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AI-Powered Smart Customer Experience:Examining the Influence of Artificial Intelligence Stimuli and Chatbots

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Abstract

Purpose: Unlike human intelligence, which naturally exists, artificial intelligence (AI) is represented by human-like and non-human-like machines that are programmed by humans to serve human and commercial purposes. This technology enables computers to analyze complex data using sophisticated algorithms and mathematical models, allowing them to learn and improve autonomously. The main objective of this research is to examine the impact of AI stimuli and chatbots on smart customer experience and recommendatory marketing, considering the moderating role of technology readiness in platform businesses, based on the Stimulus-Organism-Response framework.

Method: This study is classified as descriptive-survey research. Data were collected using a standard questionnaire. The statistical population consisted of users of the Snapp application. Due to the unlimited size of the population, G*Power software was applied for sample size determination. In total, 453 electronic questionnaires were collected, although 406 were required; analyses were conducted on the full set of 453 responses for greater reliability.

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Given the non-normal distribution of the data, Smart PLS version 4 and SPSS version 27 software were used for analysis.

Findings: Of the 12 hypotheses tested, 9 were supported while 3 were rejected. Results confirmed the impact of enthusiasm, usability, and responsiveness on relative advantage and perceived interaction. Moreover, relative advantage and perceived interaction positively influenced recommendatory marketing. The moderating effect of optimism on the relationship between enthusiasm and perceived interaction was also supported. However, the moderating effect of feelings of lack of control on usability–relative advantage and enthusiasm–interaction relationships, as well as the moderating role of optimism on usability–relative advantage, were rejected. These results may be explained by the novelty of chatbot use in Iran and cultural differences.

Conclusion: The findings indicate that AI-related stimuli, including chatbots, significantly affect the smart customer experience. In turn, perceived interaction and relative advantage influence recommendatory marketing. Organizations with proper infrastructure and sufficient human resources can therefore effectively leverage AI and chatbot capabilities.

Keywords: Artificial Intelligence, Chatbots, Smart customer experience, Technology Readiness, Platform Business, Stimulus-Organism-Response Framework

Introduction

AI technology has become widespread and demonstrates specific aspects of human intelligence through machines (Huang & Rust, 2018). Its rapid evolution has redefined customer experiences and created new opportunities for companies to interact with customers via chatbots (Sidaoui et al., 2020; Hollebeek et al., 2021; Kumar et al., 2019; De Cicco et al., 2020). Chatbots, as a subset of AI, are now deeply integrated into customer experiences to the point where distinguishing between human and chatbot interactions has become difficult (An, 2018; Luo et al., 2019). A chatbot is a program that simulates human conversation using natural language processing (Chen et al., 2020) and generally serves as a virtual assistant online (Fryer et al., 2019). During interactions, chatbots must understand customer requests, maintain updated status, keep users engaged, and ask clarifying questions (Alt et al., 2019; Quintino, 2019).

Drivers of AI technology include technological advancements, demand for automation, market competition, rising customer expectations, data analysis, and skilled human resources. These drivers enable organizations to adopt AI and optimize processes. In this study, AI drivers are categorized into three dimensions: usability, responsiveness, and enthusiasm. Usability refers to the ease of effectively using a system (Petre et al., 2006). Responsiveness refers to readiness to provide immediate service, creating convenience and a sense of being valued (Chang et al., 2020; Van den Broeck et al., 2019). Enthusiasm reflects hedonic motivations and enjoyment in using AI (Gao et al., 2022).

Smart customer experience is defined here as a consumer's cognitive, emotional, and behavioral response to AI and chatbot use. Unlike traditional experiences, it is induced through technology (Schmitt, 1999). Its dimensions include cognitive (relative advantage, perceived interaction), emotional (perceived enjoyment), and behavioral (perceived control, personalization). Relative advantage reflects the extent to which AI-driven services outperform human ones in terms of convenience, accuracy, and consistency. Perceived interaction refers to how effectively AI services help users achieve their consumption goals (Gao, 2022).

Despite growing literature, three research gaps remain: (1) the mediating role of smart customer experience between AI drivers, chatbots, and recommendation marketing; (2) the moderating role of technology readiness, including optimism and lack of control (Parasuraman & Colby, 2000); and (3) limited focus on platform businesses.

Meeting customer needs through technology is increasingly critical (Huang & Rust, 2021; Lu et al., 2019). Chatbots can address challenges of platform businesses and online shopping (Luo et al., 2019). In the Snapp application context, chatbots enable constant interaction and customer support. However, their effectiveness depends on alignment with customer needs and correct implementation (Sanzogni et al., 2017). Previous research has mostly emphasized managerial perspectives and overlooked customers' viewpoints on chatbot value (Hu et al., 2018).

This study addresses these gaps by examining how AI drivers and chatbots shape the smart customer experience of Snapp users and influence recommendation marketing, moderated by technology readiness. Insights can help the company enhance its services and meet customer expectations more effectively.

Literature Review

Artificial Intelligence

In recent years, with the development of various artificial intelligence applications across different sectors, markets have extensively utilized this technology (Chung et al., 2020; Shankar et al., 2021; Song et al., 2022). The progress of artificial intelligence has been remarkable, and experts have continuously worked on advancing artificial intelligence concepts over the past few decades. This effort has led to significant innovations, such as big data analysis and machine learning applications in diverse sectors and fields. The term artificial intelligence typically evokes images of full-time automated robot workers, as people have primarily encountered human-machine interactions in movies or shows featuring robots. Artificial intelligence is suitable for any device that requires human-like thinking for continuous learning and problem-solving. These features of artificial intelligence make it unique. With the capabilities of a machine, individuals no longer need to endure repetitive work. An artificial intelligence system continuously performs repetitive tasks on behalf of humans (Verma et al., 2021). With the assistance of artificial intelligence, businesses can deliver a more personalized experience to their customers. Artificial intelligence proves highly effective in analyzing large data sets, rapidly identifying patterns in data, and providing insights into previous customers' preferences, credits, and similar aspects for tailored communications to customers (Wang et al., 2022). It is worth noting that humans and artificial intelligence are not in opposition to each other; rather, the emphasis is on cooperation and interaction between them

(Tavallaee, 2023).

Chatbots

A chatbot is a computer program that simulates human conversations using natural language processing capabilities (Chen et al., 2021). Businesses can actively engage with customers through chatbots, as these tools can initiate conversations and monitor how users interact with websites and landing pages. Furthermore, the data gathered from this monitoring can be utilized by businesses to offer special rewards to customers and to guide website visitors in responding to future requests. Chatbots improve the detection process by making it quicker and more efficient, while also collecting data more rapidly and with higher quality, thereby enhancing the customer experience. Therefore, chatbots facilitate faster work improvements and quicker responses to queries, resulting in a significant reduction in routine requests and a greater focus on increasing revenue (Kaushal & Yadav, 2023). Chatbots can play a substantial role in addressing the challenges and shortcomings of e-commerce businesses, as well as mitigating the impersonal nature and risks associated with online shopping. By replacing and complementing frontline staff through technology-based learning, they boost effectiveness and efficiency.

Although the potential of chatbots in businesses has been confirmed, challenges continue to impede their growth, such as a lack of expertise in chatbot development and insufficient awareness in the field. In the context of platform businesses, chatbots often provide search or decision-support functions and make customer service interactions or encounters easier, more personalized, unique, interactive, and engaging. They assist in building meaningful relationships with customers, reducing customer uncertainty and anxiety, and enabling more efficient use of time along with a better understanding of products or services. For example, chatbots can identify customers and communicate with them to provide information such as product availability, total costs of products, and delivery timelines. By offering credible advice, chatbots can create the impression that communications have been personalized to meet customers' needs (Chen et al., 2021).

One of the advantages of using artificial intelligence programs like chatbots for companies and organizations is their cost-effectiveness (Davenport et al., 2020). Chatbots can reduce customer service costs by over 30% (IBM, 2017). Additionally, the benefits of quick responses and 24/7 availability are key advantages provided by chatbot customer service, particularly during critical times when customers prefer to avoid physical contact with service employees (Pantano & Pizzi, 2020; Vlačić et al., 2021). On online shopping websites, artificial intelligence chatbots address customer questions about products, including refunds, product availability, shipping, discounts, and post-purchase complaints (Adam et al., 2020).

Despite the benefits and growing adoption of chatbots, customers appear to harbor reservations about artificial intelligence factors. While customers are somewhat willing to interact with an artificial intelligence agent on a chat platform, they ultimately prefer being transferred to a human agent for conversation. Customers who dislike chatbots believe that these tools only handle simple questions, lack the ability to solve complex customer problems, and also miss certain social skills (Elliot, 2018). Overall, customers favor human agents over artificial intelligence agents. A substantial body of research has demonstrated that this negative attitude can lead to decreased customer satisfaction, even when the agents perform well technically. In summary, customers' unfavorable attitudes toward artificial intelligence agents represent an issue that necessitates an effective marketing solution (Jeon, 2022).

Artificial intelligence technology and chatbots stimuli

Artificial intelligence stimuli are regarded as an external environmental variable. As external influences, stimuli exert a fundamental impact on our psychology and behaviors. Based on various research goals or different intelligence technologies, artificial intelligence stimuli can be categorized into two types: pleasurable stimuli and beneficial stimuli. Pleasurable stimuli can be understood as motivation, referring to the positive emotions experienced by AI users due to social interaction and enjoyment of technology. Customers can form emotional connections with intelligent technologies and may experience excitement and motivation solely through artificial intelligence, such as chatbots. Excitement is viewed as an emotional or pleasure-seeking stimulus that can enhance the customer experience (Gao et al., 2022). During shopping, excitement serves as a key factor in understanding customers' acceptance of new technologies.

Ultimately, the joy derived from using intelligent technologies motivates customers in a pleasurable manner (Shirmohammadi & Bostan Manesh, 2022). Usability is a quality or feature that indicates how effective, efficient, and satisfying the use of human-computer interfaces is in achieving a specific goal. Perceived ease of use and perceived usefulness drive users' behavioral intentions toward accepting and using technology. Perceived usefulness generally enhances usability, reflecting users' expectations of technology-based applications (Flavian et al., 2006).

Usability is considered a valuable and desirable feature of e-commerce system quality, with responsiveness playing a predominant role in customer service perception. Responsiveness refers to timely responses or service availability. In other words, the more responsive a chatbot is, the more innovative customers perceive the company to be. Additionally, responsiveness is a key feature of chatbot quality and can significantly enhance customer support for chatbot systems (Chen et al., 2021).

Smart customer experience

Customer experience is defined as the outcome of interactions between an organization and a customer that elicits a response from the customer. It is important to note that this experience is entirely personal and affects customers on intellectual, emotional, physical, spiritual, and moral levels (Gentile et al., 2007). In comparison to traditional customer experience, smart customer experience is derived through technology and has close ties to the cognitive, emotional, and behavioral dimensions of customers (Palmer, 2010; Noort et al., 2012). Cognitive elements include relative advantage and perceived interaction, emotional elements include perceived pleasure, and behavioral elements include perceived control and personalization. In this study, the smart customer experience refers to a cognitive orientation in consumer behavior using artificial intelligence technology and chatbots. Relative advantage refers to the extent to which intelligent customer service robots are considered better than humans due to convenience, accuracy, reliability, and stability. Perceived interaction also refers to the extent to which services provided by intelligent customer service robots help consumers achieve their consumption goals (Gao, 2022). Customer experience is the mental and inner response of customers in direct and indirect contact with the organization. Direct experience occurs during service usage, receipt, and purchase, initiated by the customer themselves. Indirect experience, on the other hand, is an unplanned encounter with the organization's services, products, or brand through marketing recommendations, news, advertisements, etc. (Meyer and Schwager, 2007). Based on this definition, it can be said that the customer experience dimension includes customers' perspectives, attitudes, and feelings when using intelligent chatbots and the responses and behaviors they exhibit after using intelligent chatbots (Nicolescu and Tudorache, 2022). Given the above, the following hypotheses are

proposed:
-Hypothesis 1 (H1): Perceived excitement for relative advantage influences platform business customers.
-Hypothesis 2 (H2): Perceived excitement for perceived interaction influences platform business customers.
-Hypothesis 3 (H3): Usability affects the relative advantage of platform business customers.
-Hypothesis 4 (H4): Usability affects the perceived interaction of platform business customers.

User experience generally can be seen as an individual's perspectives and responses towards the use or expected use of a product, system, or service. User perspectives and responses include emotions, beliefs, preferences, comfort, behaviors, and user achievements during and after use. However, chatbot user experience relates to how users respond to chatbots and how the layout of chatbots, interactive mechanisms, and conversation content directly impact user perspectives and responses. According to the definition, it can be said that the dimension of customer experience includes the perspectives, attitudes, and emotions of customers when using smart chatbots and the responses and behaviors that customers have after using smart chatbots (Niculescu and Tudorache, 2022). Based on these points, the following hypotheses are proposed:
-Hypothesis 5 (H5): Responsiveness affects the relative advantage of platform-based business customers.
-Hypothesis 6 (H6): Responsiveness affects the perceived interaction of platform-based business customers.

Recommendation Marketing

Purchase decisions are heavily influenced by the multitude of informational resources that customers consult before buying a product. Recommendation marketing occurs informally when consumers share their experiences and opinions about services, products, or brands with others, including recommending others to buy or not buy a specific service or product or conveying a positive, negative, or neutral statement about an offer (Ramezani et al., 2022). The functions of recommendation marketing are a common form of interactive behavior that helps establish and maintain social relationships between brands and consumers. The expectation of mutual benefits, as a critical social norm, encourages customers to engage in behaviors such as making recommendations among acquaintances, posting suggestive comments on online store web pages, and sharing product recommendations on social media platforms (Wang et al., 2022). Customer satisfaction is a key element of the marketing concept; however, in some cases, customer satisfaction alone is not sufficient, and efforts must be made to create a sense of emotional attachment in customers (Shafiei et al., 2019). Therefore, the following relationships are hypothesized:

-Hypothesis 7 (H7): Relative advantage influences word-of-mouth marketing for platform business customers.

-Hypothesis 8 (H8): Perceived interaction influences word-of-mouth marketing for platform business customers.

Technology readiness

Technology readiness is a psychological state that describes consumers' preferences or the willingness of users to accept and use new technologies to achieve personal goals (Parasuraman & Colby, 2015). Technology readiness is defined as a psychological factor that motivates hedonistic and utilitarian motives in using new technologies. Technology readiness is essentially a personality trait that measures the user's orientation toward technology. Influential factors on technology readiness consist of two parts: inhibitory and empowering, each with two recognized dimensions. These 4 dimensions include optimism, the feeling of lack of control (distress), insecurity, and innovation, where optimism and innovation are attractive and positive factors, and the feeling of lack of control and insecurity are inhibitory and negative factors (Shirmohammadi & Bostan Mansh, 2022). Positive technology readiness refers to consumers' optimism, hope, and confidence that new technology, by providing more control, flexibility, and greater efficiency, improves their personal lives; while negative technology readiness refers to consumers' feelings of lack of control or insecurity about technology and becoming immersed in it (Gao et al., 2022).

The rapid dissemination and use of smart technologies (such as smartphones, tablets, smart clothing, etc.), which were primarily a trend among young people in the past, are now accepted by all segments of society. In this context, smart technology refers to a device or electronic system that can be connected to the internet and used interactively. As society has become more familiar with technology and the internet, individuals now have the opportunity to experience efficient services offered by organizations. This trend has led consumers to expect targeted, responsive, and equally efficient services from other businesses (Foroudi et al., 2018).

It is assumed that the presence of optimism leads to positive effects on individuals' attitudes towards technology (Parasuraman & Colby, 2015). Optimistic individuals generally believe that technology can provide them with more mechanisms for working, both as a job and as a business (Parasuraman, 2000). Optimism can help individuals build more trust in technology, its ease of use, and its practicality (Wang et al., 2014, 2016). Consumers are optimistic about new technology and believe they can use it and deal with uncertainty; in other words, they have better control over the technology. When they enjoy using artificial intelligence technology and are willing to help others use it, they can have more fun and interact more with this technology. Furthermore, optimism is positively associated with the ease of use and practicality of communication technology. In other words, the more consumers like innovative technology, the more likely they are to find it useful (Gao et al., 2022). Feelings of lack of control are feelings of being overwhelmed in an unknown and new world. In this regard, Chardenas et al. (2021) define the feeling of lack of control, sometimes referred to as distress, as consumers' sense of being overwhelmed by technology and having no control over it, ultimately leading to uncertainty (Shirmohammadi and Bostan Mansh, 2022). On one hand, when customers feel distressed, they perceive themselves as having no control over the technology, exaggerate the complexity of artificial intelligence technology, and become more immersed in the technology. Concerns about using new technology can also lead to doubts about its usefulness.

Although customers may want to use artificial intelligence technology, their distress reduces perceived benefits and interaction with this technology, ultimately diminishing the positive consumer experience (Shirahada et al., 2019). Therefore, the following hypotheses are proposed:

-Hypothesis 9 (H9): The moderating effect of the feeling of lack of control influences the relationship between usability and the relative advantage of platform-based business customers.

-Hypothesis 10 (H10): The moderating effect of the feeling of lack of control influences the relationship between enthusiasm and perceived interaction of platform-based business customers.

-Hypothesis 11 (H11): The moderating effect of optimism influences the relationship between usability and relative advantage of platform-based business customers.

-Hypothesis 12 (H12): The moderating effect of optimism influences the relationship between enthusiasm and perceived interaction of platform-based business customers.

Platform Business

The increasing shift from competition based on services and goods to platform-based competition in many industries and markets is driven by forces that increasingly induce software industry characteristics in many non-technological industries. This change in management approach requires the adoption of different management perspectives. The potential force of platforms stems from the specialized and unique aggregation of several independent providers, on a scale that is impossible to achieve within a single organization. Therefore, the success of a platform not only depends on the capability of its owner but also on the capabilities of multiple ecosystem partners. A platform business provides a framework for producers and consumers to easily connect with each other, engage in commercial interactions, and establish governance structures. As a result, with a focus on innovation and cost reduction, transactions will be facilitated more easily.

The design and implementation of a platform business model are much more complex than linear business models. Traditional and non-platform businesses are referred to as linear businesses because their performance is summarized in a linear supply chain, and the value creation and profitability of the business stem from investment and internal resource growth. In contrast, in a platform business, value creation results from nurturing an external network around the business. Platforms often generate their profits and revenues through creating or mediating transactions between sellers and buyers. It is worth mentioning that linear and platform business models exist on two ends of a spectrum; thus, businesses may fall somewhere in between these two. All platform businesses do not have a specific platform approach; some have chosen a hybrid approach that combines elements of platform and linear business models, allowing businesses to invest in each model's strengths. Therefore, the differentiation of platform-based businesses is not only related to their technological infrastructure but also to creating value through building communication networks that distinguish this type of business (Zangeneh et al., 2021).

Stimulus-Organism-Response Framework

The Stimulus-Organism-Response (SOR) model, also known as the environmental psychology model, was introduced by Mehrabian and Russell (1974). This model demonstrates that when a person is stimulated by an external stimulus, it triggers psychological, perceptual, emotional, cognitive, and affective states in that person (organism), which in turn leads to accepting or avoiding behavioral responses in individuals (response) (Lee et al., 2011). The theoretical Stimulus-Organism-Response model is often used in articles to understand online customer behavior (Tegtmeier & Neofotistos, 2013). This model is based on environmental psychology and assumes that environmental stimuli affect the internal states of organisms, which ultimately lead to behavioral responses in that organism (Mousavi et al., 2021). This framework suggests that some environmental dimensions stimulate perceptual and emotional states in individuals, resulting in some behavioral.

A Review of the Literature on the Research Topic

Khashan et al. (2023), in their study titled 'Smart Customer Experience, Customer Appreciation, Recommendation Marketing, and Continuous Intent to Adopt Smart Banking Services: The Moderating Role of Technology Readiness,' modeled the outcomes of smart customer experience by examining the relationships between Smart Customer Experience (SCE), customer appreciation, continuous intent, and positive word of mouth. According to the findings, SCE directly increases customer appreciation, continuous intent to adopt smart services, and recommendation marketing. Customer appreciation also enhances continuous intent and recommendation marketing. Furthermore, customer appreciation mediates the relationship between SCE, continuous intent, and recommendation marketing. Finally, the findings show that customer innovation and optimism have a significant moderating effect among the studied variables.

Shirmohammadi & Bostan Manesh (2022), in a study titled 'Designing a Model for Customers' Shopping from Smart Stores During COVID-19 with Emphasis on Artificial Intelligence,' analyzed and examined the pleasurable shopping factors of customers based on the model of hedonic information systems acceptance. The research indicates that smart stores, utilizing artificial intelligence technology, provide vast amounts of information about goods and customers through smart sensors, facial recognition, intelligent shelves, interactive displays, and automatic payment at high-speed using fifth-generation internet. Given that the COVID-19 pandemic has significantly changed the way individuals trade and live, marketers have employed new AI-based strategies to advance their goals. Ultimately, the results of this study reveal that perceived ease of use, perceived enjoyment, and perceived usefulness have a positive and meaningful effect on the purchase intention of customers through their technology readiness. The findings also indicate that the moderating variable of technology readiness is influenced by innovation, optimism, insecurity, and discomfort, and that perceived usefulness, perceived ease of use, and perceived enjoyment have a positive and meaningful effect on customers' purchase intentions from smart stores during the pandemic.

Almasi & Hosseinpour (2022) examined the factors affecting platform businesses during the COVID-19 crisis. The main research question was, 'How are the factors affecting platform businesses analyzed during a crisis?' The research population consisted of 10 experts in the field of digital and platform businesses. Ultimately, the research results showed that the absence from public gatherings during the COVID-19 pandemic, the lack of necessity to leave home, and the ability to view various products were the top three indicators in the context of platform businesses during that time. Additionally, the results indicated that Instagram ranked first, Telegram second, and Facebook third based on the factors affecting platform businesses.

Gao et al. (2022) clarified the meanings and dimensions of technology stimuli related to artificial intelligence (AI) in their research and developed a scale for AI technology stimuli to explain the relationship between these stimuli and smart customer experience. The results showed that two dimensions of AI technology stimuli (i.e., enthusiasm and usability) have a positive and significant impact on smart customer experience; the moderating effects of the opposing dimensions of technology readiness (i.e., optimism and anxiety) were significantly different; and smart customer experience has a positive and significant effect on consumers' word-of-mouth (WOM) intentions.

Chen et al. (2021) concluded in their research that the rapid transformation in artificial intelligence (AI) has redefined customer experience and created immense opportunities for companies to engage with customers through chatbots. This study examined the role of AI chatbots in influencing online customer experience and customer satisfaction in e-commerce. The findings revealed that the usability of chatbots has a positive effect on the external values of customer experience, while chatbot responsiveness has a positive effect on the internal values of customer experience. Furthermore, online customer experience is positively correlated with customer satisfaction, and personality influences the relationship between chatbot usability and the external values of customer experience.

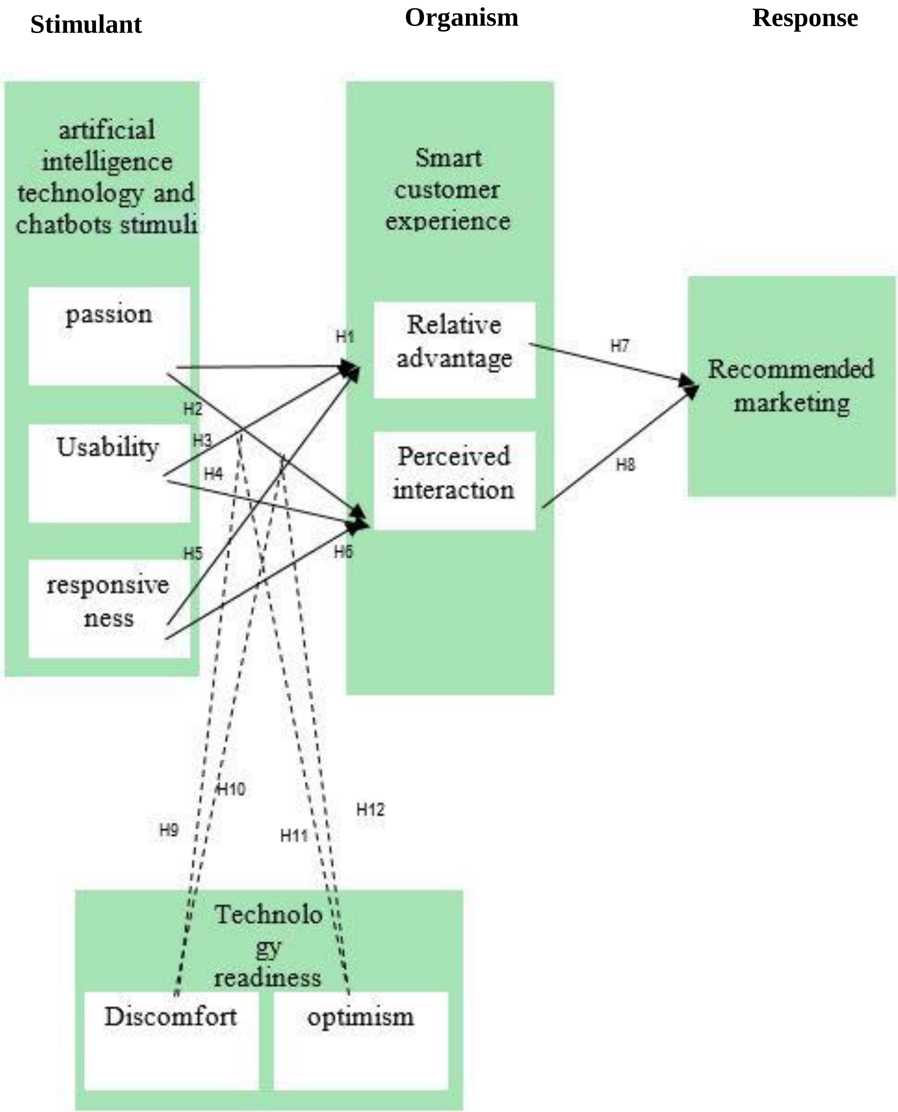

Figure 1. Conceptual model of the research

Method

Since the main goal of this research is to examine the impact of technology stimuli related to artificial intelligence and chatbots on smart customer experience and recommendation marketing, with the moderating role of technology readiness in platform businesses, based on the stimulus-organism-response framework, this study can be considered applied research. Descriptive research involves a set of techniques used to clarify, display through patterns, or describe phenomena that occur naturally without experimental manipulation. This type of research focuses on building hypotheses and testing them, analyzing the relationships between variables, and developing general laws. Moreover, in survey research, the aim is to examine the distribution of characteristics within a population, which is prevalent in management studies. In this type of research, parameters of the population are investigated. Here, the researcher studies the variables of interest by selecting a sample that represents the population.

The statistical population for this research includes customers of Snapp platform businesses who have recently started using chatbots in their activities. Given that the population is infinite, G*Power software was used to determine the sample size. According to this software, with an effect size of 0.05, a significance level of 0.05, a power of 0.9, and the number of predictor models being 9, the sample size was calculated to be 406. Ultimately, 453 electronic questionnaires were collected, and to ensure the accuracy of the research results, considering that some questionnaires are typically discarded in the software process, analyses were conducted based on this number. The questionnaire for this research consists of two sections: personal questions, for which the consent of respondents was taken into account, and specialized questions; the personal questions included 5 items, and the specialized questions included 26 items.

In this study, six standard questionnaires were used, which were translated into Persian prior to distribution among the target sample. The translation process was conducted with the consultation of experts in the field of English translation, and ultimately, for final approval and revisions, the questionnaires were submitted to the esteemed supervisor. Subsequently, the questions were provided to 11 experts in management, specifically in the field of marketing, and they were asked to classify each question based on a three-point scale. Finally, based on the calculated content validity, all questions achieved an acceptable level of validity. For reliability assessment, Cronbach's alpha coefficient was employed. The final questionnaire was randomly distributed to a sample of 30 individuals from the target population, and the results were analyzed using SPSS software. The results indicated that the Cronbach's alpha coefficient for all variables was above 0.7, indicating the desirable reliability of the research questionnaire.

After collecting the final questionnaires, descriptive statistics were initially used to describe the sample characteristics, followed by hypothesis testing using inferential statistics. SPSS Statistics 27 software was utilized for descriptive statistics. Data preprocessing of the collected sample data was then performed. This preprocessing included removing indifferent individuals by calculating the standard deviation, identifying outliers, calculating Cronbach's alpha, assessing sample size adequacy, and evaluating the normality of the data distribution through skewness and kurtosis analysis. For the inferential statistics section, since the normality condition of the data distribution, defined by the values of skewness and kurtosis coefficients falling within the ranges of [-3, 3] and [-5, 5], was not met and the data were deemed non-normal, Smart PLS version 4 software was used. Ultimately, in the inferential statistics domain, the measurement and structural model of the research were examined using the specified software.

Findings

Demographics

The frequency distribution of sample members based on gender indicates that 212 respondents, equivalent to 46.8%, are male, and the remaining 241 respondents, equivalent to 53.2%, are female. The frequency distribution of sample members based on age shows that the highest frequency belongs to the age group of 21 to 30 years, accounting for 46.8%, and the lowest frequency belongs to the age group under 20 years, accounting for 13%. Based on cumulative frequency percentage, nearly 60% of sample elements fall into the age group of under 20 to 30 years. The frequency distribution of sample members based on educational level reveals that graduates of bachelor's and master's degrees collectively have the highest frequency at 71.3%, significantly more than the remaining educational levels' share of 28.7%. Among these, the highest frequency belongs to individuals with a master's degree at 193 individuals, equivalent to 42.6%, and the lowest frequency belongs to individuals with an associate degree at 20 individuals, equivalent to 4.4%. The frequency distribution of sample members based on the frequency of using Snapp platform business services per month shows that approximately 61% of sample members use various services of the Snapp platform business less than 10 times a month, while the remaining 39% use the mentioned services more than 10 times a month.

Hypothesis Testing

Hypothesis Testing

The values of kurtosis coefficients corresponding to all observed variables are in the range of [3, -3]; on the other hand, except for the second variable, the values of skewness coefficients for all variables are in the range of [5, -5]. Furthermore, the standard deviation for the observed variables indicates the dispersion of participants' responses in the study, which should not be less than 0.5 (Moradi & Miralmasi, 2021). As evident, the responses corresponding to the questionnaire items have been characterized by an appropriate dispersion, meaning that the responses are not concentrated on one side of the spectrum.

Table 1. Numerical indices corresponding to observational variables
(Postscript: OPT= optimism, DSC= feeling of lack of control, USA= usability PSN= enthusiasm, RSP= responsiveness, RAV= relative advantage, PIT= perceived)

Skewness		Kurtosis		Standard deviation	Average	Maximum	Minimum	Number of observations	Variables
Amount of	**Standard error**	**Amount of**	**Standard error**						
0/229	3/614	0/115	-1/530	0/747	4/37	5	1	453	OPT1
0/229	7/811	0/115	-2/308	0/679	4/45	5	1	453	OPT2
0/229	3/949	0/115	-1/372	0/704	4/32	5	1	453	OPT3
0/229	-1/149	0/115	0/015	1/205	2/83	5	1	453	DSC1
0/229	-0/972	0/115	0/083	1/101	2/96	5	1	453	D

									SC 2
0/229	-1/241	0/115	0/112	1/374	2/86	5	1	453	D SC 3
0/229	-1/198	0/115	0/152	1/370	2/85	5	1	453	D SC 4
0/229	-0/202	0/115	-0/174	0/797	3/48	5	1	453	U S A1
0/229	0/187	0/115	-0/548	0/813	3/72	5	1	453	U S A2
0/229	0/195	0/115	-0/528	0/767	3/94	5	1	453	U S A3
0/229	-0/339	0/115	-0/504	1/015	3/56	5	1	453	PS N1
0/229	-0/189	0/115	-0/442	1/002	3/55	5	1	453	PS N2
0/229	-0/412	0/115	-0/319	0/983	3/52	5	1	453	PS N3
0/229	-0/128	0/115	0/072	0/938	2/89	5	1	453	RS P1
0/229	-0/578	0/115	0/141	0/994	2/72	5	1	453	RS P2
0/229	-0/209	0/115	0/273	0/998	2/72	5	1	453	RS P3
0/229	0/010	0/115	-0/480	0/795	3/67	5	1	453	R A V1
0/229	0/680	0/115	-0/698	0/809	3/87	5	1	453	R A V2
0/229	0/702	0/115	-0/803	0/900	3/79	5	1	453	R A V3
0/229	-0/529	0/115	-0/218	1/016	3/36	5	1	453	R A V4
0/229	-0/241	0/115	-0/444	0/949	3/59	5	1	453	PI T1
0/229	0/018	0/115	-0/416	0/859	3/59	5	1	453	PI T2

0/229	-0/246	0/115	-0/008	0/877	3/22	5	1	453	PIT3
0/229	-0/134	0/115	-0/269	0/916	3/27	5	1	453	WOM1
0/229	0/169	0/115	-0/135	0/858	3/12	5	1	453	WOM2
0/229	0/262	0/115	-0/069	0/819	3/01	5	1	453	WOM3

(interaction, WOM= word-of-mouth marketing)

Table 2. Numerical indices corresponding to existing structures

Skewness		Kurtosis		Standard deviation	Average	Number of observations	Variables
Amount of	Standard error	Amount of	Standard error				
0/229	11/658	0/115	-2/675	0/5657	4/3797	453	OPT
0/229	-1/505	0/115	-0/100	1/0245	2/8731	453	DSC
0/229	0/430	0/115	-0/576	0/6931	3/7152	453	USA
0/229	-0/157	0/115	-0/313	0/8246	3/5408	453	PSN
0/229	-0/338	0/115	0/336	0/8443	2/7770	453	RSP
0/229	0/483	0/115	-0/402	0/6971	3/6755	453	RAV
0/229	0/331	0/115	-0/243	0/7267	3/4665	453	PIT
0/229	0/819	0/115	-0/174	0/6908	3/1354	453	WOM

Based on the results in Table 2, the skewness coefficient for all current structures falls within the range [3,3-]; conversely, except for the optimism structure, kurtosis values for all structures are also in the range [5,5-]. Thus, the condition of normality of the data distribution, which entails having skewness and kurtosis values in the ranges [3,3-] and [5,5-] respectively (Kline, 2015), is not met according to the results of Tables 1 and 2, indicating that the data distribution is non-normal. The mean, as an indicator of central tendency, reflects the level of agreement among elements of the target population for the current structures. Therefore, if the mean corresponding to a structure is greater than 3, it means that the members of the community agree on the concept of the respective structure, otherwise, there is disagreement. Thus, elements of the target population agree with other structures except for the feeling of lack of control and responsiveness structures; hence, the highest agreement is with the optimism structure with a mean of 37.4 and the lowest agreement is with the word-of-mouth marketing structure with a mean of 13.3. The internal consistency of the current structures is also not confirmed based on the values of Cronbach's alpha in Table 3, all of which fall between 0.70 and 0.95.

Table 3. Cronbach's alpha

Current structure	Cronbach's alpha
Optimism	0/712
Discomfort	0/823
Usability	0/847
Passion	0/764
Responsiveness	0/831
Relative advantage	0/796
Perceived interaction	0/734
Recommendation marketing	0/715

Adequacy of Sample Size and KMO

Analyzing the measurement model through confirmatory factor analysis requires the use of a sample with sufficient size and confirmation of the KMO. KMO refers to the differentiation of the correlation matrix from the identity matrix. To this end, the simultaneous KMO and Bartlett test is used. If the calculated value for the KMO index is greater than 0.70, the adequacy of the sample size is determined. Therefore, if the calculated value for the KMO index is statistically significant (Sig < 0.05), the KMO will be confirmed (Field, 2018).

Table 4. Adequacy test of sample size and KMO

KMO test		0/832
Bartlett's test	Some chi square	4887/851
	Degrees of freedom	325
	Significance (Sig)	0/000

Finally, according to inferential statistics, the primary measurement model in standard coefficient estimation mode and the primary measurement model in coefficient significance mode are presented in Figures 2 and 3.

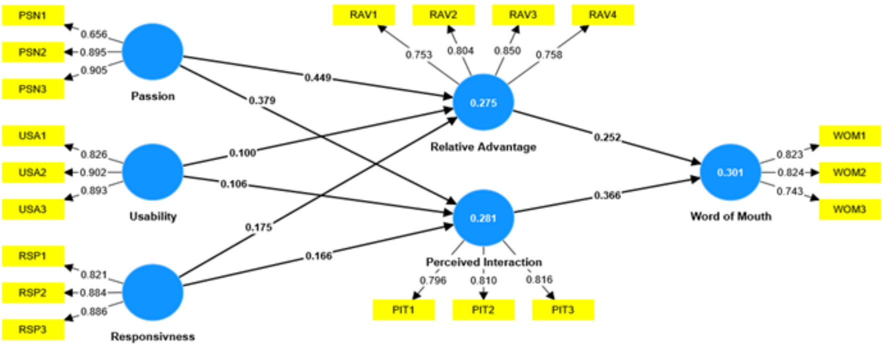

Figure 2. Primary measurement model in standard coefficient estimation mode

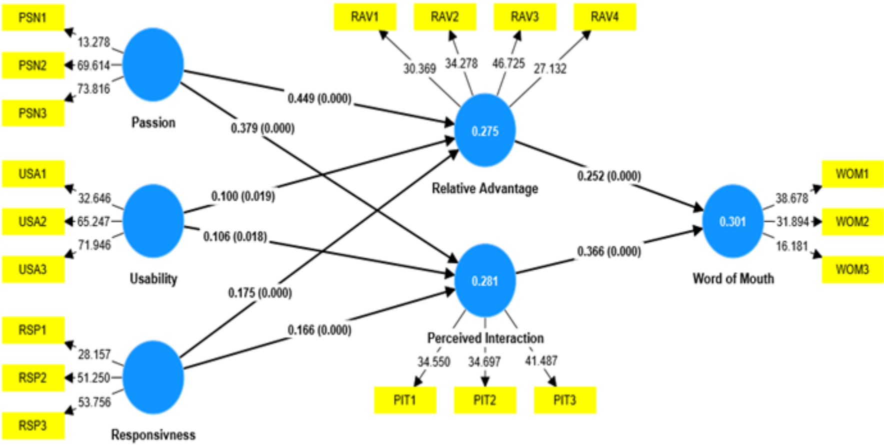

Figure 3. Primary measurement model in the significance mode of coefficients

In this test, the consistency of observational variables reflects the concept of the corresponding current structure, or more precisely, the homogeneity of questions in explaining the variance of the current structure is evaluated. This is done by assessing the factor loading value corresponding to each observational variable. Thus, a factor loading value above 0.70 indicates the homogeneity of the question with the concept of the current structure. If the factor loading of a question is less than 0.70 but greater than 0.60, sensitivity analysis regarding the removal or retention of the question should be conducted; however, if the factor loading is less than 0.60, the question should be removed from the model (Hair et al., 2016). Table 5 shows the results of the homogeneity test along with the significance of the factor loadings.

Table 5. Homogeneity test

Variables	Operational burden	T-Value	P-Value
PIT1←Perceived Interaction	0/796	34/55	0/000
PIT2← Perceived Interaction	0/810	34/69	0/000
PIT3← Perceived Interaction	0/816	41/48	0/000
PSN1←Passion	0/656	13/27	0/000
PSN2← Passion	0/895	69/61	0/000
PSN3← Passion	0/905	37/81	0/000
RAV1←Relative Advantage	0/753	30/36	0/000
RAV2← Relative Advantage	0/804	34/27	0/000
RAV3← Relative Advantage	0/850	46/72	0/000
RAV4← Relative Advantage	0/758	27/13	0/000
RSP1←Responsiveness	0/821	28/15	0/000
RSP2← Responsiveness	0/884	51/25	0/000
RSP3← Responsiveness	0/886	53/75	0/000
USA1←Usability	0/826	32/64	0/000
USA2← Usability	0/902	64/24	0/000
USA3← Usability	0/893	71/94	0/000
WOM1←Word of Mouth	0/823	38/67	0/000
WOM2 ← Word of Mouth	0/824	31/89	0/000
WOM3 ← Word of Mouth	0/743	16/18	0/000

Based on the results of Table 5, the factor loadings corresponding to all observational variables except the first variable of the construct "passion" have a factor loading greater than 0.7. Since the factor load of the above variable is greater than 0.6, it should be decided based on the result of sensitivity analysis regarding its removal or not. Based on this, if the combined reliability coefficient corresponding to the desired structure increases after removing the mentioned variable; It should be removed. Table 6 shows the result of the sensitivity analysis.

Table 6. Sensitivity analysis

Current structure	Observational variables	Operational burden	Composite reliability coefficient	Observational variable	Operational burden	Composite reliability coefficient
Passion	PSN 1	0/656	0/864	-	-	0/926
	PSN 2	0/895		PSN2	0/920	
	PSN 3	0/743		PSN3	0/938	

As it is evident, by removing the first variable from the "passion" structure, the value of the combined reliability coefficient corresponding to this structure has increased by 1.7%. In this way, the mentioned variable is removed from the model composition. Below is the modified measurement model in two modes of estimation of standard coefficients and significance of coefficients.

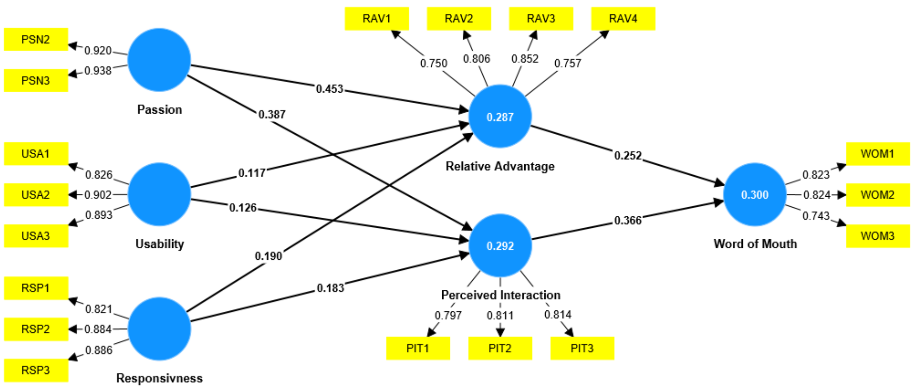

Figure 4. Modified measurement model in standard coefficient estimation mode

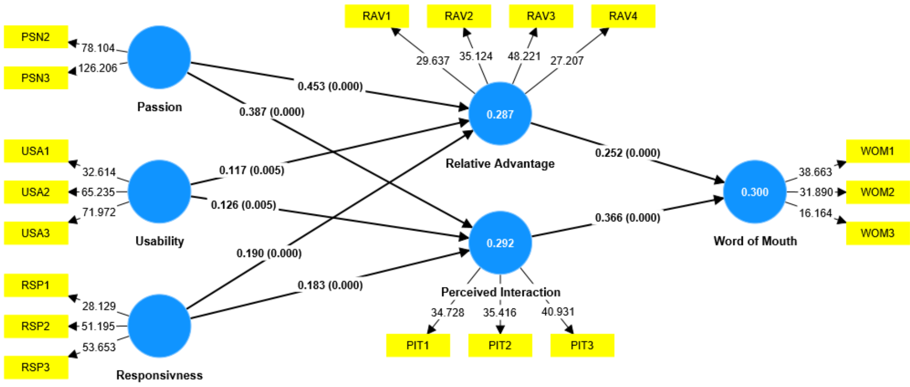

Figure 5. Modified measurement model in the significance mode of coefficients

Reliability of the measurement model

To evaluate the reliability of the measurement model, three indicators of Cronbach's alpha coefficient, combined reliability, and rho_a coefficient are used. It should be noted that the permissible values corresponding to reliability indices are between 0.7 and 0.95 (Fu et al., 2018; Latan and Noonan, 2017). Table 7 shows the reliability values corresponding to the aforementioned indicators. The reliability of the measurement model is confirmed according to the values of the reliability coefficients, which are all between 0.7 and 0.95.

Table 7. Reliability of the measurement model

Current structure	Cronbach's alpha	Composite reliability	index rho_a
Usability	0/847	0/907	0/866
passion	0/841	0/926	0/850
responsiveness	0/830	0/898	0/834
Relative advantage	0/802	0/891	0/801
perceived interaction	0/735	0/849	0/741
Recommendation marketing	0/717	0/839	0/733

Convergent validity

Validation of convergent validity requires the evaluation and confirmation of four conditions, which are, respectively: the factor loading is higher than 0.7, the significance of the factor loadings, the explanation of the variance of the current construct to at least 50%, which means that the average variance extracted from the number It is

0.5, and finally, the reliability of the combination is greater than the average variance extracted for each construct (Hair et al., 2016). Although its factor loading and significance values were checked and confirmed as the first two conditions of convergent validity in Table 5; it is important to evaluate the mentioned items after modifying the model. Table 8 examines its factor load and significance values.

Table 8. Its effectiveness and significance

Variables	Operational burden	T-Value	P-Value
PIT1←Perceived Interaction	0/797	34/72	0/000
PIT2← Perceived Interaction	0/811	35/41	0/000
PIT3← Perceived Interaction	0/814	40/93	0/000
PSN2← Passion	0/920	78/10	0/000
PSN3← Passion	0/938	126/20	0/000
RAV1←Relative Advantage	0/750	29/63	0/000
RAV2← Relative Advantage	0/806	35/12	0/000
RAV3← Relative Advantage	0/852	48/22	0/000
RAV4← Relative Advantage	0/757	27/20	0/000
RSP1←Responsiveness	0/821	28/12	0/000
RSP2← Responsiveness	0/884	51/19	0/000
RSP3← Responsiveness	0/886	53/65	0/000
USA1←Usability	0/826	32/61	0/000
USA2← Usability	0/902	65/23	0/000
USA3← Usability	0/893	71/97	0/000
WOM1←Word of Mouth	0/823	38/66	0/000
WOM2 ← Word of Mouth	0/824	31/89	0/000
WOM3 ← Word of Mouth	0/743	16/16	0/000

Based on the above results, the factor loading corresponding to each observed variable is greater than 0.7, and considering that the t-value is outside the range [1.96, -1.96], all the factor loading coefficients are significant with a probability of 99%. In this way, the first two conditions of convergent validity are confirmed. Table 9 evaluates the average results of extracted variance and compares it with composite reliability.

Table 9. Average extracted variance and composite reliability

Current structure	Average Variance Extracted (AVE)	Composite reliability (CR)
Usability	0/746	0/907
passion	0/862	0/926
responsiveness	0/747	0/898

Relative advantage	0/628	0/871
perceived interaction	0/652	0/849
Recommendation marketing	0/636	0/839

Based on the results, the average extracted variance for each existing structure is greater than 0.5. This means that the observational indicators are able to explain more than 50% of the variance of the corresponding constructs. On the other hand, the values of the combined reliability coefficient are greater than the mean of the extracted variance, and in total, by confirming the four mentioned conditions, the convergent validity is confirmed.

Divergent validity

In order to evaluate the divergent validity, cross-loading test, Fornell-Larker, and trait-method ratio are used. According to the first test, divergent validity is confirmed when the factor loading corresponding to each observed index is greater than the cross-factor loading of that index corresponding to other constructs by at least 0.1. From the perspective of the Fornell-Larker test, if the square root of the average extracted variance corresponding to any current construct is greater than the largest correlation of that construct with other constructs; The divergent validity is confirmed. Finally, based on the trait-method ratio, which has a more reliable result than the Fornell-Larker test, the construct's divergent validity is confirmed when the calculated value for each pair of constructs is less than 0.85 (Hair et al., 2021; Henseler et al., 2015).

Table 10. Fornell-Larker test

	PSN	PIT	RAV	RSP	USA	WOM
PSN	0/929					
PIT	0/468**	0/808				
RAV	0/506**	0/056**	0/792			
RSP	0/182**	0/283**	0/226**	0/864		
USA	0/253**	0/216**	0/251**	0/156**	0/874	
WOM	0/356**	0/507**	0/457**	0/312**	0/308**	0/797
P<0.01 ** ،P<0.05 *:PS						

Analysis of direct paths

Below and in Table 11, the coefficients of the direct path and their significance are calculated through the 95% confidence interval and the t-value and p-value indicators are shown. If the confidence interval calculated for the path coefficient does not have zero, it can be said that the said coefficient is statistically significant. Also, if the t-value is out of the range [1.96, -1.96] or the p-value is less than 0.05, the desired path coefficient will be statistically significant.

Table 11. Analysis of direct routes

Direct routes	Path coefficient	Confidence interval		T-Value	P-Value	Result
		lower limit	upper limit			
PIT←PSN	0/387	0/294	0/477	8/29	0/000	confirmation
RAV← PSN	0/453	0/366	0/538	1/29	0/000	confirmation
PIT←USA	0/190	0/100	0/281	4/01	0/000	confirmation
RAV←USA	0/117	0/033	0/197	2/78	0/005	confirmation
PIT←RSP	0/183	0/091	0/267	4/10	0/000	confirmation
RAV←RSP	0/126	0/038	0/211	2/81	0/005	confirmation
WOM← PIT	0/366	0/25	0/469	6/52	0/000	confirmation
WOM← RAV	0/252	0/144	0/360	4/55	0/000	confirmation

(Footnote: USA= Usability, PSN= Passion, RSP = Responsiveness, RAV = Relative Advantage, PIT = Perceived Interaction, WOM = Recommendation Marketing)

Table 12. Analysis of mutual effects

Mutual effects	Path coefficient	Confidence interval		T-Value	P-Value	Result
		lower limit	upper line			
RAV←DSC*USA	0/057	-0/026	0/154	1/23	0/218	rejection
PIT← DSC*PSN	0/044	-0/042	0/131	0/99	0/319	rejection
RAV←OPT*USA	0/013	-0/072	0/083	0/32	0/748	rejection
PIT← OPT*PSN	0/071	0/004	0/133	2/20	0/028	confirmation

(Footnote: OPT= optimism, DSC= sense of lack of control)

Based on the above results, among the four paths based on interaction, only the coefficient of the fourth path based on the interaction effect of "optimism" on the relationship between "enthusiasm" and "perceived interaction" due to the absence of zero in the 95% confidence interval, is out of t -value from the interval [1.96, -1.96] and p-value less than 0.05 is statistically significant.

Significance test of hypotheses

In this section, according to the results obtained from the analysis of direct paths and mutual effects, the proposed research hypotheses are tested. In this way, the general result of the assumptions based on the coefficients of the path and the significance of the coefficients is shown in Table 13.

Table 13. Hypothesis testing

Assumptions	Path coefficient	T-value	P-value	Result
Passion affects the relative advantage of customers of platform businesses.	10/29	0/453	0/000	confirmation
Enthusiasm affects the perceived interaction of customers of platform businesses.	8/29	0/387	0/000	confirmation
Usability affects the relative advantage of customers of platform businesses.	2/78	0/117	0/005	confirmation
Usability affects the perceived interaction of customers of platform businesses.	4/01	0/190	0/000	confirmation
Responsiveness affects the relative advantage of customers of platform businesses.	2/81	0/126	0/005	confirmation
Responsiveness affects the perceived interaction of customers of platform businesses.	4/10	0/183	0/000	confirmation
Relative advantage affects the recommendation marketing of platform business customers.	4/55	0/252	0/000	confirmation
Perceived interaction affects the recommendation marketing of platform business customers.	6/52	0/366	0/000	confirmation
The moderating effect of sense of lack of control affects the relationship between usability and the relative advantage of customers of platform businesses.	1/23	0/057	0/218	rejection
The moderating effect of sense of lack of control affects the	0/99	0/044	0/319	rejection

relationship between passion and perceived engagement of customers of platform businesses.				
The moderating effect of optimism affects the relationship between usability and the relative advantage of customers of platform businesses.	0/32	0/013	0/748	rejection
The moderating effect of optimism has an effect on the relationship between enthusiasm and perceived interaction of customers of platform businesses.	2/20	0/071	0/028	confirmation

Conclusion

The impact of artificial intelligence (AI) on people's lives and business operations is undeniable, significantly altering consumer purchasing patterns and behaviors. Consequently, businesses must acquire a comprehensive understanding of e-marketing and the broader business environment to effectively leverage these platforms for brand promotion.

The results from testing the first and second hypotheses confirm that enthusiasm positively influences both the relative advantage and perceived customer engagement in platform businesses. These findings align with those of Gao et al. (2022). Digital media now provide potent incentives for user-brand interaction, offering intelligent methods to reshape customer experiences and enhance the depth and value of brand engagements. As a cornerstone of digital marketing, AI affords marketers a wide array of advantages and tangible opportunities. It enables forecasting through data analysis, improves customer experiences, and facilitates targeted marketing, which collectively increase business return on investment and foster customer enthusiasm. Furthermore, AI tools can identify and rectify redundant, outdated, ambiguous (e.g., due to misspellings, misclassifications, or incorrect tags), and hidden data (information not shared across departments) to enrich business data sources.

The confirmation of the third and fourth hypotheses indicates that usability positively affects relative advantage and perceived customer engagement. These results are consistent with studies by Gao et al. (2022) and Chen et al. (2020). As technology and consumer interaction paradigms continuously evolve, businesses must perpetually reassess their customer engagement strategies. This dynamic environment, characterized by the rapid proliferation of devices and marketing channels, evolving customer expectations, and shifting business practices, necessitates constant innovation to capture audience attention. Customer Relationship Management (CRM) software is pivotal in optimizing customer interactions by providing detailed transaction information to inform customer strategy. Platform businesses can integrate CRM systems with AI to enhance user experiences and streamline workflows. Personalization, which varies in scope based on business scale and vision, is key to forging strong brand-buyer bonds. Tactics such as offering a discount code after a first purchase can guide customers toward brand loyalty.

However, personalization extends beyond discounts to include thank-you messages, post-purchase satisfaction surveys, and dynamic website suggestions based on customer preferences. Ultimately, making customers feel valued after a purchase significantly enhances the overall customer experience.

The fifth and sixth hypotheses confirm that responsiveness impacts relative advantage and perceived customer engagement, corroborating the findings of Gao et al. (2022). In online shopping, a swift support response reduces transaction time and fosters positive word-of-mouth marketing. Conversely, long wait times and the need to repeatedly explain an issue are primary sources of customer dissatisfaction. Research indicates that 89% of customers are highly dissatisfied when passed between multiple support agents. A fundamental solution is to develop an internal knowledge base with comprehensive information to prevent wasted customer time and improve experience. The manner in which support specialists respond is also critically important; companies that invest in their customer service representatives tend to be more successful.

The seventh hypothesis confirms that relative advantage affects customer word-of-mouth marketing in platform businesses, a result consistent with Gao et al. (2022) and Khashan et al. (2023). Relative advantage is directly linked to improved customer experience, which requires continuous adjustment, measurement, and management. Key strategies for enhancement include:

- Customer Effort Score (CES): Measures the ease of customer interaction with a product or support, typically surveyed after a support contact.
- Net Promoter Score (NPS): Primarily measures customer loyalty, categorizing customers as promoters, passives, or detractors.
- Customer Satisfaction Index (CSI): Assesses customer satisfaction with received products or services, often on a rating scale, and focuses on

specific areas of satisfaction or dissatisfaction.

The eighth hypothesis confirms that perceived engagement affects customer word-of-mouth marketing, supporting the conclusions of Gao et al. (2022), Khashan et al. (2023), and Yang and Zhou (2022), who demonstrated its subsequent impact on satisfaction and positive word-of-mouth. It is recommended that Snap's management foster a collaborative environment with its customers to help them better understand the services offered. The first step involves gathering consumer demographic data. While very small or large segments can lead to data misinterpretation and weak campaign targeting, AI enables the precise selection and evaluation of segments. Another engagement strategy is encouraging feedback and user-generated content within this collaborative environment, often through company websites that invite and evaluate ideas. Snap could incentivize feedback with a points system. Managers must also understand their customers' personalities, needs, and desires. Given social media's significant role in building trust, businesses should maintain transparency about their processes. Creating short videos featuring satisfied customers discussing their positive experiences can be highly beneficial.

Conversely, negative customer experience is a primary driver of declining business growth. Customers with negative perceptions are more likely to churn, a process accelerated in the digital world through social media and review sites. Notably, customers are more inclined to share negative experiences than positive ones. However, timely and appropriate resolution of complaints can not only retain the customer but also cultivate loyalty. Thus, customers who provide negative feedback have a significantly lower churn rate than passive customers.

The ninth, tenth, and eleventh hypotheses did not confirm the moderating effect of a sense of lack of control on the relationship between usability and relative advantage, nor on enthusiasm and perceived engagement. The moderating effect of optimism on the relationship between usability and relative advantage was also not supported, which contrasts with Gao et al. (2022). A significant challenge for AI is its "black box" nature; a lack of understanding of how decisions are made fosters discomfort and undermines trust. Demonstrating the technology's effectiveness is a potential solution. Machine learning systems rely on sensitive personal data, leading to regulations like the EU's General Data Protection Regulation (GDPR) enacted as machine-made decisions proliferated. This underscores a prevailing skepticism towards AI that businesses must address.

The twelfth hypothesis confirmed the moderating effect of optimism on the relationship between enthusiasm and perceived customer engagement. A positive customer experience entails creating meaningful relationships where brand actions demonstrate an understanding of customer needs and values. This concept extends beyond product use to include pre-purchase marketing, the research and purchasing process, and post-purchase interactions. A customer experience strategy must encompass all business parts, not just customer-facing units. Disseminating feedback across the organization steers it toward the goal of improving customer experience and facilitating effective communication. To assess and develop customer experience, businesses should collect feedback from purchasers, evaluate employee performance, and identify target customers. Providing an excellent experience is essential for fostering loyalty, generating positive reviews, and reducing complaints and returns.

The starting point of the customer experience is critical; customers typically attempt to solve issues themselves before contacting support. Therefore, company websites and apps must be designed for intuitive navigation and clear suggestions. Eighty-eight percent of users who have a poor experience are disinclined to return. To prevent this, web designers and UX specialists must provide engaging visuals and information to ensure the customer journey begins positively. Gamification can create enthusiasm around engagement by offering unique experiences and rewarding loyalty with points—for instance, a "weekly shopping challenge" for new customers. Accumulated points can then be redeemed for free products or discounts.

Like all studies, this research has limitations. The moderating variable of technology readiness was examined only through the dimensions of optimism and sense of lack of control; future studies could explore other dimensions, such as innovation and insecurity. Furthermore, customer intelligence experience could be investigated through other dimensions, including emotional (e.g., perceived pleasure) and behavioral (e.g., perceived control, personalization). A further limitation stems from respondents' limited familiarity with chatbots and their business applications in Iran, where this technology is not yet widespread. Consequently, incorporating interviews in future studies could yield richer insights. Finally, as the research focused on users of the Snap app, which has only recently begun deploying chatbots, some respondents' unfamiliarity with this feature may have influenced their responses.

CONFLICT OF INTEREST: The authors declare that they have no conflicts of interest regarding the publication of this manuscript.

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