

The Role of Moderators in Transitioning From GenAI Chatbot Customer Experience To Customer Satisfaction in Digital Marketing

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DOI: 10.46609/IJSSER.2024.v09i07.028 URL: <https://doi.org/10.46609/IJSSER.2024.v09i07.028>

Received: 17 July 2024 / Accepted: 30 July 2024 / Published: 10 August 2024

ABSTRACT

This study investigates the role of moderators in transitioning from Generative AI (GenAI) chatbot customer experience to customer satisfaction in digital marketing. As digital marketing continues to grow with technological advancements, GenAI chatbots such as ChatGPT, Copilot, and Gemini have become essential tools for enhancing customer engagement and providing personalized experiences. Despite extensive research on the technical aspects of chatbots, there is limited understanding of how perceived personalization, relevance, and usefulness of GenAI chatbots impact customer satisfaction significantly when moderated by variables like familiarity with technology and organization type. A conceptual model is developed, and data is collected through a survey of 346 consumers who interact with GenAI chatbots. The data is analyzed using moderated regression analysis to test the proposed hypotheses. The findings of this study will enhance the understanding of factors influencing customer experience and provide practical insights for businesses aiming to improve customer satisfaction through effective GenAI chatbot integration. This research contributes to the existing literature on digital marketing and offers actionable recommendations for customizing GenAI chatbots to meet the needs of different organizational types.

Keywords: GenAI chatbot; Customer experience; Customer satisfaction; Moderator variables.

1. Introduction

As internet platforms and technological usage continue growing, digital marketing has become a crucial element of business operations today (Rudolph et al., 2023). Chatbots have emerged as a

critical digital marketing tool, enhancing customer experiences by offering businesses a straightforward and personalized way to engage with their clients ([Følstad & Brandtzæg, 2017](#)). These chatbots are computer programs that mimic human-to-human conversation via text-based messages ([McCull-Kennedy & Schneider, 2000](#)) and can be programmed to perform various functions, including answering customer queries, providing recommendations, and facilitating transactions ([Taecharungroj, 2023](#)). Customer experience, on the other hand, encompasses the overall impression and perception shaped by interactions throughout the customer journey ([Van den Broeck et al., 2019](#)).

Generative Artificial intelligence (GenAI) chatbots like ChatGPT, Copilot, and Gemini can respond to text prompts in a human-like manner ([Gordijn & Have, 2023](#); [Loh, 2023](#)). GenAI chatbot is a family of language models using huge datasets ([Klang & Levy-Mendelovich, 2023](#)).

In digital marketing, there is a growing of studies investigating the influence of GenAI chatbots on customer experience ([Chen et al., 2021](#)). However, many of these studies have concentrated on technical aspects of chatbots, such as accuracy and functionality, and have not fully considered the impact of other factors on customer experience, such as perceived personalization ([Ajlouni et al., 2023](#)), perceived relevance, and usefulness ([Abdelkader, 2021](#); [Rospigliosi, 2023](#)). Considering the above arguments leads to our first research question (RQ):

RQ1. How does GenAI chatbot affect the customer experience in digital marketing?

Existing research on integrating GenAI chatbot models in marketing and enhancing customer experiences is limited. Previous research investigated how GenAI chatbots influence other aspects of the customer experience, such as perceived helpfulness and engagement ([Elkhodr et al., 2023](#)), revealing generally positive effects ([Yang & Zhang, 2024](#)). While prior investigations have examined their impact on customer satisfaction, they have overlooked the potential moderating influences of variables such as familiarity with technology ([Abdaljaleel et al., 2024](#)) and organization type ([Vij & Farooq, 2017](#)). From here, the following second research question was raised:

RQ2. How do moderator variables (i) familiarity with technology and (ii) organization type affect the link between customer experience (Perceived Personalization, relevance, usefulness) with GenAI chatbot and customer satisfaction in digital marketing?

We answer these two research questions by building the conceptual model in [Figure 1](#) and identifying five specific research objectives (RO).

RO1: To examine the relationship between customer experience with GenAI chatbot (perceived personalization, relevance, usefulness) and customer satisfaction in digital marketing.

RO2: To investigate the role of familiarity with technology in moderating the relationship between customer experience with GenAI chatbot and customer satisfaction.

RO3: To explore how the organization type moderates the relationship between customer experience with GenAI chatbot and customer satisfaction.

RO4: To provide insights and recommendations for businesses to improve customer satisfaction by enhancing the customer experience with GenAI chatbot and effectively leveraging technology.

To gather data for this study, a survey questionnaire will be administered to consumers interacting with GenAI chatbots in digital marketing. This forms part of the study's quantitative research methodology. The data collected will be analyzed using moderated regression analysis to test the study's proposed hypotheses and explore the moderating effects of variables such as familiarity with technology and organization type involved.

The outcomes of this study will enhance researchers' understanding of the factors that influence customer experience in digital marketing. Additionally, the findings will provide practical insights into how companies can leverage GenAI chatbots to boost customer satisfaction. Furthermore, this research will influence the design and implementation of GenAI chatbots in digital marketing by offering recommendations on how to customize GenAI chatbots to suit different organization types.

2. Literature review and hypothesis development

This section examines prior research relevant to the current study's topic and details the formulation of its hypotheses. Previous studies' achievements are organized into four distinct sub-sections, each aligned to support the objectives of this study effectively. These sub-sections include measuring customer experience and satisfaction, familiarity with technology, and organization type.

2.1. Customer experience with GenAI chatbot and customer satisfaction

Many researchers have mentioned GenAI chatbot in published studies. One of the GenAI chatbots mentioned by many researchers is the Chat Generative Pre-trained Transformer (ChatGPT), released in 2020. It is one of the most significant language models ever produced, with 175 billion parameters ([OpenAI, 2018](#)). GenAI chatbot using ChatGPT has been used in various natural language processing applications, including translation, software programming, medicine, authoring, and content creation ([Gilson et al., 2023](#); [Gunawan, 2023](#); [Rudolph et al., 2023](#); [Yeo-Teh & Tang, 2023](#)). GenAI chatbots have grown in popularity as a tool for improving

the customer experience in digital marketing. They offer businesses a quick and personalized way to communicate with clients and can automate customer service tasks, freeing up human agents to focus on more complex issues (Ramesh & Chawla, 2022).

On the other hand, GenAI chatbots may deliver various benefits in improving the customer experience in digital marketing (Haugeland et al., 2022), boosting customer engagement by offering rapid support, and reducing response times by eliminating the need for customers to wait for a human agent to respond (El Bakkouri et al., 2022). Additionally, GenAI chatbots can collect user data, which can be used to improve marketing campaigns and personalize the customer experience (Misischia et al., 2022), assist clients in identifying the items or services that best fit their requirements by making tailored suggestions and enhancing customer satisfaction (Ashfaq et al., 2020). As GenAI chatbots become more sophisticated, they are likely to play an increasingly important role in improving the customer experience in digital marketing.

Customers' experience is defined as the total image and perception of a brand based on their interactions across their whole usage journey (Buchanan Lunsford et al., 2018; Chen & Chen, 2021). It is essential for increasing client loyalty and repeat business (Chen et al., 2021). Customer satisfaction measures how well a company's products, services, and overall customer experience meet customer expectations (Karatepe, 2011; Jenneboer et al., 2022).

Measuring customer experience includes three main elements that should be measured: Perceived Personalization (PP), Perceived Relevance (PR), and Perceived Usefulness (PU) (Van den Broeck et al., 2019; Haugeland et al., 2022; Ramesh & Chawla, 2022). Furthermore, measuring Customer Satisfaction (CS) is essential for statistical analysis and customer experience components (Kim et al., 2021). Customer satisfaction can be measured by three main components: declaration of satisfaction (McCull-Kennedy & Schneider, 2000), recommendation to others (Kim et al., 2021), and intent to use again (Silva et al., 2023).

2.2. Familiarity with technology

Customers want GenAI chatbots to give tailored and relevant replies that are accurate and useful, as well as an easy-to-use and convenient chatbot interface. However, not all GenAI chatbots are equally easy to use. Customers' familiarity with technology may impact how they engage with GenAI chatbots and their overall pleasure with the encounter; for example, they are more inclined to utilize and find GenAI chatbots helpful (Quintino, 2019).

Familiarity with technology is a crucial factor influencing how customers experience and evaluate technological services (Parasuraman & Colby, 2007). A study on customer satisfaction in online banking found that familiarity with technology significantly impacts user experience

and overall satisfaction (Lin, 2008). Customers familiar with technology tend to have higher evaluations of ease of use and usefulness. (Kim & Lee, 2014) Studied the role of familiarity with technology in the context of mobile applications. They found that users highly familiar with technology generally have more positive experiences and higher satisfaction levels. On the other side, a few studies found that customers’ familiarity with technology significantly impacted their satisfaction with GenAI chatbots and suggested that their satisfaction with GenAI chatbots was only significant for customers already familiar with GenAI chatbots (Rieke, 2018; Jenneboer et al., 2022). Based on the literature review and the mentioned references through the previous subsections, We propose the hypothesizes:

H1a. Familiarity with technology will positively moderate the relationship between perceived personalization with GenAI chatbots and customer satisfaction in digital marketing.

H1b. Familiarity with technology will positively moderate the relationship between perceived relevance to GenAI chatbots and customer satisfaction in digital marketing.

H1c. Familiarity with Technology will positively moderate the relationship between perceived usefulness of GenAI chatbots and Customer Satisfaction in digital marketing.

2.3. Organization type

Thousands of businesses worldwide utilize GenAI chatbots to engage with consumers through the Internet in various industries (Haleem et al., 2022; Rudolph et al., 2023). Most globally recognized companies have created websites based on GenAI chatbots in a variety of industries, including retail and e-commerce (e.g., Amazon, Walmart, Alibaba, eBay...) (Haleem et al., 2022), technology and communication (e.g., Google, Microsoft, Facebook, Apple, IBM, Intel...) (Taecharungroj, 2023), transportation and travel (e.g., Uber, Grab, Agoda, Booking...) (Gilson et al., 2023; Gunawan, 2023; Rospigliosi, 2023). GenAI chatbots differ regarding purpose, optimal performance, and usage. Table 1 shows how the optimal performance of each chatbot corresponds to different types of organizations.

Table 1: The best suitable GenAI chatbots for selected organization types

Organization type	Suitable GenAI chatbot	Optimal performance
Education	ChatGPT/Gemini/Claude	Effective in providing scalable, individualized learning experiences
Retail	LiveChat/Zendesk	Customer support and experience

Technology	ChatGPT/GitHub	Content generation, research, translations, coding
Healthcare	IBM Watson Health	Patient care management, and clinical decision support capabilities
Finance	IBM Watson/ChatGPT	Capabilities in risk management, customer service, and operational efficiency
Travel	Amadeus AI	Optimize booking processes, customize travel recommendations...

Source: (Bella, 2023)

The organization type may also impact the customer experience with chatbot usage. Various organization types may have distinct qualities, and client demands that impact how chatbots are viewed and used (Klang & Levy-Mendelovich, 2023; Tlili et al., 2023). A GenAI chatbot utilized in a retail firm. For example, it may be seen differently than a chatbot used in a healthcare business (Buchanan Lunsford et al., 2018). The type of company may also impact chatbot design and deployment, such as the language used and the types of interactions enabled (Gilson et al., 2023).

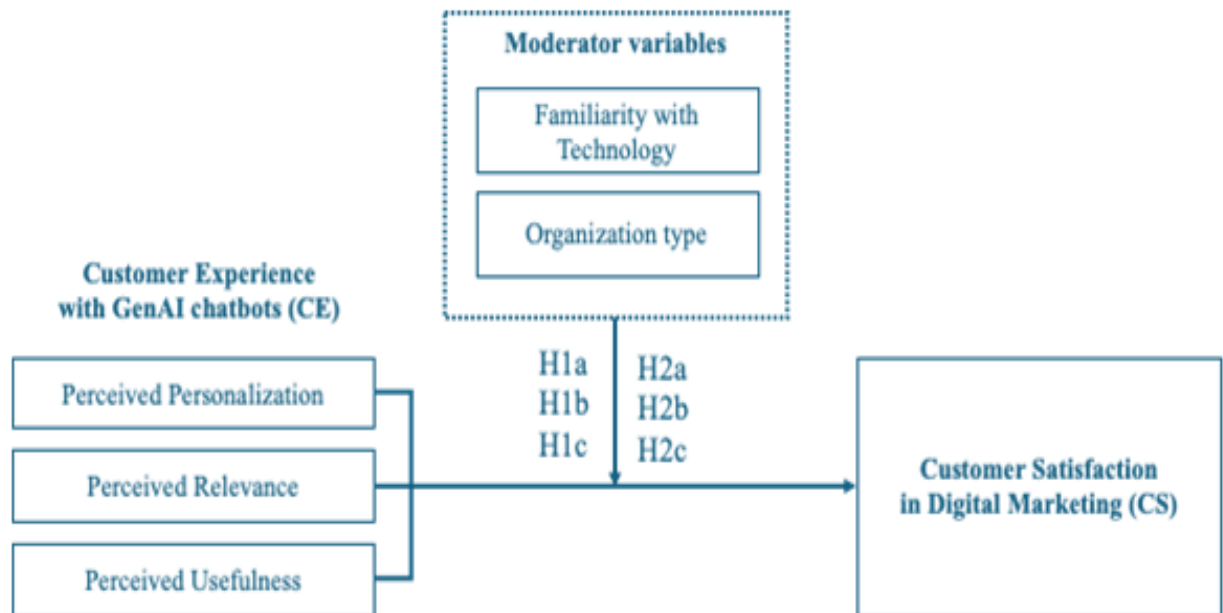
Many researchers have conducted research on the moderating role of organization type in the relationship between customer experience and satisfaction. For example, in the healthcare sector (Wolf et al., 2021), the retail sector (Verhoef et al., 2009), and the financial sector (Gunawardane, 2023). All studies confirm the moderating role of organization type in this relationship. Based on the literature review and the mentioned references through the previous subsections, We propose the hypothesizes:

H2a. *Organization type will positively moderate the relationship between Perceived Personalization with GenAI chatbots and Customer Satisfaction in digital marketing.*

H2b. *Organization type will positively moderate the relationship between Perceived Relevance with GenAI chatbots and Customer Satisfaction in digital marketing.*

H2c. *Organization type will positively moderate the relationship between perceived usefulness of GenAI chatbots and Customer Satisfaction in digital marketing.*

Figure 1: The conceptual model



3. Method

This research investigates the influence of GenAI chatbots on customer experience in digital marketing. It will use a cross-sectional survey methodology to gather data electronically via an open-access link from clients engaged with GenAI chatbots in digital marketing.

3.1. Research instrument building

The development of the questionnaire, which was used as the primary research tool, involved multiple stages to ensure its validity. Initially, the questionnaire was drafted after reviewing related literature and consulting with over 10 digital marketing clients. It was then evaluated by a panel of experts to verify its adequacy for the study's goals. A preliminary version was tested with a sample of 15 digital marketing customers to refine its language and ensure it met the survey objectives. After these revisions, the final version was prepared for distribution.

The survey questionnaire is structured into three sections, as detailed in [Table 2](#). The first section gathers data on Customer Experience with the GenAI chatbot, focusing on perceived personalization, relevance, and usefulness. The second section evaluates customer satisfaction in digital marketing. The third section analyzes the moderating effects of Familiarity with Technology and Organization type.

Table 2: The variables of the study questionnaire

Code	Variables	Source
1. Customer Experience with GenAI chatbots		
<i>Perceived Personalization</i>		
PP1	GenAI chatbot provided information tailored to my needs.	Developed from <u>Haugeland et al., 2022; Ramesh & Chawla, 2022, Shumanov & Johnson (2021)</u>
PP2	GenAI chatbot understood my preferences and needs.	
PP3	GenAI chatbot offered relevant recommendations and suggestions.	
<i>Perceived Relevance</i>		
PR1	GenAI chatbot provided relevant information.	Developed from <u>Haugeland et al., 2022; Ramesh & Chawla, 2022</u>
PR2	GenAI chatbot provided useful information	
PR3	GenAI chatbot provided me with relevant options and alternatives.	
<i>Perceived Usefulness</i>		
PU1	GenAI chatbot provided accurate and reliable information	Adapted from <u>(Van den Broeck et al., 2019)</u>
PU2	GenAI chatbot gave me useful information.	
PU3	I trust the information provided by GenAI chatbot.	
2. Customer satisfaction in digital marketing		
<i>Customer Satisfaction</i>		
CS1	I am satisfied with my experience interacting with GenAI chatbot.	Adapted from <u>(McCull-Kennedy & Schneider, 2000), (Kim et al., 2021), (Silva et al., 2023)</u>
CS2	I would recommend GenAI chatbot to others.	
CS3	I would use GenAI chatbot again in the future.	
3. Moderator variables		
<i>Familiarity with Technology</i>		
FT1	I am comfortable using technology to interact with businesses.	Developed from <u>Quintino (2019), (Rieke, 2018;</u>

FT2	I am familiar with digital marketing technology.	<u>Jenneboer et al., 2022)</u>
FT3	I feel confident using GenAI chatbot in digital marketing.	
	Organization type	Developed from <u>Tlili et al., 2023</u>
OT	Education, Retail, Technology, Healthcare, Finance, Travel, Other	

3.2. Sample selection and data collection

To select the sample, we used a non-random approach with two main criteria (Smith, 1983). First, respondents needed to be customers interacting with GenAI chatbots in digital marketing. This was verified through a screening question in the email questionnaire. In March 2024, the questionnaire was emailed to 519 potential respondents from the authors’ network in Vietnam, followed by a reminder in early May 2024. We received 346 valid responses, yielding a 66.6% response rate, which surpasses the 15% rate recommended by Hair (2009).

We checked for non-response bias between early (n=217) and late respondents (n=129) using Levene’s test for equality of variances and a t-test for equality of means (Armstrong & Overton, 1977). No significant differences were found. Additionally, Harman’s single-factor test with an exploratory factor analysis showed no standard method bias, as the first factor accounted for only 31.15% of the total variance (less than 50%, (Podsakoff et al., 2003)).

Regarding respondents’ characteristics: 69.8% were male, 30.2% female; 84.7% were aged 18-44; 13% had a high school education. In terms of organizational sector, retail was the highest at 18.5%, and finance the lowest at 11.6%. See Table 3.

Table 3: Sample characteristics (n=346)

Gender	Frequency	Percent	Age_Group	Frequency	Percent
Male	88	69.8	18-24	91	26.3
Female	38	30.2	25-34	102	29.5
Organization_type			35-44	100	28.9
Education	41	11.8	45-54	38	11
Retail	64	18.5	55 and above	15	4.3
Technology	57	16.5			

Healthcare	49	14.2	Education_level		
Finance	40	11.6	High school	45	13
Travel	51	14.7	Bachelor	170	49.1
Other	44	12.7	Master and above	131	37.9

3.3. Validity and reliability of constructs

In this step, we performed two Exploratory Factor Analyses (EFA) using Principal Component (PC) extraction to identify and validate constructs from the collected data (Fabrigar et al., 1999). The first EFA, conducted with FT, is detailed in Table 4. All three factors showed high loadings in the first PC, with an eigenvalue of 2.621, explaining 87.356% of the total variance. The reliability of the construct was confirmed with Cronbach’s alpha ($\alpha = 0.828$), exceeding the 0.6 threshold and indicating high response reliability (Meyers et al., 2016). The responses for this construct were calculated by determining the weighted average of the original responses, using factor loadings as weights.

Table 4: EFA to validate the [FT] construct

Variables	Mean	Std. Dev.	Communalities	Factor loading
FT1: "Comfortable using technology"	3.02	1.071	0.873	0.834
FT2: "Familiar with digital marketing technology"	2.98	1.099	0.876	0.836
FT3: "Confident using GenAI chatbot"	3.02	1.106	0.862	0.864
Extraction sums of squared loadings				2.621
% of variance				87.356
Cronbach’s alpha				0.828
KMO measure of sampling adequacy				0.766
Bartlett’s test of sphericity (χ^2/df)				810.554/3****

Note: Extraction Method: Principal Component Analysis, **** p-value < 0.001

The second EFA focused on responses regarding the agreement level between CE and CS. Employing a varimax rotation, four principal components (PCs) emerged, each with eigenvalues

exceeding 1: Perceived Personalization (PP=2.697), Perceived Relevance (PR=2.668), Customer Satisfaction (CS=2.634), and Perceived Usefulness (PU=2.542). These PCs collectively accounted for 87.693% of the total variance. Adhering to established guidelines (Hair, 2009), only factor loadings above 0.6 were considered.

To verify orthogonality, we replicated the analysis using an oblique rotation, yielding similar results. The unidimensionality of each component was confirmed through Principal Component Analysis conducted at the component level. Reliability assessment, using Cronbach’s alpha, indicated high reliability ($\alpha > 0.6$) for all components (Meyers et al., 2016), as detailed in Table 5.

The measures within the first component consistently related to Perceived Personalization (PP), the second to Perceived Relevance (PR), the third to Perceived Usefulness (PU), and the final component to Customer Satisfaction (CS). All constructs exhibited factor loadings exceeding 0.6, with no cross-loading observed (Hair, 2009). These results, presented in Table 5, confirm the validity of the second EFA.

Table 5: EFA to validate elements of Customer Experience and Customer satisfaction

Variables	Mean	Std. Dev.	Communalities	Factor loading			
				1	2	3	4
PP2	2.98	1.119	0.891	0.908			
PP1	2.98	1.102	0.875	0.907			
PP3	2.95	1.11	0.879	0.905			
PR1	2.96	1.112	0.891		0.915		
PR3	2.96	1.091	0.874		0.902		
PR2	2.94	1.107	0.876		0.894		
PU1	2.94	1.094	0.865			0.867	
PU3	2.95	1.11	0.874			0.866	
PU2	2.94	1.095	0.875			0.852	
CS3	2.99	1.049	0.87				0.901

CS2	3.01	1.111	0.889		0.894	
CS1	3.04	1.077	0.864		0.889	
Extraction sums of squared loadings			5.539	2.266	1.581	1.138
% of variance			46.157	18.886	13.171	9.48
Rotation Sums of Squared Loadings			2.679	2.668	2.634	2.542
% of Variance			22.329	22.234	21.948	21.183
Cronbach's alpha			0.932	0.928	0.927	0.932
KMO measure of sampling adequacy			0.854			
Bartlett's test of sphericity (χ^2/df)			3570.390/66***			

Note: Extraction Method: Principal Component, Rotation Method: Varimax with Kaiser Normalization, *** p-value < 0.001

Finally, we determined the pairwise correlations between all constructs, along with their composite reliability (CR) and average variance extracted (AVE) to assess convergent validity (see Table 6). All correlation coefficients were statistically significant (p-value < 0.05) and positive, indicating the nature of the relationships between the variables. Both CR and AVE values exceeded 0.5, confirming the convergent validity of the constructs (Fornell & Bookstein, 1982; Hair, 2009). Based on these findings, values for each validated construct were calculated using their corresponding factor loadings and represented on a continuous scale.

Table 6: Model validity measures

	CR	AVE	PR	CS	PP	PU
PR	0.932	0.820	0.906			
CS	0.928	0.810	0.421***	0.900		
PP	0.932	0.821	0.174**	0.314***	0.906	
PU	0.926	0.806	0.463***	0.469***	0.516***	0.898

Note: *** p-value < 0.001, **p-value<0.05

4. Results and discussions

This section of the current study presents and discusses the results through the following three sub-sections: the hypotheses, test results, and discussions.

4.1. The results of the hypotheses test

Table 7 summarizes the influence weights of the customer experience with GenAI chatbot elements (Perceived personalization, Perceived relevance, Perceived usefulness) on customer satisfaction in digital marketing.

Table 7: The impact weights of customer experience elements on customer satisfaction

CE* with GenAI chatbot	Mean	SD*	$\hat{\beta}$	Sig.	CI* on .05 level	VIF
Perceived Personalization	2.9701	1.04195	0.13	0.020	0.021 ≤ 0.225	1.301
Perceived Relevance	2.9538	1.03532	0.26	0.001	0.154 ≤ 0.353	1.230
Perceived Usefulness	2.9413	1.02605	0.26	0.001	0.140 ≤ 0.366	1.553

Note: *CE: Customer Experience, SD: Standard Deviation, CI: Confidence Interval.

Table 8 summarizes the results of the hypotheses test. (H1a), results of moderating regression analysis indicate that familiarity with technology does not moderate the connections between perceived personalization with GenAI chatbot ($\hat{\beta}$ = 0.092, p =0.107> 0.05) and customer satisfaction. While the results of moderating regression analysis of (H1b) and (H1c) hypotheses indicate that familiarity with technology moderates the relationship between perceived relevance ($\hat{\beta}$ = 0.001, p =0.030<0.05) and perceived usefulness ($\hat{\beta}$ = 0.130, p =0.008<0.05). The interaction effects between the independent variables and familiarity with technology were significant, indicating that perceived relevance and usefulness had a greater impact on customer satisfaction in participants who were more familiar and comfortable with technology.

For the moderator variable Organization type, according to the findings, (H2a) and (H2b) hypotheses were supported. Accordingly, Organization type moderates the relationship between perceived personalization with GenAI chatbot ($\hat{\beta}$ = 0.079, p =0.019<0.05), perceived relevance with GenAI chatbot ($\hat{\beta}$ = 0.083, p =0.017<0.05), and customer satisfaction in digital marketing. The interaction effects between the independent variables and organization type were substantial,

demonstrating that the influence of perceived personalization and perceived relevance on customer satisfaction varied significantly among organization types. While hypothesis (H2c) was rejected, organization type does not moderate the relationship between perceived usefulness with GenAI chatbot ($\hat{\beta}= 0.031, p =0.519>0.05$) and customer satisfaction (see Table 8).

Table 8: The hypotheses test results

Hypotheses	$\hat{\beta}$	t	Sig.	Test results
<u>H1a</u> : PP → FT → CS	0.092	1.617	0.107	Not supported
<u>H1b</u> : PR → FT → CS	0.001	0.026	0.030	Supported
<u>H1c</u> : PU → FT → CS	0.130	2.682	0.008	Supported
<u>H2a</u> : PP → OT → CS	0.079	1.562	0.019	Supported
<u>H2b</u> : PR → OT → CS	0.083	1.714	0.017	Supported
<u>H2c</u> : PU → OT → CS	0.031	0.645	0.519	Not supported

4.2. Discussions

The results of our study provide significant insights into the role of moderating variables in transitioning from Generative AI (GenAI) chatbot customer experience to customer satisfaction within digital marketing. By analyzing data from 346 consumers interacting with GenAI chatbots, we have identified key influencing factors and how they interact to impact customer satisfaction.

4.2.1. Impact of GenAI Chatbots on Customer Experience

Our findings indicate that GenAI chatbots, such as ChatGPT, Copilot, and Gemini, positively affect customer experience in digital marketing. Factors like perceived personalization, relevance, and usefulness of the chatbots play a crucial role in creating a positive customer experience. This aligns with previous studies (Abdelkader, 2021; Ajlouni et al., 2023; Rospigliosi, 2023), emphasizing the importance of providing relevant and personalized content to enhance customer experiences.

4.2.2. Role of Moderating Variables

The role of moderating variables in the relationship between GenAI chatbot customer experience and customer satisfaction is crucial, as these variables can significantly influence the strength

and direction of this relationship. Our study specifically examined two moderating variables: familiarity with technology and organization type. Both of these factors were found to play vital roles in shaping how customers perceive and interact with GenAI chatbots, ultimately impacting their overall satisfaction.

(i) *Familiarity with Technology:* This variable emerged as a significant moderating variable. It encapsulates the degree to which customers are comfortable and knowledgeable about modern technological tools and interfaces. Our findings suggest that customers with higher technological familiarity are more likely to interact positively with GenAI chatbots. These customers tend to appreciate the advanced functionalities of chatbots, such as natural language processing and personalized recommendations, which enhance their overall experience.

Technologically savvy customers are more adept at navigating and utilizing chatbot features, which can lead to a more seamless and satisfying experience. They are also more likely to have realistic expectations about the capabilities and limitations of GenAI chatbots, reducing the frustration that can arise from unmet expectations. This group of customers can effectively leverage the personalized and relevant interactions provided by chatbots, recognizing and valuing the sophisticated responses generated by AI.

Additionally, familiarity with technology can mitigate the cognitive load associated with using new tools. For less tech-savvy customers, interacting with GenAI chatbots might be intimidating or confusing, potentially leading to a negative experience. In contrast, those comfortable with technology can focus on the content and benefits of the interaction rather than the mechanics of using the tool, resulting in a more positive and satisfying experience.

(ii) *Organization Type:* Deploying the GenAI chatbot also plays a critical moderating role. Different industries have varying needs and customer expectations, which can influence how chatbots are perceived and their effectiveness in enhancing customer satisfaction. Our study found that the impact of GenAI chatbots on customer satisfaction can vary significantly depending on the industry context.

For instance, in retail and e-commerce, customers often seek personalized product recommendations, quick responses to product inquiries, and seamless transaction processes. Chatbots in these industries can enhance customer satisfaction by providing tailored product suggestions based on browsing history and preferences, offering instant answers to questions, and facilitating smooth purchasing processes. The ability of a chatbot to deliver personalized and relevant content in real-time can significantly enhance the shopping experience, leading to higher levels of customer satisfaction.

In contrast, service-oriented industries such as healthcare, finance, or telecommunications may prioritize immediate and accurate customer support. In these contexts, the primary value of GenAI chatbots lies in their ability to handle a large volume of inquiries efficiently, provide accurate information, and escalate issues to human agents when necessary. Customers in these industries may value the reliability and promptness of chatbot responses, which can directly impact their satisfaction levels.

Furthermore, the organizational culture and readiness for technology adoption can also influence the effectiveness of GenAI chatbots. Organizations that foster a culture of innovation and are early adopters of technology may implement chatbots more effectively, ensuring they are well-integrated into their customer service processes. These organizations will likely invest in training their staff and customers to use these tools effectively, enhancing the overall customer experience.

5. Conclusions

This section of the study focuses on its contributions to applied fields and on GenAI's impact on the relationship between customer experience and customer satisfaction in digital marketing. It also includes the implications for future research.

5.1. Interactive effects

The interaction between technology familiarity and organizational type may also provide further insights. For example, technology-savvy customers interacting with chatbots in tech-savvy organizations may experience the highest levels of satisfaction due to the combined impact of enhanced chatbot capabilities and human competence. Conversely, less tech-savvy customers may benefit more from chatbots in industries with simple core functions and less complex interactions.

5.2. Implications for businesses

Understanding the regulatory impact of these variables has practical implications for businesses. Companies can segment their customer base based on technology familiarity and tailor their chatbot interactions accordingly. For tech-savvy customers, advanced features and personalized interactions should be highlighted, while for less tech-savvy customers, simplifying the interaction process and providing clear instructions can enhance satisfaction.

Furthermore, businesses should consider their industry's specific needs when designing and implementing GenAI chatbots. Retailers may focus on personalization and seamless transactions, while service providers may emphasize reliability and quick problem resolution. By tailoring

chatbot functions to industry-specific customer expectations, businesses can optimize the impact of GenAI chatbots on customer satisfaction.

In summary, moderating variables is critical to understanding the full impact of GenAI chatbots on customer satisfaction. By considering factors such as familiarity with the technology and type of organization, businesses can better design and deploy a chatbot strategy to meet customer needs and improve overall satisfaction.

6. Limitations and future research

6.1. Limitations

Although our study provides valuable insights, it has limitations: (1) Sample size and diversity. Future studies could expand the sample size and include a more diverse group of participants to enhance the generalizability of the findings. (2) Scope of moderating variables: Our study focuses on a limited number of moderating variables. Other moderating factors, such as cultural differences, customer personality traits, and previous experience with AI technology, may also be essential in shaping customer satisfaction. (3) Self-reported data: The study relied on self-reported survey data, subject to social desirability and recall bias. Future research could incorporate more objective measures of customer interactions with chatbots, such as behavioral data and performance metrics.

6.2. Future research

To build on the findings of this study, future research could explore several promising directions: (1) Expanding on moderating variables, (2) Comparative studies across sectors, (3) Integrate behavioral data such as click-through rate, chat duration, and customer retention metrics...(4) Explore emotional responses: Investigate the emotional responses of customers during interaction with GenAI chatbot.

In summary, while our research sheds light on essential aspects of GenAI chatbot interactions and their impact on customer satisfaction, ongoing research is essential to fully understand and exploit these technologies' potential in digital marketing. By addressing limitations and exploring new research directions, scholars and practitioners can continue to improve and enhance the deployment of GenAI chatbots to meet evolving needs.

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