues and requests, which is crucial for maintaining a positive customer relationship and encouraging repeat and new customers.

Impact on Business Objectives and Consumer Experience:

The integration of AI-driven tools in e-commerce platforms no doubt aligns with the broader business objectives of increasing consumer interaction and driving sales as supported by the literature reviewed in this study. By enhancing customers' shopping experience through personalization and efficiency, these tools help in attracting and retaining customers. The positive psychological and behavioral engagement fostered by different AI tools and features translates into increased consumer interaction and higher satisfaction levels, which ultimately leads to more sales and a wider user base. This is particularly important in the highly vibrant, dynamic, and competitive e-commerce market in Türkiye, where businesses are constantly seeking innovative ways to differentiate themselves and capture consumer attention.

In addition, the study highlights the importance of psychological engagement as a mediator in the relationship between AI-driven tools efficiency and behavioral engagement. This suggests that businesses should focus not only on the technical and functional aspects of AI-driven tools but also on how these tools impact the overall consumer experience. By creating a more engaging and satisfying shopping environment, businesses can foster positive attitudes among consumers, leading to increased loyalty and advocacy.

Broader Implications for Digital Transformation:

The findings from this study also contribute to the broader discourse on digital transformation in e-commerce, particularly in emerging markets like Türkiye. As AI technology continues to evolve, its applications in e-commerce are likely to expand further, offering new opportunities for businesses to enhance consumer engagement. This study provides valuable insights for both academics and practitioners, highlighting the critical role of AI in driving digital transformation and the importance of creating and fostering an environment that supports technological innovation.

Furthermore, for policymakers, the study underscores the need to create a regulatory framework that encourages the adoption and integration of AI technologies in e-commerce. This includes addressing issues related to data privacy and security, which are critical for gaining consumer trust and ensuring the successful implementation of AI tools. By creating a supportive environment for technological innovation, policymakers can help businesses harness the full potential of AI, driving economic growth and enhancing consumer experiences.

Future Research Directions:

Given the rapid pace of technological advancements, there is a need for ongoing research to explore the evolving impact of AI in e-commerce. Future studies could examine the long-term effects of AI-driven tools on consumer engagement and business performance, as well as the potential challenges and opportunities associated with their implementation. Additionally, research could explore the impact of AI on different segments of the population, considering factors such as age, gender, and socioeconomic status, to provide a more comprehensive understanding of its implications.

As AI continues to advance, new tools and features are likely to emerge, offering further opportunities for enhancing consumer engagement. Future research could explore the potential of these new technologies and their impact on consumer behavior, providing valuable insights for businesses seeking to stay ahead in the competitive e-commerce landscape.

Recommendations for Future Studies:

To enhance the representativeness and generalizability of findings of future studies, it is essential to consider a more extensive and diverse sample. The findings of this study are based on a relatively small sample size (151 participants), due to time and resource constraints, and may be limited by the demographic profile of respondents, likely to have been primarily from Istanbul. Future research should aim to include participants from various regions and demographic backgrounds within Türkiye. This would provide a more representative understanding of consumer behavior and engagement with AI-driven tools in e-commerce across different segments of the population.

In addition, given that AI technologies, their advancements, and their adoption are continually evolving, future studies should consider employing a longitudinal research design. Unlike the cross-sectional approach used in this study, which provides a "snapshot in time," a longitudinal design would allow researchers to observe and capture changes over time. This would offer deeper and more meaningful insights into the long-term effects of AI-driven tools on consumer engagement, helping to understand how these technologies influence consumer behavior and satisfaction over extended periods as acceptance of usage of these technologies by consumers are also continually evolving.

Additionally, while this study utilized a quantitative methodology, future research should consider adopting mixed methods to provide a more comprehensive exploration of AI applications in e-commerce. Integrating qualitative methods, such as interviews or focus groups, would enrich the quantitative findings by offering deeper insights into consumers' attitudes, perceptions, and experiences. This mixed-method approach could uncover nuanced aspects of consumer engagement, psychological and behavioral, and provide a fuller understanding of the impact of AI-driven tools.

Moreover, future research should broaden the geographical scope beyond the Turkish e-commerce market to include other regions and countries. This would help to understand how cultural, economic, and technological differences influence consumer engagement with AI-driven tools. Even within Türkiye, expanding the study to include participants from diverse cities and regions would provide a more comprehensive view of consumer behavior across the country. Investigating the impact of cultural differences on the effectiveness of AI tools would be invaluable for drawing global implications and tailoring e-commerce strategies to diverse user bases.

Furthermore, future studies should consider investigating other AI tools and features that may influence consumer behavior and engagement. While this study focused on chatbots, visual search, recommender systems, and automated after-sales services, many other AI-driven innovations could be relevant. Exploring these additional tools could provide a broader understanding of the various determinants of consumer engagement in e-commerce. This exploration could include AI-driven marketing strategies, personalized content recommendations, and advanced customer service technologies.

Finally, policymakers and business leaders should consider the findings of this study when developing strategies for AI integration in e-commerce. Encouraging the adoption of AI technologies requires a supportive regulatory framework that addresses data privacy and security concerns. Businesses should focus on creating personalized and efficient shopping experiences that meet consumers' immediate needs while fostering long-term engagement. By leveraging AI tools effectively, e-commerce platforms can enhance consumer satisfaction, loyalty, and overall shopping experience.

By considering and implementing these recommendations, future research can build on the findings of this study, offering valuable insights into the evolving role of AI in e-commerce and its impact on consumer engagement. This will not only advance academic knowledge but also provide practical guidance for businesses and policymakers seeking to harness the benefits of AI technologies.

Conclusion:

In conclusion, this study provides strong and clear evidence of the significant role that efficient AI-driven tools play in enhancing consumer engagement on e-commerce platforms in Türkiye. By facilitating a more personalized, satisfying, and efficient shopping experience, these tools not only meet consumers' immediate needs but also foster psychological and behavioral engagement, supporting business objectives and contributing to a more enjoyable shopping experience. The findings emphasize and underscore the importance of AI in driving digital transformation in e-commerce and offer valuable insights for businesses and policymakers aiming to harness the benefits of AI. As AI applications continues to evolve, there is a rich potential for further integration of its tools and capabilities into e-commerce, offering exciting opportunities for both academic and practical exploration. As we move into this new era of digital commerce, AI has the power to not only enhance consumer experiences but also to reshape the entire e-commerce industry in Türkiye, opening up a future of endless possibilities and deeper engagement.

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APPENDICES

APPENDIX 1. Demographic Information Form

1. How old are you?
    - 18 – 24
    - 25 – 34
    - 35 – 44
    - 45 – 54
    - 55 – 64
    - 65 or older
2. What is your gender?
    - Female
    - Male
3. What is your current marital status?
    - Single
    - Married
    - Widowed
    - Other
4. Please indicate the highest level of education completed?
    - No Formal Education
    - Primary School
    - Secondary School
    - High School
    - Technical Degree
    - Bachelor’s Degree
    - Master’s Degree
    - Doctoral Degree
    - Other
5. Do you have any children?
    - Yes

- No

6. Are you currently employed?
   - Yes
   - No
   - Other
7. How many years of work experience do you have?
   - Less than 1 year
   - 1-5 years
   - 5-10 years
   - 11 years or more
8. What is your current work arrangement?
   - Fully at the office
   - Fully remote
   - Hybrid
   - I am not currently employed
9. Which of the following work arrangement do you prefer?
   - Fully at the office
   - Fully remote
   - Hybrid
10. How many hours a day do you work?
    - Less than 4 hours
    - 4 - 6 hours
    - 6 - 8 hours
    - 8 - 10 hours
    - 11 hours or more
    - I am not currently employed
11. In which of the following is the organization you work for?
    - Private sector
    - Public sector
    - I am not currently employed
    - Other

12. What is your monthly household income?
    - 0 - 11400 TL
    - 11401 - 30400 TL
    - 30401 - 50400 TL
    - 50401 - 70400 TL
    - 70401 TL or more
13. Have you ever used online shopping platform to make purchases?
    - Yes
    - No
14. Do you make more purchases online or offline?
    - Online
    - Offline
15. Which platform do you use the most for making online purchases?
    - Trendyol
    - Hepsiburada
    - N11
    - Getir
    - Other
16. When using online shopping platforms, what type of products do you purchase most frequently?
    - Groceries
    - Fashion and Apparel
    - Electronics
    - Home and Living
    - Beauty and Personal Care
    - Other

APPENDIX 2. Measurement Scales

1. Chatbot Efficiency

1.1. The chatbot on the online shopping platform (that you use the most) is available all the time.

- Strongly Disagree
- Disagree
- Somewhat Disagree
- Neither Agree nor Disagree
- Somewhat Agree
- Agree
- Strongly Agree

1.2. Anytime I log on to the platform, I get pop-up notifications from a chatbot.

- Strongly Disagree
- Disagree
- Somewhat Disagree
- Neither Agree nor Disagree
- Somewhat Agree
- Agree
- Strongly Agree

1.3. The requirement I type in the pop-up chat box returns beneficial results

- Strongly Disagree
- Disagree
- Somewhat Disagree
- Neither Agree nor Disagree
- Somewhat Agree
- Agree
- Strongly Agree

1.4. I can easily communicate with the chatbot.

- Strongly Disagree
- Disagree
- Somewhat Disagree
- Neither Agree nor Disagree

- Somewhat Agree
- Agree
- Strongly Agree

2. Visual Search Efficiency

2.1. The visual search function is easy to use.

- Strongly Disagree
- Disagree
- Somewhat Disagree
- Neither Agree nor Disagree
- Somewhat Agree
- Agree
- Strongly Agree

2.2. I can search for a product by pointing my camera at it or scanning a saved image on my device.

- Strongly Disagree
- Disagree
- Somewhat Disagree
- Neither Agree nor Disagree
- Somewhat Agree
- Agree
- Strongly Agree

2.3. The result from the visual search matches the item I need.

- Strongly Disagree
- Disagree
- Somewhat Disagree
- Neither Agree nor Disagree
- Somewhat Agree
- Agree
- Strongly Agree

2.4. I don’t need keyword or text searches when I use the visual search function.

- Strongly Disagree

- Disagree
- Somewhat Disagree
- Neither Agree nor Disagree
- Somewhat Agree
- Agree
- Strongly Agree

3. Recommender System Efficiency

3.1. I get product recommendations based on my previous searches.

- Strongly Disagree
- Disagree
- Somewhat Disagree
- Neither Agree nor Disagree
- Somewhat Agree
- Agree
- Strongly Agree

3.2. I get product recommendations based on my previous purchases.

- Strongly Disagree
- Disagree
- Somewhat Disagree
- Neither Agree nor Disagree
- Somewhat Agree
- Agree
- Strongly Agree

3.3. The products recommended on the platform are products that I am interested in.

- Strongly Disagree
- Disagree
- Somewhat Disagree
- Neither Agree nor Disagree
- Somewhat Agree
- Agree
- Strongly Agree

3.4. I do not spend too much time searching for products.

- Strongly Disagree
- Disagree
- Somewhat Disagree
- Neither Agree nor Disagree
- Somewhat Agree
- Agree
- Strongly Agree

4. Automated After-Sales Service Efficiency

4.1. I get automatic feedback requests after my purchase.

- Strongly Disagree
- Disagree
- Somewhat Disagree
- Neither Agree nor Disagree
- Somewhat Agree
- Agree
- Strongly Agree

4.2. Any ambiguity in products I buy or intend to buy is handled promptly.

- Strongly Disagree
- Disagree
- Somewhat Disagree
- Neither Agree nor Disagree
- Somewhat Agree
- Agree
- Strongly Agree

4.3. If I need the product replaced or refunded, there is an automated step -by -step process.

- Strongly Disagree
- Disagree
- Somewhat Disagree
- Neither Agree nor Disagree
- Somewhat Agree

- Agree
- Strongly Agree

4.4. I am aided by guidance and prompts in the entire buying cycle.

- Strongly Disagree
- Disagree
- Somewhat Disagree
- Neither Agree nor Disagree
- Somewhat Agree
- Agree
- Strongly Agree

5. Psychological Engagement

5.1. I feel no stress when shopping on the online platform.

- Strongly Disagree
- Disagree
- Somewhat Disagree
- Neither Agree nor Disagree
- Somewhat Agree
- Agree
- Strongly Agree

5.2. I am enthused and inspired when I am logged on to the online shopping platform.

- Strongly Disagree
- Disagree
- Somewhat Disagree
- Neither Agree nor Disagree
- Somewhat Agree
- Agree
- Strongly Agree

5.3. I do not realize the passage of time as I am immersed when logged on to the online shopping platform.

- Strongly Disagree
- Disagree

- Somewhat Disagree
- Neither Agree nor Disagree
- Somewhat Agree
- Agree
- Strongly Agree

6. Behavioral Engagement

6.1. I intend to continue using this online shopping platform.

- Strongly Disagree
- Disagree
- Somewhat Disagree
- Neither Agree nor Disagree
- Somewhat Agree
- Agree
- Strongly Agree

6.2. I refer friends to buy from this online shopping platform.

- Strongly Disagree
- Disagree
- Somewhat Disagree
- Neither Agree nor Disagree
- Somewhat Agree
- Agree
- Strongly Agree

6.3. I tell friends about the services provided on the online shopping platform.

- Strongly Disagree
- Disagree
- Somewhat Disagree
- Neither Agree nor Disagree
- Somewhat Agree
- Agree
- Strongly Agree

6.4. I write reviews about my service experience with the online-shopping platform.

- Strongly Disagree
- Disagree
- Somewhat Disagree
- Neither Agree nor Disagree
- Somewhat Agree
- Agree
- Strongly Agree

7. Attention to Social Comparison

7.1. I find it essential to consume reputable brands.

- Strongly Disagree
- Disagree
- Somewhat Disagree
- Neither Agree nor Disagree
- Somewhat Agree
- Agree
- Strongly Agree

7.2. I feel it is significant to purchase brands with the most consumption.

- Strongly Disagree
- Disagree
- Somewhat Disagree
- Neither Agree nor Disagree
- Somewhat Agree
- Agree
- Strongly Agree

7.3. If I am unsure of what to purchase, I rely on friends' opinions.

- Strongly Disagree
- Disagree
- Somewhat Disagree
- Neither Agree nor Disagree
- Somewhat Agree
- Agree

- Strongly Agree

7.4. I tend to pay attention to what society is consuming when I am on the online shopping platform.

- Strongly Disagree
- Disagree
- Somewhat Disagree
- Neither Agree nor Disagree
- Somewhat Agree
- Agree
- Strongly Agree