NOVA IMS Information Management School

MDDM

Master's Degree Program in

Data-Driven Marketing

How Artificial Intelligence has transformed e-commerce:

The case of chatbot on e-commerce platforms

Teresa Mariana Bento Pedro

Master Thesis

presented as partial requirement for obtaining a Master's Degree in Data-Driven Marketing

NOVA Information Management School
Instituto Superior de Estatística e Gestão de Informação
Universidade Nova de Lisboa

NOVA Information Management School
Instituto Superior de Estatística e Gestão de Informação
Universidade Nova de Lisboa

How Artificial Intelligence has transformed e-commerce

The case of chatbot on e-commerce platforms

by

Teresa Mariana Bento Pedro

Master Thesis presented as partial requirement for obtaining the Master's degree in Data-Driven Marketing, with a specialization in Marketing Intelligence

Supervised by

Tiago Oliveira, PhD, NOVA Information Management School

November, 2024

STATEMENT OF INTEGRITY

I hereby declare having conducted this academic work with integrity. I confirm that I have not used plagiarism, any form of undue use of information or falsification of results along the process leading to its elaboration. I further declare that I have fully acknowledged the Rules of Conduct and Code of Honor from the NOVA Information Management School.

Lisbon, June 09th, 2024

DEDICATION

I dedicate this work to those who have always believed in me and inspired me throughout my life.

To my family, for their unconditional love and for being my constant source of strength and motivation.

To the friends who have supported me every step of the way, showing me the value of true friendship.

And especially to my friend Carolina and my boyfriend Rúben, whose inspiration and example of determination have guided and motivated me to never give up on my goals.

This achievement is partly down to all of you.

ACKNOWLEDGEMENTS

I would like to express my sincere gratitude to everyone who, in one way or another, contributed to the realization of this work.

Firstly, I would like to thank my family for their unconditional support, patience and for being by my side at every stage of this journey. To my friends, who have always been there to encourage me and provide moments of relaxation during times of pressure.

To my colleagues and teachers, for sharing their knowledge, encouragement, and guidance throughout this academic journey. I would also like to thank the university and its staff for providing a learning and research environment that proved essential to the realization of this project.

Finally, a special thank you to everyone who participated anonymously in the data collection phase. Everyone's contribution was essential to the development of this work.

Thank you all very much.

ABSTRACT

Nowadays, consumers are increasingly turning to the digital world and with this comes the use of e-commerce platforms. With the constant use of e-commerce platforms comes a new tool, chatbots, digital agents with the ability to replace human agents in customer service, thus enabling a rapid response to requests for information. In the business context and given the increasingly specific demands of consumers, chatbots have been gaining recognition for being useful tools in customer support, offering companies the possibility of differentiating themselves in the market, distinguishing themselves through exclusivity and higher quality service, thus offering a better experience to consumers. This study proposes a theoretical model, integrating the D&M success model, the ECM model, and the Gamification model, to understand the main factors affecting the intention to continue using chatbots on e-commerce platforms. The data collected from 318 individuals was used to evaluate and validate the proposed theoretical model using partial least squares - structural equation modelling (PLS-SEM). The results indicate that to increase use and user satisfaction with chatbots on e-commerce platforms, those responsible should focus on optimizing the quality of the system, information, and service, as well as integrating gamification elements to improve the user experience.

KEYWORDS

Chatbots; Artificial Intelligence; E-commerce Platforms; User Experience

Sustainable Development Goals (SDG):

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF ABBREVIATIONS AND ACRONYMS

AI	Artificial Intelligence
B2B	Business-to-Business
B2C	Business-to-Consumer
CE	Customer Experience
IS	Information System
UTAUT	Unified Theory of Acceptance and Use Technology
TAM	Technology Acceptance Model
TTF	Task-Technology Fit
ECM	Expectation Confirmation Model
MOOC	Massive Open Online Courses

1. INTRODUCTION

In recent years, Artificial Intelligence (AI) has significantly transformed the purchasing decision process for online consumers. E-commerce enables more assertive decision-making. That said, companies need to be prepared for radical changes in the market, so that they can go with and react in a personalized way to different target audiences. As technology evolves, it tends to become more challenging to meet consumer expectations, leading companies to turn to AI as a solution. Artificial Intelligence, a tool that offers different options and information, carefully filtered, and adapted in a personalized way, plays a crucial role in personalized marketing, resulting in a new journey for consumers (Kumar et al., 2019). It should be noted that consumer's use of digital technology to make purchases is increasing significantly now and soon. However, it is essential to understand how consumers agree with and take advantage of technology to improve their shopping efficiency, and how companies can take advantage of AI to optimize and improve their e-commerce platforms.

Today's marketing is increasingly characterized by its reliance on data, automation and intelligence and their implications, such as human-machine interaction, aided by AI, chatbots (El Bakkouri et al., 2022). Chatbots, in the business world, are an advantageous tool when it comes to customer support and can thus provide companies with the chance to offer the best experiences to their consumers in a cost-effective way (Barış, 2020; Shawar & Atwell, 2007).

This paper aims to contribute to the academic discussion on chatbots in the context of e-commerce and online customer support. The main objective of this study is to gain knowledge and understand consumer perceptions and attitudes regarding the use of chatbots on e-commerce platforms and how they tend to influence the online consumer satisfaction. In this way, this study aims to answer the following research question:

RQ1: What are the key net benefits of using chatbots on e-commerce platforms?

RQ2: What are the determining factors in the confirmation of satisfaction when chatbots are used on e-commerce platforms?

This research contributes to the literature, firstly by combining the IS D&M success model with the ECM and Gamification model to improve understanding of the intention to continue using chatbots by identifying important determinants. According to previous research, this would be the first study to combine all the factors of the D&M success model, the ECM model, and the Gamification model to understand the intention to continue using chatbots. Secondly, considering that e-commerce platforms are constantly developing, this research will benefit consumers and companies that are developing IT related to the use of chatbots on e-commerce platforms by identifying the most important factors that can lead to long-term use by the end user. Thirdly, by addressing the factors of an individual's intention to continue using chatbots, the study deepens knowledge about what is important for the long-term use of an IS (Bhattacherjee, 2001).

The dissertation is organized into six different sections. The first of these, which is the most recent, includes the introduction to the project, which addresses the areas of study to be explored, the first question and the objectives to be achieved with the dissertation work. In the second section, the literature review covers a range of scientific knowledge, perspectives, and discussions between various authors on different topics, such as Marketing and its digital dimension, Artificial Intelligence, E-commerce Platforms, Customer Experience and Chatbots. Subsequently, the research models and associated statistical hypotheses will be discussed, along with an explanation of the method used. The study ends with the presentation and discussion of the results, followed by the study's conclusions.

2. LITERATURE REVIEW

2.1. ARTIFICIAL INTELLIGENCE

Artificial Intelligence (AI) involves developing systems or machines that simulate human intelligence, including learning, reasoning, and problem-solving, enabling them to perform tasks typically requiring human cognition. AI systems improve through data adaptation, a capability that has surged due to three factors: the availability of big data, scalable and affordable computing power, and advances in AI techniques like deep learning, genetic algorithms, and natural language processing (Darwiche, 2018). These advancements enable extensive data usage and computational power, expanding AI applications across sectors.

As noted by Kumar et al. (2019), AI's focus on automation and continuous learning makes it a key tool for analyzing data patterns and informing decisions. Its application in business and marketing supports process automation, information extraction, and enhanced customer and employee interaction (Davenport & Ronanki, 2018). In the business context, AI can increase revenue through better marketing decisions and reduce costs by automating tasks (Davenport et al., 2020). Importantly, AI generally augments human capabilities rather than replaces them, enhancing machines' capacity to "think" and "understand context" and enabling more effective predictions and decisions (Wirth, 2018).

2.2. CHATBOTS

Within this technological advance, chatbots have emerged as a specific application of AI, aimed at customer service. Chatbots are digital tools capable of simulating human interactions, automatically serving consumers on various platforms, such as websites and e-commerce (Chung et al., 2020). As well as responding intelligently to user requests, chatbots use AI techniques such as natural language processing (NLP) and machine learning to continuously improve their responses and personalize the interaction. These techniques allow chatbots to understand complex questions and adapt to users' preferences and behaviors, optimizing the customer experience (Ling et al., 2021).

Initially, chatbots were developed to simulate real conversations and entertain users. However, they have evolved to play complex roles in areas such as education, information retrieval and e-commerce. Today, they are configured as consumer-oriented AI tools, capable of simulating human behavior and offering personalized service. The ability of chatbots to learn from previous interactions and use historical data represents a significant advance, providing more dynamic and adaptive interactions (Pagallo, 2013).

2.3. CHATBOTS ON E-COMMERCE PLATFORMS

Chatbot evolution is closely linked to increased online consumer presence, prompting companies to adapt to digital interactions. On e-commerce platforms, chatbots address challenges like impersonal interactions and limited human support by autonomously making

decisions based on historical data, enhancing the traditional customer service experience. Their benefits include time savings, scalability, and improved customer satisfaction. For instance, luxury brands such as Burberry and Gucci use chatbots to offer distinct digital experiences that complement their in-store services, strengthening customer relationships and encouraging purchases (Chung et al., 2020).

Despite these advantages, chatbots face limitations in interpreting complex queries, which can reduce effectiveness in situations requiring human judgment. Thus, chatbots remain a complement—not a replacement—for human service. The future of chatbots and AI in e-commerce points toward advanced personalization. With further progress in NLP and machine learning, chatbots will increasingly mimic human interaction, enriching the shopping experience. AI's ongoing role in consumer data analysis will also enable more precise recommendations and targeted marketing.

In this context, AI-chatbot integration in e-commerce offers a blend of automation and personalization that enhances consumer experience and boosts company innovation and competitiveness. As AI progresses, chatbots will evolve to better serve, engage, and understand consumers, establishing themselves as vital tools for meeting digital market demands.

2.4. ADOPTION MODELS

The following topics highlight the construction of the research model that focuses on the integration of chatbots to improve customer experience and satisfaction on e-commerce platforms. Most of these studies explore the perceived usefulness and ease of use related to chatbots, seeking to explain their adoption. In addition, researchers incorporate variables related to the usability and responsiveness of chatbots into their research models. Given that empirical research shows that perceived usefulness is crucial to explaining the intention to use a particular technology (Natarajan, Balasubramanian and Kasilingam, 2017), this research adopts the same premise for the technology in focus (chatbots).

Table 1 - Empirical Studies on Chatbots and E-commerce

Authors	IT	Theory	Drivers	Data
(Nguyen et al., 2021)	Banks' Chatbot Services	D&M ISS and ECM	System Quality, information quality, service quality, trust, confirmation of expectations, perceived usefulness, satisfaction, continuance intention	359 survey responses from Vietnam banking customers
(Chen et al., 2021)	Usability and responsiveness of AI chatbots in e-retailing	D&M ISS and TAM	Perceived ease of use, perceived usefulness, responsiveness, reliability, customer satisfaction, extrinsic values, intrinsic values, and personality	425 survey responses from online retail customers

(Aparicio et al., 2021)	E-commerce usage and repurchase intention	Gamification Theory; Reputation Theory	Gamification: engagement, enjoyment, motivation, competition. Reputation: trust, credibility, reliability.	204 survey responses
(Cavalcanti et al., 2022)	Digital Transformation adoption	D&M ISS, ECM, UTAUT, TAM	Intentions, satisfaction, usefulness, individualism	Of the 88 studies found
(Aparicio et al., 2019)	MOOC Success	Gamification Theory	Gamification: engagement, motivation, enjoyment, rewards. Others: interactivities, progress tracking	1356 MOOC participants
(Ashfaq et al., 2020)	User satisfaction and continuance intention of AI-powered service agents	ECM, TAM, D&M ISS	Perceived usefulness, perceived ease of use, perceived enjoyment, service quality, trust, user satisfaction, continuance intention	370 survey responses

It is also assumed that the use of chatbots on e-commerce platforms helps consumers with online purchases, as they tend to play a crucial role in strengthening bonds with consumers and can thus increase satisfaction and stimulate more online purchases (Chung et al., 2020). This specific benefit of chatbots is explored, for example, in the article by Chen et al. (2021), which analyses the importance of their having significant effects and being able to solve problems and shortcomings in e-commerce (Table 1). Other studies have recently explored user satisfaction and continuance intention when using AI service agents. For example, according to Ashfaq et al. (2020), there has been an increase in interaction between humans and chatbots in recent years, and the main purpose of this tool on e-commerce platforms is to help consumers anytime and anywhere. This study contributes to this specific area of research, relating to perceptions of the use of chatbots on e-commerce platforms, by investigating the different levels of acceptance and utilization of the technology.

2.5. THEORICAL MODELS

2.5.1. DELONE AND MCLEAN IS SUCCESS MODEL

DeLone and McLean's (1992) IS success model is used to interpret individual and organizational performance, focusing on the individual level. It states that the quality of the system and information affects user utilization and satisfaction, while IS utilization and satisfaction influence each other. Studies confirm that the model is effective in explaining individual performance and can be combined with other models (Baabdullah et al., 2019; Sharma and Sharma, 2019).

Examples include the repurchase of online purchases (Hsu et al., 2014) and the success of e-commerce (Wang, 2008). In 2003, DeLone and McLean updated the model to include service quality as a factor influencing utilization and satisfaction.

2.5.2. EXPECTATION CONFIRMATION MODEL - INFORMATION SYSTEM CONTINUANCE MODEL

There are several theories used in studies related to information systems, such as UTAUT, TAM and TTF. The theoretical model of IS post-adoption, at the individual level, is the focus of interest. Adoption refers to the factors that explain why an individual adopts or rejects a technology, while continuance intention refers to the factors that explain why an individual uses a technology over a long period of time. Adoption involves users' first contact with the technology and their decision to use or reject it based on their experience. Continuance intention involves understanding the long-term factors that contribute to the success of information systems.

The ECM model, based on Oliver's (1986) expectancy theory, explains that the intention to continue using IS is influenced by user satisfaction and perceived usefulness, while satisfaction comes from the confirmation of expectations and usefulness, and the confirmation of expectations is crucial for perceived usefulness. This model is well validated in IS research (Carillo et al., 2017; Ryu, 2018; Talwar et al., 2020), emphasizing that satisfaction is fundamental to the continued use of IS (Bhattacherjee, 2001).

Most research into the continuity of IS use uses the ECM model, applied to fintech (Shiau et al., 2020), e-learning (Lee, 2010), MOOCs (Alraimi et al., 2015) and mobile shopping (Gao et al., 2015). In ECM and D&M models, user satisfaction is a crucial factor for performance and continuity.

2.5.3. GAMIFICATION AS A SUCCESS FACTOR IN E-COMMERCE

Gamification and serious games are approaches that use game elements in different contexts, with the aim of engaging and motivating users. Gamification is applied in online commerce, transforming the shopping experience into entertainment, and boosting sales through rewards and rankings (Insley and Nunan, 2014; Robson et al., 2016; Hamari and Koivisto, 2015). Although recent, it aims to change behavior and improve outcomes (Deterding et al., 2011). On the other hand, serious games use technology and game principles for educational, defense, health, and other purposes, solving problems through challenging and interactive activities (Garcia Pañella, 2012; Derryberry, 2007; Schell, 2008). Both approaches use “Building Blocks” to create meaningful and engaging experiences, promoting user value and involvement (Deterding et al., 2011; Marczewski, 2013). Dynamics is an important aspect, as it satisfies users' needs and desires through rewards and competitions, while aesthetics describes users' emotional responses (Bunchball Inc., 2010; Hunicke et al., 2004). Game components are specific applications that directly stimulate and engage consumers (Hunicke et al., 2004; Gatautis et al., 2016; Hunter and Werbach, 2012).

3. RESEARCH MODEL

With the strong growth of e-commerce, the industry in general is becoming increasingly relevant, but also in academic research. As already mentioned, this research combines perceived usefulness, satisfaction, and its confirmation, identified as crucial factors for the success of e-commerce (Matthew and Lee, 2001), with the metrics of the updated D&M model, ECM model and the Gamification Model. The impact of the user experience based on the technological and behavioral characteristics of consumers, i.e. what is known as satisfaction, is one of the resources addressed and evaluated by the research model in question. Figure 1 illustrates the model proposed for this study.

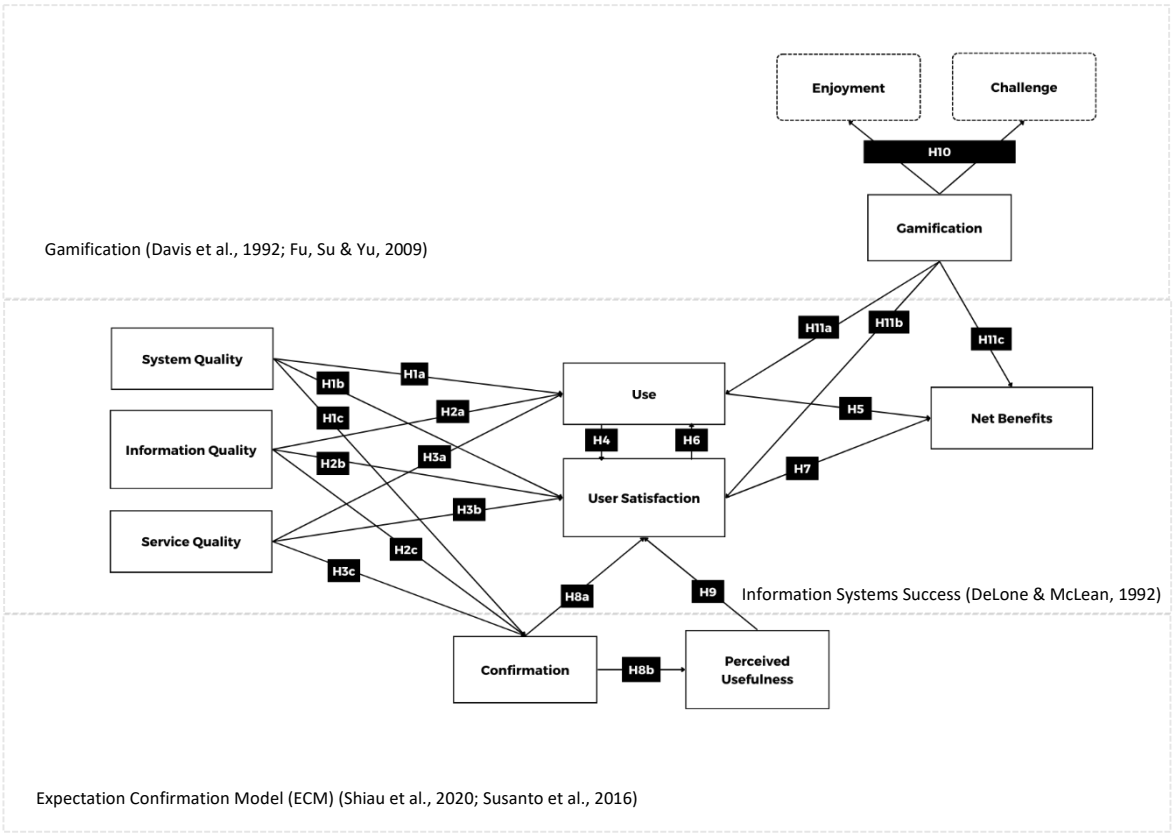


Figure 1 - Research Model

3.1. IS SUCCESS MEASURES

According to DeLone and McLean (2003), the quality of an e-commerce platform is defined by its adaptability, availability, reliability, ease of use and response time. System quality influences satisfaction, as indicated by Lilien, Rangaswamy, Van Bruggen and Starke (2004), and is based on the system's technical and qualitative characteristics (Urbach and Müller, 2012). According to DeLone and McLean's model (2003), attributes tend to positively influence customer utilization and satisfaction on e-commerce platforms. Confirming users'

initial expectations can influence the use of chatbots on e-commerce platforms. Based on this, I propose the following hypotheses:

H1a: System quality has a positive influence on the use of chatbots on e-commerce platforms.

H1b: System quality has a positive influence on user satisfaction when using chatbots on e-commerce platforms.

H1c: System quality has a positive influence on confirming the use of chatbots on e-commerce platforms.

The use of e-commerce platforms depends on the quality of their information, which is particularly important in the field of user satisfaction (Zhang, Xu, Zhao and Yu, 2018). According to Skadberg and Kimmel (2004), the desire to use a website, to use it again or to look for more information, arises through the satisfaction that the respective website invokes in the user. The quality of the information and its use, through effective harmonization, can also contribute to user satisfaction (Koufaris, 2002; Wind and Rangaswamy, 2001). However, the quality of information can have a positive influence on the confirmation of expectations. We therefore propose the following hypotheses:

H2a: Information quality positively influences the use of chatbots on e-commerce platforms.

H2b: Information quality has a positive influence on user satisfaction when using chatbots on e-commerce platforms.

H2c: Information quality has a positive influence on confirming the use of chatbots on e-commerce platforms.

According to Zhang et al. (2014) and Zeithaml, Rust and Lemon (2001), the success of e-commerce depends on the quality of the system. Wixom and Todd (2005) point out that IS utilization is influenced by service quality, and user satisfaction in e-commerce fundamentally requires the provision of high-quality services. Customer opinions, complaints and compliments have a major influence on service quality in e-commerce use, which has a major impact on the area of utilization. It should be emphasized that service quality plays a crucial role in confirming users' expectations. Based on these considerations, it is possible to formulate the following hypotheses:

H3a: Service quality has a positive influence on the use of chatbots on e-commerce platforms.

H3b: Service quality has a positive influence on the satisfaction of chatbot users on e-commerce platforms.

H3c: Service quality has a positive influence on confirming the use of chatbots on e-commerce platforms.

The main feature of the IS D&M success model is the mutual influence between utilization and user satisfaction. However, in this research, the relationship between utilization and net benefits and their influence on satisfaction is addressed. To increase user satisfaction, the following factors have been defined: enjoyment (Jarvenpaa and Todd, 1997), online user experience, control, self-efficacy (Koufaris, 2002) and user familiarity (Chen and Hung, 2010), which tend to have a positive influence on utilization. In the context of e-commerce, the relationship between utilization and net benefits and the influence on user satisfaction is expected to be like the model proposed by D&M (1992) and the literature. I therefore hypothesize that:

H4: The use has a positive influence on user satisfaction when using chatbots on e-commerce platforms.

H5: The use has a positive influence on net benefits and vice versa.

Future use can be negatively influenced by an experience that does not meet the user's expectations (Goodhue and Thompson, 1995). Katsanos, Tselios and Avouris (2010) emphasize that satisfaction is associated with a greater degree of confidence, effectiveness, and efficiency, resulting in an increase in individual performance. According to the updated version of DeLone and McLean's (2003) model, utilization precedes "user satisfaction" in the process, but a positive experience with "utilization" tends to create greater "user satisfaction". Based on these considerations, I have formulated the following hypotheses:

H6: User satisfaction has a positive influence on the use of chatbots on e-commerce platforms.

H7: User satisfaction has a positive influence on net benefits and vice versa.

3.2. DIMENSIONS OF CONFIRMATION THE USE

Confirmation involves users analysing the performance of a product, service, or technology in relation to their initial expectations. When expectations are met, positive confirmation occurs; if they are not met, negative confirmation occurs (Alraimi et al., 2015; Oghuma et al., 2016). Confirming expectations when using chatbots on e-commerce platforms tends to contribute to user satisfaction and the perceived usefulness of the service (Susanto et al., 2016). Based on these considerations, the following hypotheses were formulated:

H8a: Confirmation positively influences user satisfaction with the use of chatbots on e-commerce platforms.

H8b: Confirmation positively influences the perceived usefulness of using chatbots on e-commerce platforms.

Perceived usefulness, as described by Davis (1989), refers to how individuals understand the advantages of using IS. In the context of the use of chatbots on e-commerce platforms, recognising the benefits strengthens the long-term relationship between users and the

system, and can thus influence the frequency of use (Lee, 2010; Rezvani et al., 2017). However, the use of chatbots on e-commerce platforms and their perceived usefulness play a fundamental role in influencing users' intention to continue using the service. Previous studies show that the correlation between perceived usefulness and satisfaction becomes a crucial point, with the main factor increasing the intention to continue using IS (Cho, 2016; Joo et al., 2018; Shin et al., 2017). It is possible to hypothesise the following:

H9: Perceived usefulness positively influences user satisfaction with the use of chatbots on e-commerce platforms.

3.3. DIMENSIONS OF GAMIFICATION

Gamification is the use of game design elements in non-game environments (Deterding et al., 2011). To maintain or increase user interest and engagement, gamification needs to include emotional energy and provide users with challenging and enjoyable situations (Wu et al., 2015; Niman, 2014; Csikszentmihalyi (1997); de Paz, 2013). Based on these theories, gamification is a second-order construct that expresses itself through fun and challenging situations and, consequently, aims to engage users in a continuous cycle of active participation through tasks. Thus, our article hypothesises that:

H10: Gamification is a second-order reflexive construct made up of enjoyment and challenge.

According to Hamari (2013), services that involve rational behaviour, such as e-commerce, have a high potential for gamification. This means that the elements of the game can be designed in such a way as to guide users towards optimising the economic process. Insley and Nunan (2014) also argue that gamification allows for increased consumer commitment in online commerce. Aparicio et al. (2019) found that gamification is more associated with a positive impact on the use of information systems than with user satisfaction. Gamification is understood as the presence of game elements in a non-game environment, and these elements may not always be visible or tangible. Thus, the way systems are designed and how they react are likely to influence user behaviour. As such, the focus is on the impact of gamification on the use of the system, rather than the intention to use it. Therefore, our paper hypothesises that:

H11a: Gamification has a positive influence on the use of chatbots on e-commerce platforms.

H11b: Gamification has a positive influence on user satisfaction.

H11c: Gamification has a positive influence on net benefits.

4. RESEARCH METHODOLOGY

4.1. MEASUREMENT

An online survey was conducted to collect the essential data for evaluating the research model. The elements of the questionnaire were adjusted from published sources (see Appendix) and measured using a seven-point numerical scale, ranging from "1 - Strongly disagree" to "7 - Strongly agree". The questionnaire was originally drawn up in English and then independently translated into Portuguese (Brislin, 1970).

4.2. DATA COLLECTION

The survey was available in Portuguese and English and was shared online, namely in social media groups (Facebook, Instagram, WhatsApp) and forums related to the topic of chatbots on e-commerce platforms, between February 2024 and April 2024. The survey was therefore open to all participants, regardless of country and prior knowledge of the topic, but a special appeal was made to obtain responses from users of chatbots on e-commerce platforms. In addition, at the beginning of the questionnaire, the aim of the investigation was indicated, considering the topic of chatbots on e-commerce platforms. A total of 318 responses were obtained, of which 264 (83.02%) were considered valid and complete.

Regarding the gender of the 264 individuals, 84 are men (31.82%) and 179 are women (67.80%). The average age is 31. A total of 165 respondents (62.5%) are aged 28 or under. Regarding the level of education, 65.91% have Higher Education (Lic/Mest/Dout), 14.02% have a Postgraduate degree and 14.39% have secondary education. Firstly, Harman's one-factor test was carried out (Podsakoff, MacKenzie, Lee and Podsakoff, 2003), which showed that no single factor accounted for more than 50 per cent of the total variance. In addition, a theoretically unrelated marker variable was included in the questionnaire, revealing a maximum shared variance of 0.0533 (5.33 per cent) - a relatively low value, according to Johnson et al. (2011). As a result, no significant common method bias was identified. Table 2 gives more details on the characteristics of the respondents.

Table 2 - Sample characteristics

Age	N = 264	%	Gender	N = 264	%	Education	N = 264	%
18-24	109	41.29%	Male	84	31.82%	Primary Education	1	0.38%
25-34	83	31.44%	Female	179	67.80%	Secondary Education	38	14.39%
35-44	31	11.74%	I prefer not to classify	1	0.38%	Professional Education	14	5.30%
45-54	29	10.98%				Higher Education	174	65.91%
+54	12	4.55%				Postgraduate Degree	37	14.02%

5. DATA ANALYSIS AND RESULTS

The method used to analyse the data from the research model was partial least squares structural equation modelling (PLS-SEM). This multivariate statistical technique, part of structural equation modelling (SEM), allows researchers to incorporate latent variables measured indirectly through indicator variables, while estimating the relationships between them (Hair, Hult, Ringle, & Sarstedt, 2021). PLS, a variant of SEM, stands out for being variance-based, exploratory and predictive (Hair et al., 2021; Ringle et al., 2022). Due to its flexibility, PLS is ideal for testing new theories, as it has less restrictive assumptions regarding data distribution and allows latent variables to be measured by both reflective and formative indicators (Hair et al., 2016; Henseler, Ringle, & Sinkovics, 2009). These conditions make PLS the appropriate choice for this study, considering the novelty of the research model, the presence of variables with non-normal distribution and the inclusion of formative constructs. Smart PLS 4 software (Ringle et al., 2022) was the tool used to analyse the relationships in the theoretical model.

5.1. MEASUREMENT MODELS

The results of the model analysis are shown in Tables 3 and 4. The composite reliability (CR) shows internal consistency with values above 0.70, demonstrating that the model is consistent. The assessment of the reliability of the indicators showed loadings above 0.70, demonstrating the reliability of the instruments. To test convergent validity, we chose to use the average variance extracted (AVE), which must be greater than 0.50, according to the criteria established by Fornell and Larcker (1981), Hair et al. (2016) and Henseler et al. (2009).

Table 3 - Measurement Model

Construct	AVE	Composite Reliability	Cronbach's Alpha	Item	Loadings
Information Quality (INFQ)	0.698	0.915	0.913	INFQ1	0.863
				INFQ2	0.785
				INFQ3	0.854
				INFQ4	0.834
				INFQ5	0.839
				INFQ6	0.834
System Quality (SYSQ)	0.795	0.916	0.914	SYSQ1	0.893
				SYSQ2	0.888
				SYSQ3	0.892
				SYSQ4	0.895
Service Quality (SERQ)	0.760	0.896	0.895	SERQ1	0.881
				SERQ2	0.870
				SERQ3	0.883
				SERQ4	0.853
Use (U)	0.785	0.910	0.909	U1	0.878
				U2	0.879
				U3	0.889
				U4	0.897

				US1	0.871
User				US2	0.771
Satisfaction (US)	0.772	0.932	0.925	US3	0.919
				US4	0.900
				US5	0.923
				NB1	0.934
Net Benefits (NB)	0.886	0.937	0.936	NB2	0.955
				NB3	0.935
				C1	0.957
Confirmation (C)	0.878	0.935	0.930	C2	0.961
				C3	0.891
				PU1	0.872
Perceived	0.797	0.920	0.915	PU2	0.880
Usefulness (PU)				PU3	0.907
				PU4	0.911
				E1	0.964
Enjoyment (E)	0.880	0.936	0.931	E2	0.954
				E3	0.894
				CH1	0.905
				CH2	0.936
Challenge (CH)	0.832	0.950	0.949	CH3	0.917
				CH4	0.894
				CH5	0.907

Notes: Information Quality (INFQ); System Quality (SYSQ); Service Quality (SERQ); Use (U); User Satisfaction (US); Net Benefits (NB); Confirmation (C); Perceived Usefulness (UP); Enjoyment (E); Challenge (CH); Average Variance Extracted (AVE)

Table 4 - Constructs' descriptive statistics, composite reliability (CR), square root of average variance extracted (AVE), and correlations.

	Mean	**SD**	**CR**	**INFQ**	**SYSQ**	**SERQ**	**U**	**US**	**NB**	**C**	**PU**	**E**	**CH**
INFQ	4.598	1.357	0.915	**0.835**									
SYSQ	4.755	1.313	0.916	0.831	**0.892**								
SERQ	4.625	1.355	0.896	0.693	0.756	**0.872**							
U	4.002	1.805	0.910	0.649	0.647	0.574	**0.886**						
US	4.614	1.454	0.932	0.821	0.821	0.788	0.719	**0.879**					
NB	4.680	1.500	0.937	0.760	0.752	0.657	0.736	0.851	**0.942**				
C	4.347	1.517	0.935	0.737	0.740	0.677	0.750	0.836	0.807	**0.937**			
PU	4.250	1.685	0.920	0.712	0.690	0.656	0.767	0.799	0.812	0.834	**0.893**		
E	4.184	1.687	0.936	0.688	0.708	0.675	0.737	0.804	0.783	0.817	0.862	**0.938**	
CH	4.460	1.558	0.950	0.724	0.712	0.714	0.697	0.835	0.786	0.770	0.820	0.787	**0.912**

Notes: Information Quality (INFQ); System Quality (SYSQ); Service Quality (SERQ); Use (U); User Satisfaction (US); Net Benefits (NB); Confirmation (C); Perceived Usefulness (UP); Enjoyment (E); Challenge (CH); Standard Deviation (SD); values in diagonal (bolt) are the square root of AVE.

In Table 3, all the constructs meet the established criteria, demonstrating convergence and viability for evaluating the theoretical model. Discriminant validity was assessed using the Fornell-Larcker criterion (Table 4), cross-loadings (Table 5) and the heterotrait-monotrait correlation ratio (HTMT) (Table 6). In Table 4, the square root of the average variance extracted (AVE) is highlighted on the diagonal, while the correlations between the constructs are shown. According to Fornell and Larcker's (1981) criteria, the square root of the average variance extracted (AVE) must be greater than the correlation between the constructs, which was confirmed. In addition, to ensure discriminant validity, it has been shown that each item has a higher loading on its corresponding factor than on the cross-loadings (Chinn, 1998; Götz et al., 2010). The HTMT results (Table 6) show that some values are higher than 0.90, affecting discriminant validity (Henseler et al., 2015). These measurement model results show good internal consistency, reliability, convergent and discriminant validity, validating the use of the constructs to evaluate the structural model.

Table 5 - Cross Loadings

Construct	INFQ	SYSQ	SERQ	U	US	NB	C	PU	E	CH
INFQ1	**0.863**									
INFQ2	**0.785**									
INFQ3	**0.854**									
INFQ4	**0.834**									
INFQ5	**0.839**									
INFQ6	**0.834**									
SYSQ1	0.740	**0.893**								
SYSQ2	0.742	**0.888**								
SYSQ3	0.742	**0.892**								
SYSQ4	0.737	**0.895**								
SERQ1	0.600	0.656	**0.881**							
SERQ2	0.622	0.673	**0.870**							
SERQ3	0.561	0.641	**0.883**							
SERQ4	0.626	0.663	**0.853**							
U1	0.606	0.624	0.523	**0.878**						
U2	0.524	0.510	0.442	**0.879**						
U3	0.565	0.565	0.512	**0.889**						
U4	0.599	0.589	0.552	**0.897**						
US1	0.772	0.763	0.724	0.631	**0.871**					
US2	0.623	0.611	0.581	0.498	**0.771**					
US3	0.743	0.728	0.708	0.689	**0.919**					
US4	0.715	0.739	0.714	0.616	**0.900**					
US5	0.747	0.754	0.725	0.703	**0.923**					
NB1	0.709	0.678	0.603	0.679	0.784	**0.934**				
NB2	0.722	0.716	0.634	0.702	0.802	**0.955**				
NB3	0.715	0.728	0.620	0.698	0.817	**0.935**				
C1	0.724	0.731	0.668	0.722	0.801	0.792	**0.957**			
C2	0.724	0.702	0.665	0.737	0.807	0.776	**0.961**			
C3	0.618	0.644	0.562	0.644	0.741	0.697	**0.891**			
PU1	0.558	0.567	0.551	0.688	0.660	0.658	0.709	**0.872**		
PU2	0.587	0.568	0.586	0.631	0.665	0.662	0.683	**0.880**		
PU3	0.683	0.659	0.589	0.698	0.758	0.766	0.784	**0.907**		
PU4	0.701	0.661	0.614	0.718	0.761	0.801	0.791	**0.911**		

E1	0.682	0.708	0.682	0.704	0.800	0.775	0.809	0.824	**0.964**	
E2	0.683	0.713	0.653	0.708	0.795	0.752	0.792	0.799	**0.954**	
E3	0.566	0.564	0.559	0.663	0.660	0.671	0.692	0.806	**0.894**	
CH1	0.646	0.638	0.648	0.648	0.759	0.715	0.719	0.748	0.746	**0.905**
CH2	0.681	0.672	0.656	0.691	0.799	0.755	0.768	0.787	0.782	**0.936**
CH3	0.674	0.688	0.689	0.648	0.760	0.707	0.717	0.773	0.762	**0.917**
CH4	0.633	0.592	0.643	0.567	0.731	0.681	0.617	0.700	0.634	**0.894**
CH5	0.667	0.651	0.620	0.615	0.758	0.726	0.686	0.726	0.657	**0.907**

Notes: Information Quality (INFQ); System Quality (SYSQ); Service Quality (SERQ); Use (U); User Satisfaction (US); Net Benefits (NB); Confirmation (C); Perceived Usefulness (UP); Enjoyment (E); Challenge (CH);

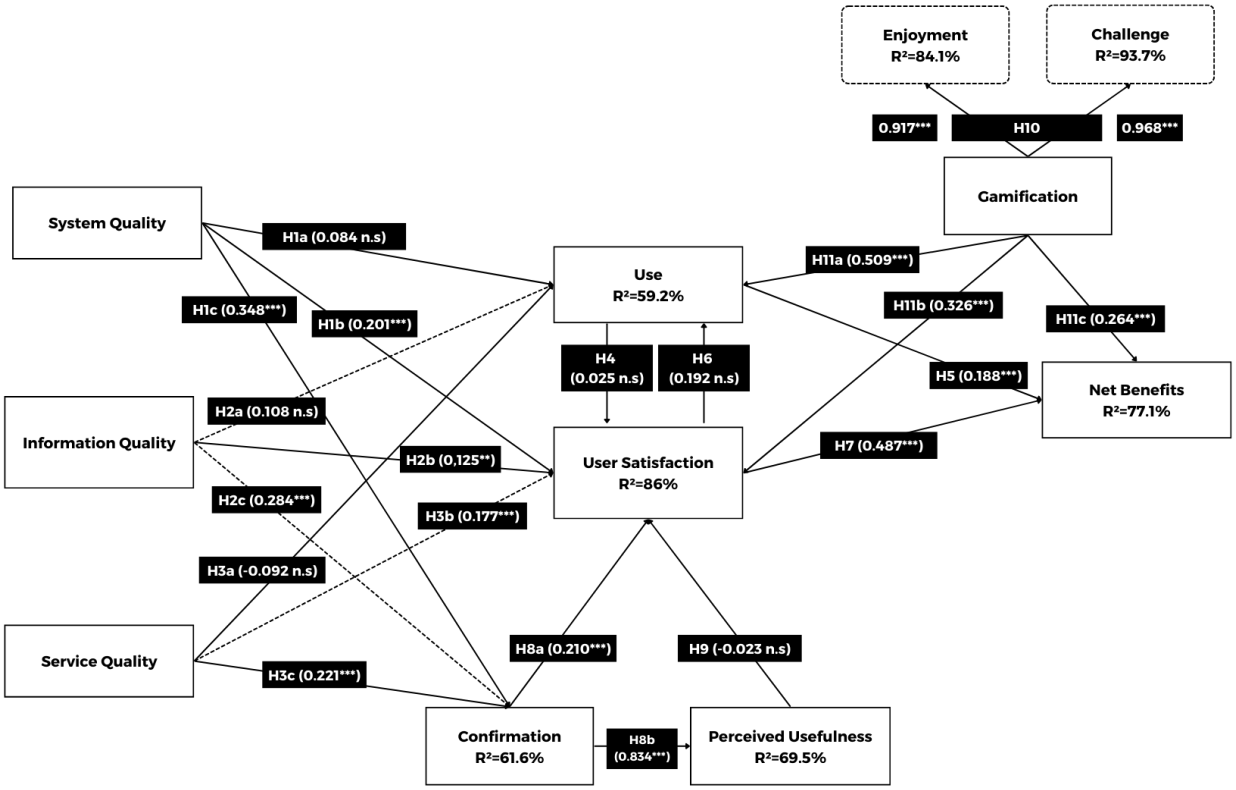
Table 6 - Heterotrait-Monotrait Ratio of Correlations (HTMT)

Construct	**INFQ**	**SYSQ**	**SERQ**	**U**	**US**	**NB**	**C**	**PU**	**E**	**CH**
INFQ										
SYSQ	0.909									
SERQ	0.764	0.833								
U	0.709	0.706	0.631							
US	0.892	0.889	0.863	0.778						
NB	0.820	0.810	0.716	0.797	0.912					
C	0.797	0.799	0.736	0.814	0.899	0.864				
PU	0.773	0.750	0.721	0.839	0.866	0.874	0.900			
E	0.742	0.762	0.735	0.801	0.863	0.837	0.874	0.935		
CH	0.777	0.761	0.774	0.747	0.893	0.833	0.819	0.877	0.834	

Notes: Information Quality (INFQ); System Quality (SYSQ); Service Quality (SERQ); Use (U); User Satisfaction (US); Net Benefits (NB); Confirmation (C); Perceived Usefulness (UP); Enjoyment (E); Challenge (CH)

5.2. STRUCTURAL MODEL

Once the measurement model had been validated, the structural model was authenticated, and the hypotheses and constructs were analysed. The research results are shown in Figure 2. This model is evaluated using 5000 bootstrap resamples to obtain an estimate of the model's significance level (Henseler et al., 2009). The VIF (Variance Inflation Factor) was also analysed to conclude multicollinearity. In short, all the constructs were below the threshold of 5, concluding that there was no multicollinearity between the constructs (Hair et al., 2016).



Notes: Integration of Expectation Confirmation Model (ECM), DeLone and McLean information system success (D&M IS) and Gamification Model; (∗∗∗p < 0.01; ∗∗p < 0.05; ∗p < 0.10).

Figure 2 - Research Model Results

The model explains 59.2% of the variation in the use of chatbots on e-commerce platforms. Gamification (β = 0.593, p < 0.01) is statistically significant in explaining usage, thus confirming H10a. Information quality (β = 0.108, p > 0.10), service quality (β = -0.092, p > 0.10) and system quality (β = 0.084, p > 0.10) are not statistically significant in explaining usage and, therefore, hypotheses H1a, H2a and H3a are not confirmed.

The model explains 86% of the variation in user satisfaction when using chatbots on e-commerce platforms. Information quality (β = 0.125, p < 0.05), system quality (β = 0.201, p < 0.01), service quality (β = 0.177, p < 0.01), confirmation (β = 0. 217, p < 0.01), utilisation (β = 0.240, p < 0. 01) and gamification (β = 0.322, p < 0. 01) are statistically significant in explaining satisfaction, thus confirming H1b, H2b, H3b, H8a and H10b. Use and perceived usefulness are

not statistically significant in explaining satisfaction, so hypotheses H4 and H9 are not confirmed.

The model explains 61.6% of the variation in the confirmation of the use of chatbots on e-commerce platforms. Information quality (β = 0.284, p < 0.01), service quality (β = 0.221, p < 0.01) and system quality (β = 0.348, p < 0.01) are statistically significant in explaining confirmation, thus confirming H1c, H2c and H3c.

The model explains 69.5% of the variation in the perceived usefulness of using chatbots on e-commerce platforms. Confirmation (β = 0.834, p < 0.01) is statistically significant in explaining perceived usefulness, thus confirming H7b.

The model explains 77.1% of the variation in net benefits. Usage (β = 0.189, p < 0.01), user satisfaction (β = 0.486, p < 0.1) and gamification (β = 0.264, p < 0.05) are statistically significant in explaining individual performance, thus confirming H5, H6 and H10c.

Gamification explains 84.1% of the variation in fun (β = 0.917, p < 0.01 in model 1 and model 2). Gamification also explains 93.7% of the challenge (β = 0.968, p < 0.01 in model 1 and model 2). Therefore, gamification is a second-order reflexive construct of pleasure and challenge, supporting H9.

The strongest relationships were gamification on challenge (β= 0.968) and fun (β = 0.917), confirmation on perceived usefulness (β = 0.834) and system quality on confirmation (β= 0.348).

6. DISCUSSION

The proposed model combines the IS success model of DeLone and McLean (2003) with the ECM of Bhattacherjee (2001) and the Gamification of Deterding, Dixon, Khaled, & Nacke (2011) to understand the intention to continue using chatbots on e-commerce platforms. According to the results presented in Table 7, of the 20 hypotheses formulated, 14 were confirmed and 6 were rejected. In this sense, we can say that most of the predicted relationships were validated. The Fun and Challenge factors are the most influential on gamification, with high R^2 values (84.1% and 93.7% respectively). Gamification, in turn, has a significant influence on Net Benefits (R^2=77.1%) and Utilization (R^2=59.2%). User Satisfaction is also highly explained by the model (R^2=86%). Information Quality and Service Quality directly affect Confirmation (R^2=61.6%). User Satisfaction is influenced by Information Quality, Utilisation, Confirmation and Perceived Usefulness. Utilisation is determined by information quality and service quality. Net Benefits are influenced by Utilization and Satisfaction with gamification. Confirmation affects Perceived Usefulness (R^2=69.5%). It should be noted that Service Quality does not affect Usage, Perceived Usefulness does not influence User Satisfaction and System Quality has no impact on Usage.

Table 7 - Research Hypotheses Results

Hypotheses	Independent Construct	→	Dependent Construct	Findings (β)	P Value	Conclusion
H1a	System Quality	→	Use	0.128	0.185	Not Suported
H1b	System Quality	→	User Satisfaction	0.200	0.000	Suported
H1c	System Quality	→	Confirmation	0.348	0.000	Suported
H2a	Information Quality	→	Use	0.139	0.173	Not Suported
H2b	Information Quality	→	User Satisfaction	0.123	0.025	Suported
H2c	Information Quality	→	Confirmation	0.284	0.001	Suported
H3a	Service Quality	→	Use	-0.057	0.445	Not Suported
H3b	Service Quality	→	User Satisfaction	0.178	0.000	Suported
H3c	Service Quality	→	Confirmation	0.221	0.001	Suported
H4	Use	→	User Satisfaction	0.025	0.550	Not Suported
H5	Use	→	Net Benefits	0.189	0.001	Suported
H6	User Satisfaction	→	Use	0.192	0.122	Not Suported
H7	User Satisfaction	→	Net Benefits	0.486	0.000	Suported
H8a	Confirmation	→	User Satisfaction	0.210	0.000	Suported
H8b	Confirmation	→	Perceived Usefulness	0.384	0.000	Suported
H9	Perceived Usefulness	→	User Satisfaction	-0.023	0.735	Not Suported
H10	Gamification	→	Enjoyment	0.917	0.000	Suported
			Challenge	0.968	0.000	Suported
H11a	Gamification	→	Use	0.593	0.000	Suported
H11b	Gamification	→	User Satisfaction	0.322	0.000	Suported
H11c	Gamification	→	Net Benefits	0.264	0.003	Suported

The indicators state that the quality of the system does not significantly affect utilisation (H1a: 0.084 n.s.), but positively affects user satisfaction (H1b: 0.201**) and does not significantly affect confirmation (H1c: -0.092 n.s.) of the use of chatbots on e-commerce platforms. This means that, in fact, a quality system does not directly increase the use of chatbots, but it does contribute to user satisfaction. This result is consistent with those of Cidral et al. (2018), who state that the quality of the system positively influences satisfaction. Satisfied users are more likely to continue using chatbots, even if the quality of the system is not a determining factor for initial use.

Information quality does not significantly affect utilisation (H2a: 0.108 n.s.), but it does positively affect user satisfaction (H2b: 0.284*) and confirmation (H2c: 0.346**). These results indicate that when users perceive the information provided by chatbots to be of high quality, their satisfaction and confirmation of expectations tend to increase. This indicator is consistent with previous studies (Cidral et al., 2018; Gao et al., 2015), which show that the quality of information is crucial for user satisfaction and confirmation of expectations.

Service quality does not significantly affect utilisation (H3a: -0.092 n.s.), but it does positively affect user satisfaction (H3b: 0.177*) and confirmation (H3c: 0.221*). These results suggest that service quality is important for maintaining user satisfaction and confirming expectations. The provision of a high-quality service through chatbots by e-commerce increases user satisfaction and confirmation that their expectations have also been met, although this does not necessarily determine an increase in the use of chatbots.

The use of chatbots does not significantly affect user satisfaction (H4: 0.025 n.s.), but it does positively affect net benefits (H5: 0.509***). This indicates that simply using chatbots does not guarantee satisfaction, however, it can contribute considerably to the benefits perceived by users. User satisfaction does not significantly affect the use of chatbots (H6: 0.1032 n.s.), but it does positively affect net benefits (H7: 0.487***). This suggests that user satisfaction, while not resulting in an increase in use, is a strong indicator that users consider that the use of chatbots on e-commerce platforms can provide significant benefits.

Confirmation has a positive impact on user satisfaction (H8a: 0.210*) and perceived usefulness (H8b: 0.854**). These results show that when users' expectations are confirmed, they lead to greater satisfaction and a higher perceived usefulness of chatbots. This finding is consistent with previous studies that emphasise the importance of confirmation for user satisfaction and perceived usefulness (Oghuma et al., 2016; Tam et al., 2020). Perceived usefulness does not significantly affect user satisfaction (H9: -0.023 n.s.). This result is surprising and suggests that although users recognise the usefulness of chatbots, this does not translate directly into satisfaction.

Gamification is positively influenced by fun (H10: 0.917*) and challenge (H10: 0.968), stating that it has a positive effect on utilisation (H11a: 0.509*), user satisfaction (H11b: 0.326*) and net benefits (H11c: 0.264**). This indicates that gamification elements, such as fun and

challenges, are the most effective way to increase utilisation, satisfaction, and the perceived benefits of using chatbots. Therefore, successful gamification can provide a significant success strategy when it comes to increasing user engagement and perceived value.

In summary, the results obtained tend to reflect that, to increase the use and satisfaction of users with chatbots on e-commerce platforms, those responsible should focus on optimising the quality of the system, information, and service, as well as integrating elements of gamification to improve the user experience.

6.1. MANAGERIAL IMPLICATIONS

There is a high level of demand for brands to obtain useful information to attract new consumers and relate better to them. Firstly, the main factors that motivate consumers to request certain products and services are performance and hedonic motivation. In other words, certain technologies involving artificial intelligence and remote control and interaction are more likely to be used if consumers see them as useful in their daily lives and if they provide them with satisfaction in addition to utility. Secondly, effective use behaviour is considered, i.e., there is a need for companies to ensure that their consumers have the necessary compatibility, resources, and knowledge to use certain products and services to their advantage. As a result, it is possible to ascertain a high degree of compatibility with habit, and there is a greater intention to use chatbot technologies when there is a developed habit on the part of the consumer in relation to these technologies.

In short, both companies and consumers have become highly aware of technological issues worldwide and, as a result, there is a high demand for products that involve them.

6.2. THEORICAL IMPLICATIONS

Based on the success and continuity models of information systems (Bhattacherjee, 2001; DeLone and Mclean, 2003), this study analyses an integrated model to understand users' continuity intention in relation to the use of chatbots on e-commerce platforms. The proposed model combines factors from the IS success model and continuity model to define the factors that influence satisfaction, individual performance, and continuance intention. It was empirically validated in the online context, highlighting the relevance of the constructs added by DeLone and Mclean (2003) in the intention to continue using chatbots on e-commerce platforms. This contribution paves the way for the use of specific models in new research contexts, reinforcing the literature on information systems and continuity. However, as information systems evolve, users may begin to consider new technological resources.

However, there is no evidence of a relationship with system quality. This result contradicts previous studies (Budiardjo et al., 2017; Cidral et al., 2018; Gao et al., 2015), showing a possible lack of importance of this concept in this context, indicating little concern on the part of users of chatbots on e-commerce platforms with the quality of the system. Future research with different technologies in the same context is needed to confirm these results. This study

reveals that both information quality and service quality are significant factors in predicting use and confirmation, which in turn influence satisfaction, net benefits, and perceived usefulness. Satisfaction, use, and net benefits are important elements that determine the intention to continue using chatbots. In addition, the model validates the IS continuance intention theory for the use of chatbots on e-commerce platforms, contrasting with previous studies that focused on developed economies (Chen & Li, 2017; Fan et al., 2018; Zhou, 2014).

6.3. LIMITATIONS AND FUTURE RESEARCH

The data that was used to analyse the research model in this study was collected through a questionnaire over a specific period. Considering the characteristic nature of the adoption of chatbots on e-commerce platforms, other studies could carry out a longitudinal analysis to explore the intentions and behaviour of consumers at different times and over an extended period. Regarding the results of the model, future research in the same context should consider adjustments to the D&M model, since three of its variables did not prove to be significant factors in the use of chatbots on e-commerce platforms. Particular attention should be paid to the role of effort expectancy since its results have not been consistent in the literature on chatbots on e-commerce platforms. Furthermore, given that around half of the answers to the questionnaire were given by Portuguese people, it would be interesting to test the proposed model in different countries to see if the results are consistent or divergent. Future research could also explore the applicability of the model to other aspects of chatbot use.

7. CONCLUSION

This research explores the topic of chatbots in the context of e-commerce platforms, analysing the specific case of their usefulness and user satisfaction. In the literature on Information Systems, the issue of continuity intention has not been widely investigated in this scenario. To fill this gap, a new theoretical framework was developed which combines the D&M success model with ECM and the Gamification model, with the aim of understanding the degree of influence of chatbots on e-commerce platforms and whether their use positively influences actual use on e-commerce platforms, as well as whether it is beneficial for the consumer and whether it has an impact on satisfaction. The empirical results show that the intention to stay is positively influenced by performance, use and individual satisfaction. The quality of information and services has a positive impact on both use and confirmation of expectations. In addition, the quality of information, use and confirmation of expectations positively affect user satisfaction. Chatbot service providers on e-commerce platforms should direct their efforts towards the quality of the information, ensuring that it is secure and up-to-date, and towards the efficient operation of the services, to influence user adoption and satisfaction. The use of chatbots on e-commerce platforms, satisfaction and the perception of individual performance are the main factors that explain the continued use of chatbots.

BIBLIOGRAPHICAL REFERENCES

Abdolmohammadi, Mohammad & Boss, Scott. (2010). Factors associated with IT audits by the internal audit function. *International Journal of Accounting Information Systems*. 11. https://doi.org/10.1016/j.accinf.2010.07.004

Alam, S.S. & Yasin, N.M. (2010). An Investigation into the Antecedents of Customer Satisfaction of Online Shopping. *Journal of Marketing Development & Competitiveness*, 5(1), 71-78.

Alraimi, K. M., Zo, H., & Ciganek, A. P. (2015). Understanding the MOOCs continuance: The role of openness and reputation. *Computers & Education*, 80, 28-38. https://doi.org/10.1016/j.compedu.2014.08.006

Aparicio, M., Costa, C. J., & Moises, R. (2021). Gamification and reputation: key determinants of e-commerce usage and repurchase intention. Heliyon, 7(3). https://doi.org/10.1016/j.heliyon.2021.e06383

Aparicio, M., Oliveira, T., Bação, F., & Painho, M. (2019). Gamification: a key determinant of massive open online course (MOOC) success. Information and Management, 56(1), 39-54. https://doi.org/10.1016/j.im.2018.06.003

Ashfaq, M., Yun, J., Yu, S., & Loureiro, S. M. C. (2020). I, Chatbot: Modeling the determinants of users' satisfaction and continuance intention of AI-powered service agents. Telematics and Informatics, 54, 101473. https://doi.org/10.1016/j.tele.2020.101473

Baabdullah, A. M., Abdallah, A., Rana, N. P., & Kizgin, H. (2019). Consumer use of mobile banking (M-Banking) in Saudi Arabia: Towards an integrated model. International Journal of Information Management, 44, 38–52. https://doi.org/10.1016/j.ijinfomgt.2018.09.002

Barış, A. (2020). A New Business Marketing Tool: Chatbot. *GSI Journals Serie B: Advancements in Business and Economics*, 3 (1): 31-46. https://doi.org/10.5281/zenodo.4030216

Bhattacherjee, A. (2001). Understanding information systems continuance: An expectation-confirmation model. *MIS quarterly*, 351-370. https://doi.org/10.2307/3250921

Brislin, R. W. (1970). Back-translation for cross-cultural research. *Journal of cross-cultural psychology*, *1*(3), 185-216. https://doi.org/10.1177/135910457000100301

Budiardjo, E. K., Pamenan, G., Hidayanto, A. N., & Cofriyanti, E. (2017). The impact of knowledge management system quality on the usage continuity and recommendation intention. *Knowledge Management & E-Learning*, *9*(2), 200.

C. Miller, The gamification of education, Dev. Bus. Simul. Exp. Learn. 40 (0) (2013) Retrieved from https://journals.tdl.org/absel/index.php/absel/article/view/40

Carillo, K., Scornavacca, E., & Za, S. (2017). The role of media dependency in predicting continuance intention to use ubiquitous media systems. Information and Management, 54(3), 317–335. https://doi.org/10.1016/j.im.2016.09.002

Cavalcanti, D. R., Oliveira, T., & de Oliveira Santini, F. (2022). Drivers of digital transformation adoption: A weight and meta-analysis. *Heliyon*, *8*(2), e08911. https://doi.org/10.1016/j.heliyon.2022.e08911

Chen, C.-J., and Hung, S.-W. (2010). To give or to receive? Factors influencing members' knowledge sharing and community promotion in professional virtual communities. *Information & Management*, Vol. 47 No. 4, pp. 226–236. https://doi.org/10.1016/j.im.2010.03.001

Chen, J. S., Le, T. T. Y., & Florence, D. (2021). Usability and responsiveness of artificial intelligence chatbot on online customer experience in e-retailing. *International Journal of Retail & Distribution Management*, 49(11), 1512-1531. https://doi.org/10.1108/IJRDM-08-2020-0312

Chen, J. V., Jubilado, R. J. M., Capistrano, E. P. S., & Yen, D. C. (2015). Factors affecting online tax filing–An application of the IS Success Model and trust theory. *Computers in Human Behavior*, *43*, 251-262. https://doi.org/10.1016/j.chb.2014.11.017

Chen, X., & Li, S. (2017). Understanding continuance intention of mobile payment services: an empirical study. *Journal of Computer Information Systems*, *57*(4), 287-298. https://doi.org/10.1080/08874417.2016.1180649

Chinn, W. W. (1998). The partial least squares approach to Structural Equation Modelling. *Modern Methods for Business Research*, 295(2), 295–336.

Cho, J. (2016). The impact of post-adoption beliefs on the continued use of health apps. *International journal of medical informatics*, *87*, 75-83. https://doi.org/10.1016/j.ijmedinf.2015.12.016

Chung, M., Ko, E., Joung, H., & Kim, S. J. (2020). Chatbot e-service and customer satisfaction regarding luxury brands. *Journal of Business Research*, 117, 587–595. https://doi.org/10.1016/j.jbusres.2018.10.004

Cidral, W. A., Oliveira, T., Di Felice, M., & Aparicio, M. (2018). E-learning success determinants: Brazilian empirical study. *Computers & education*, *122*, 273-290. https://doi.org/10.1016/j.compedu.2017.12.001

Csikszentmihalyi, M. (1997). Flow and the psychology of discovery and invention. *HarperPerennial, New York*, *39*, 1-16.

Darwiche, A. (2018). Human-level intelligence or animal-like abilities? *Communications of the ACM*, 61(10), 56-67. https://doi.org/10.1145/3271625

Davenport, T. H., & Ronanki, R. (2018). Artificial intelligence for the real world. *Harvard Business Review*, January-Fe (February), 108–117.

Davenport, T., Guha, A., Grewal, D., & Bressgott, T. (2020). How artificial intelligence will change the future of marketing. *Journal of the Academy of Marketing Science*, 48(1), 2442. https://doi.org/10.1007/s11747-019-00696-0

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS quarterly*, 319-340. https://doi.org/10.2307/249008

Davis, F. D., R.P. Bagozzi, P.R. Warshaw, Extrinsic and intrinsic motivation to use computers in the Workplace1, J. Appl. Soc. Psychol. 22 (14) (1992) 1111–1132, http://dx.doi.org/10.1111/j.1559-1816.1992.tb00945

de Paz, B. M. (2013). Gamification: A tool to improve sustainability efforts. *Unpublished Doctoral Dissertation). University of Manchester, UK*.

DeLone, W. H., and Mclean, E. R. (2003). The DeLone and McLean Model of Information Systems Success: A Ten-Year Update. *Journal of Management Information Systems*, Vol. 19 No. 4, pp. 9– 30. https://doi.org/10.1073/pnas.0914199107

DeLone, W., and McLean, E. (1992). Information Systems Success: The Quest for the Dependent Variable. *Information Systems Research*, Vol. 3 No. 1, pp. 60–95. https://doi.org/10.1287/isre.3.1.60

Deterding, S., Dixon, D., Khaled, R., & Nacke, L. (2011, September). From game design elements to gamefulness: defining" gamification". In *Proceedings of the 15th international academic MindTrek conference: Envisioning future media environments* (pp. 9-15). https://doi.org/10.1145/2181037.2181040

El Bakkouri, B., Raki, S., & Belgnaoui, T. (2022). The Role of Chatbots in Enhancing Customer Experience: Literature Review. *Procedia Computer Science*, *203*, 432-437. https://doi.org/10.1016/j.procs.2022.07.057

F.L. Fu, R.C. Su, S.C. Yu, EGameFlow: a scale to measure learners' enjoyment of elearning games, Comput. Educ. 52 (1) (2009) 101–112, http://dx.doi.org/10.1016/j.compedu.2008.07.004

Fan, J., Shao, M., Li, Y., & Huang, X. (2018). Understanding users' attitude toward mobile payment use: A comparative study between China and the USA. *Industrial Management & Data Systems*, *118*(3), 524-540. https://doi.org/10.1108/IMDS-06-2017-0268

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of marketing research*, *18*(1), 39-50. https://doi.org/10.2307/3151312

Gao, L., Waechter, K. A., & Bai, X. (2015). Understanding consumers' continuance intention towards mobile purchase: A theoretical framework and empirical study–A case of China. *Computers in Human Behavior*, *53*, 249-262. https://doi.org/10.1016/j.chb.2015.07.014

Goodhue, D. L., and Thompson, R. L. (1995). Task-Technology Fit and Individual Performance. *MIS Quarterly*, Vol. 19 No. 2, pp. 213–236. https://doi.org/10.2307/249689

Götz, O., Liehr-Gobbers, K., & Krafft, M. (2010). Evaluation of structural equation models using the partial least squares (PLS) approach. In Handbook of Partial Least Squares (pp. 691– 711). Springer. https://doi.org/10.1007/978-3-540-32827-8_30

Guo, Z., Xiao, L., Van Toorn, C., Lai, Y., & Seo, C. (2016). Promoting online learners' continuance intention: An integrated flow framework. *Information & Management*, *53*(2), 279-295. https://doi.org/10.1016/j.im.2015.10.010

Hair Jr., J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2016). A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM) (2o Edition). Sage Publications. https://doi.org/10.1007/978-3-030-80519-7

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

Hew, K. F., & Cheung, W. S. (2014). Students' and instructors' use of massive open online courses (MOOCs): Motivations and challenges. *Educational research review*, *12*, 45-58. https://doi.org/10.1016/j.edurev.2014.05.001

Hsu, M. H., Chang, C. M., Chu, K. K., & Lee, Y. J. (2014). Determinants of repurchase intention in online group-buying: The perspectives of DeLone & McLean is success model and trust. Computers in Human Behavior, 36, 234–245. https://doi.org/10.1016/j.chb.2014.03.065

Jarvenpaa, S. L., and Todd, P. A. (1997). Is there a future for retailing on the Internet? *In Electronic marketing and the consumer.*

Joo, Y. J., So, H. J., & Kim, N. H. (2018). Examination of relationships among students' self-determination, technology acceptance, satisfaction, and continuance intention to use K-MOOCs. *Computers & Education*, *122*, 260-272.

Kapp, K. M. (2012). *The gamification of learning and instruction: Game-based methods and strategies for training and education*. Pfeiffer.

Katsanos, C., Tselios, N., & Avouris, N. (2010). Evaluating website navigability: validation of a tool-based approach through two eye-tracking user studies. *New Review of Hypermedia and Multimedia*, *16*(1–2), 195–214. https://doi.org/10.1080/13614561003605179

Koufaris, M. (2002). Applying the Technology Acceptance Model and Flow Theory to Online Consumer Behavior. *Information Systems Research*, Vol. 13 No. 2, pp. 205–223. https://doi.org/10.1287/isre.13.2.205.83

Kumar, V., Rajan, B., Venkatesan, R., & Lecinski, J. (2019). Understanding the role of artificial intelligence in personalized engagement marketing. *California Management Review*, 61(4), 135-155. https://doi.org/10.1177/0008125619859317

Lee, M. C. (2010). Explaining and predicting users' continuance intention toward e-learning: An extension of the expectation–confirmation model. *Computers & education*, *54*(2), 506-516. https://doi.org/10.1016/j.compedu.2009.09.002

Levy, D. (2011). Lessons Learned from Participating in a Connectivist Massive Online Open Course (MOOC). *Proceedings of the Chais conference on instructional technologies research 2011: Learning in the technological era.* The Open University of Israel

Lilien, G. L., Rangaswamy, A., Van Bruggen, G. H., and Starke, K. (2004). DSS effectiveness in marketing resource allocation decisions: Reality vs. perception. *Information Systems Research*, Vol. 15 No. 3, pp. 216-235. https://doi.org/10.1287/isre.1040.0026

Ling, E. C., Tussyadiah, I., Tuomi, A., Stienmetz, J., & Ioannou, A. (2021). Factors influencing users' adoption and use of conversational agents: A systematic review. *Psychology & Marketing*, 1–21. https://doi.org/10.1002/mar.21491

Lowry, P., Romano, N., Jenkins, J., & Guthrie, R. (2009). The CMC interactivity model: How interactivity enhances communication quality and process satisfaction in lean-media groups. *Journal of Management Information Systems*, 26(1), 155–196. https://doi.org/10.2753/MIS0742-1222260107

Hudson, S., Huang, L., Roth, M.S., & Madden, T.J. (2016). The influence of social media interactions on consumer–brand relationships: A three-country study of brand perceptions and marketing behaviors. *International Journal of Research in Marketing, 33*, 27-41. https://doi.org/10.1016/j.ijresmar.2015.06.004

Lee, M. K. O., & Turban, E. (2001). A Trust Model for Consumer Internet Shopping. *International Journal of Electronic Commerce*, *6*(1), 75–91. http://www.jstor.org/stable/27751003

Muhannad, K., & Ahmed, G. (2014). Customer perceptions of ecommerce in the United Arab Emirate. *International Journal of Global Business*, 7(1), 95.

Niman, N. B. (2014). The Gamification of Higher Education. Palgrave Macmillan. Retrieved from http://www.palgraveconnect.com/doifinder/10.1057/9781137331465

Natarajan, T., Balasubramanian, S. A., & Kasilingam, D. L. (2017). Understanding the intention to use mobile shopping applications and its influence on price sensitivity. *Journal of Retailing and Consumer Services*, 37, 8-22. https://doi.org/10.1016/j.jretconser.2017.02.010

Nguyen, D. M., Chiu, Y. -T. H., & Le, H. D. (2021). Determinants of Continuance Intention towards Banks' Chatbot Services in Vietnam: A Necessity for Sustainable Development. *Sustainability*, *13*(14), 7625. https://doi.org/10.3390/su13147625

Oghuma, A. P., Libaque-Saenz, C. F., Wong, S. F., & Chang, Y. (2016). An expectation-confirmation model of continuance intention to use mobile instant messaging. *Telematics and Informatics*, *33*(1), 34-47. https://doi.org/10.1016/j.tele.2015.05.006

Oliver, R. L. (1986). A Cognitive Model of the Antecedents and Consequences of Satisfaction Decisions. Journal of Marketing Research, 17(4), 460–469. https://doi.org/10.2307/3150499

Pagallo, U. (2013). Robots in the cloud with privacy: A new threat to data protection? *Computer Law and Security Review*, 29(5), 501–508. https://doi.org/10.1016/j.clsr.2013.07.012

Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology, 88*(5), 879–903. https://doi.org/10.1037/0021-9010.88.5.879

Rezvani, A., Khosravi, P., & Dong, L. (2017). Motivating users toward continued usage of information systems: Self-determination theory perspective. *Computers in Human Behavior*, *76*, 263-275. https://doi.org/10.1016/j.chb.2017.07.032

Ringle, C. M., Wende, S., & Becker, J. M. (2022). SmartPLS 4. Oststeinbek: SmartPLS. *Retrieved March*, *13*, 2023. https://www.smartpls.com

Rose, S., Hair, N. e Clark, M. (2011), Online customer experience: a review of the online purchasing context between companies and consumers. *International Journal of Management Reviews*, 13: 24-39. https://doi.org/10.1111/j.1468-2370.2010.00280.x

Ryu, H. S. (2018). What makes users willing or hesitant to use Fintech?: the moderating effect of user type. Industrial Management and Data Systems, 118(3), 541–569. https://doi.org/10.1108/IMDS-07-2017-0325

Sharma, K. S., & Sharma, M. (2019). Examining the role of trust and quality dimensions in the actual usage of mobile banking services: An empirical investigation. International Journal of Information Management, 44, 65–75. https://doi.org/10.1016/j.ijinfomgt.2018.09.013

Shawar, B.A. and Atwell, E., (2007). Chatbots: are they really useful?. *Journal for Language Technology and Computational Linguistics*, 22(1), pp.29-49. https://doi.org/10.21248/jlcl.22.2007.88

Shiau, W. L., Yuan, Y., Pu, X., Ray, S., & Chen, C. C. (2020). Understanding fintech continuance: perspectives from self-efficacy and ECT-IS theories. Industrial Management and Data Systems, 120(9), 1659–1689. https://doi.org/10.1108/IMDS-02-2020-0069

Shin, D. H., Lee, S., & Hwang, Y. (2017). How do credibility and utility play in the user experience of health informatics services?. *Computers in Human Behavior*, *67*, 292-302. https://doi.org/10.1016/j.chb.2016.11.007

Skadberg, Y. X., and Kimmel, J. R. (2004). Visitors' flow experience while browsing a Web site: Its measurement, contributing factors and consequences. *Computers in Human Behavior*, Vol. 20 No. 3, pp. 403–422. https://doi.org/10.1016/S0747-5632(03)00050-5

Susanto, A., Chang, Y., & Ha, Y. (2016). Determinants of continuance intention to use the smartphone banking services: An extension to the expectation-confirmation model. *Industrial Management & Data Systems*, *116*(3), 508-525. https://doi.org/10.1108/IMDS-05-2015-0195

Talwar, S., Dhir, A., Khalil, A., Mohan, G., & Islam, A. K. M. N. (2020). Point of adoption and beyond. Initial trust and mobile-payment continuation intention. Journal of Retailing and Consumer Services, 55, 102086. https://doi.org/10.1016/j.jretconser.2020.102086

Tam, C., Santos, D., & Oliveira, T. (2020). Exploring the influential factors of continuance intention to use mobile Apps: Extending the expectation confirmation model. Information Systems Frontiers, 22(1), 243–257. https://doi.org/10.1007/s10796-018-9864-5

Tran, L. T. T. (2020). Online reviews and purchase intention: A cosmopolitanism perspective. *Tourism Management Perspectives*, 35. https://doi.org/10.1016/j.tmp.2020.100722

Urbach, N., and Müller, B. (2012). The Updated DeLone and McLean Model of Information Systems Success. *In Information Systems Theory: explaining and predicting our digital society*, Vol. 1 (Vol. 28, pp. 1–14). https://doi.org/10.1007/978-1-4419-6108-2

Wang, Y.-S. (2008). Assessing e-commerce systems success: a respecification and validation of the DeLone and McLean model of IS success. Information Systems Journal, 18(5), 529–557. https://doi.org/10.1111/j.1365-2575.2007.00268.x

Wigand, R. T. (1997). Electronic Commerce: Definition, Theory, and Context. *The Information Society*, 13, 1-16. https://doi.org/10.1080/019722497129241

Wind, J., and Rangaswamy, A. (2001). Customerization: The next revolution in mass customization. *Journal of Interactive Marketing*, Vol. 15 No. 1, pp. 13–32. https://doi.org/10.1002/1520-6653

Wirth, N. (2018). Hello marketing, what can artificial intelligence help you with? *International Journal of Market Research*, 60(5), 435-438. https://doi.org/10.1177/14707853187768

Wixom, B. H., and Todd, P. (2005). A Theoretical Integration of User Satisfaction and Technology Acceptance. *Information Systems Research*, Vol. 16 No. 1, pp. 85–102. https://doi.org/10.1287/isre.1050.0042

Wu, W., Daskalakis, C., Kaashoek, N., Tzamos, C., & Weinberg, M. (2015, March). Game theory based peer grading mechanisms for MOOCs. In *Proceedings of the Second (2015) ACM Conference on Learning@ Scale* (pp. 281-286). https://doi.org/10.1145/2724660.2728676

Zeithaml, V. A., Rust, R. T., & Lemon, K. N. (2001). The Customer Pyramid: Creating and Serving Profitable Customers. California Management Review, 43(4), 118-142. https://doi.org/10.2307/41166104

Zhang, K. Z. K., Cheung, C. M. K., and Lee, M. K. O. (2014). Examining the moderating effect of inconsistent reviews and its gender differences on consumers' online shopping decision. *International Journal of Information Management*. Vol. 34 No. 2, pp. 89-98 https://doi.org/10.1016/j.ijinfomgt.2013.12.001

Zhang, K. Z. K., Xu, H., Zhao, S., and Yu, Y. (2018). Online reviews and impulse buying behavior: the role of browsing and impulsiveness. *Internet Research*. Vol. 28 No. 3, pp. 522-543. https://doi.org/10.1108/IntR-12-2016-0377

Zhou, T. (2014). Understanding the determinants of mobile payment continuance usage. *Industrial Management & Data Systems*, *114*(6), 936-948. https://doi.org/10.1108/IMDS-02-2014-0068

APPENDIX A

Construct	Code / Indicators	Theoretical Support
Using a seven-point rating scale (1- strongly disagree, 7- strongly agree on the scale), the variables are measured by asking students to rate their perception regarding their perceptions on MOOC. (1 Strongly disagree … 7 Strongly agree)		
Information Quality (INFQ)	INFQ1 – The information provided by the e-commerce platform, with the assistance of chatbots, is useful. INFQ2 – The information provided by the e-commerce platform, with the help of chatbots, is understandable. INFQ3 – The information provided by the e-commerce platform, with the incorporation of chatbots, is interesting. INFQ4 – The information provided by the e-commerce platform, with the support of chatbots, is reliable. INFQ5 – The information provided by the e-commerce platform, with de assistance of chatbots, is complete. INFQ6 – The information provided by the e-commerce platform, with the integration of chatbots, is update.	(Urbach et al., 2010)
System Quality (SYSQ)	SYSQ1 – E-commerce platforms, with the integration of chatbots, is easy to navigate. SYSQ2 – E-commerce platforms, with the assistance of chatbots, allows me to find the information I am looking for easily. SYSQ3 – E-commerce platforms, with de implementation of chatbots, is well structured. SYSQ4 – E-commerce platforms, enhanced by chatbots, is easy to use.	(Urbach et al., 2010)
Service Quality (SERQ)	SERQ1 – The customer service team, including the use of chatbots, is always highly willing to help whenever I need support with the e-commerce platform. SERQ2 – The customer service team, including the assistance of chatbots, provides special attention when I experience problems with the e-commerce platforms. SERQ3 – The customer service team, with the help of chatbots, provides services related to the e-commerce platform ate the promised time. SERQ4 – The customer service team, with the support of chatbots, has sufficient knowledge to answer my questions with respect to the e-commerce platform.	(Urbach et al., 2010)
Use (U)	U1. I use chatbots on e-commerce platforms. U2. I use chatbots on e-commerce platforms to buy products and services. U3. I use chatbots on e-commerce platforms to search for information about products/services. U4. I use chatbots on e-commerce platforms to receive a personalised service.	(Palvia, 2009)
User Satisfaction (US)	US1 - …it's informative. US2 - …it's interactive. US3 - …it's effective. US4 - …it's efficient. US5 - …it's satisfactory.	(Palvia, 2009)
Net Benefits (NB)	NB1 – Chatbots on e-commerce platforms save me time. NB2 – Overall, the use of chatbots on e-commerce platforms is beneficial. NB3 – Chatbots on e-commerce platforms allow easy access to product/service information.	(Chen et al.,2015)

Confirmation (C)	C1 – My experience with using chatbots on e-commerce platforms was better than I expected. C2 – The service level provided by chatbots on e-commerce platforms was better than I expected. C3 – Overall, most of my expectations from using chatbots on e-commerce platforms were confirmed.	(Bhattacherjee, 2001)
Perceived Usefulness (PU)	PU1 – The use of chatbots on e-commerce platforms increases my curiosity. PU2 – Using chatbots on e-commerce platforms increases my engagement with customer service. PU3 – The use of chatbots on e-commerce platforms increases my efficiency when obtaining information and/or making purchases. PU4 – I find the integration of chatbots into e-commerce platforms useful in my product/service purchasing journey.	(Bhattacherjee, 2001)
Enjoyment (E)	E1 – I find the use of chatbots on e-commerce platforms pleasant. E2 – The process of using chatbots on e-commerce platforms is enjoyable. E3 – I have fun using chatbots on e-commerce platforms.	(Davis et al., 1992)
Challenge (CH)	CH1 – Chatbots on e-commerce platforms provide "tips" in text that help me overcome challenges. CH2 – The "online support" that chatbots on e-commerce platforms provide helps me overcome challenges. CH3 – Personalized support from chatbots on e-commerce platforms helps me overcome challenges. CH4 – The opening hours of the chatbots on the e-commerce platforms help me to overcome challenges. CH5 – The accessibility of chatbots on e-commerce platforms tends to help me overcome challenges.	(Fu, Su & Yu, 2009)

NOVA Information Management School
Instituto Superior de Estatística e Gestão de Informação

Universidade Nova de Lisboa