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Investigating how Generative AI-driven tools contribute to the improvement of CBE on an E-commerce platform: MIS perspective

تحقيق في كيفية مساهمة الأدوات المدفوعة بالذكاء الاصطناعي التوليدي في تحسين تجربة العميل على منصة التجارة الإلكترونية: من منظور نظم المعلومات الإدارية

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Abstract

This study looks at how different Generative AI-driven tools affect customer behavioral engagement on e-commerce platforms. In all, 373 surveys survey responses were considered for the study, accounting for a response rate of 67.81%. The research findings show that Ad Campaign Optimization, Chatbots, and Email Marketing Automation have a substantial and positive effect on customer behavioral engagement in E-commerce platforms. By rejecting hypotheses, the study questions traditional assumptions and suggests that Personalization Engines, Predictive Analytics, and Social Media Management may not have a statistically meaningful effect on customer involvement in this e-commerce setting. These findings highlight the significance of giving some AI tools more priority than others, which has far-reaching consequences for companies trying to improve their E-commerce operations. This research adds to what is already known about how Generative AI-driven technologies affect the dynamics of customer interaction. The complexities of long-term user experiences within the dynamic environment of AI-driven e-commerce platforms, as well as the precise elements impacting tool efficacy, might be the subject of future study that would enhance our current knowledge.

Keywords: *Ad Campaign Optimization, Conversational AI, Predictive Analytics, Social Media Management, Chatbots, customer behavioral engagement.*

المخلص:

تبحث هذه الدراسة في كيفية تأثير أدوات الذكاء الاصطناعي التوليدي المختلفة على تفاعل العملاء السلوكي على منصات التجارة الإلكترونية. تم أخذ 373 استجابة استبيان في الاعتبار للدراسة، مما يمثل معدل استجابة بنسبة 67.81%. تُظهر نتائج البحث أن تحسين الحملات الإعلانية، والردشة التفاعلية (Chatbots) وأتمتة التسويق عبر البريد الإلكتروني لها تأثير كبير وإيجابي على تفاعل العملاء السلوكي في منصات التجارة الإلكترونية. من خلال رفض الفرضيات تشكك الدراسة في الافتراضات التقليدية وتقتراح أن محركات التخصيص والتحليلات التنبؤية وإدارة وسائل التواصل الاجتماعي قد لا يكون لها تأثير ذو دلالة إحصائية على مشاركة العملاء في هذا الإطار التجاري الإلكتروني. تبرز هذه النتائج أهمية إعطاء بعض أدوات الذكاء الاصطناعي أولوية أكثر من غيرها مما له آثار بعيدة المدى على الشركات التي تسعى لتحسين عملياتها في التجارة الإلكترونية. تضيف هذه الدراسة إلى المعرفة الموجودة حول كيفية تأثير تقنيات الذكاء الاصطناعي التوليدي على ديناميكيات تفاعل العملاء. قد تكون تعقيدات تجارب المستخدمين طويلة الأمد ضمن البيئة الديناميكية لمنصات التجارة الإلكترونية المدعومة بالذكاء الاصطناعي بالإضافة إلى العناصر الدقيقة التي تؤثر على فعالية الأدوات موضوعًا لدراسات مستقبلية من شأنها تعزيز معرفتنا الحالية.

الكلمات المفتاحية: تحسين الحملات الإعلانية، الذكاء الاصطناعي التفاعلي، التحليلات التنبؤية، إدارة وسائل التواصل الاجتماعي، الردشة التفاعلية، تفاعل العملاء السلوكي.



Introduction

Artificial Intelligence (AI) has become crucial in transforming customer interaction methods in the quickly changing world of E-commerce (Lo Presti et al., 2020; Zhao et al., 2020). This study aims to examine the subtle impacts of Generative AI-driven technologies on improving consumer behavioral engagement in an E-commerce platform. To develop meaningful relationships with their audience, firms must comprehend the unique impact of AI tools such as Chatbots, Email Marketing Automation, Predictive Analytics, and other innovative technologies (Letaief et al., 2019; Momade et al., 2021; Wang et al., 2022; Yauri-Lozano et al., 2024; Zhang et al., 2023; Zheng et al., 2023). The current problem revolves on the necessity for a thorough investigation of the impact of Generative AI-driven tools on customer behavioral engagement (CBE). These tools are known for their capacity to independently generate content and replies. E-commerce systems are more dependent on these solutions to enhance operational (Cascio & Montealegre, 2016; Eren, 2021), customize customer experiences (Attia et al., 2020; Jones & Masika, 2021), and optimize marketing endeavors (Cascio & Montealegre, 2016; Henkel et al., 2020; Sidaoui et al., 2020; Stepin et al., 2024). Nevertheless, there is a significant absence of comprehensive understanding of the combined effect of several AI techniques on CBE (Brill et al., 2022; Cascio & Montealegre, 2016; Chen et al., 2023; Hew et al., 2023). Many small online retailers and new entrants to the online retail sector are eager to implement data mining and consumer-centric marketing practices but often lack the technical knowledge and expertise to do so effectively (Gholami et al., 2024; Sidaoui et al., 2020; Villarroel Ordenes & Zhang, 2019). By leveraging generative AI-driven tools, such as SAS Enterprise Guide and SAS Enterprise Miner, the retailer was able to identify



distinct customer segments using the Recency, Frequency, and Monetary model and k-means clustering algorithm (Helmuth & Schedel, 2022; Verma & Maiti, 2018). These tools allowed the retailer to personalize marketing efforts and improve CBE on their e-commerce platform. By understanding the purchasing patterns and preferences of different customer segments, the retailer was able to tailor their marketing messages and offerings to each group (Franke et al., 2009), resulting in higher customer satisfaction (Garg et al., 2023) , increased sales, and improved overall business performance (Quelch & Jocz, 2009; Yankelovich & Meer, 2006; Zheng et al., 2023). By utilizing generative AI-driven tools, the online retailer was able to enhance CBE on their e-commerce platform through personalized marketing efforts (Alsobhi & Alyoubi, 2019). This approach allowed the retailer to effectively target low or no-revenue customers and convert them into high revenue customers by recommending the next product to the market (Kanbach et al., 2023; Manimurugan, Karthikeyan, et al., 2024; Manimurugan, Narmatha, et al., 2024; Norbäck & Persson, 2023; Pakrooh et al., 2024). The analysis of customer behaviors and characteristics using generative AI-driven tools allowed the online retailer to identify customer segments and personalize their marketing efforts accordingly. The use of generative AI-driven tools in customer-centric business intelligence has proven to be highly impactful for an online retailer, as showcased in this study. The integration of generative AI-driven tools in customer-centric business intelligence has demonstrated significant positive effects on CBE within an e-commerce platform.

This study aims to fill a significant research gap by examining the distinct contributions of Generative AI-driven technologies, which have received limited attention in previous scholarly works. The significance of this study is emphasized by the



increasing dependence on AI in marketing efforts, making it crucial to determine how these technologies collectively impact user engagement in the context of E-commerce and MIS. The existing literature lacks comprehensive study on the collaborative influence of different Generative AI-driven technologies on consumer engagement, creating a research gap. Although there has been research on individual technologies, a comprehensive knowledge of their combined impact is still difficult to grasp. This study seeks to close this divide by investigating the interrelated dynamics of AI technologies and their influence on promoting significant customer connections. This study is notable for its thorough methodology, which incorporates several AI technologies such as Chatbots, Personalization Engines, and Predictive Analytics, to analyze their combined impact on consumer engagement. The research aims to assess the efficacy of these tools, detect trends in consumer behavior, and comprehend how collaboration among AI-driven technologies enhances user engagement. Previous empirical research has mostly focused on examining individual AI tools separately, with less attention given to understanding the combined effects of Generative AI-driven tools on consumer involvement in E-commerce. This study stands out by addressing this research void, offering a comprehensive understanding of how various AI technologies jointly influence consumer interactions.

What is the impact of different Generative AI-driven technologies on consumer involvement in E-commerce platforms? The influence of different Generative AI-driven technologies on CBE in E-commerce platforms is a complex investigation that occurs inside the intricate dynamics of contemporary online retail. Chatbots, Personalization Engines, Predictive Analytics, and Content Creation tools are technologies that collectively influence the customer experience in E-commerce



(Alhmiedat et al., 2023; Mehmood et al., 2024; Xu et al., 2024). They provide personalized recommendations, enable smooth interactions, and improve operational efficiency (Albelwi, 2022; Huang et al., 2023). Chatbots, such as those mentioned, offer immediate support and instruction on products, leading to increased consumer involvement (Beckmann, 2021; Schmid-Grendelmeier et al., 2019). Personalization engines customize user experiences (Franke et al., 2009; Lyu & Adams, 2022; Soprano et al., 2024), cultivating a feeling of personalized care. Meanwhile, Predictive Analytics uses advanced algorithms to forecast customer preferences, therefore optimizing the way items and services are presented (Matz et al., 2023). AI-powered content creation tools produce engaging and pertinent material, enhancing customer captivation (Shorey et al., 2019). It is crucial to comprehend and enhance the complex interaction between AI breakthroughs and the changing environment of E-commerce.

What is the combined influence of these technologies on customer happiness, response time, and the overall E-commerce experience? The combined impact of several Generative AI-powered technologies on customer satisfaction (Kumar et al., 2022), speed of response, and the entire digital retail experience is crucial in establishing a consumer-focused E-commerce environment. Chatbots, Personalization Engines, and Predictive Analytics work together to enhance customer satisfaction by offering customized suggestions, personalized engagements, and anticipating user requirements (Franke et al., 2009; Li & Li, 2022; Yun & Park, 2023). The rapid and automatic replies enabled by these technologies greatly decrease the time it takes to respond, establishing a smooth and effective communication channel between customers and the E-commerce platform. The use of these AI technologies improves the whole E-commerce experience by establishing a more customized (Parmar et al., 2023; Wang et al., 2024),



streamlined, and user-centric atmosphere (Norbäck & Persson, 2023; Zhang et al., 2023). Customers derive advantages from expedited issue resolution, tailored product recommendations, and a general feeling of involvement, eventually leading to increased contentment and allegiance in the ever-changing domain of e-commerce.

Therefore, this research postulates the following research objectives.

1. Examine the effects of generative AI-driven tools on CBE in e-commerce platforms.
2. Access the traditional assumptions and determine the most important AI tools for enhancing e-commerce operations.
3. Contribute to the comprehension of the mechanisms involved in customer interaction within AI-powered e-commerce environments

This research goes beyond merely validating current literature and making additional contributions. It presents a detailed analysis of how Generative AI-driven tools work together to impact CBE. It offers practical insights for marketers, researchers, and industry professionals who want to improve their engagement strategies in the ever-changing field of AI and E-commerce.

Literature review and the development of hypothesis

AI in Ad Campaign Optimization (ACO)

The research pertaining to the theory that CBE in e-commerce platforms is positively impacted by using ACO highlights the revolutionary effect of AI on contemporary



marketing tactics. The integration of ACO aims to improve targeting accuracy, personalize content distribution, and optimize ad placements (Jibril & Adzovie, 2024). As demonstrated by many studies (Robson et al., 2022), AI-powered solutions in ad optimization include features such as automatic bid changes, real-time targeting, and A/B testing (Lou et al., 2023). These capabilities allow marketers to customize campaigns in response to user preferences and enhance the advertising experience for customers by tailoring adverts to their specific tastes and behavior.

Furthermore, the research continually emphasizes the beneficial impact of AI-driven ad optimization on consumer engagement metrics (Rodgers & Nguyen, 2022). Research conducted by (Li, 2019; Rodgers & Nguyen, 2022; Shah & Nasnodkar, 2021) has shown that AI enhances click-through rates, conversion rates, and overall user engagement with adverts. The capacity of AI to analyze extensive information in real-time, forecast consumer behavior, and optimize ad content appropriately plays a crucial role in generating more pertinent, timely, and captivating advertising experiences (Tran & Meacheam, 2020; Tucker et al., 2014; Wahab et al., 2022). Consequently, this has a beneficial impact on CBE by attracting attention, promoting brand contact, and eventually motivating desirable behaviors, as confirmed by empirical research in the current literature. Based on these studies, the role of AI in improving ad campaign optimization becomes a crucial element in increasing consumer interaction on E-commerce platforms. This represents a significant change in how advertisers interact with their intended audience. Therefore, the following hypothesis is formulated to test this relationship.

Hypothesis H1: The use of AI tools in ACO positively influences CBE in E-commerce platforms.



Chatbots and Conversational AI (CCA)

The integration of CCA into the realm of E-commerce has grown more widespread, motivated by the potential to revolutionize customer interactions and enhance consumer engagement (Liu et al., 2024). This study explores the belief that the incorporation of CCA has a favorable impact on CBE in E-commerce platforms. These AI-powered tools have a purpose that goes beyond traditional customer service (Roslan & Ahmad, 2023). They can also provide personalized suggestions (Lewandrowski et al., 2023), track orders (Ratten & Jones, 2023; Wang et al., 2021), and engage in natural language discussions (Madureira et al., 2023; Zhou & Liu, 2022). The adaptable characteristics of Chatbots, demonstrating their ability to improve user interaction by providing customized and immediate support is vital (Rodgers & Nguyen, 2022). Empirical research continuously confirms a favorable relationship between the use of CCA and improved CBE in E-commerce. Researches demonstrates that customers consider Chatbots as important tools for streamlining the purchasing experience, decreasing response times, and offering quick support, hence enhancing overall consumer engagement (Ali et al., 2022; Franke et al., 2009). Nevertheless, there is a lack of research exploring the full extent of their influence on many aspects of consumer involvement in the distinct setting of E-commerce platforms. Extensive research is needed to gain a comprehensive understanding of the impact of CCA in the E-commerce industry by examining specific research objectives such as response times, user satisfaction, and overall consumer engagement. Therefore, the following hypothesis is formulated to test this relationship.

Hypothesis H2: The use of CCA tools positively influences CBE in E-commerce platforms.



Email Marketing Automation (EMA)

EMA has become more important since it helps to streamline and personalize contact with consumers (Paulo et al., 2022). These automated solutions go beyond standard email marketing by allowing organizations to divide their audience into segments, customize content, and plan messages according to user behavior (Järvinen & Taiminen, 2016). Studies demonstrate the efficacy of in enhancing open rates and click-through rates, highlighting its potential influence on CBE (Norbäck & Persson, 2023; Paulo et al., 2022). Furthermore, the effectiveness of these automated systems is based on their capacity to provide timely and pertinent material, promoting a feeling of customization and promptness. Nevertheless, despite these encouraging signs, there is still a lack of thorough exploration into the intricate relationship between Email Marketing Automation and other facets of customer involvement in the realm of E-commerce. Growing competition in an unpredictable digital landscape demands fresh strategies for enhancing marketing and business effectiveness. Employing automation in both business operations and marketing facilitates managerial choices focused on enhancing customer satisfaction. This is achieved through the gathering, processing, and analysis of extensive and unbiased customer data from diverse sources and software platforms. This research aims to give practical insights for E-commerce practitioners who want to enhance their communication strategies and establish long-term connections with their customer base by highlighting the distinct benefits of Email Marketing Automation. Therefore, the following hypothesis is formulated to test this relationship.



Hypothesis H3: The use of EMA tools positively influences CBE in E-commerce platforms.

Personalization Engines (PE)

PE are complex software systems that utilize advanced algorithms and machine learning approaches to examine user data and behaviors (Geetha & Thilagam, 2021; Järvinen & Taiminen, 2016; Qu et al., 2024). This allows for the customization and adaptation of information, suggestions, and interactions on digital platforms (Sen et al., 2008). In the context of E-commerce, these engines play a vital role in providing tailored experiences for consumers by knowing their preferences, forecasting their requirements, and offering targeted information and suggestions (Desai, 2021). PE have become a crucial technique in the ever-changing world of E-commerce to effectively enhance consumer interaction (Aksulu & Wade, 2010). These engines provide the growing need for personalized experiences by dynamically tailoring information and suggestions according to individual user behaviors and preferences. The studies emphasize the effectiveness of PE in improving consumer engagement (Rane et al., 2023). These engines do this by providing material that is not only relevant but also attractive to individual consumers. The engines' capability, which is based on sophisticated algorithms, allows for the precise analysis of extensive datasets to properly forecast consumer preferences. Furthermore, the favorable view of customized experiences among customers, which leads to enhanced loyalty and a rise in repeated purchases (Algahtany, 2023). However, although current literature underlines the favorable links, a complete examination of the nuanced influence of PE on many dimensions of customer involvement inside E-commerce platforms remains scarce. By giving deeper insights into the diverse contributions of PE, this research



intends to give helpful information for E-commerce practitioners aiming to optimize their tactics and develop meaningful interaction with their audience. Therefore, the following hypothesis is formulated to test this relationship.

Hypothesis H4: The use of PE tools positively influences CBE in E-commerce platforms.

Predictive Analytics (PA)

PA is the application of statistical algorithms and machine learning approaches to analyze past data, detect trends, and forecast future results (Matz et al., 2023; Sabahi & Parast, 2020). PA in the realm of E-commerce utilizes consumer data, purchase history, and online behavior to anticipate forthcoming customer behaviors, preferences, and trends. By utilizing a data-driven strategy, organizations can make well-informed decisions, tailor user experiences, and enhance marketing efforts to achieve better consumer engagement (Paulo et al., 2022). The utilization of PA has a favorable impact on customer involvement in E-commerce platforms signifies the increasing significance of data-driven decision-making in the digital retail environment (Fayoumi & Hajjar, 2020). PA, via the use of past data and advanced machine learning algorithms, has the potential to forecast customer behavior and customize interactions to improve engagement (Hair Jr, 2007). The studies highlight the efficacy of PA in enhancing product suggestions and tailoring marketing strategies (Dinov, 2018), eventually leading to enhanced CBE. PA possesses the capability to analyze extensive information, detect trends, and provide instantaneous forecasts, therefore furnishing organizations with actionable insights into customer preferences (Schwab, 2020). Although previous research confirms the beneficial effect of PA on CBE measures



(Agag et al., 2024; Al Khaldy et al., 2023; Fosso Wamba et al., 2024), there is still a lack of exploration on its specific impact in the distinct context of E-commerce platforms. This research seeks to provide significant insights for E-commerce practitioners seeking to utilize data-driven tactics for optimal CBE by exploring the diverse contributions of Predictive Analytics. Therefore, the following hypothesis is formulated to test this relationship.

Hypothesis H5: The use of PA tools positively influences CBE in E-commerce platforms.

Social Media Management (SMM)

SMM encompasses the deliberate formulation, execution, and supervision of an organization's representation on social media platforms (Desai, 2021; Kankanamge et al., 2021; Monda et al., 2024). It encompasses tasks such as generating content, organizing schedules, tracking engagement, and analyzing performance (Jacobson, 2020; Thapliyal et al., 2024). SMM tools and techniques strive to create a unified and efficient social media strategy, promoting brand exposure, audience interaction, and contact with customers (Macnamara & Zerfass, 2012). SMM has a favorable impact on CBE in E-commerce platforms highlights the crucial role of social media in molding online consumer interactions (Dongbo et al., 2023; Soprano et al., 2024; Xu et al., 2024). Effective implementation of SMM techniques, which include activities like content preparation, engagement monitoring, and strategic communication, is crucial for the success of contemporary E-commerce campaigns (Jacobson, 2020; Schwab, 2020). The studies highlight the favorable influence of SMM on CBE metrics. They demonstrate their efficacy in cultivating brand loyalty, facilitating immediate



interactions, and expanding the reach of E-commerce platforms (Macnamara & Zerfass, 2012). The essence of SMM resides in its capacity to curate engaging material, rapidly address consumer queries, and utilize analytics for ongoing enhancement. Although previous research supports the idea, there is still a need for deeper investigation into the detailed and situation-specific impacts of SMM on customer participation in E-commerce platforms. This research aims to provide significant insights for E-commerce practitioners looking to optimize their social media strategy and improve CBE in the dynamic online marketplace by exploring the many contributions of SMM. Therefore, the following hypothesis is formulated to test this relationship.

Hypothesis H6: The use of SMM positively influences CBE in E-commerce platforms.

Conceptual framework

A thorough conceptual model has been developed to provide the framework for these tools, based on a thorough assessment of the literature analyzing the impact of Generative AI-driven tools in E-commerce. The six-factor conceptual model encompasses essential components that enhance the efficacy of Generative AI in the E-commerce domain. The elements encompass (1) Chatbots and Conversational AI (CCA), (2) Email Marketing Automation (EMA), (3) Personalization Engines (PE), (4) Predictive Analytics (PA), (5) Social Media Management (SMM), and (6) Ad Campaign Optimization (ACO), (Figure 1).

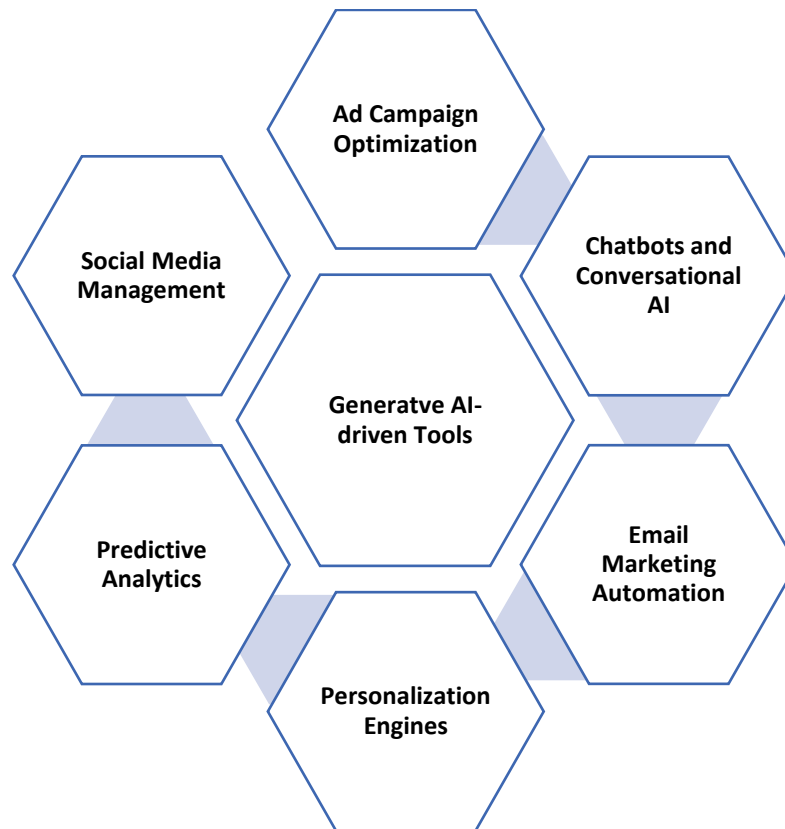


Figure 1.Generative AI driven tools framework in e-commerce

Source: Authors own

These elements collectively encompass a wide range of Generative AI technologies that are crucial in influencing customer interactions, improving marketing strategies, and boosting overall consumer engagement within the ever-changing environment of E-commerce platforms. The conceptual model acts as a fundamental framework for additional research and practical implementations, offering a comprehensive comprehension of the collaborative influence of these Generative AI-driven technologies on the E-commerce ecosystem (Table 1).

Table 1. Generative AI-driven tools in e-commerce ecosystem

AI-driven Tools	Purpose	Functionality	Contribution
<i>Ad Campaign Optimization</i> (Xu et al., 2015; Yankelovich & Meer, 2006)	Improving efficiency and performance of campaigns	Automated bid adjustments, targeting optimization, and A/B testing	Increased ad relevance, better targeting, and improved conversion rates
<i>Chatbots and Conversational AI</i> (Ahmed et al., 2023; Kanbach et al., 2023; Nadarzynski et al., 2021)	Enhancing customer interactions and support	Answering queries, guiding users, providing recommendations	Instant support, personalized assistance, improved user engagement
<i>Email Marketing Automation</i> (Järvinen & Taiminen, 2016; Paulo et al., 2022; Rane et al., 2023)	Streamlining and automating email campaigns	Segmentation, personalization, scheduling, and automation of email communication	Targeted communication, personalized promotions, increased customer loyalty
<i>Personalization Engines</i> (Desai, 2021; Järvinen & Taiminen, 2016; Rane et	Customizing user experiences for improved engagement	Analyzing user behavior to deliver personalized recommendations, product suggestions, and content	Tailored user experiences, increased customer satisfaction, and loyalty



al., 2023; Sen et al., 2008)			
<i>Predictive Analytics</i> (Dinov, 2018; Hair Jr, 2007; Schwab, 2020)	Forecasting trends and behaviors based on data	Predicting customer preferences, optimizing pricing, and identifying potential leads	Enhanced personalization, improved product recommendations, better targeting
<i>Social Media Management</i> (Jacobson, 2020; Järvinen & Taiminen, 2016; Macnamara & Zerfass, 2012)	Managing and optimizing social media presence	Content scheduling, social listening, sentiment analysis, and automated responses	Improved social engagement, brand visibility, and real-time interaction

To test the relationship of generative AI driven tools on CBE in e-commerce ecosystem a conceptual model has been proposed (Figure 2). All the six Generative AI driven tools framework in e-commerce are independent variables whereas the CBE is considered as the dependent variable.

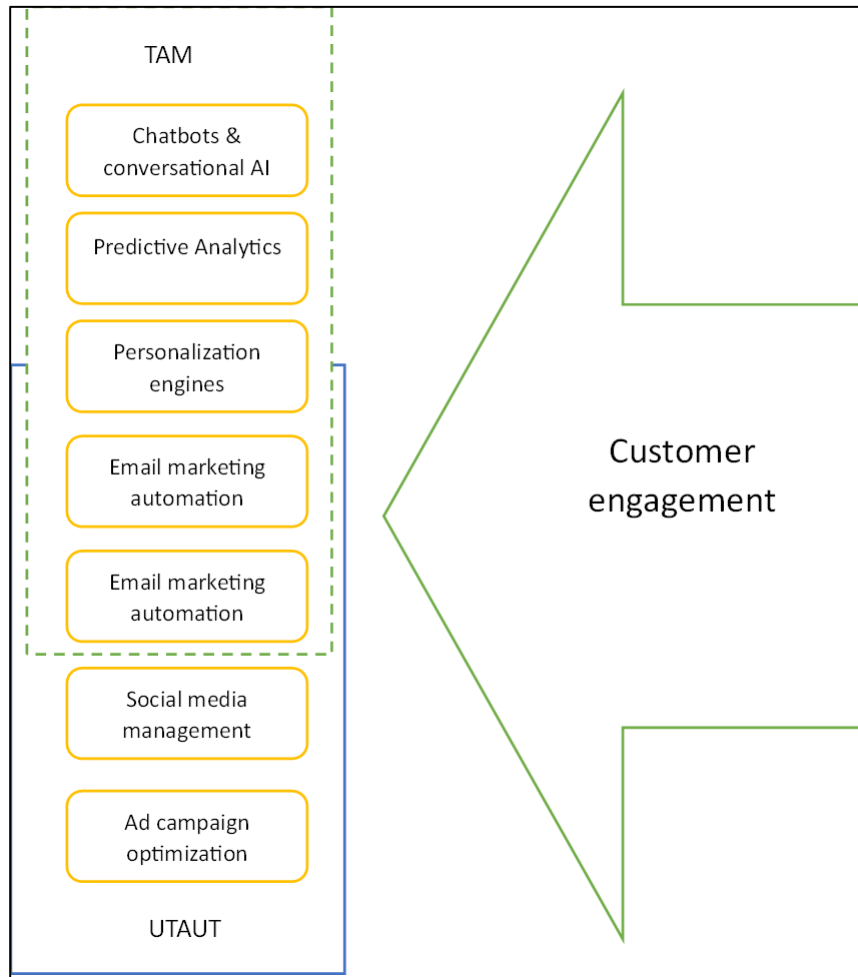


Figure 2. Conceptual model

Theoretical underpinning

The conceptual model for Generative AI-driven tools in E-commerce is based on the Technology Acceptance Model (TAM) by Davis (1989) and the Unified Theory of Acceptance and Use of Technology (UTAUT) by Venkatesh et al. (2003), both of which provide inspiration for the six-factor model. These theoretical frameworks highlight the importance of perceived utility and simplicity of use in forecasting the uptake of technology. Inside the realm of Generative AI, the elements inside the conceptual

model adhere to the concepts of TAM and UTAUT by focusing on certain features that improve user experience and involvement. The CCA aspect relates to the perceived simplicity of use since consumers often view real-time interactions with chatbots to be intuitive. PE and PA are in line with the concept of perceived usefulness since they offer customized information and predictions that improve customer pleasure. SMM and Ad Campaign Optimization are linked to the notions of social influence and performance expectancy within the model. These practices focus on the social elements of marketing and enhance the overall efficacy of advertising campaigns. This research article aims to provide a theoretical framework by including these aspects into a conceptual model. The framework will merge well-established technology adoption theories with the special functions of Generative AI tools in the E-commerce field (Table 2).

Table 2. Theoretical underpinning related to TAM and UTAUT

Generative AI-driven Tool	TAM Relevance	UTAUT Relevance
<i>Chatbots and Conversational AI</i>	Perceived Ease of Use	-
<i>Email marketing automation</i>	Perceived Usefulness, Perceived Ease of Use	Perceived Usefulness, Perceived Ease of Use
<i>Personalization engines</i>	Perceived Usefulness,	-
<i>Predictive analytics</i>	Perceived Usefulness,	-
<i>Social media management</i>	-	Social Influence, Performance Expectancy
<i>Ad campaign optimization</i>	-	Performance Expectancy

Methodology

Collection of data and sample



Data was collected from customers who have used the chatbot service in the recent past. The information was gathered in Arabic over the months of November and December 2023. The questionnaire was created in English first, and then translated into Arabic to ensure proper data gathering on the influence of generative AI tools on consumer interaction. Similar technique of back translation (Brislin, 1970; Liang et al., 2012) was used as adapted in similar studies (Algahtany & Kumar, 2016; Algahtany et al., 2019, 2022; Algahtany et al., 2018; Algahtany et al., 2016; Algahtany et al., 2014; Zia & Alzahrani, 2022). In all, 550 questionnaires were distributed by e-mail and personal visits. Only 373 completed surveys were obtained for further investigation, making a 67.81% response rate. The collected data represent almost similar gender distribution with male accounting for 48.79% whereas females accounting for 51.20 % respondents. The collected sample represents 54.15% of less than graduate and 54.48% of graduate and above. The age distribution of the sample included 16.35% below 20, 30.83% in the age group of 21 to 30, 37.80% in the age of 31 to 40 and 15.13 % in the age of 40 years and above (Table 3). The questionnaire was designed using a five-point Likert scale due to its greater versatility in social science research (Algahtany, 2023).

Table 3. Sample demographics

Characteristics	Number	Percentage (%)
<i>Gender</i>		
Male	182	48.79
Female	191	51.20
<i>Education</i>		
Less than bachelors	202	54.15



Bachelor's and above	171	54.48
<i>Age</i>		
Below 20 years	61	16.35
21 to 30 years	115	30.83
31 to 40 years	141	37.80
Above 40 years	56	15.13
Source (S): authors calculation		

Variables and the measurement scale

This scale to measure CBE has been developed using the prior TAM and UTAUT models (Table 4). The items of the CCA, PE and PA variable were modified from the Perceived Ease of Use in TAM, EMA were modified from Perceived Usefulness, Perceived Ease of Use in TAM and UTAUT, SMM from Social Influence and Performance Expectancy in UTAUT and Ad campaign optimization from Performance Expectancy in UTAUT model. It is not possible to find any references for the questions that were formed since they were developed based on general understanding of questionnaire creation and the criteria that were stated in the conceptual model. Similar techniques were used in past similar studies (Kalia et al., 2022; Zia, 2023). Furthermore, customization depends on the specific aims of this study or the distinguishing characteristics of the conceptual model.

Table 4. Items of the questionnaire.

Construct	Items	source
	How satisfied are you with the responsiveness of the chatbots on the e-commerce platform?	(Ahmed et al., 2023; Kanbach et

<i>Chatbots and Conversational AI (CCA)</i>	To what extent do you find the chatbots helpful in addressing your queries or concerns?	<i>al., 2023; Nadarzynski et al., 2021)</i>
	How often do you use the chatbot feature during your interactions with the platform?	
<i>Predictive Analytics (PA)</i>	How would you rate the accuracy of personalized product recommendations provided by the e-commerce platform?	<i>(Dinov, 2018; Hair Jr, 2007; Schwab, 2020)</i>
	To what extent do you believe that the platform understands your preferences based on your past interactions?	
	Have you experienced an improvement in your shopping experience due to personalized suggestions?	
<i>Personalization Engines (PE)</i>	How satisfied are you with the level of personalization in your user experience on the e-commerce platform?	<i>(Desai, 2021; Järvinen & Taiminen, 2016; Rane et al., 2023; Sen et al., 2008)</i>
	Do you feel that the platform tailors its content and recommendations to suit your individual preferences?	
	How likely are you to continue using the platform because of the personalized experience it offers?	
<i>Email Marketing Automation (EMA)</i>	How relevant do you find the promotional emails and offers sent by the e-commerce platform?	<i>(Järvinen & Taiminen, 2016; Paulo et al., 2022; Rane et al., 2023)</i>
	To what extent do you think the platform's automated emails align with your interests and buying patterns?	
	Have you made a purchase influenced by an email received from the platform?	
<i>Social Media Management (SMM)</i>	How often do you engage with the e-commerce platform's social media content (e.g., liking, sharing, commenting)?	<i>(Jacobson, 2020; Järvinen & Taiminen, 2016; Macnamara & Zerfass, 2012)</i>
	To what extent do the platform's social media posts influence your purchasing decisions?	
	How satisfied are you with the platform's presence on social media?	
<i>Ad Campaign Optimization (ACO)</i>	How effective do you find the advertisements displayed on the e-commerce platform?	<i>(Xu et al., 2015; Yankelovich & Meer, 2006)</i>
	Have you ever clicked on an ad from the platform that led to a purchase?	

	Do you believe that the platform's ad campaigns are relevant to your interests and needs?	
<i>Customer Behavioral Engagement (CBE)</i>	I don't think I will stop using chatbots in near future.	<i>(de Oliveira Santini et al., 2020; de Silva, 2020; McLean & Wilson, 2019; Rane et al., 2023; Shoukat & Ramkissoon, 2022; Van Doorn et al., 2010)</i>
	If I was asked, I would love to contribute with different ideas of improvement.	
	I spend a lot of time browsing through the internet, comparing other brands.	
	In general, I feel motivated to engage actively	
	I am willing to participate in collaborations.	

Data analysis and findings

Measurement model

To mitigate the potential issue of common method bias in our study, we utilized Harman's single factor test as a diagnostic tool. The results reveal that the initial component accounts for 42.55% of the variation, which is lower than the widely recognized criterion of 50% (Endara et al., 2019). Hence, the study seems to be free from any biases in the response data. The assessment of validity and reliability, including discriminant and convergent validity, for the first-order constructs is included in our measurement approach (Agrawal et al., 2023; Garg et al., 2023; Momade et al., 2021). The independent variables in this study are CCA, PA, PE, EMA, SMM, and ACO. The dependent variable is CBE, which forms a first-order formative structure.

The initial analysis focused on assessing the convergent validity, which was evaluated using markers such as Cronbach's alpha, average variance extracted (AVE), loadings,

and composite reliability (CR). During this procedure, six items were removed because their factor loadings fell below the threshold limit of 0.5 (Hair Jr et al., 2021). The AVE, CR, and Cronbach alpha values were above the required thresholds of 0.50, 0.70, and 0.70, respectively (Lai et al., 2009) see Table 5.

Table 5. Measurement model results

Construct	Item	Loading	VIF	Cronbach	CR	AVE
CCA	CCA1	0.869	1.464	0.763	0.820	0.670
	CCA2	0.808	1.667			
	CCA3	0.777	1.559			
PA	PA1	0.665	1.255	0.734	0.782	0.654
	PA2	0.891	1.836			
	PA3	0.853	1.709			
PE	PE1	0.868	1.446	0.714	0.807	0.623
	PE2	0.600	1.380			
	PE3	0.868	1.836			
EMA	EMA1	0.848	1.530	0.721	0.741	0.641
	EMA2	0.813	1.643			
	EMA3	0.736	1.278			
SMM	SMM1	0.840	1.808	0.801	0.821	0.716
	SMM2	0.903	2.110			
	SMM3	0.792	1.551			
ACO	ACO1	0.774	1.416	0.656	0.704	0.594
	ACO2	0.654	1.157			
	ACO3	0.868	1.474			
CBE	CBE1	0.686	1.312	0.663	0.674	0.501
	CBE2	0.761	1.437			
	CBE4	0.604	1.172			
	CBE5	0.767	1.358			

Source (S): authors calculation

After validating convergent validity, two approaches were used to assess discriminant validity. The initial criteria were examining the cross-loadings of indicators, wherein the loadings on the pertinent construct were required to be superior to those of other constructs. The second criterion Fornell and Larcker (1981), assessed the squared values of AVE. Higher values for each indicator diagonally indicate the attainment of necessary discriminant validity (Endara et al., 2019) see Table 6.

Table 6. Discriminant validity: Fornell–Larcker criterion

Constructs	ACO	CBE	CCA	EMA	PA	PE	SMM
ACO	0.771						
CBE	0.596	0.708					
CCA	0.498	0.660	0.819				
EMA	0.548	0.511	0.341	0.800			
PA	0.558	0.672	0.578	0.407	0.809		
PE	0.385	0.536	0.233	0.677	0.317	0.789	
SMM	0.302	0.433	0.277	0.481	0.194	0.404	0.846

Structural model

The path coefficient values in the structural model show the level and the direction of the impact of these variables on CBE (Figure 3). The values indicate that Ad Campaign Optimization ($\beta = 0.354, p < 0.000$), CCA ($\beta = 0.252, p < 0.05$), EMA ($\beta = 0.423, p < 0.000$) significantly influence the CBE. PE ($\beta = 0.078, p > 0.05$), PA ($\beta = -0.040, p > 0.05$) and SMM ($\beta = 0.006, p > 0.05$) has no significant impact on the CBE. The R-square value for CBE is 0.906 which indicates that 90.60% of the variance is explained by these six constructs. Out of these six variables EMA has the highest whereas CCA has the lowest significantly positive influence on CBE (Table 7). The bootstrapping

was performed to find the impact of independent variables on the dependent variables (Figure 4).

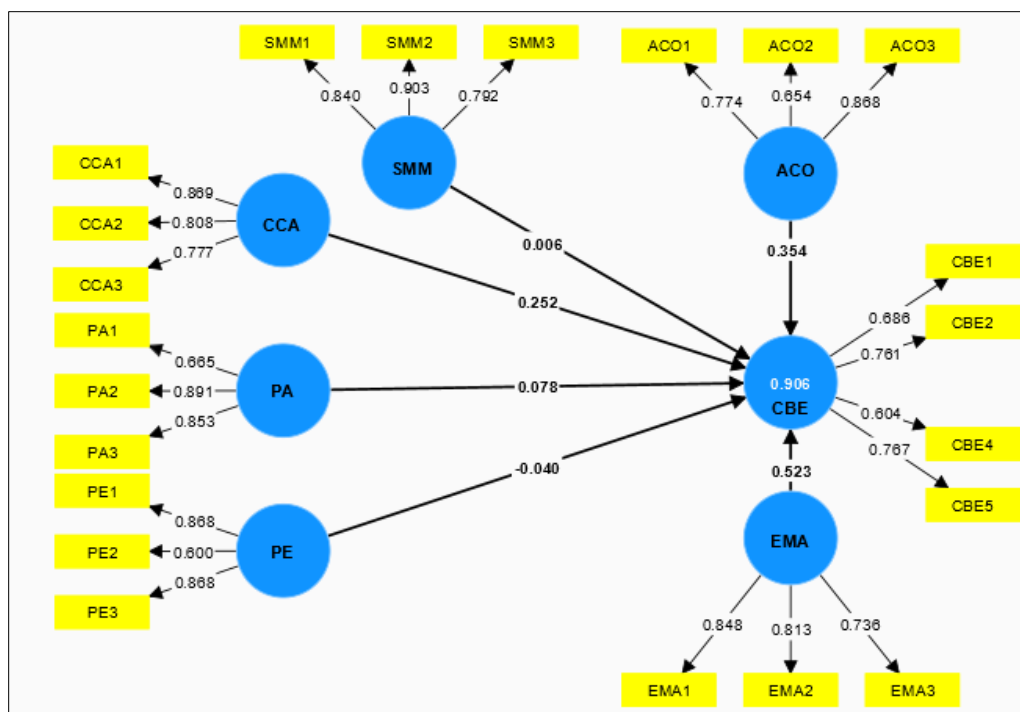


Figure 3. Path coefficient values

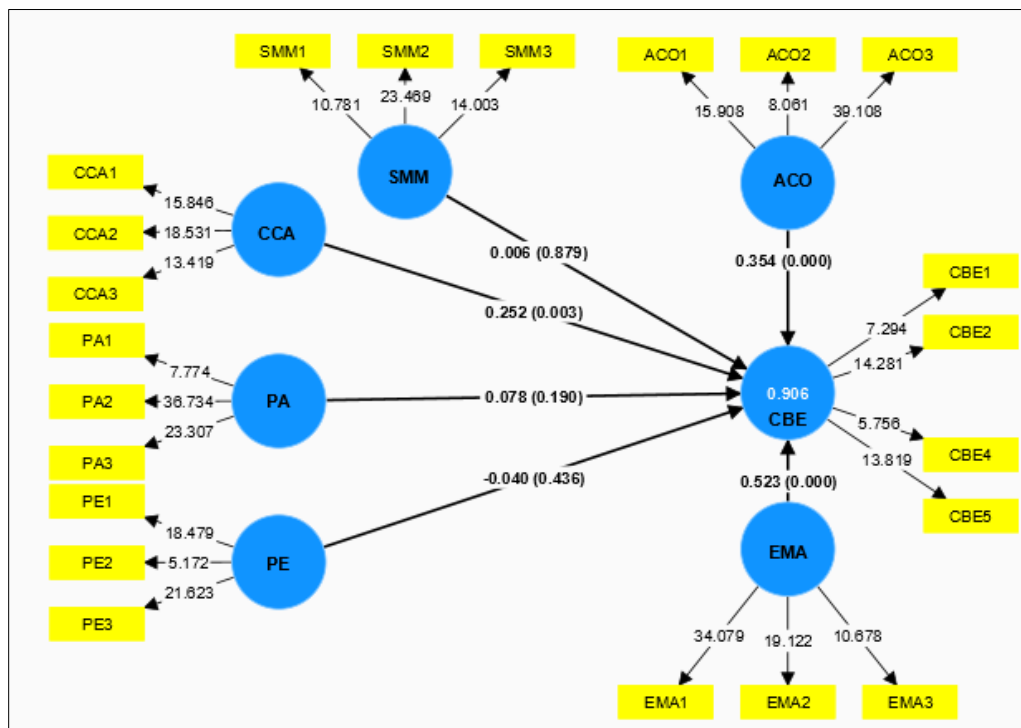


Figure 4. Bootstrapping results for significance level

Table 7. Structural model results

Hypothesis	Variables	Path coefficients	t-statistics (O/STDEV)	p-values	Results
H1	ACO→CBE	0.354	6.496	0.000	Accepted
H2	CCA→CBE	0.252	3.011	0.003	Accepted
H3	EMA→CBE	0.523	6.821	0.000	Accepted
H4	PE→CBE	0.078	1.311	0.190	Rejected
H5	PA→CBE	-0.040	0.778	0.436	Rejected
H6	SMM→CBE	0.006	0.152	0.879	Rejected

Discussions



This research explores the impact of AI driven tools on CBE. To this aim there were six hypotheses to test this relationship and significance level. The results of this study strongly support Hypothesis H1, indicating that AI technologies in ACO have a beneficial impact on CBE in E-commerce platforms. This outcome is consistent with an increasing amount of research that highlights the profound influence of AI in improving user engagement in online settings (Bilal et al., 2024; Mondal et al., 2023). Multiple previous studies have emphasized the crucial significance of artificial intelligence (AI) tools in optimizing advertising campaigns and, as a result, improving CBE. Utilizing AI-driven ad campaigns resulted in heightened user interactions and extended engagement durations (Shah & Nasnodkar, 2021; Xu et al., 2015). The user engagement metrics were significantly boosted by personalized content recommendations based on AI algorithms (Li, 2019). The present study's confirmation of hypothesis H1 that supports these findings, highlighting the favorable correlation between AI technologies in ACO and CBE in E-commerce platforms.

In contrast to previous studies that suggested limitations or inconclusive findings about the effectiveness of AI in generating CBE, our study establishes a distinct and positive correlation. Although several studies have raised concerns about the relevancy of AI-generated content and its potential detrimental influence on user privacy, our findings indicate that AI technologies have a positive effect on consumer behavioral engagement when used for ACO. This difference may be explained by the elusive use of AI in particular situations, highlighting the importance of a focused and planned incorporation of AI technologies to optimize their beneficial impact on customer involvement inside E-commerce platforms. This study's confirmation of Hypothesis H1 contributes useful knowledge to the existing literature by offering empirical proof



that AI technologies in ACO have a significant impact on CBE. Although it supports certain earlier studies, it also raises issues with some opposing viewpoints and emphasizes the significance of contextual elements and deliberate AI use in the context of e-commerce.

Further, results of this study significantly support Hypothesis H2, demonstrating a favorable influence of CCA technologies on CBE inside E-commerce platforms. This finding aligns with other studies that have investigated the impact of conversational AI on user interactions and the improvement of the overall customer experience. Several recent studies have emphasized the effectiveness of CCA technologies in enhancing CBE in digital contexts (Ahmed et al., 2023). Chatbots, by means of personalized interactions and immediate support, substantially enhanced user engagement and happiness (Bian et al., 2020; Kanbach et al., 2023). In addition, the integration of Conversational AI into customer service interfaces improved consumer engagement levels, namely in the areas of query resolution and smooth transaction facilitation. The results of this study are consistent with previous research, confirming that using CCA technologies in E-commerce platforms is an effective approach to promote favorable consumer interaction.

Although this study provides evidence for the significant impact of CCA technologies on CBE, previous research has offered contradictory viewpoints. There are studies that have found that chatbots as obtrusive or ineffectual, resulting in reduced interaction (Shah & Nasnodkar, 2021). Nevertheless, the present study's results contradict these opposing perspectives by highlighting the efficacy of CCA technologies in improving CBE on E-commerce platforms. The apparent inconsistency might arise from variations in the design, functionality, or implementation approaches of Chatbots,



underscoring the significance of thoughtful deliberation and tailoring in maximizing their influence on customer interaction. Ultimately, this study's confirmation of Hypothesis H2 offers significant contributions to the existing body of knowledge. It provides empirical data that supports the notion that CCA technologies have a favorable impact on CBE in E-commerce platforms. While corroborating some prior studies, it also contradicts opposing viewpoints, emphasizing the intricate nature of Chatbot efficacy and the necessity for deliberate deployment to improve total customer interaction.

The empirical results of this study provide evidence in favor of Hypothesis H3, confirming the positive impact of EMA technologies on CBE inside E-commerce platforms. This finding is consistent with other studies that have examined the effectiveness of automation in email marketing for improving customer interactions and promoting engagement (Järvinen & Taiminen, 2016; Paulo et al., 2022). Prior research has consistently highlighted the favorable impact of EMA solutions on CBE. The customized and prompt automated emails had a substantial impact on user engagement and led to improved conversion rates (Rane et al., 2023). Comparably, the deliberate implementation of EMA technologies resulted in enhanced customer interactions and increased levels of engagement (Paulo et al., 2022). The results of this study align with previous research, emphasizing the significance of utilizing EMA solutions to improve CBE in the ever-changing realm of E-commerce platforms.

This study agrees with previous research that shows how effective EMA technologies are increasing CBE, but it also acknowledges that other studies have shown conflicting results. In their study, situations in which consumers saw automated emails as invasive or irrelevant, which might potentially result in disengagement (Pavlov et al., 2008).



Nevertheless, the present study's results contradict these opposing viewpoints by highlighting the overall beneficial impact of EMA technologies on customer involvement in E-commerce platforms (Zhang et al., 2017). The apparent inconsistency may be ascribed to differences in the structure and substance of automated email campaigns, indicating that the efficacy of EMA solutions depends on aspects such as customization and pertinence. Eventually, this study's acceptance of Hypothesis H3 adds to the existing literature by offering empirical proof that EMA solutions have a favorable impact on customer involvement in E-commerce platforms. While corroborating with certain prior research, it also underscores the need for strategic deliberations in crafting EMA to maximize customer participation, possibly challenging studies that emphasize adverse consumer views.

Hypothesis H4 proposed that PE tools have a beneficial impact on CBE in E-commerce platforms. Nevertheless, the idea was rejected based on empirical evidence. Within the framework of E-commerce platforms, our study is consistent with a larger group of research that has examined the relationship between CBE and personalization tools. Several previous research has shown that personalization has a positive impact on user happiness, loyalty, and overall engagement (Zhang et al., 2017). The connecting thread across these studies is the acknowledgment of the need to customize user experiences based on individual preferences using PE. Although our study has similarities with past research, it diverges in its emphasis on the overall use of Generative AI-driven technologies. Our investigation takes a comprehensive approach by considering a range of Generative AI tools. Unlike other studies that focus solely on personalization or specific tools, we examine the broader spectrum of these tools. This unique viewpoint



allows for a thorough comprehension of how different Generative AI methods together enhance customer involvement in the field of E-commerce.

The results of Hypothesis H4 indicates that the use of PE tools did not exhibit a statistically significant positive impact on CBE in the specific setting of our investigation. There are several factors that may have led to this unanticipated outcome. The study suggests that the individual impact of PE may have been eclipsed by other Generative AI technologies. Furthermore, variables such as the successful execution of the plan, user inclinations, or the characteristics of the E-commerce system may have contributed to weakening the expected favorable correlation. Furthermore, the rejection is consistent with the acknowledgment that the acceptance of personalization tactics might fluctuate depending on various circumstances and platforms (Desai, 2021). The ever-changing nature of e-commerce environments and the complex array of elements that impact consumer behaviors make it difficult to create a universally applicable relationship between PE and CBE. Although our research did not find evidence of a direct positive impact of PE tools on consumer engagement in the specific context we studied, our unique approach to analyzing various Generative AI tools provides valuable insights for future research and practical implications for businesses aiming to improve CBE in the E-commerce field.

The hypothesis H5, which suggested that PA technologies had a beneficial impact on CBE, was rejected because of empirical evidence. While our analysis contradicts earlier studies showing the possible benefits of PA for user engagement, it stands out by using a comprehensive approach that includes a range of Generative AI-driven technologies. This technique enables a thorough analysis of how PA integrates into the wider ecosystem that influences customer involvement in E-commerce. The



dismissal of H5 necessitates contemplation of possible contributory elements. The efficacy of PA tools relies on contextual factors such as the quality of data, accuracy of algorithms, and the characteristics of the E-commerce platform. Moreover, the interaction between PA and other Generative AI tools may bring intricacy that was not completely accounted for in our work (Dinov, 2018; Schwab, 2020). The ever-changing nature of consumer perceptions and preferences in the field of E-commerce implies that the influence of PA is likely to change as well. To summarize, our research does not provide evidence for a direct positive impact of PA on CBE in the specific context of our study. However, our detailed examination of various Generative AI tools enhances our comprehension of the complex factors that influence user engagement on E-commerce platforms. This opens opportunities for future studies to investigate contextual elements and tool interactions that affect these outcomes in greater depth.

The investigation into the relationship between the use of SMM tools and CBE within E-commerce platforms, as suggested by Hypothesis H6, resulted in an unexpected consequence that led to its rejection. Our study contradicts previous research that has examined the influence of SMM tools on customer involvement, specifically within the wider scope of digital marketing and e-commerce. Prior research has frequently highlighted the potential benefits of well-executed social media tactics in enhancing consumer engagement indicators, including brand loyalty, customer happiness, and purchase behavior (Jacobson, 2020; Macnamara & Zerfass, 2012). Nevertheless, this research stands out due to its distinctive use of several Generative AI-powered technologies, in addition to SMM. This complete approach enables a thorough comprehension of the role of SMM tools in the broader ecosystem of Generative AI, namely in shaping consumer interaction on E-commerce platforms. Although earlier



research has emphasized the beneficial influence of SMM on customer involvement, the rejection of Hypothesis H6 necessitates a careful review. A possible reason for the rejection might be based on the ever-changing nature of social media platforms and the changing tastes of users (Kalia et al., 2022). The dynamic nature of social media trends and user behaviors can undergo swift transformations, hence influencing the efficacy of management techniques. Moreover, the interaction between SMM and other Generative AI technologies might potentially complicate matters, hence impacting the reported results. Moreover, the rejection may be ascribed to discrepancies in the efficacy of SMM solutions based on the E-commerce platform being examined. Various platforms can appeal to distinct user groups, each exhibiting distinct expectations and reactions to social media engagement techniques.

Ultimately, our empirical data did not support Hypothesis H6. However, the study is valuable in shedding insight on the complex factors that impact customer participation in E-commerce platforms. Further investigation should focus on the temporal dimensions of social media strategies and examine the interplay between SMM and other Generative AI technologies to get a more intricate comprehension of their combined influence on CBE.

Implications

The evidence suggests that AI solutions, including chatbots, email marketing automation, and ad campaign optimization, have a favorable impact on customer behavior engagement on e-commerce platforms. Based on these results, companies who want to make the most of their online presence should priorities incorporating



these technologies into their E-commerce plans so that they can increase customer interaction. It appears that PE, PA tools, and SMM may not significantly improve consumer engagement in E-commerce platforms, according to your study's rejection of hypotheses about their positive influence on engagement. The need to thoroughly assess these technologies' efficacy before making substantial investments in their adoption cannot be overstated. Companies should prioritize developing and executing strategies for email marketing automation, chatbots, and ad campaign optimization based on the agreed hypothesis. A more tailored and engaging online shopping experience may be realized with the help of these solutions, which have a proven track record of increasing CBE. PE, Predictive Analytics, and SMM techniques should be reevaluated considering the failure of linked theories. If companies want to meet customer expectations and preferences, they need to refine their strategy, maybe investigate other technologies, or change how they accomplish things. Our study's managerial implications provide valuable insight into how generative AI-driven technologies affect CBE on e-commerce platforms. Recognizing the interdependence of technologies like chatbots, PE, email marketing automation, SMM, ad campaign optimization, and PA is the first and main recommendation for implementing an integrated strategy. There is a clear need to enhance personalization tactics, streamline email marketing automation, and monitor important indicators to optimize advertising campaigns.

Additionally, to develop trust and improve overall CBE, organizations should make user education and openness in interactions a priority, particularly when it comes to CCA. Companies may successfully use Generative AI technologies to navigate the E-commerce market and increase consumer happiness and long-term performance by



paying attention to these consequences. To keep up with evolving customer preferences and technology developments, constant vigilance and change are important (Allil et al., 2024).

Conclusions

Finally, this study has shown how different AI technologies affect E-commerce platform user engagement in a complex way. Evidence supporting the beneficial effects of chatbots, email marketing automation, and ad campaign optimization points to the importance of these technologies in boosting CBE. Insights like this should motivate companies to make these technologies a top priority and improve their strategy for E-commerce so customers have a more tailored and engaging experience. But we must proceed with caution and more investigation because our PE, PA tools, and SMM theories were rejected. Despite the lack of a statistically significant effect on customer involvement in the present study, the complexity of these tools makes them worthy of further investigation. Companies need to reevaluate existing tactics or come up with new ones to meet the changing expectations of their customers.

Limitations and future research directions

This study concluded that AI technologies complexly affect E-commerce platform user engagement. Chatbots, email marketing automation, and ad campaign optimization have been shown to improve CBE. These insights should encourage organizations to prioritize these technologies and strengthen their E-commerce strategy to give



customers a more personalized and engaging experience. Starting with a deeper look at PE's efficacy factors is crucial. To maximize consumer engagement with customized experiences, further queries may examine content relevancy, user preferences, and real-time adaptation. Scholarly research might also add variables and algorithms to PA systems to improve their capacity to predict and respond to changing customer behaviors. Future study may examine the synergies and conflicts that may arise when several AI technologies are incorporated into e-commerce systems. This would identify ideal configurations for an AI-driven approach that is comprehensive and efficient. Finally, longitudinal study is needed to determine the long-term effects of AI technologies. This involves examining how continued usage affects e-commerce consumer loyalty, satisfaction, and brand perception.



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