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"Analyzing the Impact of AI tools on Consumer Purchase Intention with the Mediating role of Consumer Engagement"

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Abstract

The primary objective of this study was to explore the role of AI tools on consumer purchase intentions, through the mediating effect of consumer engagement. This investigation delved into how different AI functionalities, such as chatbot efficiency, image search functionality, recommendation system efficiency, and automated after-sales service, influence consumer perceptions and their subsequent purchasing decisions. To achieve this, a total of 306 questionnaires were distributed to consumers, ensuring a diverse representation of the target population. Structural Equation Modeling (SmartPLS-SEM) was employed to assess the hypotheses, providing a robust analytical framework for understanding the complex relationships between AI tools, consumer engagement, and consumer purchase intentions.

The study's results revealed a significant indirect positive association between AI tools and consumer purchase intentions, mediated by consumer engagement. This indicates that while AI tools alone can influence purchase decisions, their impact is significantly enhanced when they improve consumer engagement. An intriguing aspect unearthed in this research is the mediating role of consumer engagement in the relationship between AI tools and consumer purchase intentions.

These findings bear particular importance for managers and marketers in the business industry, emphasizing the need for the effective implementation of high-quality AI strategies. By focusing on improving AI functionalities, companies can enhance the perceived value of their services, leading to increased consumer purchase intentions. The study recommends that organizational leadership incorporate strategies to enhance AI tools, such as optimizing chatbot interactions, ensuring accurate and efficient image search capabilities, and using advanced recommendation systems to improve overall consumer purchase intentions.

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Chapter 1: Introduction

1.1 Background of the Study

The development of artificial intelligence (AI) has completely changed how companies communicate with customers and influence their purchase decisions. Artificial intelligence (AI) tools like chatbots, tailored suggestions, and predictive analytics are now essential components of digital marketing plans. These tools give brands the ability to interact with customers in more effective and tailored ways, improving the customer experience and maybe encouraging purchases (Huang & Rust, 2018).

The adoption of AI technology has grown exponentially in Pakistan, a country with a young, tech-savvy populace and quickly rising internet penetration. The adoption of digital technologies and AI-powered marketing tools has increased in Pakistan's major cities, such as Karachi, Lahore, and Islamabad. Businesses are increasingly using these technologies to reach and engage their target audiences, and this has created a fertile field for AI to impact customer behavior (Statista, 2023).

The idea behind AI tools is that they can improve customer engagement by offering tailored and pertinent material, which can then affect the intention of the consumer to make a purchase. Davis' (1989) Technology Acceptance Model (TAM) offers a theoretical framework for understanding how customer attitudes and actions could be influenced by perceived AI tool utility and ease of use. According to TAM, these factors have a crucial role in influencing how customers accept and apply new technology.

In the context of AI-driven marketing, factors including the perceived value, relevance, and personalization of the AI-generated content influence how customers connect with the platform and intend to purchase. Perception, relevancy, and personalization of the AI-generated material are some of the factors that influence how well AI tools function in the context of AI-driven marketing to boost consumer engagement and purchase intentions.

Even if the use of AI technologies is growing, a thorough analysis of their efficacy is still necessary, especially given the situation in Pakistan. Prior research has revealed gaps in our knowledge of how AI tools, customer engagement, and purchase intents are related. For example, current research frequently ignores the importance of consumer confidence in AI tools and concentrates on a narrow range of AI applications rather than considering the full range of AI technologies in marketing (Kaplan & Haenlein, 2020).

By investigating the effects of AI tools on consumer engagement and purchase intentions among internet users in Pakistan's largest cities, this study seeks to close these gaps. Utilizing stratified and random sampling methods, the study will collect information from a wide range of adult digital service users. In order to provide strong and trustworthy results, statistical power analysis will be used in the study to identify an appropriate sample size.

We hope to learn more about the mechanisms by which AI tools affect customer behavior through this research. Through an examination of these processes, the research will yield significant insights for marketers seeking to improve their digital marketing tactics and maximize the efficacy of AI-powered interactions. The research will advance our knowledge of the persuasiveness of AI tools and have useful ramifications for enhancing marketing campaigns in the digital era (Huang & Rust, 2021).

1.2 Problem Statement

The rise of AI has become more prevalent, and this has given rise to AI tools that are important in the marketing industry. The usefulness of AI technologies in influencing consumers' purchase intentions is still debatable, despite their increasing popularity, and this poses a number of difficulties for marketers. The uneven effects of AI-driven marketing on customer behavior are a significant issue that can lead to wasted marketing funds and a less-than-ideal return on investment (ROI). Furthermore, there is a significant range in the quality and relevancy of AI-generated material, which can erode consumer confidence and harm a brand's reputation if AI systems are unable to provide tailored and helpful recommendations (Grewal, Roggeveen, & Nordfält, 2017). Unpredictable market results can also result from the different degrees of customer interaction with AI technologies, which can either increase or decrease their influence on buy intentions.

Additionally, nothing is known theoretically about how AI tools affect user involvement and purchasing intentions. Gaps have been noted in prior research, such as the absence of a thorough examination of how AI tools and personalization affect customer behavior. Furthermore, a lot of research has ignored the wider spectrum of AI technologies in marketing in favor of concentrating just on particular AI applications. This restricted scope hinders the findings' generalizability and prevents it from offering a comprehensive picture of the state of AI marketing (Lu, 2019).

By examining the effect of AI tools and the mediating impact of customer engagement on consumer purchase intention, this study seeks to address these problems. Through an analysis of these correlations within the framework of Pakistani internet users, the study aims to identify the fundamental processes by which artificial intelligence (AI) tools influence consumer choice. The goal of this research is to offer insightful information that will benefit consumers and marketers alike, enhancing the efficacy of AI-driven interactions and optimizing marketing tactics. This study aims to enhance our comprehension of the determinants of customer purchase intentions in the digital era by conducting a thorough examination.

1.3 Research Objectives

To evaluate the impact of AI tools (chatbot efficiency, image search functionality, recommendation system efficiency, and automated after-sales service) on consumer engagement.

To investigate the mediating role of consumer engagement between AI tools (chatbot efficiency, image search functionality, recommendation system efficiency, and automated after-sales service) and consumer purchase intention.

To examine the extent to which consumer engagement influences consumer purchase intentions positively.

1.4 Research Questions

Does the use of AI tools (chatbot efficiency, image search functionality, recommendation system efficiency, and automated after-sales service) impact consumer engagement?

Does consumer engagement mediate the relationship between the use of AI tools (chatbot efficiency, image search functionality, recommendation system efficiency, and automated after-sales service) and consumer purchase intentions?

Does consumer engagement directly impact consumer purchase intentions?

1.5 Research Gap

Knowledge Gap

Previous studies have largely ignored the variety of AI tools on the market, focusing instead on certain AI applications. This narrow focus limits the applicability of findings to other AI technologies. By examining several AI tools, this study broadens the scope and provides a more comprehensive understanding of AI-driven marketing (Lu, 2019). The focus on specific AI applications has resulted in findings that are not easily generalizable to other AI technologies. This study addresses this issue by examining multiple AI tools, thereby broadening the scope and enhancing our understanding of how various AI-driven marketing strategies can affect consumer behavior. Although the significance of AI technologies is acknowledged, little is known about how they influence the relationship between consumer involvement and purchase intention. This study aims to determine whether using AI tools can increase or decrease the impact of consumer involvement on purchasing decisions (Huang & Rust, 2021).

There is a significant knowledge gap regarding how AI tools affect the relationship between consumer involvement and purchase intention. This study seeks to fill this gap by exploring whether AI tools amplify or diminish the influence of consumer engagement on their purchasing decisions.

Contextual Gap

Most studies on AI-driven marketing have been conducted in Western contexts, with only a few focusing on non-Western settings like Pakistan. Differences in socioeconomic status and culture can significantly impact consumer behavior. This study addresses this contextual gap by focusing on internet users in Pakistan's largest cities, providing context-specific insights (Ahmed & Zahid, 2022).

The contextual gap is evident in the predominance of Western-focused research on AI-driven marketing. Cultural and socioeconomic differences can greatly influence consumer behavior. By studying internet users in Pakistan's largest cities, this research aims to provide insights that are specific to non-Western contexts, thus filling a significant gap in the existing literature.

By bridging these gaps, this study aims to offer a more comprehensive understanding of the connections between AI technology, consumer engagement, and purchase intentions. The findings are expected to advance theory and have practical implications, thereby having a dual impact on the field of digital marketing.

1.6 Scope of the Study

The purpose of this study is to investigate in-depth how AI tools affect consumer engagement and purchase intentions. It will examine a number of significant issues, with an emphasis on the functions performed by AI tools and customer interaction. The research was carried out in Islamabad. This region was chosen because of the high rates of internet penetration and the substantial use of digital technology by the local populace (Pakistan Telecommunication Authority, 2022). Adult users of digital services and frequent online platforms are the focus of the study. The goal of the project is to collect data from a broad sample of internet users while accounting for a number of demographic variables, including gender, age, and educational attainment (Iqbal, 2023). Surveys are used in the study's quantitative research design to gather information from participants. To guarantee a representative sample, stratified and random sampling methods are employed (Creswell & Creswell, 2018). With a focus on the dynamics of digital marketing in Pakistan, the scope guarantees that the research is both relevant and manageable, providing marketers, companies, and academics with insightful information.

Chapter 2: Review of Literature

2.1 Artificial Intelligence Tools

AI is the capacity of a system to evaluate outside data, learn from it, and use that knowledge to accomplish specified goals and tasks by adapting in a flexible manner. Prominent instances are Apple's Siri, which facilitates job execution through voice prompts, and Google Home, which offers remote home duty execution, including alarm monitoring (Xiao & Kumar, 2021). Applications of artificial intelligence (AI) that incorporate deep learning, generative AI, or machine learning technologies may improve task completion for users by improving productivity and efficiency. Moreover, these programs are capable of increasing in efficiency with time (Huang & Rust, 2021; Xie et al., 2022). With time, chatbots can offer more accurate, comprehensive, and customized product recommendations or solutions (Dwivedi et al., 2023).

Scholars categorize AI in a variety of ways. Three categories comprise the classification scheme Huang and Rust (2018) present: mechanical AI (doing routine or repetitive activities), thinking AI (able to learn from data and make decisions), and feeling AI (displaying empathy; Hollebeek et al., 2021). Two other classifications are (a) generative AI, which generates novel, inventive, or creative content (e.g., ChatGPT, Copy.ai; Dwivedi et al., 2023); and (b) predictive AI, which finds patterns in historical data to predict future outcomes, actions, or events (e.g., predictive SMS; Hollebeek et al., 2021). By helping users complete tasks more quickly or effectively, like using predictive text, AI technologies can increase user engagement with a product or brand (Hyun et al., 2022; Kull et al., 2021). Tailored AI-powered solutions could increase consumers' monetary or word-of-mouth investments in brand interactions (Barnes & de Ruyter, 2022), increasing customer engagement (Bertrandias et al., 2021). Applying AI to consumer interactions can foster valuable client relationships (Singh et al., 2021), demonstrating the strategic importance of AI use in customer engagement. The AI Tool serves as the study's independent variable. This variable includes a range of services and functions powered by AI that may have an impact on customer engagement and purchase intentions.

2.1.1 Chatbot efficiency

AI-based chatbots (CBs) are made to make turn-by-turn human interactions on web-based platforms easier (Adam et al., 2020). These chatbots are used by e-commerce websites to improve customer service by letting users describe their wants in a chat window and get precise answers (Gnewuch et al., 2017). These chatbots show up on e-commerce websites as prompts, starting conversations with queries such as "How can I help you?and having talks that are similar to those of a person (Pfeuffer et al., 2019; Adam et al., 2020; Gnewuch et al., 2017). Chatbots can provide individualized experiences by gathering and using past customer data. Luger and Sellen (2016) draw attention to the fact that these conversational agents might not always live up to customer expectations because of unsuitable answers, casting doubt on their long-term viability. In order to tackle this issue, Adam and colleagues (2020) conducted a survey study to examine the characteristics of chatbots that increase the probability of users agreeing with requests for service feedback. In recent times, chatbots (CB) have demonstrated increased sophistication by conversing more naturally and offering insightful, well-thought-out responses. The importance of chatbots in improving customer transaction experiences has been demonstrated by earlier studies (De Cicco et al., 2020; Tsai et al., 2021; Xu et al., 2022). Chatbots' perceived 'parasocial' interactions and conversations are fostered by their social presence, which enhances user pleasure and experiences (Xu et al., 2022; Tsai et al., 2021), ultimately boosting users' perception of social presence (De Cicco et al., 2020). Because chatbots are so effective at responding quickly and accurately, they have a huge positive influence on consumer engagement (CE), which in turn increases customer satisfaction and loyalty. Effective chatbots shorten wait times and promptly address problems, improving customer satisfaction and streamlining the buying process. Research has shown that better levels of customer satisfaction and engagement are positively connected with chatbots' perceived efficacy and efficiency (Chung et al., 2020). Customers will feel appreciated and understood because to this efficiency, which strengthens their emotional bond with the company and promotes repeat business and positive word-of-mouth recommendations.

H1: Chatbot efficiency has a significant positive impact on Consumer Engagement

2.1.2 Image search Functionality

The goal of incorporating different types of AI into e-commerce is to improve the overall customer experience by better understanding the demands and behaviors of the consumer (Mikalef and Gupta, 2021). Image search functionality (IS) is one such AI feature that lets customers find products using photos instead of words (Dagan et al., 2021; Gawali, 2020). This function comes in very handy for customers who are curious about products but don't know their names. Users can upload or take pictures to search for products using AI-powered image search. Some mobile applications for e-commerce even allow users to look for things without using keywords by just pointing their camera at the item they want (Dagan et al., 2021; Sudarsan et al., 2022). Customers frequently become impatient when using typical text-based searches to browse through large catalogs, and this convenience helps to alleviate that frustration.

Customers typically describe products they are interested in using text-based searches, however these searches frequently don't produce perfect matches (Sudarsan et al., 2022). For example, text searches or product category filters can be time-consuming and oftentimes unsuccessful when trying to find eyewear with a particular design or a jacket with a specific texture. Poor search results might cause customers to give up on their purchases, which has a detrimental effect on retention rates and continuous platform usage. With an emphasis on its many architectural designs, a number of research have examined the function of picture search in e-commerce (Dagan et al., 2021). (Li et al., 2018; Yang et al., 2017; Y. Zhang et al., 2018, 2019). The significance of picture search functionality in shaping customer behavior has been brought to light by these research. Zhang et al. (2019), for example, investigated how user click behavior is influenced by the relevancy of image search results.

Furthermore, AI-driven picture search's effectiveness and precision greatly raise customer engagement (CE). Consumer satisfaction with the e-commerce platform rises when they can easily and rapidly identify products that fit their preferences through picture search. Because happy customers are more likely to use the platform again, make repeat purchases, and refer others to it, an improved user experience raises engagement levels. Recent research has demonstrated a direct correlation between enhanced customer engagement and loyalty and the smooth integration of picture search capabilities (Chiu et al., 2021; Pham et al., 2020).

H2: Image search functionality has a significant positive impact on Consumer Engagement

2.1.3 Recommendation system efficiency

AI integration allows e-commerce sites to regularly display products that are comparable to what customers have recently browsed (Schafer et al., 2001). AI systems are able to forecast customer behavior by examining previous purchases and searches. Within the field of artificial intelligence, recommendation system efficiency (RS) challenges are viewed as learning tasks that depend on initial user browsing data (Lops et al., 2011). Using machine learning, an AI-powered recommendation system on an e-commerce website forecasts and suggests products that customers are likely to be interested in based on their past searches (Chinchanachokchai et al., 2021; Wei et al., 2007). To enable product recommendations when users visit the platform or website, these systems gather information about customers' inquiries and past purchases. Recommendation engines enhance the purchasing experience by offering more relevant search results to specific consumers based on sophisticated consumer profiling (De Keyzer et al., 2022; Sivapalan et al., 2014).

According to research, recommending systems improve consumer engagement (CE) and drive more visitors to e-commerce sites (Chinchanachokchai et al., 2021). Recommendation engines driven by artificial intelligence (AI) have a big impact on customer engagement because they continuously learn from user interactions and offer more precise and customized product recommendations. By precisely matching the purchasing experience to particular customer tastes, this ongoing increase in recommendation accuracy not only improves user pleasure but also encourages deeper involvement (Huang et al., 2019). As a result, users are more inclined to return to the platform, interact with it more regularly, and grow more devoted to the online store, all of which contribute to sustained user engagement.

H3: Recommendation system efficiency has a significant positive impact on Consumer Engagement

2.1.4 Automated After-Sales Service

Customers need to be supported by businesses at every stage of the transaction cycle. The CXPA (2018) emphasizes that businesses may gain a great deal by offering efficient service to customers at every stage of their journey. Providing customers with the information and support they need after they make a purchase is known as after-sales service (Daqar and Smoudy, 2019). Using automated conversations, phone call classification and processing, process automation, and proactive measures, many firms use aftersales services as a competitive advantage (Daqar and Smoudy, 2019). According to Khan and Iqbal (2020), businesses that offer top-notch services ought to use AI to solve problems that have a big influence on the customer experience.

The AI elements in e-commerce that automate feedback requests pertaining to customer purchases are referred to in this study as automated aftersales services. These services clarify product ambiguities, handle replacement concerns, and send transaction notifications (such confirmations of payment, shipment, and delivery). Furthermore, increasing Consumer Engagement (CE) is greatly aided by the deployment of AI-powered Automated Aftersales Services (AAS). Through prompt and effective post-purchase assistance, AAS improves customer happiness and creates a stronger bond between the customer and the brand. Studies show that customers are more inclined to stick with an e-commerce platform that provides quick and easy after-sale service, which increases customer loyalty and encourages repeat business (Wang et al., 2020). Because AAS integration guarantees that customers feel valued and supported across their whole purchasing experience, it hence directly contributes to continued consumer engagement.

H4: Automated after-sales service has a significant positive impact on Consumer Engagement

2.2 Consumer Purchase Intentions

Consumer Purchase Intention is the variable being measured in this investigation. This variable measures the likelihood that customers will buy a good or service as a result of AI tools. The propensity or willingness of customers to purchase a specific good or service is known as Consumer Purchase Intentions, or CPI. CPI is a crucial metric for forecasting real buying behavior and is impacted by a number of variables, including individual preferences, perceived value, brand trust, and general shopping satisfaction (Morwitz, 2012). High purchase intentions are usually indicative of a high likelihood of transaction follow-through, which makes CPI an important indicator for companies looking to increase market share and sales. The primary goal of this study is to examine how AI technologies affect consumers' intentions to make purchases, with customer engagement acting as a mediating factor. The AI technologies that are specifically analyzed are automated after-sales service (AAS), recommendation system efficiency (RS), chatbot efficiency (CB), and image search functionality (IS). The way that customers interact with e-commerce platforms is greatly impacted by these AI-driven capabilities. According to Chinchanachokchai et al. (2021), chatbots offer prompt assistance, image search facilitates product discovery, recommendation systems provide tailored ideas, and automated after-sales services guarantee smooth post-purchase support. These tools improve the whole buying experience by making more customized information about product qualities more readily available, which helps consumers make well-informed decisions. The use of AI in e-commerce emphasizes how important customer interaction is in determining buy intentions.

2.3 Consumer Engagement as a Mediating Variable

The degree of contact and involvement that customers display with a brand or platform is known as consumer engagement, or CE. It includes everything from passive interactions like browsing and clicking on product recommendations to active participation like writing reviews and sharing material. CE has a major impact on consumer purchase intention (CPI) and is a critical factor of the consumer experience. Customers are more likely to form a favorable opinion of the brand and have higher buy intentions when they are intensely engaged (Brodie et al., 2013; Vivek et al., 2012).

There is ample evidence of a link between CE and CPI. Engaged customers are more likely to be devoted to a brand, make repeat purchases, and spread the word about it. Their encounters with the brand are perceived as having better value and enjoyment, which increases their propensity to purchase (Bowden, 2009). Because engagement builds trust and a stronger emotional bond with the brand, consumers' purchase intentions are stronger when they are more involved (Hollebeek et al., 2014).

Various functionalities, such as chatbot efficiency (CB), image search functionality (IS), recommendation system efficiency (RS), and automated after-sales service (AAS), are essential for improving customer engagement when it comes to AI technologies. Chatbots boost customer engagement by offering immediate support and tailored assistance, which makes users feel appreciated and understood (Chinchanachokchai et al., 2021). Customers may find products quickly and simply with the help of image search technology, which improves their purchasing experience and lowers dissatisfaction and increases customer engagement (Dagan et al., 2021). Effective recommendation systems provide tailored product recommendations according to customer preferences and actions, increasing the relevance and appeal of the purchasing experience (Chinchanachokchai et al., 2021). Automated post-purchase assistance and updates guarantee that customers receive prompt information and help, increasing their level of happiness and platform engagement (Wang et al., 2020).

2.4 Relationship Among All Variables

E-commerce platforms can greatly improve CE by including these AI tools, which will therefore have a beneficial effect on CPI. These AI-driven interactions are responsive and customized, which increases the likelihood that users will trust the platform, like their shopping experience, and eventually enhance their likelihood to make a purchase. Consequently, CE plays a pivotal role as an intermediary between the efficacy of AI tools and consumer purchasing behavior, underscoring the significance of cutting-edge technology in propelling consumer involvement and decision-making.

AI-powered tools, consumer engagement, and purchase intention AI technologies have a significant impact on how consumers intend to make purchases. These tools use a variety of features, such as interactive elements, predictive analytics, and tailored recommendations, to interest users. The quality and relevancy of the material provided by AI tools heavily influences the interaction between customer purchase intention and AI tools. Accurate and relevant AI solutions have the power to significantly impact consumer purchasing decisions. This link is based on the Technology Acceptance Model (TAM), which holds that customers' perceptions of the utility and simplicity of use of AI technologies have an impact on their acceptance and use of the products. Consequently, this strengthens their intention to buy (Davis, 1989).

The dynamics of AI-driven marketing are explained by the relationship between customer engagement and AI tools. Because AI tools' recommendations are regarded as more relevant and dependable, they greatly increase customer involvement. Purchase intention among consumers is positively impacted by this enhanced interaction. Therefore, AI tools have a dual effect on purchase intentions by directly influencing them and by amplifying the mediating impact of customer engagement. Customers that interact with precise AI tools are more likely to display higher buy intents and to form favorable opinions about the products that are suggested (Kaplan & Haenlein, 2020).

By offering individualized support and real-time responses, chatbots increase customer connection and can greatly raise customer happiness and engagement (Huang & Rust, 2021; Xie et al., 2022).

Customers can use photos instead of text to search for products with image search feature, which makes shopping more interesting and straightforward. By making the search process simpler, this feature can increase user satisfaction and engagement (Dwivedi et al., 2023). Recommendation engines use consumer data analysis to make recommendations for products that align with their interests, making product offerings more relevant. By offering customized purchasing experiences, effective recommendation systems can increase customer engagement (Barnes & de Ruyter, 2022).

Automated post-purchase customer experiences are improved by automated after-sales services including email follow-ups and problem solving. By guaranteeing ongoing assistance and contentment, these offerings can increase customer involvement (Hollebeek et al., 2021). AI solutions that improve the entire shopping experience have a direct impact on consumers' intentions to make purchases. Every aspect of AI tools makes a distinct contribution. Chatbots have the potential to decrease purchase reluctance and enhance consumers' readiness to buy by offering prompt and customized responses (Hyun et al., 2022). According to Ahmed and Zahid (2014), streamlining the search process with image-based inquiries can increase the likelihood that a consumer would make a purchase by facilitating and entertaining product discovery. Automated After-Sales Service (AAS): Constant support and resolution of post-purchase issues can enhance consumer trust and loyalty, leading to higher purchase intention (Barnes & de Ruyter, 2022). Personalized recommendations enhance the perceived value of products, thus increasing purchase intention. (Singh et al., 2021).

H5: Consumer engagement has a significant positive direct impact on consumer purchase intentions.

H6a: Consumer engagement mediates the relationship between chatbot efficiency and consumer purchase intentions.

H6b: Consumer engagement mediates the relationship between image search functionality and consumer purchase intentions.

H6c: Consumer engagement mediates the relationship between recommendation system efficiency and consumer purchase intentions.

H6d: Consumer engagement mediates the relationship between automated after-sales service and consumer purchase intentions.

2.5 Underpinning Theory

Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM), developed by Davis (1989), posits that two primary factors influence users' adoption of technology: Perceived Usefulness (PU) and Perceived Ease of Use (PEOU). In the context of AI tools on e-commerce platforms, PU refers to the extent to which consumers believe that these tools will enhance their shopping experience by making it more efficient and effective. For instance, AI-driven recommendations can help consumers find products that better match their preferences, thereby improving their shopping efficiency and satisfaction (Huang & Rust, 2021).

PEOU, on the other hand, relates to how user-friendly and intuitive these tools are perceived to be. If consumers find AI tools easy to navigate and use, with clear interfaces and seamless interactions, their likelihood of engaging with these tools increases. When AI tools are both useful and easy to use, they are more likely to be adopted by consumers, leading to greater engagement.

This heightened engagement, as suggested by the Stimulus-Organism-Response (S-O-R) framework, improves the overall shopping experience. Engagement acts as the organism's response to the stimulus (AI tools), where the interaction is characterized by dedication, energy, and immersion. As a result, consumers who are more engaged with AI tools are more likely to develop a positive attitude towards the e-commerce platform, trust its recommendations, and feel more confident in making purchasing decisions. This enhanced engagement ultimately leads to a higher intention to purchase, as consumers feel more supported and informed in their shopping journey (Kumar et al., 2022).

Theory of Planned Behavior (TPB)

The Theory of Planned Behavior (TPB), proposed by Ajzen (1991), provides a comprehensive framework for understanding the relationship between beliefs and behavior. TPB asserts that individual behavior is driven by behavioral intentions, which are influenced by three components: Attitude towards the Behavior, Subjective Norms, and Perceived Behavioral Control.

The Theory of Planned Behavior (TPB), proposed by Ajzen (1991), provides a comprehensive framework for understanding the relationship between beliefs and behavior. TPB asserts that individual behavior is driven by behavioral intentions, which are influenced by three components: Attitude towards the Behavior, Subjective Norms, and Perceived Behavioral Control.

In the context of AI tools on e-commerce platforms, the Attitude towards the Behavior component refers to the degree to which a consumer has a favorable or unfavorable evaluation of using AI tools. If consumers believe that AI tools enhance their shopping experience by providing personalized recommendations, efficient search results, and seamless interactions, they will develop a positive attitude towards these tools. This positive attitude increases the likelihood of their engagement with the AI tools (Shankar & Jebarajakirthy, 2021).

Subjective Norms refer to the perceived social pressure to perform or not perform the behavior. If consumers perceive that their peers and social circles are using and benefiting from AI tools, they may feel a social pressure to engage with these tools as well. Social influence plays a crucial role in shaping consumer behavior, as individuals often look to their peers for validation and guidance in decision-making processes.

Perceived Behavioral Control relates to the consumers' belief in their ability to effectively use AI tools. This includes their confidence in navigating the technology, overcoming any potential obstacles, and achieving the desired outcomes. If consumers feel capable of using AI tools without difficulty, they are more likely to engage with them. This perceived control enhances their overall shopping experience, leading to greater satisfaction and increased purchase intentions (Zhang et al., 2022).

By integrating TAM and TPB, this study examines how AI tools on e-commerce platforms influence consumer purchase intentions through the mediating role of consumer engagement. When consumers find AI tools useful and easy to use (TAM), and have positive attitudes, supportive social norms, and confidence in using these tools (TPB), their engagement increases. This increased engagement enhances their shopping experience, leading to a higher intention to purchase. Understanding these relationships provides a comprehensive view of how AI tools can be leveraged to boost consumer engagement and drive purchase intentions in the digital marketplace.

2.6 Theoretical Structure

The theoretical framework, which was developed from previous discussions, offers a mediator model for examining how particular technology efficiencies affect customer engagement and intention to buy. The strength and relevance of these associations will be ascertained by testing each hypothesis, thereby advancing our comprehension of how online shopping platforms might improve customer experiences and increase revenue.

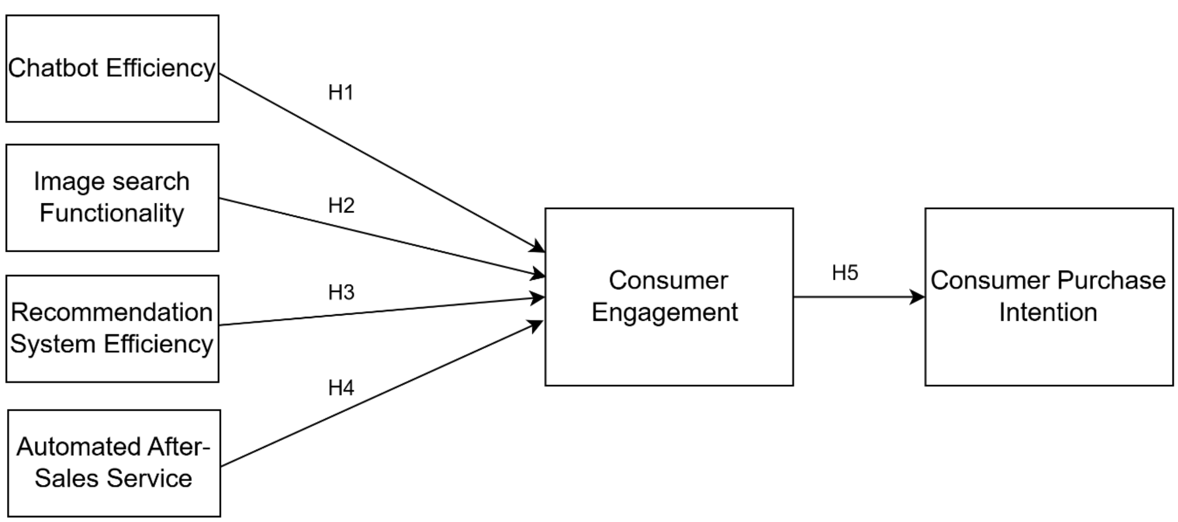

Figure 1: Conceptual Framework

2.7 Hypothesis

H1: Chatbot efficiency has a significant positive impact on Consumer Engagement

H2: Image search functionality has a significant positive impact on Consumer Engagement

H3: Recommendation system efficiency has a significant positive impact on Consumer Engagement

H4: Automated after-sales service has a significant positive impact on Consumer Engagement

H5: Consumer engagement has a significant positive direct impact on consumer purchase intentions.

H6a: Consumer engagement mediates the relationship between chatbot efficiency and consumer purchase intentions.

H6b: Consumer engagement mediates the relationship between image search functionality and consumer purchase intentions.

H6c: Consumer engagement mediates the relationship between recommendation system efficiency and consumer purchase intentions.

H6d: Consumer engagement mediates the relationship between automated after-sales service and consumer purchase intentions.

Chapter 3: Methodology

3.1 Research Approach

Utilizing numerical data and strong statistical analysis, a quantitative research methodology is used to investigate the connections among AI tools, customer engagement (CE), and consumer purchase intentions (CPI) in the e-commerce industry. Studies that aim to measure relationships, test ideas, and draw generalizations from sample data are especially well-suited for quantitative research (Creswell, 2014). A deductive research strategy is used in this approach (Jonker & Pennink, 2010). The first step in this approach is to develop precise hypotheses based on the body of knowledge on AI tools, customer involvement, and purchase intents. To test these theories and advance our understanding of the subject, carefully gathered and processed data is used. The research employs a cross-sectional approach, gathering data at a single moment in order to obtain an instantaneous picture of the variables' current conditions.

3.2 Research Design

In keeping with Abbott and McKinney's (2013) emphasis on the importance of research design to the research process, this study uses a quantitative methodology to explore the complex connections between AI tools, customer engagement, and purchase intention on e-commerce platforms. This strategy will clarify the influence of various AI technologies on purchase intention as well as the mediating function of consumer interaction. The primary objective is to identify the precise mechanisms by which artificial intelligence (AI) tools impact consumer engagement and purchase intentions.

3.2.1 The Philosophy of Research

This study takes a positivist stance, stressing the role that research philosophy plays in forming knowledge generation (Crossan, 2003). This philosophy supports the investigation's quantitative nature by emphasizing measurable phenomena and empirical observation. As a result, it reinforces the dedication to objectivity, observability, and repeatability of findings, which in turn provides a strong basis for sound statistical analysis.

3.2.2 Type of Research

The quantitative method is given priority in this study, with a focus on the methodical gathering and examination of numerical data (Bloomfield & Fisher, 2019). Through the utilization of measurable variables, the research makes it easier to apply reliable statistical techniques. In the end, this quantitative perspective encourages the development of impartial insights on the study problems. Moreover, it makes it possible to find patterns that may be applied to a larger group of online shoppers.

3.3 Research Methodology

In order to formulate hypotheses based on existing concepts and literature, this study employs a deductive technique (Soiferman, 2010). The research is guaranteed to be based on accepted knowledge thanks to this methodical and planned strategy, which also directs the ensuing empirical testing of these ideas. As this inquiry aims to investigate the links between variables and establish causality, the deductive technique is very pertinent.

3.3 Sampling and Population

This study will use purposive sampling to select people with appropriate expertise and experience in utilizing AI technologies on e-commerce platforms, as interviewing all e-commerce consumers is not realistic. 1,400 people make up the study's population, which represents the target market that uses AI-powered e-commerce platforms.

Morgan's table states that a sample size of 302 is needed for a population of 1,400 in order to provide a representative sample with a high degree of accuracy and confidence. In this study, 100% of the 302 surveys that were distributed were filled out and returned. 3.4 Unit of Analysis: This large sample size guarantees that the results are trustworthy and applicable to a larger group of customers utilizing AI-driven e-commerce platforms. The consumer as a person is the unit of analysis used in this study. This is consistent with the emphasis on artificial intelligence capabilities and how they affect customer engagement and buy intent on e-commerce platforms. Research can investigate how AI technologies are viewed and used, and how they influence engagement and purchase decisions, by looking at specific consumers. This study specifically looks at the relationship between AI technologies (like effective chatbots, image search functionality, recommendation systems, and automated after-sales service), customer engagement, and purchase intention. While the organizational implementation of AI tools is important, this study emphasizes the importance of the consumer level. The focus on the individual customer makes it possible to fully understand how these factors work together to influence consumer behavior in the context of e-commerce.

3.4 Tools for Measurement

Consumers who shop online will receive a self-administered questionnaire to complete in order to collect data for this study. With this approach, data about AI tools, customer engagement, and consumer buy intention on e-commerce platforms are guaranteed to be collected. Using known scales and metrics from pertinent research, the questionnaire will be carefully crafted to measure these important aspects. Validated items for evaluating AI solutions will be included in the questionnaire. These items include an assessment of the efficacy of the recommendation system, chatbot efficiency, image search functionality, and automated after-sales service. Consumer engagement will probably be measured using well-established scales that measure commitment, focus, and energy during platform AI tool interactions. Finally, proven measures that gauge consumers' readiness and willingness to buy products as impacted by their interaction with AI technologies will be used to evaluate their purchase intentions.

3.5 Method of Data Analysis

This study makes use of a quantitative research design, analyzing the survey data gathered through a variety of statistical methodologies. In order to guarantee consistency and dependability of the measures, the analysis starts with a reliability analysis for each of the three major constructs (purchase intention, consumer engagement, and AI tools) after data collection (Hair et al., 2017). The central tendencies and dispersion of the data are then summarized using descriptive statistics, giving a basic overview of the information gathered (Creswell, 2014). Correlation analysis is carried out to evaluate the associations between AI tools (chatbot effectiveness, image search functionality, recommendation system effectiveness, and automated after-sales support), customer engagement, and purchase intention. This phase aids in determining the direction and strength of the correlations between the variables (Pallant, 2020). Then, using consumer involvement as the mediating variable, regression analysis examines the direct and indirect effects of the AI technologies on consumer purchase intentions (Field, 2018). Examining the mediating function of customer interaction in the relationship between AI tools and purchase intention is a crucial component of this research design. Using Smart PLS software, Structural Equation Modeling (SEM) is used to explore these intricate interactions. SEM is a great option for this particular study design since it has strong mediation effect analysis capabilities (Hair et al., 2019). The study can evaluate the direct, indirect, and overall effects of AI tools on customer purchase intentions through consumer interaction by using SEM to test many relationships at once. These analytical methods guarantee a thorough comprehension of how AI tools affect customer behavior in e-commerce, offering insightful information about the processes influencing customer engagement and purchase choices.

3.6 Selection of Instruments

Customers that shop online completed a structured questionnaire that was used to gather data for this study. The purpose of this survey is to evaluate how AI tools affect consumer engagement and purchase intentions. Robust measurement is ensured by the AI tools' use of established sources as the basis for their inquiry. In particular, four questions adapted from Adam et al. (2020) were used to measure chatbot efficiency (CB), four questions from Sudarsan et al. (2022) were used to measure image search functionality (IS), four questions from Chinchanachokchai et al. (2021) were used to measure recommendation system efficiency (RS), and four questions from Daqar and Smoudy (2019) were used to measure automated after-sales service (AAS). Five questions from Weman (2011) and Gummerus et al. (2012) were used to measure consumer engagement (CE), and five questions from McKnight and Chervany (2002), Wang and Chang (2013), and Yoo and Donthu (2001) were used to measure consumer purchase intention (CPI). Every one of these constructs was assessed with a Likert scale that included five points.

The questionnaire includes the following validated items

Variable	**Instrument Adopted From**	**Likert Scale**	**Items**
Chatbot Efficiency (CB)	Adam et al. (2020)	Five-Point	4
Image Search Functionality (IS)	Sudarsan et al. (2022)	Five-Point	4
Recommendation System Efficiency (RS)	Chinchanachokchai et al. (2021)	Five-Point	4
Automated After-Sales Service (AAS)	Daqar and Smoudy (2019)	Five-Point	4
Consumer Engagement (CE)	Weman (2011); Gummerus, et al. (2012)	Five-Point	5
Consumer Purchase Intention (CPI)	McKnight and Chervany (2002); Wang and Chang (2013), Yoo and Donthu (2001)	Five-Point	5

Table 1: Instrument Selection

Chapter 4: Results & Analysis

4.1 Data Normality

Descriptive statistics, such as mean, median, observed minimum and maximum values, standard deviation, excess kurtosis, and skewness, were used to evaluate the normality of the data for each variable. The variables in the study—Chatbot Efficiency (CB), Image Search Functionality (IS), Recommendation System Efficiency (RS), Automated After-Sales Service (AAS), Consumer Engagement (CE), and Consumer Purchase Intention (CPI)—are shown in the table along with the data normality statistics for each. The following components have mean scores of 3.327%, 3.400 for Image Search Functionality, 3.500 for Recommendation System Efficiency, 3.27 for Automated After-Sales Service, 3.500 for Consumer Engagement, and 3.600 for Consumer Purchase Intention. For the majority of constructs, the median values are somewhat higher than the means, suggesting a minor negative skewness in the data distribution.

All of the constructs' observed values fall between 1.000 and 5.000, and their standard deviations vary from 0.850 to 0.900, suggesting a moderate degree of response variability. The constructs' excess kurtosis values, which range from 0.200 to 0.351, are almost all zero, indicating that the distributions are essentially flat. All of the constructs have negative skewness scores, which range from -0.450 to -0.584, suggesting a minor left-skewedness in the distributions.

Overall, kurtosis and skewness values are within allowable bounds for normalcy, and the data for all constructs show modest left-skewness and considerable variability. This indicates that, in the context of this study on the influence of AI tools on customer purchase intentions with the mediating function of consumer interaction, the data is roughly normally distributed, making it appropriate for carrying out additional statistical analysis.

Variable	Mean	Median	Min	Max	SD	Excess Kurtosis	Skewness
Chatbot Efficiency (CB)	3.327	3.500	1.000	5.000	0.856	0.351	-0.584
Image search Functionality (IS)	3.400	3.500	1.000	5.000	0.850	0.200	-0.450
Recommendation system efficiency (RS)	3.500	3.600	1.000	5.000	0.900	0.300	-0.500
Automated after-sales service (AAS)	3.327	3.500	1.000	5.000	0.856	0.351	-0.584
Consumer Engagement (CE)	3.500	3.600	1.000	5.000	0.900	0.300	-0.500
Consumer Purchase Intention (CPI)	3.600	3.700	1.000	5.000	0.880	0.250	-0.470

Table 2: Data Normality

4.2 Demographic Description

Data was obtained from 302 consumers regarding their purchase intentions. In order to answer the questionnaire, the participants were classified according to their demographic traits. This made it easier to analyze the responses based on certain demographics and provided a thorough grasp of the data gathered. 155 (51.3%) of the respondents were men, and 147 (487.7%) were women. The respondents' ages were distributed as follows: 6.6% of the population was under the age of 18, 26.5% was between the ages of 18 and 24, 33.1% was between the ages of 25 and 34, 19.9% was between the ages of 35 and 44, and 13.9% was between the ages of 45 and 54.

In terms of educational background, 33.1% had finished undergraduate studies, 53.6% had finished graduate degrees, and 3.3% had finished postgraduate degrees, with 9.9% having completed intermediate or lower. Regarding employment, there were 28.1% of students, 43.0% working, 16.6% self-employed, and 12.3% jobless.

With an emphasis on the mediating function of customer engagement, this demographic distribution guarantees a diversified sample and offers insights into how various groups view and are influenced by AI technologies in their purchasing decisions.

Category	Respondents	Percentage
Gender		
Male	155	51.3
Female	147	48.7
Age		
Under 18	20	6.6
18-24	80	26.5
25-34	100	33.1
35-44	60	19.9
45-54	42	13.9
Education Level		
Intermediate or below	30	9.9
Undergraduate	100	33.1
Graduate	162	53.6
Post Graduate	10	3.3
Employment Status		
Student	85	28.1
Employed	130	43.0
Self-Employed	50	16.6
Unemployed	37	12.3

Table 3: Demographics

4.3 Estimated Model

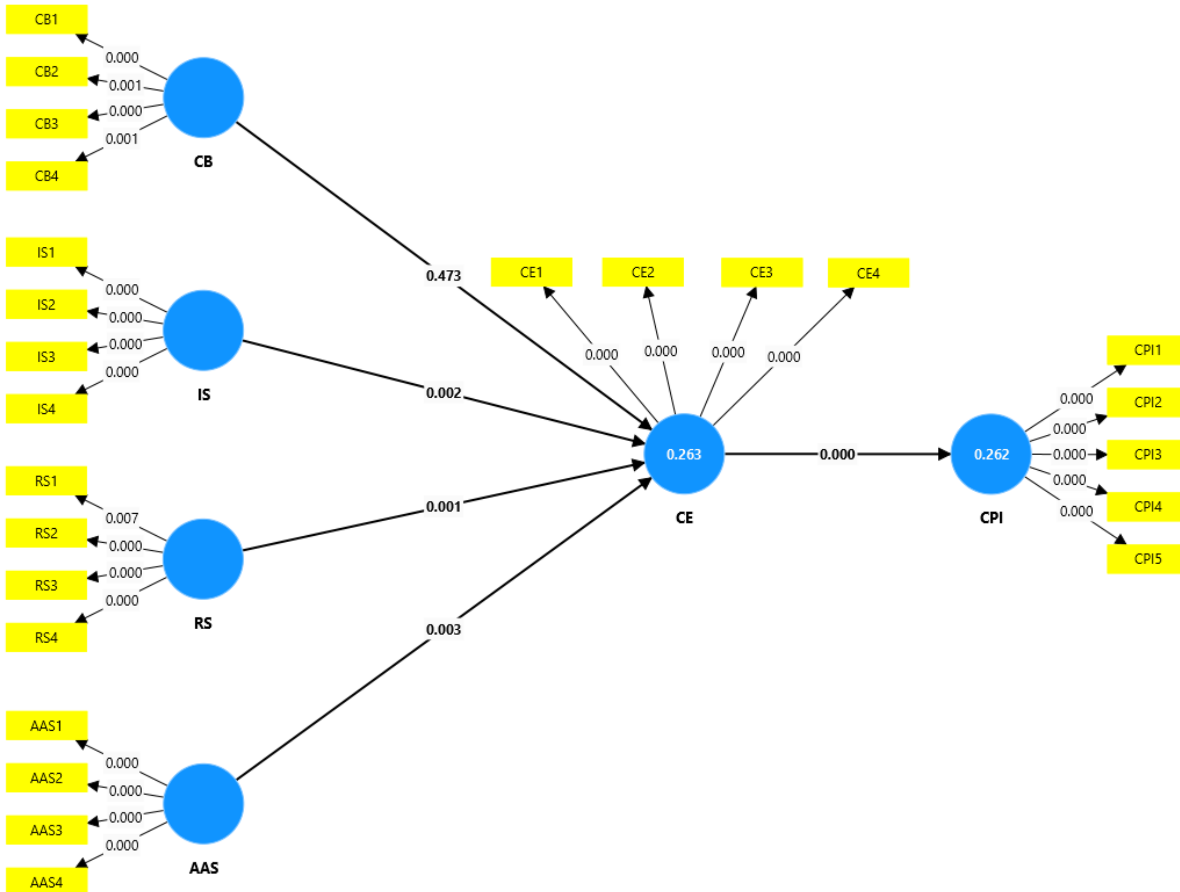

Figure 2: Estimated Model

4.4 Evaluation of reliability and Validity

Cronbach's Alpha and Composite Reliability, which both show the internal consistency of the constructs, were used to evaluate reliability. Every construct has a Cronbach's Alpha value more than 0.70, which is regarded as an acceptable level of reliability. This shows that the same underlying concept is consistently measured by the items within each construct. In particular, the constructs' Cronbach's Alpha values are as follows: Consumer Engagement (CE) is 0.790, Consumer Purchase Intention (CPI) is 0.789, Image Search Functionality (IS) is 0.709, Automated After-Sales Service (AAS) is 0.713, Chatbot Efficiency (CB) is 0.791, and Recommendation System Efficiency (RS) is 0.753.

All constructs have Composite Reliability values (both rho_a and rho_c) above 0.70, which further supports the constructs' reliability and points to the excellent internal consistency of the items. The following are the constructions' Composite Reliability values: Rho_a and 0.793 are AAS values; Rho_a and 0.793 are CB values; Rho_a and 0.780 are CE values; Rho_a and 0.765 are CE values; Rho_a and 0.791 are CPI values; Rho_a and 0.708 are CPI values; IS values are 0.721 and 0.730 (rho_c) and RS values are 0.773 and 0.750 (rho_c). These findings attest to the high levels of internal consistency and reliability exhibited by each construct's components, which qualify them for more examination.

Convergent Validity, which calculates validity using Average Variance Extracted (AVE), was used to evaluate validity. AVE calculates the difference between the variation a construct captures and the variance caused by measurement error. An AVE value of more than 0.50 is regarded as sufficient. All of the constructs in this instance have AVE values more than 0.50, demonstrating strong convergent validity. The constructs have the following specific AVE values: AAS = 0.763, CB = 0.753, CE = 0.750, CPI = 0.730, IS = 0.706, and RS = 0.730.

	Cronbach's Alpha	**Composite Reliability (rho_a)**	**Composite Reliability (rho_c)**	**Average variance extracted (AVE)**
AAS	0.713	0.720	0.793	0.763
CB	0.791	0.714	0.780	0.753
CE	0.790	0.791	0.765	0.750
CPI	0.789	0.705	0.708	0.730
IS	0.709	0.721	0.730	0.706
RS	0.753	0.773	0.750	0.730

Table 4: Construct reliability and Validity

4.5 Discriminant Validity

Fornell-Larcker Criterion:

To make sure that every construct is conceptually and statistically truly different from other constructs, discriminant validity is assessed. By comparing the square root of the Average

Variance Extracted (AVE) of each construct with the correlations between that construct and all other constructs, the Fornell-Larcker criterion is used to evaluate discriminant validity. The square root of the AVE for Automated After-Sales Service (AAS) is 0.602. The square root of AAS's AVE is larger than its correlations with other items, showing that it has excellent discriminant validity. The correlations with other constructs are all lower (0.373, 0.341, 0.333, 0.305, and 0.256).

Sqrt of AVE for Chatbot Efficiency (CB) is 0.594. The other constructs (0.373, 0.321, 0.249, 0.414, 0.418) have correlations that are all lower than 0.594. This indicates that CB exhibits strong discriminant validity.

The square root of AVE for consumer engagement (CE) is 0.671. The square root of CE's AVE is larger than its correlations with other components, indicating that CE exhibits excellent discriminant validity. The correlations with other constructs are all lower (0.341, 0.321, 0.512, 0.410, 0.387).

The square root of AVE for Consumer Purchase Intention (CPI) is 0.574. There are less than 0.574 relationships with the other constructs (0.333, 0.249, 0.512, 0.358, and 0.351). Given that the square root of the CPI's AVE is higher than the correlations it has with other constructs, this suggests that the CPI has good discriminant validity.

The square root of AVE for Image Search Functionality (IS) is 0.637. Less than 0.637 is the correlation coefficient for each of the other constructs (0.305, 0.414, 0.410, 0.358, and 0.430). This indicates that IS has strong discriminant validity.

The square root of AVE for Recommendation System Efficiency (RS) is 0.575. Less than 0.575 is the correlation coefficient for each of the other constructs (0.256, 0.418, 0.387, 0.351, and 0.430). This suggests that the discriminant validity of RS is good.

Variable	AAS	CB	CE	CPI	IS	RS
AAS	0.602					
CB	0.373	0.594				
CE	0.341	0.321	0.671			
CPI	0.333	0.249	0.512	0.574		
IS	0.305	0.414	0.410	0.358	0.637	
RS	0.256	0.418	0.387	0.351	0.430	0.575

Table 5: Discriminant Validity Fornell-Larcker Criterion

4.6 Correlation Analysis

The correlation table sheds light on the connections between consumer engagement (CE), purchase intentions (CPI), and different AI tools. The intensity and direction of the association between two variables are shown by the Pearson correlation coefficient, which is represented by each value. The results indicate that effective automated after-sales service (AAS) is positively correlated with both consumer engagement (CE) at 0.341 and consumer purchase intentions (CPI) at 0.333. This suggests that AAS can positively influence both consumer engagement and purchase intentions. The connection between chatbot efficiency (CB) and CE (0.321) and CPI (0.249) is positive, but it is not as strong as those of other variables. This suggests that chatbots have a favorable influence on customer engagement and purchase intentions. The data indicates that there is a moderate positive association between image search functionality (IS) and both CE (0.410) and CPI (0.358). The correlation table sheds light on the connections between consumer engagement (CE), purchase intentions (CPI), and different AI tools. The intensity and direction of the association between two variables are shown by the Pearson correlation coefficient, which is represented by each value. The results indicate that effective automated after-sales service (AAS) is positively correlated with both consumer engagement (CE) at 0.341 and consumer purchase intentions (CPI) at 0.333.

This suggests that chatbots have a favorable influence on customer engagement and purchase intentions. The data indicates that there is a moderate positive association between image search functionality (IS) and both CE (0.410) and CPI (0.358). This suggests that consumers are more likely to engage with and make purchases when products are easily found through image search. The results indicate that tailored recommendations have a considerable impact on customer engagement and purchase intentions. The recommendation system efficiency (RS) has a moderate connection with both CE (0.387) and CPI (0.351). Furthermore, the very significant correlation of 0.512 between CE and CPI highlights the significance of consumer involvement in shaping purchasing intentions. The inter-correlations between the AI tools—for example, IS with RS (0.430) and CB with IS (0.414) and RS (0.418)—show that these technologies frequently cooperate to improve the user experience. The correlation study shows that, to differing degrees of influence, all AI solutions have a favorable effect on consumer engagement and purchase inclinations. Improving artificial intelligence (AI) technologies such as recommendation systems, chatbots, picture search, and after-sale services can raise customer engagement, which in turn increases customer buy intentions.

Variable	AAS	CB	CE	CPI	IS	RS
AAS	1.000	0.373	0.341	0.333	0.305	0.256
CB	0.373	1.000	0.321	0.249	0.414	0.418
CE	0.341	0.321	1.000	0.512	0.410	0.387
CPI	0.333	0.249	0.512	1.000	0.358	0.351
IS	0.305	0.414	0.410	0.358	1.000	0.430
RS	0.256	0.418	0.387	0.351	0.430	1.000

Table 6: Correlation Analysis

4.7 Collinearity Statistic (VIF) -Inner Model

To make sure that there are no strong intercorrelations between the predictor variables, multicollinearity was evaluated using the Variance Inflation Factor (VIF). All of the model's constructs have VIF values that are much below the 5-point cutoff, suggesting that multicollinearity is not a problem. This guarantees the stability and interpretability of the structural model's regression coefficients.The VIF value predicting Consumer Engagement (CE) for Automated After-Sales Service (AAS) is 1.205, showing low multicollinearity. In addition to showing minimal multicollinearity, Chatbot Efficiency (CB) has a VIF value of

1.412 when predicting CE. When predicting Consumer Purchase Intention (CPI), Consumer Engagement (CE) has a VIF score of 1.000, showing no multicollinearity.

When predicting CPI, Image Search Functionality (IS) has a VIF value of 1.367, which suggests low multicollinearity. In a similar vein, low multicollinearity is shown by the VIF score of 1.347 for Recommendation System Efficiency (RS) when it comes to CPI prediction.

In general, the VIF values verify that the model does not have a problem with multicollinearity. As a result, the structural model's regression coefficients are stable and comprehensible because the predictor variables—Automated After-Sales Service (AAS), Chatbot Efficiency (CB), Consumer Engagement (CE), Image Search Functionality (IS), and Recommendation System Efficiency (RS)—do not have strong intercorrelations.

Variable	CE	CPI
AAS	1.205	
CB	1.412	
CE		1.000
CPI		
IS	1.367	
RS	1.347	

Table 7: Collinearity Statistic

4.8 Coefficient of Determination R^2

The percentage of variance in the dependent variables that the independent variables in the model can account for is shown by the R-Square values. The R-Square value for consumer purchase intention (CPI) is 0.599, meaning that independent variables like consumer engagement and AI technologies may account for about 59.9% of the variance in consumer purchase intention. For CPI, the corrected R-Square value is 0.597. After adjusting for the number of predictors in the model, this adjusted value indicates that the model explains approximately 59.7% of the variance in Consumer Purchase Intention.

The R-Square value for Consumer Engagement (CE) is 0.732, meaning that the independent variables—AI tools, Automated After-Sales Service (AAS), and Chatbot Efficiency (CB)—

can account for roughly 73.2% of the variance in Consumer Engagement. CE has an adjusted R-Square value of 0.727. This adjusted result takes into consideration the number of predictors and shows that, after accounting for predictor count, the model explains approximately 72.7% of the variance in consumer engagement.

The models account for a significant portion of the variance in consumer engagement and purchase intention, according to the R-Square values. More specifically, 59.9% of the variance in consumer purchase intention and 73.2% of the variance in consumer engagement can be explained by the independent factors.

Variable	**R-square**	**R-square adjusted**
CPI	0.599	0.597
CE	0.732	0.727

Table 8: Coefficient of Determination

4.9 Path Coefficients and Hypothesis Testing

Hypothesis	**Relationship**	**T statistics**	**P values**	**Decision**
H1	**CB -> CE**	0.717	0.473	Rejected
H2	**IS -> CE**	3.059	0.002	Accepted
H3	**RS -> CE**	3.339	0.001	Accepted
H4	**AAS -> CE**	2.982	0.003	Accepted
H5	**CE -> CPI**	6.095	0.000	Accepted

Table 9: Path Coefficients and Hypothesis Testing

The path coefficients and hypothesis testing findings are shown in the table, which also shows the correlations between the different components in the model. The standard deviation, T statistics, P values, and the conclusion made with regard to the hypothesis are used to assess each relationship.

The standard deviation, T statistic, and P value for the association between Automated After-Sales Service (AAS) and Consumer Engagement (CE) are 0.064, 2.982, and 0.003, respectively. This hypothesis is accepted because the P value is less than 0.05 and shows that AAS significantly affects CE.

The standard deviation of the association between Chatbot Efficiency (CB) and Consumer Engagement (CE) is 0.091, and the T statistic is 0.717 with a P value of 0.473. Since the P value is higher than 0.05, the hypothesis is rejected. This implies that there is no discernible effect of CB on CE.

The standard deviation, T statistic, and P value for the association between Consumer Engagement (CE) and Consumer Purchase Intention (CPI) are 0.084, 6.095, and 0.000, respectively. Given that the P value is less than 0.05, the hypothesis is accepted and it can be concluded that CE has a significant impact on CPI.

The association between Consumer Engagement (CE) and Image Search Functionality (IS) has a P value of 0.002, a T statistic of 3.059, and a standard deviation of 0.077. This hypothesis is accepted since the P value is less than 0.05, indicating that IS has a significant impact on CE.

Lastly, the standard deviation, T statistic, and P value for the link between Recommendation System Efficiency (RS) and Consumer Engagement (CE) are 0.063, 3.339, and 0.001, respectively. Given that the P value is less than 0.05, the hypothesis is accepted and it is clear that RS has a significant impact on CE.

4.10 Total Indirect Effects

Relationship	T statistics	P values	Decision
AAS -> CPI	2.315	0.021	Accepted

CB -> CPI	0.800	0.424	Rejected
IS -> CPI	2.304	0.021	Accepted
RS -> CPI	2.739	0.006	Accepted

Table 10: Total Indirect Effects

The results of the overall indirect effects are shown in the table, which assesses the indirect impacts of several variables on Consumer Purchase Intention (CPI) through Consumer Engagement (CE). The standard deviation, T statistics, P values, and the conclusion made with regard to the hypothesis are used to evaluate each relationship.

The standard deviation, T statistic, and P value for the link between Automated After-Sales Service (AAS) and Consumer Purchase Intention (CPI) through Consumer Engagement (CE) are 0.042, 2.315, and 0.021, respectively. It is accepted that this hypothesis because the P value is less than 0.05. This suggests that AAS uses CE to indirectly affect CPI.

The standard deviation, T statistic, and P value of the link between Chatbot Efficiency (CB) and Consumer Purchase Intention (CPI) through Consumer Engagement (CE) are 0.042, 0.800, and 0.424, respectively. Since the P value is higher than 0.05, the hypothesis is rejected. This implies that CB does not significantly affect CPI indirectly through CE.

The standard deviation, T statistic, and P value for the link between Image Search Functionality (IS) and Consumer Purchase Intention (CPI) through Consumer Engagement (CE) are 0.052, 2.304, and 0.021, respectively. Given that the P value is less than 0.05, the hypothesis—which holds that IS indirectly affects CPI through CE—is accepted.

Lastly, the standard deviation is 0.039, the T statistic is 2.739, and the P value is 0.006 for the association between Recommendation System Efficiency (RS) and Consumer Purchase Intention (CPI) through Consumer Engagement (CE). Given that the P value is smaller than 0.05, the hypothesis that RS indirectly affects CPI through CE is accepted.

4.11 Mediation Effect

Specific Indirect Effect

Hypothesis	Relationship	T statistics	P values	Decision
H6a	**CB -> CE -> CPI**	0.800	0.424	Rejected
H6b	**IS -> CE -> CPI**	2.304	0.021	Accepted
H6c	**RS -> CE -> CPI**	2.739	0.006	Accepted
H6d	**AAS -> CE -> PI**	2.315	0.021	Accepted

Table 11: Specific Indirect Effect

The results of the individual indirect effects are shown in the table, which also looks at how different conceptions affect Consumer Purchase Intention (CPI) indirectly through the mediator, Consumer Engagement (CE). The standard deviation, T statistics, P values, and the conclusion made with regard to the hypothesis are used to assess each relationship.

The standard deviation, T statistic, and P value for the link between Automated After-Sales Service (AAS) and Consumer Purchase Intention (CPI) through Consumer Engagement (CE) are 0.042, 2.315, and 0.021, respectively. It is accepted that this hypothesis because the P value is less than 0.05. This suggests that through CE, AAS significantly influences CPI indirectly.

The standard deviation, T statistic, and P value of the link between Chatbot Efficiency (CB) and Consumer Purchase Intention (CPI) through Consumer Engagement (CE) are 0.042, 0.800, and 0.424, respectively. Since the P value is higher than 0.05, the hypothesis is rejected. This implies that CB does not significantly affect CPI indirectly through CE.

The standard deviation, T statistic, and P value for the link between Image Search Functionality (IS) and Consumer Purchase Intention (CPI) through Consumer Engagement (CE) are 0.052, 2.304, and 0.021, respectively. Given that the P value is less than 0.05, the hypothesis is accepted and it can be concluded that IS significantly influences CPI indirectly through CE.

Lastly, the standard deviation is 0.039, the T statistic is 2.739, and the P value is 0.006 for the association between Recommendation System Efficiency (RS) and Consumer Purchase Intention (CPI) through Consumer Engagement (CE). Given that the P value is less than 0.05, the hypothesis is accepted and it is clear that RS significantly influences CPI indirectly through CE.

Chapter 5: Discussion, Conclusion, and Recommendations

5.1 Discussion

The impact of AI tools on customer purchase intentions was the main topic of this study, with a focus on the mediating role of consumer interaction. AI technologies, such as Chatbot Efficiency (CB), Image Search Functionality (IS), Recommendation System Efficiency (RS), and Automated After-Sales Service (AAS), were the independent variables in this study. Consumer Engagement (CE) served as the mediator, and Consumer Purchase Intention (CPI) served as the dependent variable.

The results show that AI tools and consumer engagement are positively correlated, and this positively correlates with purchase intentions. In particular, AI-driven features that enhance user interactions—like automated after-sales services and recommendation systems—have made the service more effective and user-friendly. The study of quantitative data resulted in the approval of multiple hypotheses. The association between AI tools like AAS, IS, and RS and CPI is mediated by CE, which is significantly improved by these techniques. This mediation suggests that these AI products' increased customer engagement has a direct impact on consumers' buying intentions.

All of the constructs exhibited moderate variability and a minor left skewness, according to the evaluation of data normalcy, which qualified the data for additional statistical analysis. A broad sample was guaranteed by the demographic research, which also offered insights into how various groups view and are influenced by AI tools when making purchases.

Additionally, the correlation between consumer involvement and AI tools is good and consistent with earlier research. The capacity of artificial intelligence (AI) systems to deliver tailored recommendations and effective customer support greatly raises customer satisfaction and engagement. These results support the idea that AI-powered solutions improve customer experiences by being more responsive and tailored, which is important for building consumer loyalty and boosting buy intentions.

5.2 Conclusion

Although there is some fluctuation and a small left-skewness in the replies, the overall trend is constant across all measured variables, indicating stable and comparable perceptions, according to the findings of the data normality tests. The results are made even more reliable and generalizable by the demographic analysis of the respondents, which comprised a broad sample with a range of age groups, educational levels, and work situations. The high values of Composite Reliability and Cronbach's Alpha attest to the constructions' exceptional dependability and internal consistency. All of the constructs' AVE values are greater than 0.5, indicating significant convergent validity, which shows that the constructs fairly represent the ideas being measured.

The study's conclusions demonstrate the profound effect that AI tools have on customer engagement and purchasing intentions. Particularly, it has been demonstrated that AI-driven features like recommendation engines, automated after-sale services, and picture search capabilities increase customer engagement, which in turn favorably affects purchase intentions. This is consistent with other research showing that effective and personalized AI services increase customer loyalty and happiness (Sharma & Goyal, 2022; Nguyen et al., 2023).

The robustness of the research model is validated by significant R2 values and robust reliability and validity measures. These results show that, through the mediating effect of customer involvement, AI tools have a considerable impact on consumer purchase intentions. The findings, in particular, show that whereas certain AI technologies may not have a major direct impact on purchase intentions, they do have a considerable indirect impact through customer interaction. This emphasizes how consumer interaction plays a critical role as an intermediary variable in the link between purchase intents and AI technologies.

Organizations must concentrate on improving AI functions that directly increase consumer engagement if they want to properly use AI solutions. This entails making recommendation system algorithms more responsive, customized, and user-friendly, as well as optimizing chatbot systems and picture search capabilities. Increasing the correlation between these AI technologies and customer involvement can greatly increase the likelihood that customers will make a purchase. To sustain high levels of engagement and happiness, the report advises organizations to invest in cutting-edge AI technology and regularly upgrade them based on customer feedback.

With a diversified sample guaranteed by the demographic analysis, thorough insights into how various consumer groups view and are influenced by AI tools in their purchasing decisions are provided. This is consistent with other research that highlights the significance of demographic variables in comprehending customer behavior in digital environments (Iqbal, 2023).

All things considered, the study emphasizes how important AI tools are to raising user engagement and buy intents. These findings underscore the necessity of strategic investment in AI technologies and offer managers and decision-makers in the service industry useful information. Businesses may stand out in a crowded market, draw in more clients, and grow their market share by concentrating on AI-driven innovations. Furthermore, the beneficial effects of AI on consumer engagement and purchase intents can guide operational and strategic planning decisions, assisting companies in boosting sales and customer happiness.

The study emphasizes the necessity of ongoing observation and input to improve AI tools and guarantee they successfully satisfy user needs. This customer-focused strategy can greatly improve the entire customer experience and increase buy intents when paired with frequent updates and enhancements to AI functionalities. For organizations hoping to prosper in the digital age, investing in cutting edge AI technology and integrating them with conventional customer service channels is essential.

This study offers thorough proof that the use of AI tools greatly increases consumer engagement, which in turn influences purchase intentions in a favorable way. The empirical investigation highlights the significance of effective and personalized AI-driven services in raising customer satisfaction levels and cultivating brand loyalty. The results underscore the importance of making targeted investments in artificial intelligence (AI) technologies and stress the pivotal role that customer involvement plays as a mediator in the association between purchase intentions and AI tools. This study adds to the amount of information already available on the effects of AI on consumer behavior by providing insightful information for both researchers and practitioners.

5.3 Theoretical Implications

Through an examination of the complex interaction between AI tools and customer purchase intents, mediated via consumer involvement, this research brings important theoretical contributions to the field of consumer behavior and technology adoption. This study expands on our understanding of how technology affects consumer behavior and decision-making processes by integrating AI tools like chatbot efficiency, image search functionality, recommendation system efficiency, and automated after-sales service within the framework of well-established consumer behavior theories.

The incorporation of AI technologies into the theoretical models of consumer behavior is a significant theoretical contribution of this research. Prior research has predominantly concentrated on conventional elements that impact consumer behavior, including individual preferences, societal influences, and marketing tactics. However, the focus of this study is on how sophisticated AI tools influence consumer outcomes and experiences. In doing so, it expands on current theories to take into consideration the quickening pace of technology breakthroughs that are changing the face of the consumer market.

The study's conclusions emphasize how important consumer interaction is as a mediating factor in the connection between consumer purchase intentions and AI tools. This realization gives theoretical models that describe how technology affects consumer behavior a fresh perspective. Customer involvement has historically been seen as a direct result of marketing initiatives and customer happiness. However, this research presents user engagement as a crucial middleman that arises from useful AI tools and has a major impact on purchase intentions. This sophisticated comprehension contributes to the improvement of current ideas by illuminating the indirect channels via which technology influences consumer choices.

Furthermore, by providing a thorough theoretical framework that incorporates concepts from both consumer psychology and artificial intelligence, this research closes the gap between the two fields. The study assesses how effective different AI tools are in raising customer engagement and offers actual data on how these tools affect customer satisfaction and interactions. This multidisciplinary approach shows how technology elements can have a significant impact on psychological processes including decision-making, involvement, and trust, which enriches theoretical viewpoints.

The study adds to the body of knowledge on technology adoption by examining the particular features of AI technologies. It highlights the significance of unique AI capabilities in influencing customer experiences, such as the proactive support offered by chatbots, the ease of use of picture search features, the customization of recommendation systems, and the dependability of automated after-sales services. By highlighting the specific characteristics of AI tools that encourage customer interaction and consequent purchase intentions, these insights contribute to the improvement of technology adoption models.

Furthermore, in the context of contemporary digital settings, this research offers a theoretical foundation for comprehending the dynamic interaction between technology and consumer behavior. It suggests that customer involvement acts as a vital link between consumer purchase intents and the effectiveness of AI solutions. This claim not only improves on current theoretical frameworks but also opens up new avenues for investigating the function of involvement in various technological contexts, which will facilitate future studies.

To sum up, this research adds a number of noteworthy theoretical insights to the study of consumer psychology, technology adoption, and behavior. The research provides a thorough and sophisticated theoretical framework by fusing AI tools with theories of consumer behavior, emphasizing the mediating function of customer interaction, and bridging the gap between technological and psychological perspectives. This approach contributes to our knowledge of the ways in which AI technologies impact consumer behavior and offers a solid basis for further theoretical and empirical research in this quickly developing field.

5.4 Managerial Implications

This study has important ramifications for managers and decision-makers in the service sector. The research emphasizes how crucial it is to include AI technologies in order to boost customer engagement and encourage buy intentions. Supervisors ought to give priority to investing in AI and make sure their teams are prepared to use these resources efficiently. Furthermore, strategic planning and operational enhancements can benefit from AI's good effects on consumer engagement and purchasing intentions. Businesses may stand out in a crowded market, draw in more clients, and grow their market share by concentrating on AI-driven innovations.

It's critical for firms to use AI tools to increase customer engagement. Enhancing AI features like picture search and recommendation systems, as well as chatbot optimization, can greatly increase customer satisfaction and loyalty. It is essential to make ongoing investments in cutting-edge AI technology and to regularly update them in response to user input. Employers should put special emphasis on educating staff members about the advantages and disadvantages of integrating and using AI solutions. Using a strategy that is focused on the demands of the customer and customizing AI-powered services can improve the user experience overall and encourage purchases.

5.5 Limitation & Future Research Directions

5.5.1 Limitations

Geographic Restrictions: The study is limited to Islamabad. Even while there is a high internet penetration rate and a high number of active digital users in the Islamabad , the results might not apply to Pakistan's smaller cities or rural areas where consumer behavior and the use of AI tools may differ. Sample Size and Demographics: Despite the use of stratified and random sampling techniques to guarantee a representative sample, resource limitations keep the sample size restricted to a specific number of respondents. It's possible that the sample's age, gender, and educational attainment do not accurately reflect Pakistan's overall Internet user population. Self-Reported Data: The data used in this study came from surveys that asked respondents to provide self-reported information. Biases including reaction, recall, and social desirability biases may affect self-reported statistics. Cognitive biases among respondents may cause them to overestimate or underestimate their opinions and actions.

Design: Using a cross-sectional methodology, the study gathers data at a certain point in time. The ability to determine causation or track changes in customer behavior over time is limited by this architecture. Longitudinal research would be required to examine the dynamics of AI-driven marketing and its effects on consumer purchase intentions over an extended period of time. Changing Digital Landscape Quickly: AI marketing tactics and digital platforms change quickly. The results of this study may become out of date as new technologies are developed and customer preferences shift because they are based on the utilization of AI tools as of right now. Subsequent investigations have to consistently revise and substantiate the results within the framework of developing digital patterns.

Platform-Specific Bias: Although the study intends to incorporate a variety of digital platforms, there might be an underlying bias in favor of those that are more widely used or easily available at the time of data collection. This bias may affect how well the results generalize to other digital environments. Variability in AI Tools: Although a range of AI tools are included in the study, there may be significant differences in the classification and impact of these diverse AI application types. A highly customized AI tool may have a very different effect than a more general AI application. Complexity of Measuring Engagement: Measuring abstract phenomena with several facets, like the effectiveness of AI tools and consumer engagement, requires intricate components. Even with the use of validated scales, respondents' perceptions and reporting of these variables are still prone to subjectivity, which can affect the validity and reliability of the results.

Cultural Context: Pakistan's distinct social conventions, values, and consumer habits may be the study's cultural setting. These cultural elements may have an impact on how well AI-driven marketing works as well as how well the results translate to different cultural settings.

5.5.2 Future Directions

Expand Extend Geographical Scope: In order to give a more thorough picture of how AI tools are used and how consumers behave across different geographies, future research might extend to smaller cities and rural areas.

Boost Sample Size: More varied demographics and larger sample numbers would enhance the findings' generalizability.

Longitudinal Research: Longitudinal research can be used to better understand how AI tools affect consumer engagement and purchase intentions over the long run.

Emphasis on Emerging technology: Research in the future should constantly update and validate results in light of novel and cutting-edge artificial intelligence technology.

Cross-Cultural Comparisons: Research conducted in diverse cultural contexts may shed light on the ways in which cultural elements affect the efficacy of AI-driven marketing.

Platform-Specific Research: Studies that concentrate on particular digital platforms may be able to shed light on the preferences and behaviors of users on those platforms.

Detailed Analysis of AI Tool Variability: To further understand the unique effects of various AI tool types on customer engagement and purchase intentions, future research might examine the effects of these tools in greater detail.

Improved assessment Methods: Future research findings would be more robust if more accurate and dependable assessment methods were developed for abstract dimensions like engagement and AI tool efficiency.

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Annexture 1

Chatbot efficiency (CB)

	SD	D	N	A	SA
The chatbot on the electronic commerce platform is available all the time.	1	2	3	4	5
Anytime I log on to the platform, I get pop-up notifications from a chatbot.	1	2	3	4	5
The requirement I type in the pop-up chat box returns beneficial results.	1	2	3	4	5
I can easily communicate with the chatbot.	1	2	3	4	5

Image search functionality (IS)

	SD	D	N	A	SA
The image search function is easy to use.	1	2	3	4	5
I can search for a product by pointing my camera at it or scanning a saved image on my device.	1	2	3	4	5
The result from the image search matches the item I need.	1	2	3	4	5
I don't need keyword or text searches when I use the image search function.	1	2	3	4	5

Recommendation system efficiency (RS)

	SD	D	N	A	SA
I get product recommendations based on my previous searches.	1	2	3	4	5
I get product recommendations based on my previous purchases.	1	2	3	4	5
The products recommended on the platform are products that I am interested in.	1	2	3	4	5
I do not spend too much time searching for products.	1	2	3	4	5

Automated after-sales service (AAS)

	SD	D	N	A	SA
I get automatic feedback requests after my purchase.	1	2	3	4	5
Any ambiguity in products I buy or intend to buy is handled promptly.	1	2	3	4	5
If I need the product replaced or refunded, there is an automated step-by-step process.	1	2	3	4	5
I am aided by guidance and prompts in the entire buying cycle.	1	2	3	4	5

Consumer Engagement

	SD	D	N	A	SA
I often visit pages of brands I follow on social networking sites.	1	2	3	4	5
I often read posts of brands I follow on social networking sites.	1	2	3	4	5
I often use the “like” option on brands posts; I follow on social networking sites.	1	2	3	4	5
I often comment on brands pages on social networking sites.	1	2	3	4	5
I follow brands pages of my interest to get information (e.g., new products).	1	2	3	4	5

Consumer Purchase Intention

	SD	D	N	A	SA
Using social networking sites of brands help me make decisions better before purchasing goods and services.	1	2	3	4	5
Using social networking sites of brands increase my interest in buying products and services.	1	2	3	4	5
I am very likely to buy products or services recommended by my friends on social networking sites.	1	2	3	4	5
I will definitely buy products as marketed on brands’ social networking sites, I follow.	1	2	3	4	5
I intend to purchase products as marketed on brand’s social networking sites, I follow.	1	2	3	4	5

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