OPTIMIZATION OF CONSUMER ENGAGEMENT WITH ARTIFICIAL INTELLIGENCE ELEMENTS ON ELECTRONIC COMMERCE PLATFORMS

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ABSTRACT

Artificial intelligence (AI) is reshaping the online shopping experience. However, there is limited information on consumers' interaction with AI elements embedded in electronic commerce (e-commerce) platforms and the behavioral outcomes of such interactions. AI application studies have focused on consumers' reluctance to use AI-powered services due to failed machine-human conversations. On the contrary, this study exploits the bright side of AI applications in e-commerce. It applies the stimuli-organism-response (S-O-R) paradigm to examine the effects of AI elements on consumer engagement attitudes, beyond purchase intentions, towards e-commerce platforms. Specifically, it examined the impact of chatbot efficiency, image search functionality, recommendation system efficiency, and automated after-sales service on consumer engagement. Furthermore, the study examined the moderating role of consumers' attention to the social comparison of consumption choices on the relationships between the AI capability elements and consumer engagement. The partial least square-structural equation modeling (PLS-SEM) approach was employed in analyzing 464 responses collected via an online survey from consumers of different e-commerce platforms. The findings indicate that AI capability elements, directly and indirectly, attract consumers' observable engagement behaviors. Also, attention to social comparison dampens the positive effects of chatbot efficiency and automated after-sales service on behavioral engagement. In contrast, it positively moderates the impact of recommendation system efficiency. The study contributes to academia by introducing consumers'

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attention to social comparison to advance the understanding of consumer engagement with AI applications in e-commerce. Practitioners can gain insight into improving consumer experience on e-commerce platforms.

Keywords: AI capability elements; Chatbot; Image search; Recommendation system; Automated after-sales service

1. Introduction

The recess of physical businesses, implementation of physical contact restrictions, and social distancing rules by governments around the world due to the COVID-19 outbreak altered the mode of operations of many firms. The outbreak forced firms to adapt their business model by infusing the existing electronic modus operandi (electronic commerce). Externally, electronic commerce (e-commerce) improved firms' interactions with their stakeholders. Most firms halted their physical shopping enterprises and initiated or strengthened their online presence by migrating to existing e-commerce platforms. According to the United Nations Conference on Trade and Development (UNCTAD) 2021 report, global e-commerce suddenly increased by 4% in 2020 compared to 2018, indicating the growing importance of online activities as the dramatic rise in e-commerce, including business-to-business (B2B) and business-to-consumer (B2C) sales (UNCTAD, 2021).

Despite the shift in demand from brick-and-mortar retail to e-commerce, some e-commerce firms performed more than others in digital inclusion. E-commerce firms like Alibaba, Amazon, JD.com, and Pinduoduo were the top four B2C e-commerce companies in 2020 based on the gross merchandise value (GMV) (UNCTAD, 2021). Companies like Expedia, Booking holdings, and Airbnb experienced sharp declines in their 2020 GMV compared to 2019 (UNCTAD, 2021). The top-ranking e-commerce firms performed well in digital inclusion due to their competence in Artificial Intelligence (AI) capability (Mikalef and Gupta, 2021). AI has evolved as a technology priority, enabled by big data, for most e-commerce firms over the past few years (Davenport et al., 2018). The application of AI has witnessed over a 300% increase in the past few years and delivers potential business value (Howard and Rosewell-Jones, 2019). The application of AI on e-commerce platforms is overdue for exploration and analysis. However, the critical concern rests in the interactive efficiency of AI applications on e-commerce platforms to boost the satisfaction of consumers' perceived needs. It is evident from the IS literature that e-commerce platforms build competitive advantage through their unique (hardly imitable) capabilities (Bharadwaj, 2000; Gupta and George, 2016; Kohli, 2008; Schryen, 2012). Previous reports on AI applications stress the requirement of human and organizational resources to deliver AI capability value (Chui and Malhotra, 2018; Davenport et al., 2018; Ransbotham et al., 2018). Most studies on AI applications in e-commerce have focused on the adoption (Jenkins, 2003) and the application technicalities (Khrais, 2020; Song et al., 2019) with less attention to the consumer-AI application interaction efficiency (Cheng et al., 2022; Luo et al., 2019); thus, not fully comprehending the bright side of AI application in e-commerce. The end-users (consumers) of the application expect a satisfactory experience from their interactions with new technological applications on e-commerce platforms.

In bridging this gap, the current study, from the consumers' perspective, builds on previous research to evaluate the specific sophisticated technologies and structures on e-commerce platforms as AI capabilities that draw positive consumer engagement attitudes. Specifically, this study evaluates chatbots, image search, recommendation systems, and after-sales services as AI elements on an e-commerce platform and how well they interact with consumers to attract positive unobserved (psychological) and observed (behavioral) engagement attitudes. This study draws on the stimuli-organism-response (S-O-R) model to examine how the AI elements (S) initiate behavioral engagement attitudes (R) from consumers based on their psychological engagement (O) and attention to social comparison. The organism, psychological engagement, refers to a consumer's positive, fulfilling, and e-commerce platform-related state of mind characterized by dedication, absorption, and vigor resulting from the consumers' interaction with the AI elements on the platform. The response, behavioral engagement, refers to consumers' continued observable interaction with the e-commerce platform induced by their experience with the AI elements present on the platform and their positive platform-related state of mind. This study attempts to answer the question: *"How does the application of AI on e-commerce platforms attract positive engagement attitudes from consumers?"*

This study draws on the IT capabilities and AI applications literature in information system research. Also, we developed a survey instrument to quantify consumers' satisfaction with the AI capabilities and the effects on consumer engagement attitudes by adhering to the scale development guidelines established in the management information system literature (MacKenzie et al., 2011).

The rest of the article is organized as follows. The next section briefly introduces relevant literature on the S-O-R model, consumer engagement, and the background of e-commerce platforms selected for the study. The explanations for the AI constructs for this study, hypotheses, and the study's conceptual framework are then developed. The methodology is then explained, followed by the result of the analysis and its interpretation. Finally, we discuss the findings and highlight the study's implications, limitations, and directions for future research.

2. Literature Review

2.1. The Stimuli-Organism-Response Paradigm

This study's theoretical foundation rests on applying the Stimuli-Organism-Response (S-O-R) paradigm. The paradigm's development resulted from the extension of human internal mental evaluation of an environment (Nunthiphatprueksa and Suntrayuth, 2018). It suggests that an individual's exposure to external factors in an environment (S) triggers inner emotions (O), which then leads to a resulting behavior (R) (Asante et al., 2019; Mehrabian and Russell, 1974). In the fields of information systems and e-commerce, a significant volume of S-O-R-based studies has undoubtedly backed website attributes (for instance, website aesthetics, website security features, website interactivity, and navigability) as external factors with the tendency to trigger several approach behaviors from consumers (Amirpur and Benlian, 2015; Asante et al., 2019; Chen et al., 2017; Fang et al., 2017). An e-commerce platform, comparable to commercial websites, is a multi-feature platform on which a combination of its attributes can initiate consumer engagement attitudes resulting from perceived interaction experiences. To support this, Peters et al. (2016) posited that software quality attributes such as ease of use, flexibility, and attractiveness influence mobile business intelligence usage through psychological engagement. An online shopping study by Asante et al. (2019) also found that the quality of electronic services experienced by consumers during an online shopping transaction influences consumer psychological and behavioral engagement. These findings support the validity of the S-O-R paradigm examining consumer engagement. They provide facile and structured guidance to develop an integrated framework exhibiting how consumers' satisfaction with the AI elements applied on an e-commerce platform will initiate unobserved and observed engagement attitudes from them.

The S-O-R paradigm refers to stimuli as circumstantial indications external to individuals with several manifestations through attention attraction. It is agreed upon that website attributes related to quality, like the design or other characteristics, are the significant environmental factors that cause psychological evaluation processes leading to behavioral responses. For instance, a study by Zhang et al. (2014) conceptualized technological attributes represented by perceived interactivity, perceived personalization, and perceived sociability as stimuli (S) that influence purchase intentions (R) indirectly through benefit evaluation (O) by consumers. Analogous to prior research, this study operationalizes AI application elements on e-commerce platforms - reflected by the Chatbot feature, Image Search function, Recommendation System, and Automated After-Sales Service - as environmental stimuli (S). These stimuli effectuate consumers' innate affective and cognitive evaluation recoils (O). These internal affective and cognitive evaluations will, in turn, invoke observable behavioral engagement attitudes (R). We further investigate moderating effects of different levels of consumers' attention to social comparison consumption on the relationships between the AI application elements and consumer engagement.

2.2. Consumer Engagement

Researchers from different fields have studied the concept of consumer engagement. These fields are marketing, information systems, service management, social psychology, and organizational behavior. The traditional association of consumer engagement with constructs such as loyalty, trust, and satisfaction (Cheung et al., 2015; Oh et al., 2017) has triggered debates and disagreements on the definition and dimensionality of the construct. Researchers have studied consumer engagement mainly from three different perspectives, despite the controversies and varied conceptualizations surrounding the concept. Studies have examined consumer engagement from a motivational psychological perspective (Peters et al., 2016; Ray et al., 2014), a psychological process perspective (Bowden, 2009), and behavioral manifestations perspective (Doorn et al., 2010). From the psychological process perspective, studies posit engagement as a psychological process that influences consumer retention and loyalty, therefore suggesting a fusion of the motivational psychological perspective and the behavioral manifestation perspective (Bowden, 2009). However, due to its complexity, researchers suggest a multidimensional approach to effectively measure the consumer engagement concept. For a complete comprehension of the engagement concept in the context of AI applications on e-commerce platforms, this study examined both psychological and behavioral.

Inspired by the works of Asante et al. (2020), Fang et al. (2017), and Schaufeli et al. (2002), this study interprets psychological engagement as the level of a consumer's positive, fulfilling, and e-commerce platform-related state of mind defined by dedication, absorption, and vigor; as a result of the consumers' interaction with the AI elements present on the platform. Consumer dedication represents their inspiration and enthusiasm towards e-commerce platforms due to their interaction with the AI application elements. Absorption explains consumers' concentration and immersion in the e-commerce platform without measuring the passage of time. Finally, vigor is the consumers' level of mental resilience, and energy whiles conduction a transaction or surfing on the e-commerce platform. Psychological engagement happens when consumers interact with AI applications to satisfy their intrinsic needs.

Previous studies support this definition by focusing on the less observable and more inherent nature of the psychological engagement construct (Ramey et al., 2019; Ruiz-Fernández et al., 2021). The psychological engagement construct has been defined as individuals' cognitive, affective, and relational attitudes formed during an activity (Ramey et al., 2019). Ruiz-Fernández et al. (2021), in the context of violent video games, posited that unobservable factors, including presence, flow, and immersion, define psychological engagement. The S-O-R paradigm considers the organism as the mediator for the relationship between the stimuli and the response. It establishes the organism as the internal cognitive and affective attitudes. Therefore, psychological engagement in this study represents the unobservable organism in the model that mediated the relationship between the AI application elements and behavioral engagement.

On the other hand, this study defines behavioral engagement as a consumer's continued observable interaction with the e-commerce platform due to their experience with AI elements present on the platform and their positive platform-related state of mind. The conceptualization of consumer engagement by several studies supports the definition of the concept in the current study (Brodie et al., 2013; Doorn et al., 2010). The behavioral engagement construct is acknowledged as consumers' interaction in a virtual brand community (Brodie et al., 2013) and behavioral manifestations beyond the purchase process, resulting in observable brand-related attitudes (Doorn et al., 2010). Behavioral engagement in this study, inspired by Asante et al. (2020) and Verhagen et al. (2015), is characterized by consumer retention (consumers' decision to continue using the e-commerce platform), referrals (referring friends and family to the e-commerce platform), Word of Mouth (WOM: telling friends and family about the AI-enhanced services on the e-commerce platform), and information generation (writing reviews about service experience with the e-commerce platform) following a satisfied interacting with the AI application elements on the e-commerce platform. Contrary to psychological engagement, behavioral engagement is the observable behaviors consumers perform on an e-commerce platform induced by their interactions with the AI application elements on the platform. The S-O-R defines the response as the reaction from consumers to the stimuli they have been exposed to, explained by the presence of formed internal cognitive and affective attitudes. Behavioral in this study, therefore, represents the observable behavioral reactions of consumers on an e-commerce platform after a perceived experience with the AI application elements on the platform.

2.3. The State of the E-commerce Platforms

The e-commerce market has evolved significantly over the past few years, revolutionizing the traditional commerce system for firms and consumers. Through the development of cutting-edge technologies, Chinese Internet giants have made a real run to become the top e-commerce platforms in China (Chou, 2019). Many e-commerce platforms, through the applications of AI, have developed and improved their platforms to adapt to the demanding and progressing needs of Chinese consumers whiles making transactions very easy and faster to complete (Agency, 2021). E-commerce sales in China reached $1.8 billion in 2020, primarily driven by sales from Taobao and Tmall (Ma, 2021). However, the share of these two e-commerce platforms is shrinking as the market diversifies and more e-commerce platforms are improving their AI application features. In 2021, a list of the top e-commerce platforms (Tmall, Pinduoduo, JD.com, Kaola, Xiao hong shu, Taobao, VIP, and Suning) in China was presented based on persistent improvement and application of cutting-edge AI technologies on these platforms (Agency, 2021).

2.4. AI and Electronic Commerce

The advancement in Science and Technology has improved the maturity of AI technology and has dramatically refashioned the way of life of individuals, especially in e-commerce. AI technology has progressively evolved as a powerful tool to optimize transaction operations on e-commerce platforms. Some studies have examined AI's "dark side" from end-user perspectives (Hornung and Smolnik, 2021; Zarifis et al., 2020). Zarifis et al. (2020) investigated AI applications on health insurance platforms and found that individuals have low trust and privacy concerns when AI is applied visibly on websites. Hornung and Smolnik (2021) studied employees' reactions toward introducing personal virtual assistants based on AI in the workplace. They found that threat emotions are the drawbacks of AI-based technological applications in organizations. However, AI applications have ensured innovational patterns for the development of e-commerce and promise an infinite directional value to e-commerce (Song et al., 2019). AI technology relies on machine learning primarily. With the help of machine learning, AI applications can undertake automatic operations regarding transactions on e-commerce platforms. In e-commerce, AI applications are reflected in intelligence assistants (chatbots), recommendation engines, intelligent logistics, optimal pricing, and optimal pricing systems (Adam et al., 2020; Song et al., 2019). This study, however, focuses specifically on the online shopping platform aspect of e-commerce, therefore, examining specific AI application elements on such e-commerce platforms. The study evaluates the relationships between the *chatbot*, *image search*, *recommendation system*, and *automated after-sales service* elements of AI application and consumer engagement. It further assesses the strength of the relationship between the elements and consumer engagement at different levels of consumers' *attention to social comparison of consumption*.

3. Hypotheses Development

3.1. Chatbot and Consumer Engagement

An AI-based chatbot is a specific kind of conversational software agent designed for a turn-by-turn human conversation with users of a web-based platform (Adam et al., 2020). E-commerce websites use chatbots to improve customer support service, where consumers can tell their requirements in the provided chat box and be served with significantly filtered responses (Gnewuch et al., 2017). Chatbots are conversational agents that appear as chat box prompts upon visiting any recognized e-commerce website with the AI-based chatbot feature (Pfeuffer et al., 2019). The prompts initiate conversation starters like "How can I help you?", providing consumers with human-like conversations in these chat box prompts with the help of the AI-based chatbot enhancement (Adam et al., 2020; Gnewuch et al., 2017). Chatbots collect and utilize consumers' past data to tailor personalized user experiences. According to Luger and Sellen (2016), website conversational software agents may create a gap between consumers' expectations and system performance arising from inappropriate responses to consumers' requests. Therefore, the question of the chatbot's continued effectiveness was unresolved. As a resolution, Adam et al. (2020) explored the characteristics of chatbots that improve the likelihood of users' compliance with chatbot requests for service feedback through a survey study. Notably, AI chatbots for e-commerce have become increasingly sophisticated as of late, being able to conduct more human-like conversations and give more thoughtful, informative answers. The importance of chatbots as a significant AI element in improving consumer transaction experience has been confirmed by previous studies (De Cicco et al., 2020; Tsai et al., 2021; Xu et al., 2022). The social presence nature of chatbots ensures perceived 'parasocial' interaction and dialogue that improves consumer experience (Tsai et al., 2021) and satisfaction (Xu et al., 2022). It increases users' perception of social presence (De Cicco et al., 2020).

According to the S-O-R model, when an individual is exposed to environmental characteristics (S), they initiate some levels of cognitive and affective actions (O) that, in turn, cause observable behavioral attitudes (R) (Nunthiphatprueksa and Suntrayuth, 2018). Several S-O-R-based studies have also supported the claim that factors external to an individual in an environment are causalities of consumer behavior through unobserved affective processes (Amirpur and Benlian, 2015; Chen et al., 2017). In the context of e-commerce, this study evaluates the attributes of AI-based chatbots (S) that increase consumers' psychological (O) and behavioral engagement (R) attitudes toward the e-commerce platform. This study defines the chatbot as the sophisticated human-like conversations held in the chat box when consumers log on to e-commerce platforms. Upon perceiving a satisfying experience from interactions with a chatbot on an e-commerce platform, consumers are likely to remain permanent users, write reviews about their transaction experience, and talk about the platform's AI-enhanced services to family and friends, referring them to the platform. We, therefore, hypothesize that:

H1a: *Chatbot efficiency positively influences consumers' behavioral engagement.*

H1b: *Chatbot efficiency positively influences consumers' psychological engagement.*

H1c: *Consumers' psychological engagement positively mediates the relationship between chatbot efficiency and behavioral engagement.*

3.2. Image Search and Consumer Engagement

Embedding different forms of AI in e-commerce is to simplify the understanding of consumer requirements and behavior and ensures an improved consumer experience (Mikalef and Gupta, 2021). Image search is a form of AI element in e-commerce platforms that allows consumers to search for products using images instead of text (Dagan et al., 2021; Gawali, 2020). Consumers come across a situation where they are interested in some products but do not know the products' names; AI service solves this problem. The concept of image search, powered by artificial intelligence, allows buyers to conduct product searches based on images. Mobile applications of some E-commerce websites can search for products by pointing the camera toward the item of interest, eliminating the need for keyword searches (Dagan et al., 2021; Sudarsan et al., 2022). Consumers do not have the patience to surf a catalog of thousands of products using traditional text-based searches.

Traditionally, consumers use text-based search to describe products they like; however, they often do not find the exact match in the search results (Sudarsan et al., 2022). For instance, when consumers try to find a jacket with a specific texture or sunglasses with a unique pattern. Traditional text-based searches or product category filtering are incredibly time-consuming and often unsuccessful. Consumers are more likely to give up on a purchase when results from product searches are unsatisfactory, reducing retention rate and continuous interaction with the firm. A large percentage of studies investigating image search has been focused on e-commerce (Dagan et al., 2021), and most such investigations are into the varied architecture of the image search functionality (Li et al., 2018; Yang et al., 2017; Y. Zhang et al., 2018, 2019). These studies have established the relevance of image search functionality to consumer behavior in e-commerce. For instance, Zhang et al. (2019) examined the effect of the relevance of image search results on user click behavior. In this study, we define image search as an AI element that reduces the time consumed searching for a product. Image search is an AI-based search option with an exact or close match to a searched product which leads to an improved search result, a positive effect on consumer retention, and continuous observable interactions with the e-commerce platform. It is a feature on an e-commerce platform that is external to consumers (S) with the ability to attract a behavioral engagement (R) from consumers based on their satisfaction with the feature's efficiency and their psychological engagement (O) with the e-commerce platform. We, therefore, hypothesize that:

H2a: *A satisfactory image search result positively affects consumers' behavioral engagement.*

H2b: *A satisfactory image search result positively affects consumers' psychological engagement.*

H2c: *Consumers' psychological engagement positively mediates the relationship between image search and behavioral engagement.*

3.3. Recommendation System and Consumer Engagement

The application of AI makes it possible for e-commerce platforms to habitually display products similar to what consumers have just browsed (Schafer et al., 2001). AI algorithms predict consumers' behavior based on their previous product purchases and searches. From the AI perspective, the recommendation system is a learning problem based on preliminary user surfing data (Lops et al., 2011). An AI-powered recommendation system on an e-commerce website uses machine learning to predict and recommend products of high interest to consumers based on previous searches (Chinchanachokchai et al., 2021; Wei et al., 2007). The recommendation system is possible through data collection regarding consumers' inquiries and purchase histories. It assists in product recommendations to consumers when they go on the e-commerce platform or the website. Through intelligent consumer profiling, the recommendation system helps tailor the e-commerce platform to specific consumers with a more personalized search result (De Keyzer et al., 2022; Sivapalan et al., 2014).

The recommendation system increased the rate of consumer retention and increased traffic on e-commerce platforms (Chinchanachokchai et al., 2021). This study defines the recommendation system as an AI application on e-commerce platforms that improves the consumer experience by significantly reducing the hassle of spending hours on finding products. A satisfactory experience gives consumers a feeling of absorption and dedication to the e-commerce platform. Hence, convincing them to build a positive e-commerce platform-related state of mind (psychological engagement behaviors) and triggering observable behavioral attitudes (behavioral engagement) toward the e-commerce platform. The recommendation system is the environmental stimuli that attract consumers' behavioral engagement (R) based on their psychological engagement (O) with the e-commerce platform. From the above discussion, we hypothesize that:

H3a: *The recommendation system positively influences consumers' behavioral engagement.*

H3b: *The recommendation system positively influences consumers' psychological engagement.*

H3c: *Consumers' psychological engagement mediates the relationship between the recommendation system and behavioral engagement.*

3.4. Automated After-Sales Service and Consumer Engagement

E-commerce platform transactions do not end with consumers' purchases. Businesses have to aid consumers through the entire transaction cycle. According to the CXPA (2018), applying an effective service throughout the journey of a consumer leads to significant benefits for organizations. After-sales service refers to the assistance given to consumers regarding all necessary information after a product has been bought (Daqar and Smoudy, 2019). Many organizations turn after-sales services into a competitive advantage by embedding automated conversations, automatically processing phone calls into separate classifications, process and automation, and proactive actions (Daqar and Smoudy, 2019). According to Khan and Iqbal (2020), organizations delivering superior services should adopt AI to tackle issues that significantly impact the consumer experience.

This study defines automated aftersales services as the AI element in e-commerce that automate the feedback request form directed to consumers' purchases; to tackle product replacement issues, resolve product ambiguity, and transaction notifications (for instance, payment, dispatch, and delivery confirmations). These automated services serve as an external stimulus that consumers interact with on the e-commerce platform. The positive experiences from these services are expected to convert consumers into loyal advocates who execute observed behavioral engagement (R) and unobserved psychological engagement attitudes (O), thus, improving the value of the e-commerce platform. Based on the above discussion, we hypothesize that:

H4a: *Automated after-sale service positively impacts consumers' behavioral engagement.*

H4b: *Automated after-sale service positively impacts consumers' psychological engagement.*

H4c: *Psychological engagement of consumers positively mediates the relationship between automated after-sale service and behavioral engagement.*

3.5. Psychological Engagement and Behavioral Engagement

Consumer engagement is a loyalty-related relationship that primarily focuses on commitment and trust through consumers' continuous interaction with a firm (Oh et al., 2017; Sashi, 2012). Previous studies on consumer engagement in the context of e-commerce have posited that the concept is a process that begins with a psychological attitude formation, leading to behavioral attitudes toward e-commerce firms (Asante et al., 2019; Peters et al., 2016; H. Zhang et al., 2015).

This paper defines 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. Consumers form unobserved platform-related psychological engagement when they are satisfied with their experience of AI elements in e-commerce; these attitudes, in turn, lead to observed behavioral engagement attitudes toward the e-commerce platform. Based on the explanation above, we hypothesize that:

H5: *Consumers' psychological engagement positively influences their behavioral engagement.*

3.6. The Moderating Role of Attention to Social Comparison-Consumption (ASC)

This term refers to an individual's awareness and sensitivity to the reactions of other consumers concerning their own consumption choices or behaviors (Lennox and Wolfe, 1984). The underlying assumptions of the concept are that individuals who try to avoid negative evaluations adhere significantly to social cues, and individuals with low self-esteem generally conform to the pressures of social norms, intending to prevent disapproval (Lennox and Wolfe, 1984). Studies have shown that individuals with high ASC are less likely to share transaction experiences when they consume products tagged as "less prestigious" brands by social rating (Kim et al., 2014; Lin et al., 2014). For instance, a consumer may enjoy a satisfying transaction experience from an e-commerce platform and yet be hardly triggered to perform any observed behavioral engagement attitude. The decision to not engage is because the product they purchased is considered "inferior" (concerning brand name) by society, therefore refraining from sharing transaction experience to avoid faux pas. Consumers' ASC, therefore, plays a vital role in the engagement formation process. Consumer behavioral researchers were faced with the issue of explicitly clarifying the circumstances under which normative influences play an essential part regarding behavioral intentions. Over the past years, studies have applied ASC as a factor associated with consumer behaviors (Asante et al., 2019; Phua et al., 2017; Yoon et al., 2016). A study by Yoon et al. (2016) investigated the moderation effect of ASC on the relationship between interactions with public service advertisements and individuals' savings behavior. In the context of SNSs, Phua et al. (2017) examined the moderating effect of ASC on the relationship between the frequent use of social media platforms and brand community-related outcomes. In the context of e-commerce, Asante et al. (2019) investigated how ASC moderated the effect of consumer satisfaction with online shopping platforms' service quality on their engagement formation. As demonstrated by Bearden and Rose (1990), individuals high (vs. low) ASC individuals; worry about being judged by others regarding their purchases, attach great importance to interpersonal considerations in buying branded products, and adhere more to the preferences of their peers during consumption choices. Thus, confirming the significant role played by consumers ASC in affecting the engagement process.

In this study, ASC refers to consumers' level of attention to society's evaluation of their consumption choices and their sensitivity in maintaining congruence to avoid societal embarrassment. In this study, the concept defines the extent to which an individual will reduce or prevent behavioral engagement attitudes toward an e-commerce platform due to society's evaluations despite perceived satisfaction of the AI elements.

Consumers who pay more attention to social comparison of consumption choices will be reluctant to engage in behavioral attitudes toward the e-commerce platform, reducing the strength of the effect of AI elements and psychological engagement on behavioral engagement. Given that consumers with high (vs. low) ASC might have interacted and perceived a satisfying experience with the chatbot feature, image search function, personalized recommendation system, and automated after-sales services on the e-commerce platform during a transaction. However, the product involved in the transaction is socially considered an "inferior brand." Hence, such consumers will be reluctant to write a review, post a comment or make recommendations (behavioral engagement) about their transaction as they try to avoid embarrassment from society's evaluation of their consumption choices. Additionally, consumers with high (vs. low) ASC that formed dedication, absorption, and immersive attitudes (psychological engagement) during their interaction with the AI elements on the e-commerce platform are more likely to reduce their behavioral engagement willingness. Despite the psychological engagement (unobservable attitudes) formed by such consumers, they will be reluctant to engage in observable behavioral attitudes due to their "less prestigious" product consumption choices. We, therefore, hypothesize that:

H6a-H6d: *High consumer ASC negatively moderates the impact of AI elements on behavioral engagement.*

H7: *High consumer ASC negatively moderates the impact of psychological engagement on behavioral engagement.*

Figure 1 displays a summary of the hypothesized relationships.

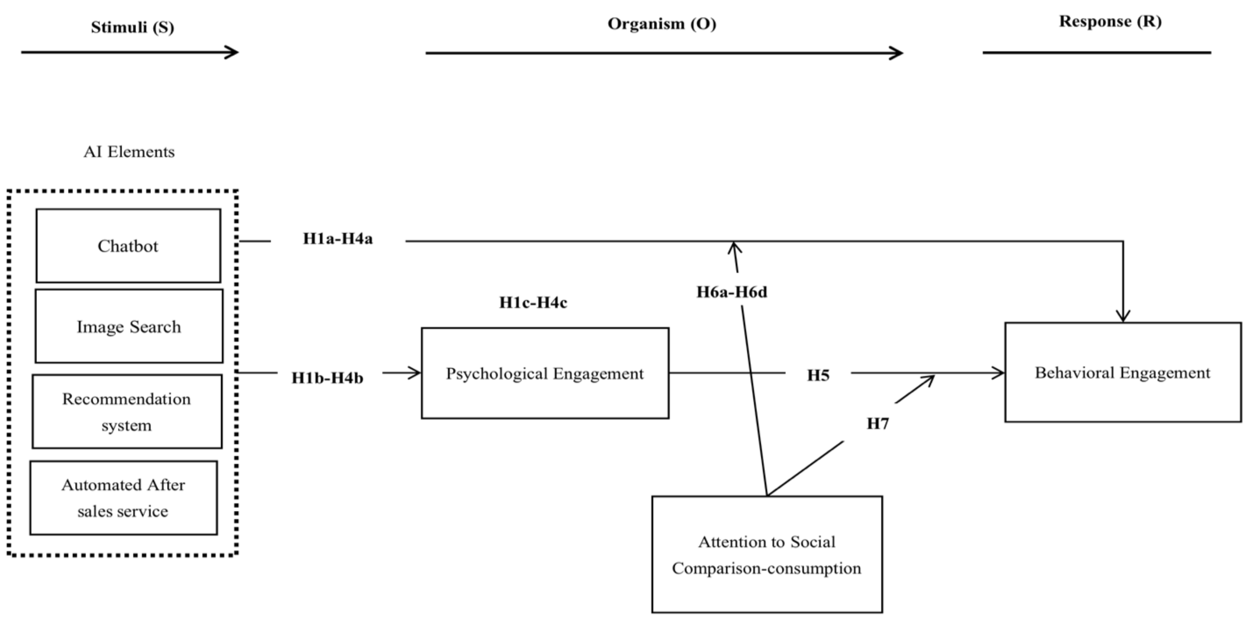


Figure 1: Conceptual Framework

4. Methodology

4.1. Data Collection

The current study used an online questionnaire to gather data from the target respondents. According to Evans and Mathur (2005), a survey questionnaire is an authentic instrument for collecting an individual's attitude and behavior-related data. University students in China who have made at least one purchase on e-commerce platforms in China were eligible for participation. This eligibility requirement relies on considering that University students are mostly 18 years and above, have a basic understanding of how an e-commerce platform works, and possess purchasing power (Quoquab et al., 2018). Questionnaires were distributed through a hyperlink and a QR code through WeChat private messaging and user-created groups to reach more respondents since WeChat is a leading social media and messaging app in China (Brennan, 2017). A study by Sutikno et al. (2016) posited that individuals prefer social media messaging apps due to their easy accessibility and extensive participation among users in user-created groups. The survey yielded 464 completed and usable responses to conduct the analysis.

4.2. Data Sample

The study adopted a judgmental sampling technique in gathering the data to run the analysis. Theoretical generalizability was preferred over population generalizability; therefore, choosing a non-probability was acceptable (Calder et al., 1981). By considering three specific factors, the "A priori": minimum required sample size was computed using power analysis in the G*Power software; setting the desired power, statistical level of significance (alpha), and effect size at <0.80, >0.05, and ≥0.15 respectively (Cohen, 1988). The output parameters from the power analysis suggested a sufficient sample size of 103. Thus, the sample size of 464 responses used for this study was proven acceptable.

4.3. Measurement

The study constructs were measured on a seven-point Likert scale ranging from 1 (strongly disagree) to 7 (strongly agree). As presented in Appendix 1, the four-item scale used to measure chatbot (CB) was adapted from Adam et al. (2020). The four-item scale to measure image search (IS) was adapted from Sudarsan et al. (2022). This study adapted the four-item scale from Chinchanachokchai et al. (2021) to measure the recommendation system (RS). The four-item scale for measuring the automated after-sale service (AAS) construct was adapted from Daqar and Smoudy (2019). The four items used to measure consumers' attention to social comparison (ASC) were adapted from Asante et al. (2019). The item scale used to measure the psychological engagement (PE) and behavioral engagement (BE) constructs were adapted from Fang et al. (2017). As the respondents were primarily Chinese, a bilingual scholar proficient in English and Chinese first translated the items from English to Chinese. Another bilingual scholar conducted a back-translation version (Chinese to English) to ensure that the measurement item scales in the Chinese version are similar to the English version and accurately measure the same constructs. Two scholars from the management information system department confirmed the validity and clarity of the survey items, after which we pre-tested the questionnaire with 40 graduate students to finalize the clarity of the survey items.

4.4. Common Method Variance

Common method variance (CMV) is a method bias that arises from critical issues in the measurement scales of a specific construct (Podsakoff et al., 2003). The Harman single-factor test, using principal component analysis with no rotation, was adopted to investigate the presence of method bias and ensure the absence of CMV threats in the survey dataset. The test result indicated less than 50 percent of the total variance explained by the first factor, concluding that CMV did not pose a threat in this study. In addition, a full collinearity test was conducted to rule out CMV issues (Kock, 2015). The result shows that values of variance inflation factor (VIF) fell below 3.3, confirming the absence of method bias in this study.

4.5. Demographics of Respondents

The respondents' demographic data, as presented in Table 1, shows that all respondents included in the study have had experience on an e-commerce platform (100%), with most of them having greater online transactions (76.3) than offline transactions. Regarding the platforms, the respondents mostly frequented Taobao/Tmall (37.1%), and the most consumed product type was groceries (26.1%).

Table 1: Demographic Profile of Respondents

Characteristics	Category	Frequency	Percentage (%)
Transaction experience	Yes	464	100
	No	0	-
Usage frequency	Greater online transactions	354	76.3
	Lesser online transactions	110	23.7
Most used platforms	VIP	4	0.9
	Little red book (xiao hong shu)	2	0.4
	JD.com	142	30.6
	Kaola	2	0.4
	Pinduoduo	96	20.7
	Taobao/Tmall	172	37.1
	Suning	41	8.8
	Other	5	1.1
Product type	Groceries	121	26.1
	Apparel	106	22.8
	Electronic	100	21.6
	Home appliances	12	2.6
	Education accessories	41	8.8
	Other	84	18.1

5. Data Analysis

The Partial Least Squares-Structural Equation Modeling (PLS-SEM) technique using the SmartPLS software was employed to analyze the hypothesized conceptual framework (Ringle et al., 2015). This technique was chosen because the study's objective was to achieve greater statistical power regarding the sample size. Acquiring a higher statistical power renders PLS-SEM particularly suitable for investigating the current study's research question`. Secondly, using PLS-SEM enables the estimation of our model from a combination of predictive and explanation perspectives (Hair et al., 2017). Finally, the current study estimates mediating and moderating effects among the relationships between seven distinct variables, with each variable having multiple measuring scales, making the model relatively complex; thus, the motivation behind choosing PLS-SEM (Hair, Sarstedt, et al., 2017; Matthews, 2017). SmartPLS software was used due to its benefits of creating, validating, and calculating models in management science (Sander, 2014). The software can accommodate complex models with varied relationships (Hair et al., 2017) and predict the dependent constructs whiles maximizing their variance (Chin and Marcoulides, 1998). The software also fits scenarios where knowledge of the structural model relationships is less (Henseler et al., 2009). The study confirmed the reliability and validity by testing the measurement model and then examined the significance of the path coefficient by testing the structural model (Anderson and Gerbing, 1988).

5.1. Model Fit Assessment

According to Müller et al. (2018), assessing the model in terms of goodness of fit is the first step in data analysis. The fit assessment result will determine the extent of discrepancies between the theoretical model and the correlation matrix of the empirical model (Henseler et al., 2016). The standardized root-mean-square (SRMR) is primarily used in the PLS context with an acceptable value of 0.08 or less (Hu and Bentler, 1999). An SRMR value was generated for the saturated model using the PLS algorithm; the result presented a value of less than 0.08, thus, meeting the requirement of the goodness of fit.

5.2. Measurement Model

The measurement model must meet a reliability and validity assessment standard before testing the structural model, as it represents the varied relationships between the latent constructs and their indicators (Jamil et al., 2018; Quoquab et al., 2020). The assessment is subjected to the results of the indicator reliability (IR) test, internal consistency reliability test (values from composite reliability, Cronbach's alphas, and Dijkstra-Henseler's "rho_A"), convergent validity test (values from average variance extracted), and discriminant validity (using the Fornell-Larcker criterion) (Cepeda-Carrion et al., 2019; Fornell and Larcker, 1981; Hair et al., 2016; Henseler et al., 2014; Quoquab and Mohammad, 2020). According to Hair et al. (2017), the outer loadings of the construct indicators must be 0.70 and above to establish indicator reliability (IR). The values of composite reliability (CR), Cronbach's alphas (CA), and "rho_A" must be greater than 0.70 to confirm internal consistency reliability (Müller et al., 2018). To confirm discriminant validity, each latent variable's square root of average variance explained (AVE) must be larger than other correlation values among the latent variables (Fornell and Larcker, 1981). We further checked the heterotrait-monotrait ratio of correlations (HTMT) to support the discriminant validity established. The HTMT method examines the average correlation between indicators across constructs relative to average correlations between indicators of the same construct (Henseler et al., 2015). An HTMT value less than the strictest criterion of 0.85 confirms discriminant validity (Henseler et al., 2015). Finally, the threshold for ascertaining a convergent validity is an AVE of 0.50 (Bagozzi and Yi, 1988).

In Table 2, the factor loadings were all greater than 0.70; CR, CA, and "rho_A" values were higher than 0.70, and the AVE values for all latent variables were greater than 0.50. Therefore, the measurement model for this study was confirmed to be valid and reliable. The square root of AVE for all latent constructs, as presented in Table 3, was larger than other correlation values among the latent variables, thus establishing discriminant validity. Table 4 shows the highest HTMT value of 0.801 (lower than the strictest criterion), indicating adequate discriminant validity.

Table 2: Reliability and Convergent Validity

Latent variables	Indicators	Loadings	CA	"rho_A"	CR	AVE
CB	CB1	0.925	0.903	0.936	0.930	0.769
	CB2	0.826				
	CB3	0.825				
	CB4	0.926				
IS	IS1	0.834	0.792	0.820	0.865	0.817
	IS2	0.881				
	IS3	0.825				
	IS4	0.893				
RS	RS1	0.861	0.943	0.944	0.959	0.855
	RS2	0.959				
	RS3	0.963				
	RS4	0.913				
AAS	AAS1	0.939	0.961	0.963	0.972	0.896
	AAS2	0.964				
	AAS3	0.956				
	AAS4	0.928				
ASC	ASC1	0.879	0.900	0.928	0.931	0.772
	ASC2	0.725				
	ASC3	0.942				
	ASC4	0.950				
PE	PE1	0.947	0.951	0.952	0.968	0.911
	PE2	0.958				
	PE3	0.959				
BE	BE1	0.848	0.960	0.963	0.972	0.896

	BE2	0.984				
	BE3	0.982				
	BE4	0.966				

Table 3: Fornell-Larcker Discriminant Validity Criterion

	CB	IS	RS	AAS	ASC	PE	BE
CB	**0.877**						
IS	0.571	**0.903**					
RS	0.635	0.672	**0.925**				
AAS	0.620	0.701	0.718	**0.947**			
ASC	0.628	0.676	0.699	0.741	**0.879**		
PE	0.555	0.632	0.653	0.638	0.662	**0.955**	
BE	0.663	0.643	0.724	0.693	0.654	0.633	**0.946**

Notes: Discriminant validity is established if the square root of AVE (on the diagonal in bold) is greater than inter-correlations between latent constructs (off the diagonal)

Table 4: Heterotrait-Monotrait of Correlations

	CB	IS	RS	AAS	ASC	PE	BE
CB	1.000						
IS	0.658	1.000					
RS	0.674	0.668	1.000				
AAS	0.654	0.801	0.735	1.000			
ASC	0.684	0.689	0.693	0.779	1.000		
PE	0.589	0.560	0.529	0.519	0.606	1.000	
BE	0.681	0.536	0.792	0.542	0.698	0.445	1.000

HTMT value below 0.85 indicates an established discriminant validity

5.3. Hypotheses Testing

A collinearity test is required to precede a structural model assessment. The values of the variance inflation factor (VIF) should be lower than 5 (that is, a tolerance level of 0.2 or higher) to confirm the absence of collinearity issues (Hair et al., 2011; Hair et al., 2017). Before examining the hypotheses, a collinearity test was conducted. The VIF values from the collinearity test ranged from 1.557 to 1.915, with the lowest tolerance at 0.522, as presented in Table 5. The in-sample predictive power of the model was then ascertained with the coefficient of determination (R2) (Becker et al., 2013). According to Cohen (1988), R2 values of 0.02, 0.13, and 0.26 are considered weak, moderated, and strong, respectively. The structural model of this study produced R2 values of 0.881 (BE) and 0.763 (PE), indicating that the independent variables in the model substantially explained 88.1% and 76.3% of the variance in BE and PE, respectively (see Figure 3). The size and significance of the path coefficient were examined with a 5000 resample and 0.05 significance level bootstrap, as suggested by (Hair et al., 2017). The result in Table 6 shows that CB (c1'= 0.123; t = 3.678; $p < 0.001$), IS (c2' = 0.128; t = 3.366; $p < 0.05$), RS (c3' = 0.164; t = 4.379; $p < 0.001$), AAS (c4' = 0.239; t = 3.827; $p < 0.01$), and PE (β = 0.128; t = 2.561; $p < 0.05$) have a positive effect on BE. Additionally, CB (α_1' = 0.123; t = 2.075; $p < 0.05$), IS (α_2' = 0.305; t = 2.792; $p < 0.01$), RS (α_3' = 0.246; t = 3.031; $p < 0.01$), and AAS (α_4' = 0.153; t = 3.827; $p < 0.01$) have a positive effect on PE. Therefore, hypotheses H1a → H4a, H1b → H4b, and H5 are supported.

Table 5: Collinearity Assessment

Latent Variables	VIF	Tolerance	Collinearity problem
CB	1.715	0.583	No
IS	1.915	0.522	No
RS	1.721	0.581	No
AAS	1.557	0.642	No
PE	1.647	0.607	No
ASC	1.574	0.635	No

Note: VIF ≤ 5 (tolerance level ≥ 0.2) = absence of collinearity problems (Hair, Sarstedt, et al., 2011)

Table 6: Results of Hypothesized Direct Effects

Hypotheses	Relationship	Path coefficient	t-statistics (|O/STDEV|)	f^2	Decision
H1a	CB → BE	0.123	3.678***	0.183	Supported
H2a	IS → BE	0.128	3.366*	0.151	Supported
H3a	RS → BE	0.164	4.379***	0.353	Supported
H4a	AAS → BE	0.239	3.827**	0.155	Supported
H1b	CB → PE	0.123	2.075*	0.158	Supported
H2b	IS → PE	0.305	2.792**	0.069	Supported
H3b	RS → PE	0.246	3.031**	0.168	Supported
H4b	AAS → PE	0.153	3.827**	0.163	Supported
H5	PE → BE	0.153	2.561*	0.171	Supported

Notes: Path is significant at t-statistics > 1.96 and p < 0.05 (NS p>0.05, * p<0.05, ** p<0.01, *** p<0.001. $f^2 \geqq 0.02$ (small effect); $f^2 \geqq 0.15$ (medium effect); $f^2 \geqq 0.35$ (large effect) (Aguinis et al., 2005)

The effect size of the relationship between the constructs was then examined using the f2 values to weigh the practical relevance and magnitude of the significant effect, as suggested by (Benitez et al., 2020). The result from the hypothesized relationships presented in Table 6 shows f2 values ranging from 0.069 to 0.353 (weak to large) (Cohen, 1988). The blindfolding procedure in SmartPLS was finally conducted to assess Stone-Geisser's predictive relevance (Q2). Hair et al. (2017) argued that an exogenous construct has a small, medium, and large predictive relevance if the Q2 values are 0.02, 0.15, and 0.35, respectively. Fornnel and Cha (1994) also argued that a model has predictive relevance for endogenous variables if a Q2 is larger than 0. This study's analysis indicated that PE and BE have substantial predictive relevance with Q2 values of 0.687 and 0.798, respectively.

5.3.1. Mediation Effect

The study followed Preacher and Hayes' (2008) procedure in testing the mediating effect of PE. The procedure required a 5000-resample bootstrap of the indirect effect, and the result, as presented in Table 7, indicated that the hypothesized indirect effects are significant. PE significantly mediated the effects of CB ($\alpha_1\beta = 0.064$; t = 3.062; p < 0.01; 95% Boot CI: [0.051 → 0.131]), IS ($\alpha_2\beta = 0.116$; t = 3.325; p < 0.001; 95% Boot CI: [0.029 → 0.221]), RS ($\alpha_3\beta = 0.221$; t = 4.335; p < 0.01; 95% Boot CI: [0.057 → 0.279]), and AAS ($\alpha_4\beta = 0.128$; t = 3.668; p < 0.01; 95% Boot CI: [0.052 → 0.179]) on BE. Therefore, hypotheses H1c → H4c are supported.

Table 7: Results of Hypothesized Mediation Effects

Hypotheses	Relationship	Path coefficients	t-statistics (|O/STDEV|)	95% (BootLLCI → BootULCI)	Decision
H1c	CB → PE → BE	0.064	3.062**	0.051 → 0.131	Supported
H2c	IS → PE → BE	0.116	3.325***	0.029 → 0.221	Supported
H3c	RS → PE → BE	0.221	4.335**	0.057 → 0.279	Supported
H4c	AAS → PE → BE	0.128	3.668**	0.052 → 0.179	Supported

Notes: Path is significant at t-statistics > 1.96; 95% BootLLCI → BootULCI excluding 0; p < 0.05 (NS p>0.05, * p<0.05, ** p<0.01, *** p<0.001.

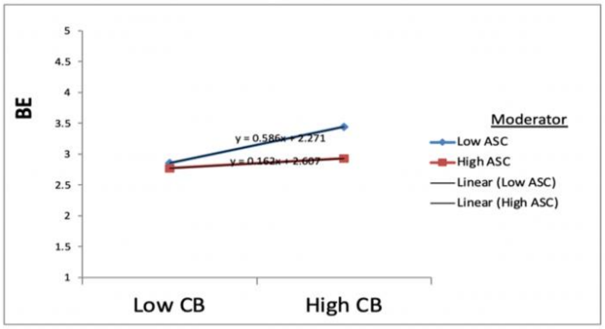
Table 8: Results of Hypothesized Moderating Effects

Hypotheses	Relationship	Interaction effect	t-statistics (|O/STDEV|)	95% (BootLLCI → BootULCI)	Decision
H6a	Moderated CB → BE	-0.106	2.384*	-0.217 → -0.042	Supported
H6b	Moderated IS → BE	0.116	1.177(NS)	-0.119 → 0.274	Not supported
H6c	Moderated RS → BE	0.265	2.292*	0.008 → 0.472	Opposite
H6d	Moderated AAS → BE	-0.255	2.125*	-0.549 → -0.019	Supported
H7	Moderated PE → BE	0.013	0.126(NS)	-0.050 → 0.339	Not supported

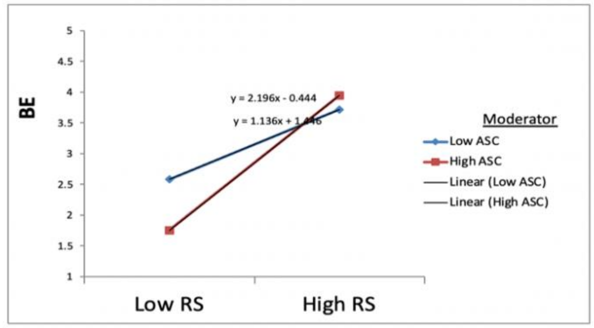
Notes: Path is significant at t-statistics > 1.96; 95% BootLLCI → BootULCI excluding 0; p < 0.05 (NS p>0.05, * p<0.05, ** p<0.01, *** p<0.001

5.3.2. Moderating Effect

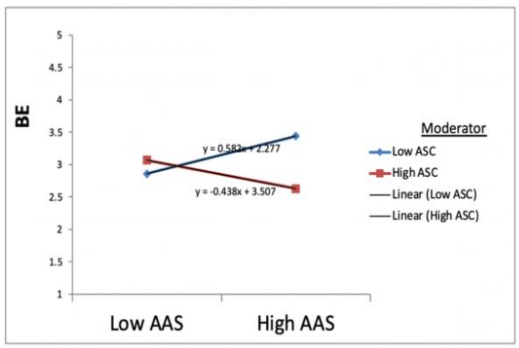
In testing the moderating effect of ASC, the study employed the two-stage approach suggested by (Henseler and Fassott, 2010). Table 8 presents the outcome of the moderation analysis. ASC has significant moderating effects on the positive impacts of CB (X_1W= -0.106; t = 2.384; p < 0.05; 95% Boot CI [-0.217 → -0.042]) and AAS (X_4W= -0.255; t = 2.125; p < 0.05; 95% Boot CI [-0.549 → -0.019]) on BE; supporting H6a and H6d respectively. ASC dampens the positive effect of CB and AAS on BE. On the other hand, the moderating effects of ASC were not significant on the positive impact of IS (X_2W= 0.116; t = 1.177; $p > 0.05$; 95% Boot CI [-0.119 → 0.274]), and PE (M_1W= 0.013; t = 1.126; $p > 0.05$; 95% Boot CI [-0.050 → 0.339]) on BE; thus, rejecting H6b and H7. Contrary to expectations, ASC positively moderated the relationship between RS (X_3W= 0.265; t = 2.292; $p < 0.05$; 95% Boot CI [0.008 → 0.472]) and BE; hence opposite to H6c. ASC strengthens the positive effect of RS on BE. The significant interaction effects of ASC are presented in the simple slope diagram in Figure 2 and the structural model results are presented in Figure 3.



ASC dampens the positive relationship between CB and BE



ASC strengthens the positive relationship between RS and BE



ASC dampens the positive relationship between AAS and BE

Figure 2: Interaction Slopes of Significant Moderation Effects

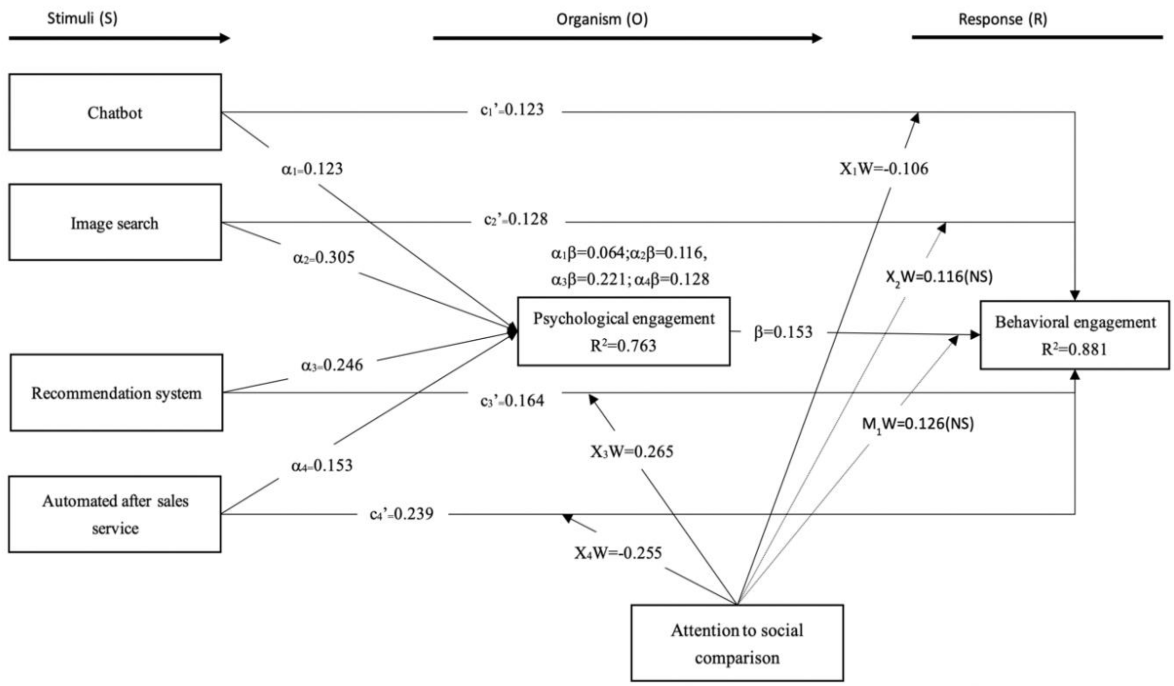


Figure 3: Structural Model Results

6. Discussion

The results reveal that the AI elements on the e-commerce platforms all significantly and positively affect consumers' psychological and behavioral engagement. The study aimed to answer the research question, "How does the application of AI on e-commerce platforms attract positive consumer engagement attitudes." The results demonstrate that chatbot efficiency, image search functionality, efficient recommendation system, and automated after-sales services are critical AI capability elements for attracting behavioral engagement attitudes from consumers. As hypothesized, chatbot efficiency is strongly associated with psychological engagement (0.123) and behavioral engagement (0.123), indicating that perceived chatbot efficiency can attract consumers' positive psychological and behavioral engagement. Furthermore, image search functionality is strongly associated with consumer behavioral (0.128) and psychological (0.305) engagement, demonstrating the crucial role of reduced product search time in motivating consumers' engagement with e-commerce platforms. In addition, the outcome of this study revealed a strong positive relationship between recommendation systems and psychological engagement (0.246) and behavioral engagement (0.164), respectively. Automated after-sales service is strongly associated with psychological (0.153) and behavioral (0.239) engagement. These findings indicate that enhancing the consumer experience with a personalized transaction system and automated support services will attract positive consumer engagement with the e-commerce platform. These results are different from the findings of previous studies. Singaraju et al. (2022) found no significant relationship between personalized web searches (recommender system) and consumer response. Zarifis et al. (2020) posited reduced consumer participation resulting from the explicit implementation of AI-enabled services on electronic service platforms. Cheng et al. (2021) investigated the good and bad sides of big data analytics (BDA) and AI technology implementations in a ridesharing platform and found adverse effects of the "dark side" of BDA and AI on passenger participation. Finally, the findings demonstrated a positive relationship between psychological and behavioral engagement (0.153), indicating that consumers will demonstrate observable behaviors when forming a positive platform-related state of mind based on their experience with AI elements. The result is similar to Asante et al. (2020), who posit that consumers' psychological engagement will directly lead to behavioral attitudes.

Interestingly, the findings support the mediating effect of psychological engagement through the AI elements and the behavioral engagement links. Notably, consumers' observable behaviors, like writing reviews and making recommendations, can be enhanced when the interaction experience with the AI elements is satisfactory; however, this enhancement is partly possible because consumers have a positive platform-related state of mind. These results agree with the S-O-R paradigm (Mehrabian and Russell, 1974; Nunthiphatprueksa and Suntrayuth, 2018; Ruiz-

Fernández et al., 2021). AI elements will attract behavioral engagement from the consumer; however, this attraction is partly explained by psychological engagement. However, the positive mediating effect of psychological engagement is different from the findings of Cheng et al. (2021). They found no significant mediating effect of perceived risk (a psychological construct) on the relationship between their BDA and AI-related privacy control and passenger participation (a behavior construct) on ridesharing platforms.

As expected, the positive effects of chatbot efficiency and automated after-sales services on behavioral engagement attitudes were dampened by consumers' attention to social comparison with interaction effects of X_1W= -0.106 and X_4W= -0.255, respectively. These findings suggest that consumers with high attention to social comparison of consumption are less willing to engage in observable behaviors, despite satisfying chatbots and automated after-sales service interactions experience on the e-commerce platform. These findings are similar to the works of Kim et al. (2014) and Asante et al. (2019).

On the contrary, consumers' attention to social comparison strengthened the positive relationship (X_3W = 0.265) between recommendations system efficiency and behavioral engagement. Consumers with high attention to social comparison of consumption are more willing to engage in behavioral attitudes when satisfied with their experience with the recommendations system. A possible explanation is that an efficient recommendation system reduces the time consumers spend surfing an e-commerce platform. Consumers enjoy a personalized transaction experience with product recommendations based on their interests; therefore, they are more willing to post and talk about such experiences. This result contradicts studies by Lin et al. (2014) and Kim et al. (2014), who posit that individuals with high attention to social comparison are less likely to share transaction experiences. However, attention to social comparison of consumption did not moderate the effects of image search functionality and psychological engagement on behavioral engagement. A possible explanation will demonstrate observable behaviors on the e-commerce platforms as long as they are satisfied with the image search functionality and have a positive platform-related state of mind.

6.1. Implication for Theory

The study contributes significantly to information system research, the literature on AI technologies, and this Special Issue. First, the study expands the knowledge on electronic commerce research by examining AI technology applications on e-commerce platforms that drive consumer engagement. The relevant literature review reveals that AI technology research focuses mainly on AI adoption and application technicalities (Jenkins, 2003; Khrais, 2020). This study provides a comprehensive understanding of consumers' interactions with AI technologies adopted and applied in the e-commerce. Mainly, our research explores the bright side of AI elements on e-commerce platforms by examining the significance of chatbot efficiency, image search functionality, recommendation system efficiency, and automated after-sales services as the antecedents of consumer engagement. In the setting of an e-commerce platform, we investigate consumers' perceived experience from their interactions with the AI elements and the consequences of the interactions on engagement behaviors.

Second, the study evaluates the consumer engagement construct as an attitude formation process to investigate the consumers' unobservable and observable behaviors induced by interactions with the AI elements. The consumer engagement construct has been studied as a process of attitude formation toward service quality on shopping platforms (Asante et al., 2019). This study contributes to the body of knowledge on consumer engagement by examining it as a process of beginning with unobservable attitude formation (psychological engagement), leading to observable attitude formation (behavioral engagement). Specifically, we employed the S-O-R paradigm to examine psychological engagement as an explanatory factor for the indirect effect of consumers' interaction with the AI elements on their behavioral engagement.

Finally, this study extended the S-O-R model's context of an organism mediating the effects of stimuli on a response by introducing a second organism. However, the introduced organism is evaluated as strengthening or weakening the positive impact of the stimuli on the response. Mainly, attention to the social comparison was introduced as an external organism to the S-O-R model to moderate the strength of the impact on behavioral engagement caused by consumers' interaction with the AI elements on e-commerce platforms. The findings provided some significant moderating roles played by the construct and allowed for further investigation of the construct in different AI application contexts.

6.2. Implication for Practice

This study aims to assist e-commerce stakeholders in comprehending the AI application elements that consumers find most beneficial and enhance their transaction experience. The results of this study will further inform e-commerce platform operators on how to effectively ascertain consumers' psychological and behavioral engagement by writing reviews on social media, referring friends to the e-commerce platform, and becoming permanent consumers of the platform. E-commerce platforms should enhance AI elements that directly or indirectly attract consumers' behavioral engagement attitudes. The following specific practical implications are noted.

First, the findings of this study suggest that recommendation system efficiency possesses the most apparent effect on behavioral engagement. Thus, e-commerce firms must tailor the platform to specific consumers with a more personalized search result through intelligent consumer profiling to attract more observable behavioral engagement from consumers. E-commerce platforms can enhance the recommendation system by using machine learning algorithms that have significant predictive relevance to recommend products of high interest to consumers based on their search histories. Therefore, consumer experience will improve by significantly reducing time spent on product search and increasing engagement behaviors.

Second, psychological engagement notably explained the indirect effects of all the AI elements on behavioral engagement. This result indicates that the chatbot efficiency, image search functionality, efficient recommendation system, and automated after-sales services attract observable behavioral engagement partially through consumers' positive platform-related state of mind. Therefore, e-commerce platforms are advised to improve the interactive efficiency of the AI elements by employing anthropomorphism in their application to ensure that consumers enjoy a more personalized experience and close-to-human interactions.

Third, consumers' behavioral engagement attitudes resulting from interactions with chatbots and automated after-sales service are weakened when more attention is given to the social comparison of consumption choices. Therefore, requiring e-commerce platforms to ensure only products meeting the quality standard should be allowed on the platforms to attract engagement behaviors from all consumers. Furthermore, consumers with great attention to social comparison increase their engagement behaviors as long as they are satisfied with the recommendation system experience. E-commerce platforms are required to improve the recommendations system efficiency as consumers who pay more attention to social comparison are willing to post reviews, make referrals, and WOM activities about the e-commerce platforms. Finally, consumers will engage in observable behaviors towards an e-commerce platform as long as they are satisfied with the image search functionality and form a positive platform-related state of mind, regardless of their attention to social comparison. Thus, e-commerce firms should simplify product searches by significantly replacing text-based searches with more reliable image-based searches and promoting consumers' psychological engagement attitudes to ensure observable consumer engagement behaviors.

6.3. Limitations and Directions for Future Research

Despite this study's implications for theory and practice, it is not without limitations. However, these limitations can serve as directions for future research. First, a quantitative methodology was employed for this study; future studies can consider a mixed method to extend the comprehension of AI applications in attracting consumer engagement on e-commerce platforms. Secondly, this study adopted a cross-sectional study. Future studies can counter this limitation by considering a longitudinal design to assess consumer engagement attitudes towards variations of AI applications in e-commerce over time. Finally, the antecedents examined in the study are certainly not the only determinants of consumer engagement as far as AI application is concerned. Factors such as the platform's ease of use can be included in the model to examine the phenomenon from a different perspective.

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REFERENCES

Adam, M., Wessel, M., & Alexander, B. (2020). AI-based chatbots in customer service and their effects on user compliance. *Electronic Markets*, *35*, 427–445.

Agency, G. E. (2021, February 25). *Chinese eCommerce platforms in 2021: Which is the most suitable for your brand? - Ecommerce China*. GMA E-Commerce Agency. https://ecommercechinaagency.com/great-chinese-online-marketplaces-for-e-commerce/

Aguinis, H., Beaty, J. C., Boik, R. J., & Pierce, C. A. (2005). Effect size and power in assessing moderating effects of categorical variables using multiple regression: A 30-year review. *Journal of Applied Psychology*, *90*(1), 94–107. https://doi.org/10.1037/0021-9010.90.1.94

Amirpur, M., & Benlian, A. (2015). Buying under Pressure : Purchase Pressure Cues and their Effects on Online Buying Decisions. *International Conference on Information Systems*, *April*, 1–18.

Anderson, J. C., & Gerbing, D. W. (1988). Structural equation modeling in practice: A review and recommended a two-step approach. *Psychological Bulletin*, *103*(3), 411–423. https://doi.org/10.1037/0033-2909.103.3.411

Asante, I. O., Fang, J., & Darko, D. F. (2019). Consumers' role in the survival of e-commerce in sub-Saharan Africa: consequences of e-service quality on engagement formation. *2019 IEEE 10th Annual Information Technology, Electronics and Mobile Communication Conference (IEMCON)*, 0763–0770.

https://doi.org/10.1109/IEMCON.2019.8936291
Author, Fang, J., & Darko, D. F. (2020). Consequences of consumer engagement on the performance of e-commerce firms in Ghana: moderating effects of consumer-owned resources. *Journal of Psychology in Africa*, *30*(5), 403–407. https://doi.org/10.1080/14330237.2020.1821305
Bagozzi, R. P., & Yi, Y. (1988). On the evaluation of structural equation models. *Journal of the Academy of Marketing Science*, *16*(1), 74–94. https://doi.org/10.1007/BF02723327
Bearden, W. O., & Rose, R. L. (1990). Attention to social comparison information: an individual difference factor affecting consumer conformity. *Journal of Consumer Research*, *16*(4), 461. https://doi.org/10.1086/209231
Becker, J.-M., Rai, A., Ringle, C. M., & Volckner, F. (2013). Discovering Unobserved Heterogeneity in Structural Equation Models to Avert Validity Threats. *MIS Quaterly*, *37*(3), 665–694. https://www.jstor.org/stable/43825995
Benitez, J., Henseler, J., Castillo, A., & Schuberth, F. (2020). How to perform and report an impactful analysis using partial least squares: Guidelines for confirmatory and explanatory IS research. *Information & Management*, *57*(2), 103168. https://doi.org/10.1016/J.IM.2019.05.003
Bharadwaj, A. S. (2000). A resource-based perspective on information technology capability and firm performance: an empirical investigation. *MIS Quarterly: Management Information Systems*, *24*(1), 169–193. https://doi.org/10.2307/3250983
Bowden, J. L.-H. (2009). The process of customer engagement: a conceptual framework. *Journal of Marketing Theory and Practice*, *17*(1), 63–74. https://www.tandfonline.com/doi/full/10.2753/MTP1069-6679170105
Brennan, M. (2017). *2017 WeChat User Report Is Out! - China Channel*. China Channel. https://chinachannel.co/1017-wechat-report-users/
Brodie, R. J., Ilic, A., Juric, B., & Hollebeek, L. (2013). Consumer engagement in a virtual brand community: An exploratory analysis. *Journal of Business Research*, *66*(1), 105–114. https://doi.org/10.1016/J.JBUSRES.2011.07.029
Calder, B. J., Phillips, L. W., & Tybout, A. M. (1981). Designing Research for Application. *Journal of Consumer Research*, *8*(2), 197–207. https://www.jstor.org/stable/2488831
Cepeda-Carrion, G., Cegarra-Navarro, J. G., & Cillo, V. (2019). Tips to use partial least squares structural equation modelling (PLS-SEM) in knowledge management. *Journal of Knowledge Management*, *23*(1), 67–89. https://doi.org/10.1108/JKM-05-2018-0322/FULL/XML
Chen, X., Huang, Q., & Davison, R. M. (2017). The role of website quality and social capital in building buyers' loyalty. *International Journal of Information Management*, *37*(1), 1563–1574. https://doi.org/10.1016/j.ijinfomgt.2016.07.005
Cheng, X., Su, L., Luo, X. R., Benitez, J., & Cai, S. (2021). The good , the bad , and the ugly : impact of analytics and artificial intelligence-enabled personal information collection on privacy and participation in ridesharing. *European Journal of Information Systems*, *00*(00), 1–25. https://doi.org/10.1080/0960085X.2020.1869508
Cheng, X., Zhang, X., Cohen, J., & Mou, J. (2022). Human vs. AI: Understanding the impact of anthropomorphism on consumer response to chatbots from the perspective of trust and relationship norms. *Information Processing & Management*, *59*(3). https://doi.org/10.1016/J.IPM.2022.102940
Cheung, C. M. K., Shen, A. X. L., Lee, Z. W. Y., Chan, T. K. H., Cheung, C. M. K., Shen, X.-L., Lee, Z. W. Y., & Chan, T. K. H. (2015). *Promoting sales of online games through customer engagement*. *14*(4), 241–250. https://doi.org/10.1016/j.elerap.2015.03.001
Chin, W. W., & Marcoulides, G. (1998). The Partial Least Squares Approach to Structural Equation Modeling. *Advances in Hospitality and Leisure*, *8*(2), 294–336. https://www.researchgate.net/publication/311766005_The_Partial_Least_Squares_Approach_to_Structural_Equation_Modeling
Chinchanachokchai, S., Thontirawong, P., & Chinchanachokchai, P. (2021). Journal of Retailing and Consumer Services A tale of two recommender systems : The moderating role of consumer expertise on artificial intelligence based product recommendations. *Journal of Retailing and Consumer Services*, *61*(January), 102528. https://doi.org/10.1016/j.jretconser.2021.102528
Chou, C. (2019, April 4). *Taobao Helping Farmers Reap Gains in Livestream Boom*. Alizila. https://www.alizila.com/taobao-helping-farmers-reap-gains-in-livestream-boom/
Chui, M., & Malhotra, S. (2018). AI adoption advances, but foundational barriers remain – Blogging on Business. *Mckinsey and Company*. https://bobmorris.biz/ai-adoption-advances-but-foundational-barriers-remain
Cohen, J. (1988). Statistical Power Analysis for the Behavioral Sciences. In *Statistical Power Analysis for the Behavioral Sciences* (2nd ed.). Routledge. https://doi.org/10.4324/9780203771587
CXPA. (2018). *Artificial Intelligence (AI) An Introduction: What Every Customer Experience Professional Should*

Know. CXPA. https://www.cxpa.org/HigherLogic/System/DownloadDocumentFile.ashx?DocumentFileKey=f6cc83e5-67f9- ec07-450c-e336cf8e1a76

Dagan, A., Guy, I., & Novgorodov, S. (2021). An Image is Worth a Thousand Terms Analysis of Visual E-Commerce Search. *Proceedings of the 44th International ACM SIGIR Conference on Research and Development in Information Retrieval*, 102–112. https://doi.org/10.1145/3404835.3462950

Daqar, M. A. M. A., & Smoudy, A. K. A. (2019). *The Role of Artificial Intelligence on Enhancing Customer Experience*. *9*(4), 22–31.

Davenport, T. H., Ronanki, R., Wheaton, J., & Nguyen, A. (2018). Artificial Intelligence for the real world. *Havard Business Review*, *96*(1), 108–116.

De Cicco, R., e Silva, S. C., & Alparone, F. R. (2020). Millennials' attitude toward chatbots: an experimental study in a social relationship perspective. *International Journal of Retail and Distribution Management*, *48*(11), 1213–1233. https://doi.org/10.1108/IJRDM-12-2019-0406/FULL/HTML

De Keyzer, F., van Noort, G., & Kruikemeier, S. (2022). Going Too Far? How Consumers Respond To Personalized Advertising From Different Sources. *Journal of Electronic Commerce Research*, *23*(3), 138–159.

Doorn, van J., Lemon, K. N., Mittal, V., Nass, S., Pick, D., Pirner, P., & Verhoef, P. C. (2010). Customer engagement behavior - theoretical foundations and research directions. *Journal of Service Research, 13*(3), 253–266. https://doi.org/10.1177/1094670510375599

Evans, J. R., & Mathur, A. (2005). The value of online surveys. *Internet Research*, *15*(2), 195–219. https://doi.org/10.1108/10662240510590360/FULL/XML

Fang, J., Zhao, Z., Wen, C., & Wang, R. (2017). Design and performance attributes driving mobile travel application engagement. *International Journal of Information Management*, *37*(4), 269–283. https://doi.org/10.1016/j.ijinfomgt.2017.03.003

Fornell, C., & Larcker, D. F. (1981). Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. *Journal of Marketing Research*, *18*(1), 39–50. https://doi.org/10.1177/002224378101800104

Fornnel, C., & Cha, J. (1994). Partial Least Squares. *Advanced Method of Marketing Research*, *40*(7), 52–78. https://www.scirp.org/(S(lz5mqp453edsnp55rrgjct55))/reference/ReferencesPapers.aspx?ReferenceID=1960153

Gawali, S. N. (2020). Artificial Intelligence in E-Commerce. *International Journal of Management and Economics*, *I*(28), 15–17.

Gnewuch, U., Morana, S., Adam, M., & Maedche, A. (2017). Towards designing cooperative and social conversational agents for customer service. *International Conference on Information Systems*, *December*, 0–11.

Gupta, M., & George, J. F. (2016). Toward the development of a big data analytics capability. *Information & Management*, *53*(8), 1049–1064. https://doi.org/10.1016/J.IM.2016.07.004

Hair, J. F., Hult, T. M., Ringle, C. M., & Sarstedt, M. (2016). A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM). In *Sage*. SAGE Publication, Inc.

Hair, J. F., Matthews, L. M., Matthews, R. L., & Sarstedt, M. (2017). PLS-SEM or CB-SEM: updated guidelines on which method to use. *International Journal of Multivariate Data Analysis*, *1*(2), 123. https://doi.org/10.1504/IJMDA.2017.087624

Hair, J. F., Ringle, C. M., & Sarstedt, M. (2011). PLS-SEM: indeed a silver bullet. *Journal of Marketing Theory and Practice*, *19*(2), 139–152. https://doi.org/10.2753/MTP1069-6679190202

Hair, J. F., Sarstedt, M., Ringle, C. M., & Gudergan, S. P. (2017). Advanced Issues in Partial Least Squares Structural Equation Workshop : Advanced Issues in Partial Least Squares Structural Equation Modeling. In *saGe publications* (Issue 1). SAGE Publications, Inc. https://books.google.com.my/books?hl=en&lr=&id=-f1rDgAAQBAJ&oi=fnd&pg=PP1&ots=vY_2fpD1cU&sig=yGGPkxdCk9anwhI5532WZE_aTJU

Hair, J. F., Sarstedt, M., Ringle, C. M., & Mena, J. A. (2011). An assessment of the use of partial least squares structural equation modeling in marketing research. *Journal of the Academy of Marketing Science*, *40*(3), 414–433. https://doi.org/10.1007/S11747-011-0261-6

Henseler, J., Dijkstra, T. K., Sarstedt, M., Ringle, C. M., Diamantopoulos, A., Straub, D. W., Ketchen, D. J., Hair, J. F., Hult, G. T. M., & Calantone, R. J. (2014). Common Beliefs and Reality About PLS: Comments on Rönkkö and Evermann (2013). *Organizational Research Methods*, *17*(2), 182–209. https://doi.org/10.1177/1094428114526928

Henseler, J., & Fassott, G. (2010). Testing Moderating Effects in PLS Path Models: An Illustration of Available Procedures. *Handbook of Partial Least Squares*, 713–735. https://doi.org/10.1007/978-3-540-32827-8_31

Henseler, J., Hubona, G., & Ray, P. A. (2016). Using PLS path modeling in new technology research: Updated guidelines. *Industrial Management and Data Systems*, *116*(1), 2–20. https://doi.org/10.1108/IMDS-09-2015-0382/FULL/PDF

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, *43*(1), 115–135. https://doi.org/10.1007/S11747-014-0403-8/FIGURES/8

Henseler, J., Ringle, C. M., & Sinkovics, R. R. (2009). The use of partial least squares path modeling in international marketing. *Advances in International Marketing*, *20*, 277–319. https://doi.org/10.1108/S1474-7979(2009)0000020014

Hornung, O., & Smolnik, S. (2021). AI invading the workplace: negative emotions towards the organizational use of personal virtual assistants. *Electronic Markets*, *1*, 3. https://doi.org/10.1007/s12525-021-00493-0

Howard, C., & Rosewell-Jones, A. (2019, January 3). *2019 CIO Survey: CIOs Have Awoken to the Importance of AI*. https://www.gartner.com/en/documents/3897266

Hu, L. T., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: conventional criteria versus new alternatives, structural equation modeling. *Structural Equation Modeling*, *6*(1), 1–55. https://doi.org/10.1080/10705519909540118

Jamil, R., Mohammad, J., & Ramu, M. (2018). Antecedents of Unethical Behaviour Intention: Empirical Study in Public Universities in Malaysian Context. *Journal of Academic Ethics*, *17*(1), 95–110. https://doi.org/10.1007/S10805-018-9312-7

Jenkins, A. (2003). *Artificial intelligence and the real world*. *35*, 779–786. https://doi.org/10.1016/S0016-3287(03)00029-6

Khan, S., & Iqbal, M. (2020). AI-Powered Customer Service: Does it Optimize Customer Experience? *International Conference on Reliability, Infocom Technologies and Optimization (Trends and Future Directions)*, 590–594. https://doi.org/10.1109/ICRITO48877.2020.9198004

Khrais, L. T. (2020). *Role of Artificial Intelligence in Shaping Consumer Demand in E-Commerce*.

Kim, E., Sung, Y., & Kang, H. (2014). Brand followers' retweeting behavior on Twitter: How brand relationships influence brand electronic word-of-mouth. *Computers in Human Behavior*, *37*, 18–25. https://doi.org/10.1016/j.chb.2014.04.020

Kock, N. (2015). Common method bias in PLS-SEM. *International Journal of E-Collaboration*, *11*(4), 1–10. https://doi.org/10.4018/ijec.2015100101

Kohli, R. (2008). Business Value of IT: An Essay on Expanding Research Directions to Keep up with the Times. *Journal of the Association for Information System*, *9*(1), 23–39. https://aisel.aisnet.org/cgi/viewcontent.cgi?article=1430&context=jais

Lennox, R. D., & Wolfe, R. N. (1984). Revision of the self-monitoring scale. *Journal of Personality and Social Psychology*, *46*(6), 1349–1364. https://doi.org/10.1037/0022-3514.46.6.1349

Li, J., Liu, H., Gui, C., Chen, J., Ni, Z., Wang, N., & Chen, Y. (2018). The design and implementation of a real time visual search system on JD E-commerce platform. *International Middleware Conference Industry*, 9–16. https://doi.org/10.1145/3284028.3284030

Lin, H., Fan, W., & Chau, P. Y. K. (2014). Determinants of users' continuance of social networking sites: A self-regulation perspective. *Information & Management*, *51*(5), 595–603. https://doi.org/10.1016/J.IM.2014.03.010

Lops, P., de Gemmis, M., & Semeraro, G. (2011). Content-based Recommender Systems: State of the Art and Trends. *Recommender Systems Handbook*, 73–105. https://doi.org/10.1007/978-0-387-85820-3_3

Luger, E., & Sellen, A. (2016). "Like having a really bad pa": The gulf between user expectation and experience of conversational agents. *Conference on Human Factors in Computing Systems*, 5286–5297. https://doi.org/10.1145/2858036.2858288

Luo, X., Tong, S., Fang, Z., & Qu, Z. (2019). Machines versus Humans: The Impact of AI Chatbot Disclosure on Customer Purchases. *Marketing Science, Forthcoming*, *38*(6), 20–33. https://doi.org/10.2139/SSRN.3435635

Ma, Y. (2021). • *China: market size of live commerce 2023* . https://www.statista.com/statistics/1127635/china-market-size-of-live-commerce/

MacKenzie, S. B., Podsakoff, P. M., & Podsakoff, N. P. (2011). Construct measurement and validation procedures in MIS and behavioral research: Integrating new and existing techniques. *MIS Quarterly: Management Information Systems*, *35*(2), 293–334. https://doi.org/10.2307/23044045

Matthews, L. (2017). Applying multigroup analysis in PLS-SEM: A step-by-step process. In *Partial Least Squares Path Modeling: Basic Concepts, Methodological Issues and Applications* (pp. 219–243). Springer, Cham. https://doi.org/10.1007/978-3-319-64069-3_10/COVER

Mehrabian, A., & Russell, J. (1974). An approach to environment psychology. In *Cambridge, MA*.

Mikalef, P., & Gupta, M. (2021). Information & Management Artificial intelligence capability : Conceptualization ,

measurement calibration , and empirical study on its impact on organizational creativity and firm performance. *Information & Management*, *58*(3), 103434. https://doi.org/10.1016/j.im.2021.103434
Müller, T., Schuberth, F., & Henseler, J. (2018). PLS path modeling-a confirmatory approach to study tourism technology and tourist behavior. *Journal of Hospitality and Tourism Technology*, *9*(3), 249–266. https://doi.org/10.1108/JHTT-09-2017-0106
Nunthiphatprueksa, A., & Suntrayuth, S. (2018). The application of stimulus-organism-response paradigm: the role of social media in Thailand's destination image and behavioral intentions. *Asean Journal of Management and Innovation*, *5*(1), 15–29. https://doi.org/10.14456/ajmi.2018.2
Oh, C., Roumani, Y., Nwankpa, J. K., & Hu, H.-F. (2016). Beyond likes and tweets: consumer engagement behavior and movie box office in social media. *Information & Management*. https://doi.org/http://dx.doi.org/10.1016/j.im.2016.03.004
Oh, C., Roumani, Y., Nwankpa, J. K., & Hu, H. F. (2017). Beyond likes and tweets: consumer engagement behavior and movie box office in social media. *Information and Management*, *54*(1), 25–37. https://doi.org/10.1016/j.im.2016.03.004
Peters, T., Işık, Ö., Tona, O., Popovič, A., & Is, Ö. (2016). How system quality influences mobile BI use: the mediating role of engagement. *International Journal of Information Management*, *36*(5), 773–783. https://www.sciencedirect.com/science/article/pii/S0268401216300779
Pfeuffer, N., Adam, M., Toutaoui, J., Hinz, O., & Benlian, A. (2019). Mr. and Mrs. conversational agent - gender stereotyping in judge-advisor systems and the role of egocentric bias. In G. Balint, B. Antala, C. Carty, J.-M. A. Mabieme, I. B. Amar, & A. Kaplanova (Eds.), *ICIS* (pp. 343–354). Uniwersytet Śląski. Wydział Matematyki, Fizyki i Chemii. https://doi.org/10.2/JQUERY.MIN.JS
Phua, J., Jin, S. V., & Kim, J. (2017). Gratifications of using Facebook, Twitter, Instagram, or Snapchat to follow brands: The moderating effect of social comparison, trust, tie strength, and network homophily on brand identification, brand engagement, brand commitment, and membership intentio. *Telematics and Informatics*, *34*(1), 412–424. https://doi.org/10.1016/J.TELE.2016.06.004
Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: a critical review of the literature and recommended remedies. *Journal of Applied Psychology*, *88*(5), 879–903. https://doi.org/10.1037/0021-9010.88.5.879
Preacher, K. J., & Hayes, A. F. (2008). Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models. *Behavior Research Methods*, *40*(3), 879–891. https://doi.org/10.3758/BRM.40.3.879
Quoquab, F., Jaini, A., & Mohammad, J. (2020). Does It Matter Who Exhibits More Green Purchase Behavior of Cosmetic Products in Asian Culture? A Multi-Group Analysis Approach. *International Journal of Environmental Research and Public Health 2020, Vol. 17, Page 5258*, *17*(14), 5258. https://doi.org/10.3390/IJERPH17145258
Quoquab, F., & Mohammad, J. (2020). Cognitive, Affective and Conative Domains of Sustainable Consumption: Scale Development and Validation Using Confirmatory Composite Analysis. *Sustainability*, *12*(18), 7784. https://doi.org/10.3390/SU12187784
Quoquab, F., Mohammad, J., Yasin, N. M., & Abdullah, N. L. (2018). Antecedents of switching intention in the mobile telecommunications industry: A partial least square approach. *Asia Pacific Journal of Marketing and Logistics*, *30*(4), 1087–1111. https://doi.org/10.1108/APJML-06-2017-0121/FULL/XML
Ramey, H. L., Lawford, H. L., & Rose-Krasnor, L. (2019). Psychological engagement and behavioral activity participation as predictors of positive youth development. *Journal of Youth Development*, *14*(3), 88–109. https://doi.org/10.5195/JYD.2019.769
Ransbotham, S., Gerbert, P., Reeves, M., Kiron, D., & Spira, M. (2018). Artificial Intelligence in Business Gets Real. *MIT Sloan Business Review*. https://sloanreview.mit.edu/projects/artificial-intelligence-in-business-gets-real/
Ray, S., Kim, S. S., & Morris, J. G. (2014). The Central Role of Engagement in Online Communities. *Information Systems Research*, *25*(3), 528–546. https://doi.org/10.1287/isre.2014.0525
Ringle, C. M., Wende, S., & Becker, J.-M. (2015). *SmartPLS 3*. SmartPLS GmbH.
Ruiz-Fernández, A., Junco-Guerrero, M., & Cantón-Cortés, D. (2021). Exploring the Mediating Effect of Psychological Engagement on the Relationship between Child-to-Parent Violence and Violent Video Games. *International Journal of Environmental Research and Public Health*, *18*(6), 1–15. https://doi.org/10.3390/IJERPH18062845
Sander, T. and T. P. L. (2014). SmartPLS for the Human Resources Field to Evaluate a Model. *New Challenges of Economic and Business Development*, *May 2014*, 346–357.

Sashi, C. M. (2012). Customer engagement, buyer-seller relationships, and social media. *Management Decision*, *50*(2), 253–272. https://doi.org/10.1108/00251741211203551

Schafer, J. Ben, Konstan, J. A., & Riedl, J. (2001). E-Commerce Recommendation Applications. *Data Mining and Knowledge Discovery*, *5*(1), 115–153. https://doi.org/10.1023/A:1009804230409

Schaufeli, W., Salanova, M., González-romá, V., & Bakker, A. (2002). The measurement of engagement and burnout: a two sample confirmatory factor analytic approach. *Journal of Happiness Studies*, *3*(1), 71–92. https://doi.org/10.1023/A:1015630930326

Schryen, G. (2012). Revisiting IS business value research: what we already know, what we still need to know, and how we can get there. *European Journal of Information Systems*, *22*(2), 139–169. https://doi.org/10.1057/EJIS.2012.45

Singaraju, P. S., Rose, L. J., Arango-Soler, A. L., Khaksar, M. S. S., & Brouwer, R. A. (2022). THE DARK AGE OF ADVERTISING: AN EXAMINATION OF PERCEPTUAL FACTORS AFFECTING ADVERTISING AVOIDANCE IN THE CONTEXT OF MOBILE YOUTUBE. *Journal of Electronic Commerce Research*, *23*(1), 13–32.

Sivapalan, S., Sadeghian, A., Rahnama, H., & Madni, A. M. (2014). Recommender systems in e-commerce. *World Automation Congress Proceedings*, 179–184. https://doi.org/10.1109/WAC.2014.6935763

Song, X., Yang, S., Huang, Z., & Huang, T. (2019). The application of artificial intelligence in electronic commerce. *Journal of Physics*. https://doi.org/10.1088/1742-6596/1302/3/032030

Sudarsan, S., Shirode, A., Chavan, N., & Shaikh, R. (2022). E-commerce Website with Image Search and Price Prediction. *Evolutionary Computing and Mobile Sustainability Networks*, *116*, 823–837. https://doi.org/10.1007/978-981-16-9605-3_57/COVER/

Sutikno, T., Handayani, L., Stiawan, D., Riyadi, M. A., & Subroto, I. M. I. (2016). WhatsApp, viber and telegram: Which is the best for instant messaging? *International Journal of Electrical and Computer Engineering*, *6*(3), 909–914. https://doi.org/10.11591/IJECE.V6I3.10271

Tsai, W. H. S., Liu, Y., & Chuan, C. H. (2021). How chatbots' social presence communication enhances consumer engagement: the mediating role of parasocial interaction and dialogue. *Journal of Research in Interactive Marketing*, *15*(3), 460–482. https://doi.org/10.1108/JRIM-12-2019-0200/FULL/XML

UNCTAD. (2021, May 3). *Global e-commerce jumps to $26.7 trillion, COVID-19 boosts online sales | UNCTAD*. United Nations Conference on Trade and Development. https://unctad.org/news/global-e-commerce-jumps-267-trillion-covid-19-boosts-online-sales

Verhagen, T., Swen, E., Feldberg, F., & Merikivi, J. (2015). Benefitting from virtual customer environments: An empirical study of customer engagement. *Computers in Human Behavior*, *48*, 340–357. https://doi.org/10.1016/J.CHB.2015.01.061

Wei, K., Huang, J., & Fu, S. (2007). A survey of E-commerce recommender systems. *International Conference on Service Systems and Service Management*. https://doi.org/10.1109/ICSSSM.2007.4280214

Xu, Y., Zhang, J., Chi, R., & Deng, G. (2022). Enhancing customer satisfaction with chatbots: the influence of anthropomorphic communication styles and anthropomorphised roles. *Nankai Business Review International*. https://doi.org/10.1108/NBRI-06-2021-0041/FULL/HTML

Yang, F., Kale, A., Bubnov, Y., Stein, L., Wang, Q., Kiapour, H., & Piramuthu, R. (2017). Visual search at eBay. *ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, *Part F129685*, 2101–2110. https://doi.org/10.1145/3097983.3098162

Yoon, H. J., La Ferle, C., & Edwards, S. M. (2016). A normative approach to motivating savings behavior: The moderating effects of attention to social comparison information. *International Journal of Advertising*, *35*(5), 799–822. https://doi.org/10.1080/02650487.2016.1145094

Zarifis, A., Kawalek, P., & Azadegan, A. (2020). Evaluating If Trust and Personal Information Privacy Concerns Are Barriers to Using Health Insurance That Explicitly Utilizes AI. *Journal of Internet Commerce*, *20*(1), 66–83. https://doi.org/10.1080/15332861.2020.1832817

Zhang, H., Lu, Y., Gupta, S., & Zhao, L. (2014). What motivates customers to participate in social commerce? The impact of technological environments and virtual customer experiences. *Information & Management*, *51*(8), 1017–1030. https://doi.org/10.1016/J.IM.2014.07.005

Zhang, H., Lu, Y., Wang, B., & Wu, S. (2015). The impacts of technological environments and co-creation experiences on customer participation. *Information & Management*, *52*(4), 468–482. https://doi.org/10.1016/J.IM.2015.01.008

Zhang, Y., Pan, P., Zheng, Y., Zhao, K., Wu, J., Xu, Y., & Jin, R. (2019). Virtual ID discovery from E-commerce media at alibaba: Exploiting richness of user click behavior for visual search relevance. *International Conference on Information and Knowledge Management*, 2489–2497.

https://doi.org/10.1145/3357384.3357800
Zhang, Y., Pan, P., Zheng, Y., Zhao, K., Zhang, Y., Ren, X., & Jin, R. (2018). Visual search at alibaba. *ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, 993–1001. https://doi.org/10.1145/3219819.3219820

Appendix 1: Measurement Scales

Constructs	Items
Chatbot efficiency (CB)	1. The chatbot on the electronic commerce platform is available all the time
	2. Anytime I log on to the platform, I get pop-up notifications from a chatbot.
	3. The requirement I type in the pop-up chat box returns beneficial results
	4. I can easily communicate with the chatbot.
Image search functionality (IS)	1. The image search function is easy to use
	2. I can search for a product by pointing my camera at it or scanning a saved image on my device
	3. The result from the image search matches the item I need
	4. I don't need keyword or text searches when I use the image search function
Recommendation system efficiency (RS)	1. I get product recommendations based on my previous searches
	2. I get product recommendations based on my previous purchases
	3. The products recommended on the platform are products that I am interested in
	4. I do not spend too much time searching for products
Automated after-sales service (AAS)	1. I get automatic feedback requests after my purchase
	2. Any ambiguity in products I buy or intend to buy is handled promptly
	3. If I need the product replaced or refunded, there is an automated step-by-step process.
	4. I am aided by guidance and prompts in the entire buying cycle
Psychological engagement (PE)	1. I feel no stress when shopping on the online platform
	2. I am enthused and inspired when I am logged on to the e-commerce platform
	3. I do not realize the passage of time as I am immersed when logged on to the e-commerce platform
Behavioral engagement (BE)	1. I intend to continue using this e-commerce platform
	2. I refer friends to buy from this e-commerce platform
	3. I tell friends about the services provided on the e-commerce platform
	4. I write reviews about my service experience with the e-commerce platform
Attention to social comparison (ASC)	1. I find it essential to consume reputable brands
	2. I feel it is significant to purchase brands with the most consumption
	3. If I am unsure of what to purchase, I rely on friends' opinions
	4. I tend to pay attention to what society is consuming when I am on the e-commerce platform