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Artificial Intelligence in Electronic Commerce: Investigating the Customers' Acceptance of Using Chatbots

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Abstract. Artificial intelligence (AI) has become an important tool for companies trying to gain a competitive edge in the online market. Business to Consumer (B2C) e-commerce firms are increasingly integrating chatbots as virtual shopping assistants for providing more personalized and efficient shopping experiences to online customers. Chatbots are AI-powered software programs that can communicate with users through text or voice interfaces. However, there is a lack of research on the acceptance of chatbots in B2C e-commerce in Egypt. Therefore, this research tries to fill the gap in e-commerce chatbot literature by investigating the acceptance of the use of chatbots in online shopping among Egyptian users by applying the Use and Gratification theory. This is an exploratory study using a quantitative survey-based approach for collecting data from online Egyptian customers on their attitudes or intentions to use Chatbots in online shopping. The data were analysed by using regression analysis for identifying factors that influence user acceptance and usage of chatbots. The results revealed that both of hedonic and technology factors have positive influence on users' behavioural intention. While the risk factor which has two sub-factors namely; privacy and immature technology has negative influence on customers' behavioural intentions. The study contributes to the expanding body of literature on the acceptance and use of Chatbots among customers in B2C e-commerce context. In addition, the study's findings give significant insights for Egyptian online retailers looking to implement Chatbots in their customer service strategy.

Keywords: Chatbot/s; B2C E-commerce; Use and Gratification Theory; customer service; customer acceptance.

1.Introduction

Artificial intelligence (AI) has become an essential aspect of our lives and has integrated into numerous applications to be capable of performing a variety of tasks (Lavanya, & Pradeep, 2021). Consumers and end users may not be aware of many of the business applications for AI, such as modelling complex business scenarios (Yanyong, T.,2021). Industry 4.0 is the newest generation of applied technology, and AI is one of its driving forces (Ikhasari & Faturohman,2021; Yuphin & Ruanchoengchum, 2020). As technologies advance, AI has become more approachable and has recently become widespread in many end-user applications, including real-time human-computer interactions, or chatbots (Adamopoulou &Moussiades, 2020). According to Adam et al. (2021), real-time chat interfaces are becoming more and more popular for communicating with customers. The use of chatbots has grown over the past few years, partly due to user preference; people prefer to interact with computers using the same languages they use to communicate with other people (Shawar &Atwell, 2007). The goal of chatbots, which are computer programs, is to communicate with people by simulating human-to-human communication through the use of language (Anbananthen et al., 2022), giving users the impression that they are speaking with another person (Hussain et al., 2019). There are two primary methods for interacting with computers: voice communication and text communication. The first Chatbot, named Eliza, was introduced 1966. Since that, the community of chatbot has investigated several intriguing concepts (Pereira et al., 2016). With advances in the underlying technology, chatbot development—in particular speech-based chatbot development—has picked up in recent years (Huang et al., 2022). Chatbots' main goal is to assist users in achieving their objectives by streamlining processes through verbal interactions.

Chatbots are flexible and hold a lot of promise. Human service workers frequently reach the limits of their abilities; they might be unable to coordinate different resources for the benefit of the business and might get tired (Johannsen et al., 2020). However, chatbots are accessible all the time thanks to scalable technology, so users won't have to wait for long to use them. For firms, Chatbots have the potential to significantly reduce costs and automate processes for businesses (Akhtar et al.,2019).

The use of chatbots for various practical purposes is expanding, and some chatbots, like Amazon Alexa and Apple Siri, are well-known. Watson, a question-and-answer program from IBM, is a prime example. Chatbots can be used in all spheres of life and are not just applicable to information technology companies. More than 85% of customer interactions in 2020 were handled by different types of chatbots (Li et al., 2021). For instance, "Businesses can use chatbots for internal communication in addition to using them for external communication (with customers)" (Johannsen et al., 2020). Large corporations frequently use chatbots for employee support, training, and recruitment. Meet Frank, for instance, is a chatbot that can anonymously connect businesses with talent (Cohen T., 2019). In many contexts, including e-commerce, communicating with customers through live chat interfaces has grown in popularity as a way to offer real-time customer service. Human chat service agents are frequently replaced by conversational software agents, or chatbots. AI-based chatbots were widely adopted to take advantage of cost and time-saving opportunities, but they still frequently fall short of customer expectations, which could make users less likely to follow the chatbot's instructions and use it themselves (Hussain et al., 2019).

Based on social response and commitment-consistency theory, earlier research has looked at how verbal anthropomorphic design cues and the foot-in-the-door technique affect user request compliance. This study empirically investigates the user's experience through a randomized online experiment (Adam et al.,2021). The findings show that users are much more likely to comply with a chatbot's request for service feedback when it is anthropomorphic and consistent (Adams et al., 1992). Furthermore, those findings demonstrate that social presence mediates the influence of anthropomorphic design cues on user compliance. Artificial intelligence has recently entered the Egyptian e-commerce market and has taken a significant portion of it. Chatbots have witnessed a rise in development in the first half of the year 2020 increasing by 100 percent based on Egyptian online companies' requests (Moneim, 2020).

This study's foundation is provided by related research on the use of chatbots in the education sector (Ragheb, M.A. et al., 2022), but e-commerce is still unexplored. In a similar vein, recent studies have investigated how user characteristics influence user acceptance of chatbots in e-commerce using the social presence theory (Min et al., 2021) and the actual usage theory to investigate chatbot usage in the hospitality industry (Pillai & Sivathanu, 2020). A thorough examination of the body of research on Chabot acceptance, however, reveals a gap in the application of the Use and Gratification Theory to gauge consumer acceptance of e-commerce in Egypt.

Therefore, this study focuses on; determining the significant and/or non-significant factors that impact the acceptance of chatbots among Egyptian online users in the B2C e-commerce field by using the Use and Gratification model as a theoretical framework. The theory suggests that users who use technology to satisfy specific needs or gratifications. The theory suggests that the behaviour of users' intention to utilize technology is influenced by the perceived ability of the technology to satisfy those needs.

The remaining parts of the paper are organised as follows: Section 2 explains the literature review of Chatbots, and explanation of the Use and Gratification theory. Section 3 offerings the conceptual framework, followed by Sections 4 which presents the research methodology, and section 5 that displays the analysis and results of the research. Finally, section 6 that displays the Discussion and Conclusions.

2. Literature Review

2.1. Chatbots

A Chatbot is an intelligent program and Human-Computer Interaction model (Bansal & Khan, 2018), which is designed to use Natural Language processing (Toh, & Tay, 2022) and sentiment analysis to simulate conversation with users through text or oral speech in real-time (Khanna et al., 2015). In addition to simulating the conversations of humans via text commands or voice messages, Chatbots are serving users as virtual assistants (Luo, 2019). The users communicate with Chatbots through an interface, which may be an application, a website, or a social network like Facebook Messenger. This interaction management is done by a conversation management system (Rajman, Bui, & Rajman, 2004).

In the 1960s, MIT scientist Joseph Weizenbaum created Eliza, the first chatbot ever created. Eliza simulated the operation of psychotherapist, returning the sentences of users in the interrogative form (Weizenbaum, 1966). Its communication capabilities were limited, nonetheless, it influenced the Chatbots' development later (Klopfenstein et al., 2017). Eliza used pattern matching and substitution methodology to simulate conversation (Brandtzaeg & Følstad, 2017). Since then, Chatbot have been built upon first model offered to strive towards interactions more similar to human. Passing the Turing test, which evaluates new machines' conversational skills against a panel of human judges, has become a common goal. In 2001, the America Online (AOL) and Microsoft Messengers applications offered the Smarter Child Chatbot on them which was represented a significant technological advancement in the field of chatbots (Molnár & Zoltán, 2018). It was the first time a chatbot could assist with actual everyday chores by getting information on movie timings, sports scores, news, and the weather from databases.

The development of Chatbots by Artificial Intelligence resulted in new intelligent personal voice assistants' development, which were integrated into smartphones, and home speakers, and understand voice commands, spoke in digital voices, and performed tasks like as calendars, and email (Eleni and Lefteris, 2020). For instance, the most popular voice assistants available now are, Siri (from Apple), Watson assistant (from IBM), Google Assistant (from google), Cortana (from Microsoft), and Alexa (from Amazon) (Eleni and Lefteris, 2020).

Beginning in 2016, advancements in Artificial Intelligence Technology radically impacted how users interact with business owners. On social media platforms, developers were able to integrate chatbots for their marketing functions and service, allowing users to do routine operations within messaging apps. Moreover, in the same year, 34,000 chatbots were utilised in a variety of industries, including health care, entertainment, marketing, and education (Wizu, 2018). Another use of Chatbots, many text-based chatbots for different purposes were built and integrated into varieties of messaging networks, industrial applications, and research centres (Dale, 2016).

The manner in which modern chatbots engage in conversation is entirely distinct from Eliza's. As with humans, personal thoughts can be shared, be relevant but also confusing, and deceive (Shah, Warwick, Vallverdú, & Wu, 2016). Chatbots can now be incorporated into messaging platforms like Facebook Messenger and WhatsApp. These chatbots can be used for a variety of purposes and have a significant impact on organisations by reducing costs, building a good relation with loyal customers, and providing the service in multiple languages (Trappey et al., 2018), as well as enhancing client relationships and incorporating them into the organisation (Hong et al., 2019).

2.2. The Use and Gratification Theory

The Use and Gratification theory is communication and media studies theory that emerged in the 1940s and 1950s (Ruggiero, 2000). The theory was developed as a response to the traditional approach of communication research, which focused on the effects of media on individuals and society, without considering the active role of the audience in selecting and using media (Ruggiero, 2000). recently, it is from the audience's perspective to explain what meets the audience's needs by analysing audience contact's motivation. According to the Use & Gratification model, the social and psychological needs of people can be satisfied by media use which are divided into five dimensions for needs; cognitive, affective, integrative, social integrative, and tension-release (Katz, Blumler, & Gurevitch, 1973).

In the 1970s, the Use and Gratification theory was applied to the study of new forms of communication, such as the telephone, and the internet. Researchers started to focus on how individuals use communication technology to satisfy specific needs, such as the need for social connection, the need for information, and the need for entertainment. Recent years have also seen the addition of "technical satisfaction" and "social satisfaction" to the Use & Gratification Model (Wang, Zhang, & Zhao, 2020). Where, technical satisfaction is of utmost importance as it is a prerequisite to the activity to e-commerce. It relates to whether humans can accomplish their intended impact with the available technology effectively and precisely, which in the case of Chatbots is strongly dependent on the satisfaction of the Chatbot-to-human contact or "authenticity". The theory of Use and Gratification has been applied to surveys in a variety of fields, such as examining the acceptance of people for information service from internet-based (Luo, Remus, & Chea, 2006) and reasons why individuals utilise virtual goods (Kaur et al., 2020), where it was shown that acceptance of technology depends on a number of factors, risk (privacy and security) in the e-commerce case, being the most prominent. The Use & Satisfaction model is popular due to the rejection of the passive theory of audience experience and promotes audience initiative. It has been demonstrated that the Use and Gratification theory is a superior tool for examining customer motivation, yielding valuable insights (Rese, Ganster, & Baier, 2020).

2.2.1. Behaviour intention (BN)

Behavioural intention (BN) refers to an individual’s likelihood of engaging in a specific behaviour or action. It is a key concept in many behavioural theories and models, like the theory of Planned Behaviour (TPB) and the Technology Acceptance Model (TAM). Theory of TPB, developed by Ajzen, suggests that (BN) is determined by three factors; attitude towards the behaviour, subjective norm, and perceived behavioural control (Miniard, & Cohen, 1981). Attitudes refer to the individual’s evaluation of the potential consequences of the behaviour. Subjective norms refer to the perceived societal pressure to do or not execute the behaviour. Perceived behavioural control refers person' confidence in their capacity to perform the behaviour

The (BN) of users in virtual environment is influenced by the loyalty of users to the virtual environment (Lin, 2006). From the science and technology perspectives, if digital products can provide “technical satisfaction," the user’ loyalty to the virtual environment will increase; this means that users will exhibit a propensity for positive behavior. Interactivity and sociability in virtual worlds influence the social and business paradigms of virtual worlds significantly (Animesh et al., 2011). BN and the perceived risk are influenced by the presence, magnitude, and immediacy of the risk (Lo, 2014). Frequently, risk and behavioral intentions have a negative correlation (Lo, 2014). It has been discovered that in a virtual environment, privacy and immature technology contribute to the decline of user loyalty

(Anic, Škare, & Milakoviˊc, 2019). So, the behavioural intentions will be explored from three aspects that can impact on the loyalty of consumers toward Chatbots and may be reflect behaviour intentions of consumers.

2.2.2. Technology Acceptance

2.2.2.1. Authenticity of Conversation and (BN)

Authenticity of conversation refers to the degree to which the Chatbot's responses are perceived as natural and human-like. If users feel that the Chatbot is not providing authentic responses, they may be less likely to trust the Chatbot and may have lower behavioral intention to use it. On the other hand, if users perceive the Chatbot's responses as authentic, they may be more likely to trust the Chatbot and have a higher behavioral intention to use it. Also, authenticity of conversation can also affect the perceived usefulness of the Chatbot. Users may perceive a Chatbot to be more useful if they believe that the Chatbot can provide accurate and helpful responses (Gilmore, 2007). Additionally, if users feel that the Chatbot's responses are authentic, they may be more likely to trust the Chatbot and perceive it as more useful (Ischen et al., 2020).

This indicates that authenticity may be applied to both the quality of a person and the consumer's confidence in a product or service. Consumers' knowledge of and need for authenticity reflect the distinction between truth and falsehood (Gilmore, 2007). For instance, the ability of a user to acquire meaningful information from a Chatbot is a crucial element for customers when selecting a product. The consequence is customers' will to behave (Zogaj, Mähner, & Tscheulin, 2021). This means this means if the Chatbot has a good simulation effect, it will deliver objective and trustworthy information to users and will be closer to the typical human user experience in terms of communication. The Chatbot may be enhanced by interaction with the user. the use of Chatbot will increase the authenticity of the application, user acceptability, and even user loyalty. Authenticity is a crucial aspect in the acceptance of Chatbots by users (Blut, Wang, & Wünderlich, 2021). Therefore, the authenticity of conversation' importance as a one of technology acceptance factor affects on consumers' behavior, so, the first hypothesis was set as follows: -

(H1): The authenticity of conversations has a significant impact on (BN) of users.

2.2.2.2. Convenience and (BN)

Convenience can be defined as the degree to which the chatbot is perceived as easy to use and accessible. The convenience use may be evaluated from the perspectives of both physical and cognitive demands (Kang et al.,2019). For instance, while purchasing, physical needs mean about that individuals may purchase with a Chatbot regardless of location. Comparing to cognitive needs, imply that individuals may choose to purchase anything they like using a Chatbot. Especially, from the pandemic of Coronavirus, online purchasing has gained a new significance, and personalized interactions role has become a critical element in the experiences of online shopping. This means that convenience can raise customer loyalty by decreasing the shopping time. When customers be observing a significant likelihood of inconvenience, their behavioral intention is impacted negatively, particularly when doing shopping (Moshrefjavadi et al., 2012). Additionally, Chatbots are used in several areas due to their convenience, such as the acceptance of students in colleges to use Chatbots for educational purposes (Malik et al., 2021). It is supposed that the convenience that Chatbots is, partially due to a lack of time, and thus sets constraints on users' ability to utilize Chatbots, this will increase the users' dependence on Chatbots and their loyalty, influencing their (BN). Therefore, the convenience' importance as a one of technology acceptance factor affects on consumers' behavior, so, the second hypothesis was set as follows: -

(H2): The convenience has a significant impact on (BN) of users.

2.2.3. Hedonic and (BN)

Hedonic refers to the enjoyment that users experience while using a product or service. In the context of technology acceptance, hedonic factors which are behaviour intention, enjoyment, and passing time can play a significant role in determining the user's behavioural intention to use a product or service

(Batra, & Ahtola, 1991). In virtual environment, users may feel with difficulty due to the new, distinctive, and odd atmosphere, which is the virtual environment's uniqueness (Ha, & Stoel, 2009), this may lower the demand of users from the products in a virtual world, and cause consumers to have attitudes negatively, which means that hedonism plays an important role. on the internet, higher levels of mental enjoyment and pleasure facilitate the development of positive attitudes for users (Kim, Lee, 2013). This means in the case of Chatbots, perceived enjoyment which is a psychological consequence and an antecedent to the attitudes of consumers (Hussain, Ameri, Ababneh, 2019). Additionally, people prefer to spend most of their free time in the virtual world (Marjerison et al., 2022), and Chatbots are one of the tools that will be used as a form of entertainment in this world (Brandtzaeg, Følstad, 2018). From the literature, there are positive relationship between BI and pass time, and also the same with enjoyment. Therefore, the Hypothesis three and four were set as follow: -

(H3): Enjoyment perception has a significant impact on BN of users.
(H4): Hedonic (pass time) has a significant impact on BN of users.

2.2.2.4. Risk

2.2.2.4.1. Privacy and (BN)

Privacy concerns refer to the fear that personal information may be collected, used or shard without the user’s knowledge or consent. When it comes to chatbots, privacy concerns can be related to the collection and use of personal information. Users are becoming increasingly irritated by complicated privacy rules, inaccessible privacy settings, and the proliferation of developing standards for ensuring online security (Harkous et al., 2016). According to prior research, humanoid Chatbots regularly experience information leakage, and their anthropomorphic perception-mediated suggestion compliance and reduced privacy concerns have been the subject of significant study (Ischen et al., 2020). Users who using Chatbots did not see a reduction in privacy issues, but their feeling of social presence increased (Ng et al., 2020). As Chatbots are widely employed in a variety of areas, their employment in the finance business increased people's mistrust. When it comes to exchanging financial information and the use of Chatbots for financial assistance, consumers have a very low level of confidence in them (Ng et al., 2020). In addition, Baudart (Baudart et al., 2018) observed that Chatbots may supply viral-carrying material to users, which may create privacy problems, be hostile or harmful, and cause Chatbot providers considerable reputational, or legal harm. So, Users may be hesitant to use chatbots if they believe that their personal information will be collected and used without their consent or if they believe that their information may be shared with third parties. Therefore, Information leakage, the propagation of viruses, and other concerns must thus be taken into account while utilising Chatbots. Thus, the fifth hypothesis was set as follows: -

(H5): Privacy has negative impact on BN of users.

2.2.2.4.2 Immature technology and (BN)

Immature technology refers to technology that is still in the early stages of development and may not be fully functional or reliable. Immaturity technology is one of the factors that can impact the acceptance of technology is its perceived immaturity. When a technology is perceived as being immature, users may be less likely to adopt it due to concerns about its reliability, functionality, and stability (Wu, & Wang, 2005). In the context of Chatbots, immature technology can include chatbots that are not able to understand or respond to user input correctly, or poor-quality feedback, or are not able to perform certain tasks as expected. This can lead to a negative effect on the customers and cause dissatisfaction (Nichifor et al., 2021). As Chatbots technology is still immature (Zhu et al., 2022), the reputation of the practical impact of chatbot technology is still questionable (Lin et al., 2022). The immaturity of Chatbot technology is evidenced by its inaccuracy in text recognition, failure to understand voice input, and inability to offer precise replies. (Han et al., 2021).

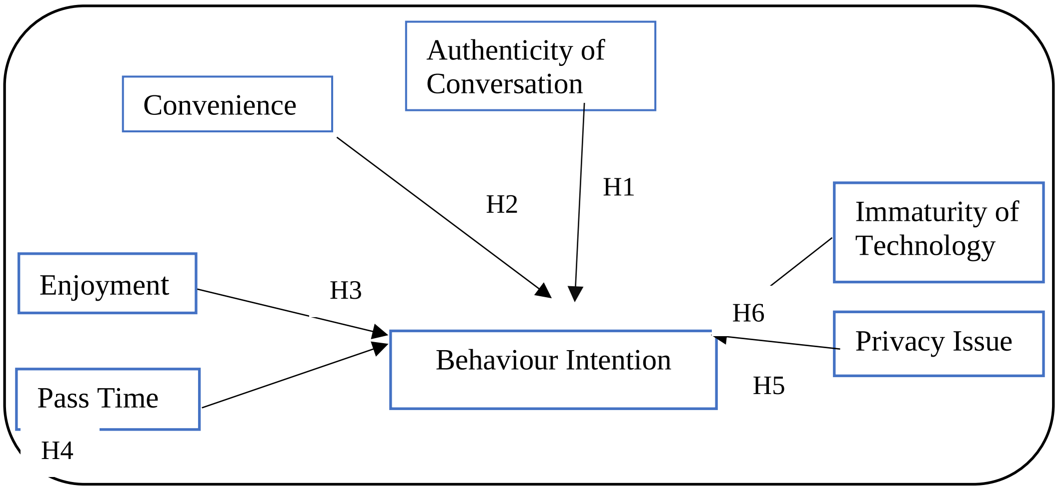
Therefore, perceived immaturity of the technology can negatively impact on the user’s behavioural intention to use chatbots. Users may be hesitant to use chatbots if they believe that the chatbot is not functional or reliable. They may also be less likely to trust the chatbot if its performance is not meeting their expectations, or if they believe that the chatbot is not able to perform certain tasks as expected (Marjerison et al., 2022). Thus, the sixth hypothesis was set as follows: -

(H6): The immaturity technology has negative impacts on users' (BN).

3. Research Methodology

This study's objective is to investigate the adoption of Chatbots in Egyptian online shopping and the elements that lead to favourable and negative opinions about them. The study utilised a quantitative research method to analysis online survey data in order to measure the acceptance of Chatbots among online customers. The items of the survey were drawn from earlier researches with few alterations to cope with the study context, on the basis of the Use and Gratification theory. The main criteria of the use and gratifications models which are; Technology, Hedonics, and Risk were incorporated, and each criterion was treated from two sub-criteria with different perspectives. The authenticity of conversation and convenience for Technology, enjoyment and pass time for Hedonic, and privacy and immature technology for Risk. Three separate questions have been posed for each of the six criteria. The questions were modified from earlier research: How to gauge the acceptance of chatbots in-retailer customer communications (Rese et al., 2020).

Each question in the survey has been checked and verified. The six sub-criteria are considered the independent variables, were used to measure Egyptian users' adoption of Chatbots, while (BN) of users is considered the dependent variable. To ascertain whether there is a direct correlation between them, linear regression was applied. Participants in the survey expressed their opinions using a Likert scale, which ranged from "1" (strongly disagree) to "5" (strongly agree).



The proposed model

The above figure represents the relationship among variables (dependent variable (BN) and independent variables (technology, hedonic, and risk). As the study aims to explore the acceptance of the use of chatbots in B2C e-commerce in Egypt by applying the theory of Use and Gratification.

3.1. Survey

To address the research objectives, online survey was used as tool for data collection. The survey included two parts; the first part included general information about demographic characteristics, and the second part contained an 18-item questionnaire to explore the attitudes of users toward Chatbots from the three main criteria (technology, hedonic, and risk), and six sub-criteria (Authenticity of Conversation, convenience, enjoyment, pass time, privacy, and immaturity of technology). A total number of 448 online surveys were collected, and after inspection; 24 respondents were excluded due to not being completed, and the rest which counts 424 were determined as valid.

4. Analysis and Results

4.1. Sample Characteristics

Table 1 displays demographic sample characteristics, age, gender and education information for all 424 participants. For demographic breakdown information, 56.1% males and 43.8% females. The respondents' ages ranged from 18 to above 45 years old. Fifty users aged 18-25 accounted for 11.7% of the total respondents, one fifty-three users aged 26-35 accounted for 36% of the total respondents, and one thirty-four forty-one aged 36-45 accounted for 31.6% of total population. Of the respondents, 65% obtained bachelor degrees, followed by 31.3% are in high school. For having experience with Chatbots, there were 405 respondents accounted for 95.5% of total population who already used Chatbots once or many times during the last three years, and 19 respondents who had never tried Chatbots but they are welling to use them in the future.

Table 1. Sample Demographics analysis.

Characteristics	Categories	Frequency	Percent (%)
Gender	Male	238	56.1
	Female	186	43.8
Age	18-25	50	11.7
	26-35	153	36.
	36-45	134	31.6
	>45	87	20.5
Education	High school	133	31.3
	Bachelor's degree	276	65
	Graduate degree	15	3.5
Experience in using Chatbot	Under 1 year	192	45.2
	1-3 years	213	50.2
	Did not try before	19	4.4

4.2. Measurement Model

4.2.1. Reliability Analysis

Before analysing data, factor analysis was undertaken to confirm the (BN) dimensions' underlying structure. (Table 2). The factor loading results of observed variables were all larger than 0.4. in addition, the eigenvalues of all factors are greater than one. Also, the reliability data of technology, hedonic, risk and behaviour intentions questions are adequate at 0.786 and all factors above 0.7. This indicates that the data are trustworthy and that additional research is justified.

Table 2. Scale items of constructs and factor loading weight values.

Factor	Item	Mean	Factor Loading	Eigenvalue	Reliability
Tech. Convenience				1.946	0.780
	Conv1	2.05	0.798		
	Conv2	2.43	0.841		
	Conv3	2.53	0.702		

Tech. Authenticity of conservation				1.937	0.769
	Auc1	2.27	0.753		
	Auc2	2.30	0.771		
	Auc3	2.31	0.784		
Hedonic (enjoyment)				1.932	0.763
	Enj1	2.37	0.751		
	Enj2	2.54	0.794		
	Enj3	2.33	0.745		
Hedonic (Pass time)				1.933	0.819
	PT1	2.30	0.785		
	PT2	2.32	0.860		
	PT3	2.39	0.813		
Risk. Privacy				1.929	0.82
	Priv1	2.41	0.796		
	Priv2	2.56	0.807		
	Priv3	2.53	0.857		
Risk. Immature technology				1.926	0.785
	IMT1	2.40	0.799		
	IMT2	2.57	0.779		
	IMT3	2.42	0.777		
BN					0.766
	BI1	2.46	0.784		
	BI2	2.38	0.704		
	BI3	2.52	0.810		
Overall reliance					0.786

From the above table, the reliability of the sub-two factors of technology which are the authenticity of conservation and convenience were 0.780 and 0.769 respectively. Also, the reliability of the sub-two factors of hedonic which are the enjoyment and pass time were 0.763 and 0.819 respectively. For the last independent factor of the model which is risk, the reliability of its sub-factors (privacy and immaturity of technology) were 0.82 and 0.785 respectively. For (BN), the dependent variable, all its questions measuring were loaded separately, and its reliability coefficient was 0.766. Thus, the model and the research hypotheses were tested.

4.3. Correlation Analysis for Independent Variables

4.3.1. Correlation analysis of Authenticity of Conversation & (BN)

As indicated in Table 3, the model of regression analysis was applied between (BN) and authenticity of conservation, and the value of the R square is 0.184, which indicates that authenticity of conversation (a sub-factor of technology) can explain 18.4% of the change that occurs in the dependent variable (BN).

Table 3. Result of Regression analysis between Authenticity of Conversation & (BN).

Predictor	Estimate	SE	t	P	R	R2
Intercept	4.107	0.326	12.598	< 0.001		
BN	0.447	0.046	9.768	< 0.001	0.429	0.184

Moreover, the value of P is less than 0.01. Also, the value of the coefficient test is 0.447, which indicates that an increase in one unit of authenticity of conversation will result in an increase by 0.447 units of (BN). This proves that authenticity of conversation has a significant impact upon (BN) which supports the first research hypothesis. Consequently, the first hypothesis which is (The authenticity of conversations has a significant impact on (BN) of users) is accepted.

4.3.2. Correlation Analysis of Convenience & (BN)

As indicated in Table 4, the model of regression analysis was applied between (BN) and convenience, and the value of the R square is 0.138, which indicates that the convenience (a sub-factor of technology) can explain 13.8% of the change that occurs in the dependent variable (BN).

Table 4. Result of Regression analysis between Convenience and (BN).

Predictor	Estimate	SE	t	P	R	R2
Intercept	4.272	0.362	11.796	< 0.001		
BN	0.394	0.048	8.229	< 0.001	0.372	0.138

Furthermore, the value of P is less than 0.01. Also, the value of the coefficient test is 0.394, which indicates that an increase in one unit of convenience will result in an increase by 0.394 units of (BN). This proves that the convenience has a significant impact upon (BN) which supports the second research hypothesis. Consequently, the second hypothesis which is (The convenience has a significant impact on (BN) of users*)* is accepted.

4.3.3. Correlation analysis of Enjoyment & (BN)

As indicated in Table 5, the model of regression analysis was applied between (BN) and enjoyment, and the value of the R square is 0.220, which indicates that the enjoyment (a sub-factor of hedonic) can explain 22% of the change that occurs in the dependent variable (BN).

Table 5. Result of Regression analysis between enjoyment and (BN).

Predictor	Estimate	SE	t	P	R	R2
Intercept	3.823	0.319	11.978	< 0.001		
BI	0.467	0.043	10.924	< 0.001	0.470	0.220

Moreover, the value of P is less than 0.01. Also, the value of the coefficient test is 0.467, which indicates that an increase in one unit of enjoyment will result in an increase by 0.467 units of (BN). This proves that the enjoyment has a significant impact upon (BN) which supports the second research hypothesis. Consequently, the third hypothesis which is (Enjoyment perception has a significant impact on (BN) of users) is accepted.

4.3.4. Correlation analysis of Passing Time & (BN)

As indicated in Table 6, the model of regression analysis was applied between (BN) and privacy, and the value of the R square is 0.240, which indicates that the pass time (a sub-factor of hedonic) can explain 24% of the change that occurs in the dependent variable (BN).

Table 6. Result of Regression analysis between passing time and (BN).

Predictor	Estimate	SE	t	P	R	R2
Intercept	3.817	0.304	12.541	< 0.001		
BN	0.473	0.041	11.534	< 0.001	0.490	0.240

Furthermore, the value of P is less than 0.01. Also, the value of the coefficient test is 0.473, which indicates that an increase in one unit of pass time will result in an increase by 0.473 units of (BN). This proves that the pass time has a significant impact upon (BN) which supports the fourth research hypothesis. Consequently, the fourth hypothesis which is (pass time perception has a significant impact on (BN)) is accepted.

4.3.5. Correlation analysis of Privacy & (BN)

As indicated in Table 7, the model of regression analysis was applied between (BN) and privacy, and the value of the R square is 0.247, which indicates that the privacy (a sub-factor of risk) can explain 24% of the change that occurs in the dependent variable (BN).

Table 7. Result of Regression analysis between Privacy and (BN).

Predictor	Estimate	SE	t	P	R	R2
Intercept	3.863	0.3003	13.081	< 0.001		
BN	-0.446	0.0386	-11.772	< 0.001	0.497	0.247

Moreover, the value of P is less than 0.01. Also, the value of the coefficient test is -0.446, which indicates that an increase in one unit of pass time will result in decrease by 0.446 units of (BN). This proves that the privacy has a negative impact upon (BN) which supports the fifth research hypothesis. Consequently, the fifth hypothesis which is (privacy perception has a negative impact on (BN) is accepted.

4.3.6. Correlation analysis of Immature Technology & (BN)

As indicated in Table 8, the model of regression analysis was applied between (BN) and immature technology, and the value of the R square is 0.236, which indicates that the immaturity of technology (a sub-factor of risk) can explain 23.6% of the change that occurs in the dependent variable (BN).

Table 8. Result of Regression analysis between immature technology and (BN).

Predictor	Estimate	SE	t	P	R	R2
Intercept	4.00679	0.295319	13.56769	< 0.001		
BN	-0.43179	0.038111	-11.3298	< 0.001	0.486	0.236

Furthermore, the value of P is less than 0.01. Also, the value of the coefficient test is -0.431, which indicates that an increase in one unit of immature technology will result in decrease by 0.431 units of (BN). This proves that the immature technology has a negative impact upon (BN) which supports the sixth research hypothesis. Consequently, the sixth hypothesis which is (immature technology perception has a negative impact on (BN) is accepted.

5. Discussion

The study's goal was to measure the acceptance of using Chatbots in B2C e-commerce in Egypt and to investigate the positive and negative factors that impact the users' attitudes towards them. Based on earlier market research survey insights into Chatbots, the theory of Use and Gratification was applied as theoretical framework to measure the chatbots acceptance in online retail, and the tests of confirmatory were performed, taking into consideration the Technology, Hedonistic, and Risk factors. The correlation between the dependent variable (BN), and all independent variables of the Use and Gratification model namely; the authenticity of conversation, convenience, enjoyment and passing time, privacy concerns, and immaturity of the technology, were investigated by using linear regression analysis to assess the acceptance of Chatbots among consumers.

The theory of use and Gratification was applied in previous research to chatbots in many different sectors such as healthcare (Bates, 2019; Bhirud et al., 2019), and education (Smutny, Schreiberova, 2020; Winkler, Söllner, 2018). None of the current research on chatbots in B2C e-commerce utilizes the Use and Gratification theoretical constructs, namely Hedonistic, Risk, and Technology, as they are given in this paper. Although the theory of Use and Gratification has been applied to a number of similar models, such as online information services (Luo et al., 2006; Luo, Chea, Chen, 2011) and online video entertainment content (Nanda, Banerjee, 2020; Steiner, Xu,2020), the potential to learn more about how consumers in the Egyptian e-commerce sector perceive Artificial intelligence has not yet been investigated.

The results showed that the Hedonic factor which includes; enjoyment and passing time and Technology which include; convenience and authenticity of convenience both have a positive influence on users' behavioural intention. This may be due to the fact that technology has significantly enhanced people's quality of life. For Egyptian customers who primarily rely on smartphones, these two criteria may also play a significant role in their adoption of chatbots. The sub-criteria of risk which are immutably technology, and privacy, are observed to have a negative influence on customers' behavioural intentions. Customers are concerned about potential privacy even if the development of artificial intelligence has reached an astonishing and unprecedented level with remarkable levels of protection since information leakage, data theft, and similar problems continue to occur often. Users' continued mistrust of chatbots is also a result of their continued concerns that they cannot fully understand human speech or communicate with them in a clear and efficient manner.

By expanding on earlier research and extending the technique to the application of Chatbot acceptance in Egypt, these findings add to the body of information connected to the theory of Use and Gratification. A further contribution is made regarding the acceptance of chatbots in the B2C e-commerce sector as well as in the more general application of user acceptance of artificial intelligence. This is a relatively new area of exploration where consensus is forming but has not yet been solidified and is becoming more relevant and interesting. Thus, by experimentally establishing and proving the connections between users' pleasure and Chatbot adoption, our study adds to the theory of Use and Gratification. The application of an expanded understanding of the theory of Use and Gratification to a relatively new field (e-commerce) and a highly unique set of circumstances (e-commerce—Egypt) is the article's contribution. From a larger viewpoint, the relevance and interest of user acceptance of artificial intelligence is significant, and our results show that, even though some research suggests otherwise, customers, at least in Egypt, are not open to embrace the dangers associated with artificial intelligence in online transactions for financial issues at this time. This indicates that more research has to be done on the development of artificial intelligence, and specifically chatbots, before we can reap the potential benefits.

These results also have practical ramifications. Egypt is considered the largest e-commerce market in the middle east, with a high smartphone penetration rate, and the potential for Chatbots is huge. As chatbots are the most popular and are widely considered the future of customer service, and have the potential to greatly improve the efficiency of businesses. So, overall, these results are encouraging for the use of Chatbot in Egypt since they show a context-limited acceptability and a favourable acceptance to use Chatbot in B2C e-commerce. In order to boost adoption, developers can utilise these insights for further investigation and optimizations in the areas of immature technologies and security. Also, it can assist businesses in developing effective strategies for the implementation of Chatbots in the Egyptian B2C e-commerce market. In addition, businesses that are interested in implementing chatbots in e-commerce should ensuring security to increase the acceptance of chatbots among Egyptian users. Therefore, the findings give light on possible future directions for Chatbot development and identify present difficulties.

6. Conclusion

The research study aimed to investigate the acceptance of online users to use Chatbots in online shopping in Egypt. The results revealed that the technology factor which includes authenticity conversation and convenience, and the hedonic factor which has two sub-factors namely; enjoyment and passing time have a positive influence on users' behavioural intentions. While the risk factor which has two sub-factors namely; privacy and immature technology has a negative influence on customers' behavioural intentions. Therefore, based on the findings of the study and the acceptance of customers to use Chatbots in online shopping, The study revealed some crucial suggestions that the researcher offers to online retailers as well as for additional study. The first recommendation to online retailers is to determine the chatbot's purpose before integrating a chatbot and determine what purpose it will serve. The second recommendation is to develop a conversational flow that guides customers through the shopping process which could include answering frequently asked questions, suggesting products, and facilitating the checkout process. The third recommendation is to ensure that the chatbot is prominently displayed on the website or mobile applications so that customers can easily access it if they need assistance. And the final recommendation is continuously to monitor the chatbot's performance and use analytics to identify areas for improvement. This will help ensure that the chatbot is delivering the desired outcomes, such as increased sales and customer satisfaction.

7. Limitations and future work

The study tried to examine the acceptance of chatbots in the online shopping process with regard to Egyptian customers. To further validate the study's findings, a study with a larger sample size and greater population representation should be taken into consideration. Furthermore, future research needs more investigation by adding other new variables to the Use and Gratification model that may affect the adoption of chatbots and its influence on behaviour intention of users. Moreover, Investigations into different population segments are possible. Additionally, Future research could pay more attention to how people with various professions and income levels feel about chatbots. For instance, chatbots could be beneficial for academic students, while for those working in the financial, the purposes of the services sector may vary. As a result, various scenarios use chatbots in various ways, which may result in various attitudes.

Since the subject of this research study was measuring to what extent the acceptance of the use of chatbots in online shopping and what factors influence the behaviour intention of both those who have already used a chatbot as well as those who have never used one before, Future research should concentrate more on examining Egyptians who have already used a chatbot and their attitudes. This would aid in gaining a more in-depth understanding of the other factors that drove them to use chatbots in addition to those covered in this study. Also, there are restrictions on the results of the data collection method used by online surveys. If data collection is done through interviews, more thorough results might be attained. So, In-depth interviews with various companies that already use chatbots as a tool in their marketing strategies can also be conducted to gain more knowledge about how Egyptian companies can use chatbot technology to provide high-quality online services. Finally, Future studies might examine how well-designed chatbots are for users and how satisfied users are with them.

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Appendix A

Appendix A. Hypothesis Related to the Theoretical Model Proposed

Construct	Items	Adapted from
Technology (convenience)	shopping with Chatbots is more convenient.	(Childers et al., 2001; Ko et al., 2005)
	I am pleased that shopping can be done without installing a new app.	
	I can shop with Chatbots anytime, anywhere.	
	It is simple for me to communicate with Chatbots in a normal manner.	(Rese et al., 2020)

Technology (authenticity of conservation)	Speaking with a Chatbot is nearly similar to chatting with a real person.	
	I can converse with the Chatbot in a really natural manner.	
Hedonic (enjoyment)	The use of chatbots is entertaining	Rauschnabel et al., 2017.
	The use of a Chatbot may be relaxing	
	The use of a Chatbot can be exciting	
Hedonic (pass time)	The using of Chatbots is a pleasant way to spend some time.	(Papacharissi, and Rubin, 2000)
	The using of Chatbots can help fight boredom	
	When I have nothing better to do, I can spend my time using Chatbots.	
Risk (privacy concerns)	I am concerned about the privacy of my personal data.	Rauschnabel et al., 2017.
	Chatbots collect too much information about my privacy	
	Chatbots make it hard for me to secure my personal information.	
Risk (immature technology)	The text recognition of Chatbots is not accurate.	(Rese et al., 2020)
	Chatbots do not understand inquiries	
	Chatbots usually give me ambiguous responses.	
Behaviour intention	I will recommend the use of Chatbots to others.	(Venkatesh and Davis, 2000; Moon and Kim, 2001)
	I intend to use Chatbots in the future	
	I intend to use more Chatbot devices and applications in the future	

Appendix B

(1) Factor Analysis

Factor Analysis

Descriptive Statistics

	Mean	Std. Deviation	Analysis N	Missing N
Conv1	2.05	1.038	424	0
Conv2	2.43	1.185	424	0
Conv3	2.53	1.171	424	0
Auc1	2.27	1.105	424	0
Auc2	2.30	1.036	424	0
Auc3	2.31	1.000	424	0
Enj1	2.37	.983	424	0
Enj2	2.54	1.089	424	0
Enj3	2.33	1.119	424	0
PT1	2.30	1.134	424	0
PT2	2.32	.982	424	0
PT3	2.39	1.035	424	0
Priv1	2.41	1.204	424	0
Priv2	2.56	1.132	424	0
Priv3	2.53	1.102	424	0
IMT1	2.40	1.123	424	0
IMT2	2.57	1.258	424	0
IMT3	2.42	1.162	424	0
BI1	2.46	1.121	424	0
BI2	2.38	1.082	424	0
BI3	2.52	1.154	424	0

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.920
Bartlett's Test of Sphericity	Approx. Chi-Square	3081.406
	df	210
	Sig.	.000

(1) Regression of AUC

Regression

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Tot_Auc[b]	.	Enter

a. Dependent Variable: BI

b. All requested variables entered.

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.429[a]	.184	.182	2.343	1.900

a. Predictors: (Constant), Tot_Auc

b. Dependent Variable: BI

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	523.989	1	523.989	95.416	.000[b]
	Residual	2317.464	422	5.492		
	Total	2841.453	423			

a. Dependent Variable: BI

b. Predictors: (Constant), Tot_Auc

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	4.107	.326		12.598	.000		
	Tot_Auc	.447	.046	.429	9.768	.000	1.000	1.000

a. Dependent Variable: BI

(2) Regression of Convenience

Regression

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Tot_Conv[b]	.	Enter

a. Dependent Variable: BI

b. All requested variables entered.

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.372[a]	.138	.136	2.409	1.891

a. Predictors: (Constant), Tot_Conv

b. Dependent Variable: BI

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	392.892	1	392.892	67.713	.000[b]
	Residual	2448.562	422	5.802		
	Total	2841.453	423			

a. Dependent Variable: BI

b. Predictors: (Constant), Tot_Conv

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	VIF
1	(Constant)	4.272	.362		11.796	.000		
	Tot_Conv	.394	.048	.372	8.229	.000	1.000	1.000

a. Dependent Variable: BI

(3) Hedonic- Enjoyment

Regression

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Tot_Enj[b]	.	Enter

a. Dependent Variable: BI
b. All requested variables entered.

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.470[a]	.220	.219	2.291	1.920

a. Predictors: (Constant), Tot_Enj
b. Dependent Variable: BI

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	626.369	1	626.369	119.331	.000[b]
	Residual	2215.084	422	5.249		
	Total	2841.453	423			

a. Dependent Variable: BI
b. Predictors: (Constant), Tot_Enj

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	VIF
1	(Constant)	3.823	.319		11.978	.000		
	Tot_Enj	.467	.043	.470	10.924	.000	1.000	1.000

a. Dependent Variable: BI

(4)Hedonic – Pass Time

Regression

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Tot_PT[b]	.	Enter

a. Dependent Variable: BI
b. All requested variables entered.

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.490[a]	.240	.238	2.263	1.999

a. Predictors: (Constant), Tot_PT
b. Dependent Variable: BI

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	681.058	1	681.058	133.034	.000[b]
	Residual	2160.395	422	5.119		
	Total	2841.453	423			

a. Dependent Variable: BI
b. Predictors: (Constant), Tot_PT

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	3.817	.304		12.541	.000		
	Tot_PT	.473	.041	.490	11.534	.000	1.000	1.000

a. Dependent Variable: BI

(5) Risk - Privacy

Regression

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Tot_Priv[b]	.	Enter

a. Dependent Variable: BI
b. All requested variables entered.

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.497[a]	.247	.245	2.251	1.958

a. Predictors: (Constant), Tot_Priv
b. Dependent Variable: BI

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	702.418	1	702.418	138.577	.000[b]
	Residual	2139.035	422	5.069		
	Total	2841.453	423			

a. Dependent Variable: BI
b. Predictors: (Constant), Tot_Priv

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance
1	(Constant)	3.863	.295		13.081	.000	
	Tot_Priv	-.446	.038	.497	-11.772	.000	1.000