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The consumers perception about the use of Artificial Intelligence in the area of e-commerce with emphasis on chatbots

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Department of Marketing, Operations and General Management

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To my supervisors,

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I want to thank for the guidance during this journey.

To my mother and my father,

I want to thank for all the support and encouragement.

To my family,

I want to thank for all the kindness.

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I want to thank for all the patient.

Resumo

A Inteligência Artificial está a ganhar notoriedade na nossa sociedade, estando presente no nosso dia a dia. Os avanços e inovações revolucionárias estão a ser cada vez mais adotadas por vários setores de entre os quais, o setor de e-commerce. O e-commerce está a experienciar um crescimento progressivo, permitindo um fácil acesso às transações eletrónicas de bens e serviços. Por conseguinte, o envolvimento por parte dos consumidores é essencial para as empresas, sendo desta forma relevante explorar potenciais estratégias que otimizem a interação entre os consumidores e as marcas.

De forma a impulsionar a interação com os clientes, diversas estratégias foram adotadas, sendo as mais notáveis o uso dos chatbots, formas emergentes de atendimento ao cliente. Estes agentes virtuais fornecem soluções personalizadas de forma a aumentar o compromisso com o cliente. Esta dissertação visa avaliar quais os fatores que influenciam o uso dos chatbots no e-commerce, de forma a perceber a aceitação por parte dos consumidores de produtos baseados em inteligência artificial.

Assim, as motivações psicológicas dos consumidores para usar chatbots no e-commerce foram analisadas através de análises quantitativas. Os resultados realçam que, a “Atitude em Relação ao Comportamento”, a “Perceção da Facilidade de Uso”, a “Perceção da Utilidade”, a “Perceção do Controlo Comportamental”, a “Expectativa de Esforço”, a “Motivação Hedônica” e o “Hábito”, são os fatores que influenciam o uso dos chatbots no e-commerce.

Palavras-chave: Perceção do Consumidor; Inteligência Artificial; E-commerce; Chatbots

Classificação JEL:

M31 – Marketing

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Abstract

Artificial Intelligence is conquering a spotlight in our society, being present on our daily lives. The revolutionary advancements and innovations are being increasingly adopted by several sectors, among which, the sector of e-commerce. E-commerce is experiencing a progressively growth, enabling an easy access to electronic transactions of goods and services. Therefore, customer engagement is essential for companies, being in this way relevant to explore potential strategies that optimize the interaction between consumers and brands.

In order to drive customer interaction, several strategies were adopted, being the most notable the use of chatbots, emerging forms of customer assistance. These virtual agents provide customized solutions to increase customer engagement. Accordingly, this dissertation aims to assess which are the factors that influence the use of chatbots on e-commerce in order to understand the consumers acceptance about the use of AI based intelligent products.

In that manner, the consumers psychological motivations to use chatbots in e-commerce were analysed through quantitative analysis. The results highlight that “Attitude Toward Behavior”, “Perceived Ease of Use”, “Perceived Usefulness”, “Perceived Behavioral Control”, “Effort Expectancy”, “Hedonic Motivation” and “Habit” are the factors that influence the use of chatbots in e-commerce.

Keywords: Consumer Perception; Artificial Intelligence; E-commerce; Chatbots

JEL Classifications:

M31 – Marketing

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List of Abbreviations

A	Attitude Toward Behavior
AI	Artificial Intelligence
ANNs	Artificial Neural Networks
B2B	Business to Business
B2C	Business to Costumer
BI	Behavioral Intention
C2B	Consumer to Business
C2C	Consumer to Consumer
CI	Computational Intelligence
EDI	Eletronic Data Interchange
EOU	Perceived Ease of Use
GA	Genetic Algorithms
KBSs	Knowledge Based Systems
NFNs	Neuro-fuzzy networks
PET	Tomography by Positron Emission
SEM	Structural Equations Model
SN	Subjective Norm
TAM	Technology Acceptance Model
TPB	Theory of Planned Behavior
TRA	Theory of Reasoned Action
U	Perceived Usefulness
UTAUT	Unified Theory of Acceptance and Use of Technology
WWW	World Wide Web

Chapter I - Introduction

The technology's advancements over the years have revolutionized the society and our daily lives. Nowadays' Artificial Intelligence is a driving force behind digital transformation, encompassing innovations, which are becoming progressively more integrated among several sectors and businesses. Thereby, the Digital Era is evolving in our society generating industry disruption and creating a set of challenges and opportunities, among which, the expansion of online shopping.

At the same time as e-commerce is being equipped with new possibilities driven by AI, customers are also progressively seeking to be influenced by new technologies, as well as, are continuously searching for new experiences and exploring alternative ways of searching products and services, increasingly demanding accessible and highly rewarding multichannel interactions with brands. In this way, it is relevant to explore potential digital strategies that can optimize the interaction between consumers and brands within the online context (Song, X. et al., 2019).

Customer engagement is therefore essential to the success of every company's online retail presence (Harmeling et al., 2017). In recent years, businesses have been experimenting ways to drive customer interaction and increase sales through technological means. The most prominent strategy in this regard is the use of chatbots.

Chatbots are virtual agents designed to conduct automated conversations with humans over the internet to automatically answer customer questions and requests, helping them find suitable products, check the order of products status, compare different products, and help consumers with their payments. Chatbots can also help consumers with complaints, redirecting them to contact the adequate customer support (Kar, R. & Haldar, R., 2016; Song, X. et al., 2019; Soni, V. D., 2020).

Therefore, the development of chatbots that are capable of providing the kind of personalized assistance that human customer service representatives can, is essential for the successful adoption of this technology by businesses.

As a matter of fact, the purpose of this dissertation, is to understand consumers perception about the use of Artificial Intelligence in the area of e-commerce with emphasis on chatbots. To achieve this goal, Portuguese consumers perspectives will be assessed, in order to bring a comprehensive view in regard to the research topic.

The research question to be answered is: "Which factors influence the use of chatbots on e-commerce?" The intended with this dissertation is to understand the consumers acceptance

of AI based intelligent products on e-commerce, with a particular focus on chatbots. In this sense, the main objective of this dissertation is to answer the research question referred above. In order to achieve the objective, it is important to gather a set of indicators based on technology acceptance theories, that suit the best to the research problem. In such manner, is possible to understand which are the psychological motivations considered by the Portuguese consumers that influence their intention to use and the effective use of Chatbots on e-commerce.

As so, the present dissertation aims to contribute to the development of the literature combining the field of AI and the consumer's acceptance of AI based products on e-commerce, more specifically, the consumer's acceptance of chatbots on e-commerce, ultimately closing some of the perceived gaps on currently available research, namely the need to provide empirical evidence to existing theoretical constructs in this field.

In order to achieve the proposed objectives, the present study is organized in six chapters, which intend to reflect the different phases of this dissertation until the conclusion. The first chapter introduces the research topic, the motivations and the objectives, as well as a brief description of the work structure. The second chapter reflects the theoretical framework, designated by Literature Review, in which several theories and points of view related to the topic of AI, e-commerce and chatbots are discussed. The third chapter presents the Theoretical Approach of this study where the objectives and the research question are addressed. The fourth chapter is dedicated to the Methodology, including the presentation of the approach selected for this investigation, as well as, the data analysis methods used. This chapter also includes the sample characterisation and the content of the developed surveys. The fifth chapter presents the Results along with the Critical Discussion regarding the data collected, allowing to answer the research question and confirming the hypotheses formulated. In the sixth and last chapter the Main conclusions of this study are presented, as well as, the contributions to the scientific and business community, limitations and recommendations for future research on the topic.

Chapter II – Literature Review

2.1 Artificial Intelligence

All the technological advances adopted until today, have come to create value for society both, economically and also have improved the quality of life of the populations (Oliveira, 2019).

2.1.1 Artificial Intelligence Evolution

The ability to manipulate symbols, although it is present to a lesser extent in other primates and non-primates, is specially developed in Homo Sapiens, which allows our species to exhibit characteristics that we associate with intelligent behavior (Oliveira, 2019).

Is difficult to define intelligent behavior, however is intuitive to think that it is necessary to process spoken language, to understand abstract concepts, such as mathematics or physics, to play chess or checkers and to transmit these skills to the following generations, through written records. We usually do not associate intelligent behavior with abilities such as: recognizing objects or animals in the visual field or escaping danger. However, the processing of information that allows an animal to recognize a predator or react to a danger is extremely complex, requires intelligence and is not easy to reproduce in an artificial system (Oliveira, 2019).

Many of these abilities are innate, are encoded in the brain by genes and require only some interaction with the outside world and some learning in order to be useful in the struggle for survival. However, symbolic manipulation tasks, including the ability to speak, understand language, read, write, or a set of other tasks, require effort and learning. This difference in effort requirements results from a set of genetic mutations that led to modern man (Oliveira, 2019).

Those genetic mutations generated the unique ability of human beings to create and communicate culture. The capacity for technological development arises from the spread of knowledge between generations, through culture. This was how the cultural revolution allowed human beings to settle across the planet, dominate other species and change the environment (Oliveira, 2019).

The revolution that followed was the agricultural revolution, that brought a profound change in society. The possibility of growing plants and raising animals, made it possible to ensure food throughout the year, in the same region. In this way, humans stopped living in small, often nomadic communities and started to establish in large population concentrations (Oliveira, 2019).

The invention of writing, was also a technological innovation, which possibly arose as a consequence of the need to keep records on agricultural production and also on herds. The first systems of writing were related to numerical and counting records, having enabled the development of mathematics, another essential technology for humanity (Oliveira, 2019).

Thus, with the help of writing, humanity continued to develop new techniques in a progressive way. Those developments led to the pre-industrial society that existed at the beginning of the 18th century, where consumer goods were created by artisans, agriculture continued to be the main source of wealth for societies and many tasks depended on animal or human strength to be carried out (Oliveira, 2019).

In this century, the steam engine was invented, which came to replace human and animal strength, triggering the first industrial revolution. It was thus possible to develop trains and several machinery that came to replace much of the handmade work that started to be done in large manufacturing facilities (Oliveira, 2019).

The first industrial revolution was followed by the second, characterized by profound social changes caused by the internal combustion engine and by the use of electricity in the most diverse applications, including communications. The combination of both revolutions corresponded to the most profound social changes in the history of technology. The concept of technology emerged and with it the idea that the world would change in the future (Oliveira, 2019).

In the second half of the 20th century, the third industrial revolution began, aimed at the development of technologies that enabled the creation, manipulation and transmission of information. Initially, electromechanical devices appeared, then electronic valves and, later, transistors and integrated circuits, what enable design and make digital computers, machines which only goal is to process, transform and generate information, from the data that is provided (Oliveira, 2019).

The third industrial revolution was also characterized by nuclear fission as a new source of energy for both civil and military purposes. In the second half of the 20th century, a better understanding of the laws of physics led to a more effective mastery of materials (Oliveira, 2019).

Thus, the changes caused by digital technologies were those that in the last half of the 20th century, had a deeper impact on society. Gradually, the technologies created the possibility of making the omnipresent communication of diverse contents such as videos, books, newspapers and music. The appearance of the internet in 1960 made the world globally connected (Oliveira, 2019).

In this way, a question arose, whether a computer could behave intelligently, exhibiting a similar behavior to a human being in an equivalent situation? The attempt to answer this question was what generated the area that we currently call Artificial Intelligence (Oliveira, 2019).

According to Gunkel (2017) artificial intelligence concept appeared in 1957 at a conference per McCarthy. However, the definition of intelligence was characterized by Alan Turing in his article previously in 1950. Alan Turing raised the question of whether or not machines can think. In order to investigate, was created the well-known Turing Test, or imitation test, which is performed by three people: a man, a woman and an interrogator, who can be of any gender (Gunkel, 2017).

The interrogator remains in a room, separated from the other two, and has to determine who is the man and who is the woman based on simple questions and answers. For the tone of voice not being a determining factor in deciding the gender of the respondent, Turing stipulated that, responses must be typed (Gunkel, 2017).

The initial configuration of the game is the interaction between the interrogator with the two unknown participants via a computer-mediated interaction called a chat. Thus, the only way for the interrogator to perceive the identity of the two interlocutors is based on the answers given to the questions (Gunkel, 2017).

Turing takes his experience to another level and questions arise: what will happen when a machine replaces one of the interlocutors? Will the interrogator decide wrongly? Will he think the interlocutor was a human? These are the questions that replace the initial question "Can machines think?" (Gunkel, 2017).

Therefore, Turing concludes that if a computer can indeed become capable of simulating a human being of both genders in communicative exchanges with a human interrogator, so, that the interrogator cannot tell whether he is interacting with a machine or another human being, then these machines must be considered "intelligent" (Gunkel, 2017).

At that time a limitation arose that it would take approximately 50 years to program a computer with sufficient memory capacity to play the imitation game. However, in 1966, the first natural language processing application, ELIZA, was created by Joseph Weizenbaum, which was able to talk to human interrogators in order to look like a human, demonstrating what Turing initially predicted (Gunkel, 2017).

2.1.2 Artificial Intelligence Concept

According to Akrimi, J. A. et al. (2013) artificial intelligence is considered a science that mimic human mental faculties in a computer. Developing a machine that would equate or exceed human mental capabilities, such as reasoning, understanding, imagination, perception, recognition, creativity and emotions. The research into AI has resulted in the development of extremely useful computing tools, which allowed, many problems until then faced with a high level of difficulty, being addressed in a more efficient way or even solved (Akrimi, J. A. et al., 2013).

Lobo (2017) states that artificial intelligence (AI) is a branch of computer science that aims to develop systems that simulate human capacity in the perception of a problem, as well as, in the decision making. An additional definition of artificial intelligence would be the creation of intelligent computing systems capable of performing tasks without receiving direct instructions from humans, such as robots (Lobo, 2017).

There are several steps covered by artificial intelligence, such as recognizing patterns and images, understanding open written and spoken language, perceiving relationships and nexuses, following decision algorithms, being able to process information, as well as understanding concepts and acquiring "reasoning" by the ability to integrate new experiences, self-learning and improve the ability to solve problems or perform tasks (Lobo, 2017).

According to Suresh and Rani (2020), AI consists in the simulation of human intelligence process by machines, especially computer systems, being considered one among those technologies which helps in many areas of individual's routine life.

As stated by Agrawal, A. et al. (2020), Artificial Intelligence has been perfecting many "human" jobs, such as: disease diagnosis, customer service, and translation. It is a scenario that raises plausible fears that AI will ultimately replace human workers across the economy.

However, while AI will radically change the way that work is done and who does it, the biggest impact of this technology will be to complement and enhance human capabilities, not to replace human jobs. Some many companies have used AI to automate processes and replaced employees, however such companies, will see productivity increases only in the short term (Agrawal, A. et al., 2020). In a study with 1500 companies, it was concluded that performance improvements are most significant when man and machine work together. Through this collaborative intelligence, humans and AI can improve each other's strengths, such as: the leadership, teamwork, creativity, and man social skills; and the speed, scalability and quantitative capabilities of artificial intelligence. What is considered natural for people as making a joke, can be complicated for machines, and what is simple for machines such as

analyzing gigabytes of data remains practically impossible for humans. In this way, business requires both types of capabilities, so companies need to understand how humans can extend the benefits of machines and how machines can value and improve what humans do, as well as, redesign the business process to support the partnership (Agrawal, A. et al., 2020).

2.1.3 Artificial Intelligence Categories

Artificial Intelligence can be classified in two different categories: Knowledge based systems (KBSs), known as symbolic paradigm, which are explicit models using words and symbols; and Computational intelligence (CI), also known as connectionist paradigm (Smolenski, 1990), is an implicit model with numerical techniques (Akrimi, J. A. et al., 2013).

Knowledge based systems, comprises different techniques like rule-based, model-based, frame-based, and case-based reasoning. When the set of rules and processes is applied to the set of symbols, the system produces new structures. Symbols have semantic meanings and can represent concepts or objects. In order to deal with these concepts, propositional logic and predicate logic are used, which allows the problem solving using a rules-based system.

Thus, a symbolic system is able to solve problems which involve data and the rules on that data (Costa, 2009). The symbolics systems are not good in dealing with the unknown, not allowing models to expand with experience (Akrimi, J. A. et al., 2013).

Computational intelligence allows the computer to build up its own model, based on observations and experiences. In this system, the knowledge is not explicitly stated but is represented by numbers that are adjusted as the system improves its accuracy. In this way, computational intelligence includes neural network, which are the dynamics of connections between small nodes called neurons where such dynamics are capable of representing knowledge, genetic algorithms and also optimization algorithms and techniques to handle with uncertainty, like for example fuzzy logic (Akrimi, J. A. et al., 2013).

Unlike the symbolic paradigm, in the connectionist model the state of the neurons represents a concept or an object and, the dynamics that lead to the representation of the concept or object establishes the rules on such objects and concepts. In practice, the two paradigms can come together to form a third paradigm (Costa, 2009).

This third paradigm is related to heuristics, which means discovery. The human act of solving a problem implies a heuristic action in the systematic of solving the problem. This system is based on experience, rational ideas, and rules. In fact, heuristic is based more in common sense than in a mathematical formalism, what at first does not imply that heuristics will guarantee the best solution for a given problem, but surely the solution will be great in

terms of cost and time. An example of this, is the way how humans solve problems, which does not have a formula or algorithms to find the exact and direct solution such as diagnosing a defect in a car or create a plan to increase the milk production of a given farm (Costa, 2009).

The AI challenge is to establish the mechanisms that allow to systematize heuristic methods in order to solve problems and transcribing them for a mathematical and algorithmic formalism thus enabling its use in automatic machines such as the computer. The two examples most elucidative of heuristics are: Genetic algorithms and Artificial neural networks (Costa, 2009).

Genetic algorithms (GA) introduced and systematized in the academic environment by John Holland in 1975, are capable of solving complex problems of combinatorial and organizational problems and are inspired by natural laws of evolutionary genetics. Within AI, genetic algorithms can be classified as a symbolic paradigm (Costa, 2009).

Artificial Neural Networks, under a simplistic view, correspond to brains formed by basic units called neurons. The neurons are connected in a complex network and dynamics. In living beings this structure is able to solve complex problems. In this way, within AI, arises the connectionist model which is a heuristic method inspired by the functioning of neural networks. The artificial neural networks systems are therefore a computational algorithm of a network of artificial neurons. An artificial neuron is on the other hand, a mathematical model inspired by a real neuron (HAYKIN, 2001).

2.1.4 Sectors of Artificial Intelligence Application

The applicability of AI can be visible in various sectors which will be presented.

Has been observed the applicability of AI in the education sector, creating new opportunities and also challenging the educational practices (Ouyang & Jiao, 2021). The advancements in education, promoted by AI are significant, such as the development of techniques through real-world and standard modular prototypes in statistical reasoning, data visualisation, and learning analytics (Alam, 2021). A crucial goal of AI in this sector is to provide personalised learning guidance or individual support based on students learning status, preferences and personal characteristics (Hwang, 2014; Hwang et al., 2020).

The introduction of AI in Human Resources sector has a positive effect. AI can help with blind hiring, conducting smoother and optimized recruitment process (Galanaki et al., 2019), since AI can be used to extract information through techniques, making the process of resume scanning and extraction of relevant information automated (Kaczmarek et al, 2005). Also, AI can use digital data from employee software use, communications, manufacturing and

service delivery sensors, as well as audio, video images to analyse the employee performance more accurately than human managers, and in this way to make decisions such as which worker should employee, where and when, which employee to promote and into which role, to optimize motivation and retention in companies (Angrave et al., 2016; Guenole & Feinzig, 2018; Kellogg et al., 2020; Charlwood, 2021).

Artificial Intelligence finds diverse applications in the healthcare sector, where AI is capable of proposing solutions for several areas in medicine through the analysis of a large volume of data and following defined algorithms. The registration of data regarding a large number of cases with the respective diagnosis scheme, as well as, prescribed treatments, and results obtained, thus allow an expansion of medical knowledge (Lobo, 2017). Some areas of medicine experience these AI advantages are dermatology (Lobo, 2017), radiology (Paiva & Prevedello, 2017), cardiology (Obermeyer & Emanuel, 2016; Mesquita, 2017), among others.

Artificial Intelligence in Agriculture is used to identify defects and nutrient deficiencies in the soil. This is done using computer vision, robotics, and machine learning applications, AI can help develop, simulate and optimize important processes in agriculture (Martins et al., 2017; Dornelles et al., 2018).

Automotive industry is in constant innovations. Artificial Intelligence is used to build self-driving vehicles. AI can be used along with the vehicle's camera, radar, cloud services, GPS navigation, and control signals to operate the vehicle. AI can improve the in-vehicle experience and provide additional systems like emergency braking, blind-spot monitoring, and driver-assist steering, make driving safer than if a human drove (Safarti, 2016).

AI technology can help to significantly improve a wide range of financial services. AI provide easier access to individual users, improving the service with the use of chatbots for self help solutions which reduces workload to the call centers. Voice-controlled virtual assistants are providing services, such as, check balances, schedule payments, browse account activity, among others. In addition, there are apps in the market, which suggest personalized financial tips according to personal income, expenses and spending habits, offering an optimized plan (Murugesan, R., & Manohar, V., 2019).

Artificial Intelligence is also revolutionizing the e-commerce sector, which will be addressed in the next section.

2.2 E-commerce

2.2.1 E-commerce Concept

Electronic commerce, also known as e-commerce can be defined as activities or services related to buying and selling products or services over the internet (Bawack et al., 2022).

2.2.2 E-commerce Evolution

During the 1980s, the digital exchange of information was achieved using Electronic Data Interchange (EDI). However, due to the need to pre-arranged agreements and the high implementation effort on an expensive value-added network, EDI was considered to have limited commercial viability (Chu et al., 2007).

In the early 1990s, the commercialization of the Internet and the appearance of open computer technology and connectivity became affordable for individuals and businesses. In this way, these interconnections enabled the creation of the World Wide Web (WWW) and the occurrence of powerful search engines and Web sites turned the Web into a rich information resource (Chu et al., 2007).

By providing marketing information and sharing product catalog online, businesses began to reach potential customers (Chu et al., 2007).

During the mid-1990s, the WWW evolved from an information resource to a location for e-commerce sites, requiring secure and interactive environment. E-commerce activities went from single buyer–seller connections to multiple exchanges (Chu et al., 2007).

In such manner, the internet revolution has led to the advancement of online business throughout the world. E-commerce is a technology product that has been successfully accepted by the individuals (Haryanti & Subriadi, 2020).

2.2.3 E-commerce Advantages

For retailers, there are some advantages of e-commerce such as a larger number of customers served, a larger number of orders and even as better provision of information. Online retailers can run an online store at lower operating costs than a physical store, which in turn translates into higher sales (Fedorko, R. et al., 2022).

E-commerce allows consumers to shop online easily, anytime, and with a secure payment system. Ease of access in shopping allowed customers to compare a wide range of products and switch to other e-commerce, having in this way the effect of shifting competition

patterns and support e-commerce sustainability. E-commerce promotes the availability of information, not only for consumers but also for competitors, whom can identify and improve product innovation. The easy implementation and use of the internet and other technological support enabled e-commerce to grow exponentially due to reduced costs, increased efficiency, and improved customer service. (Haryanti & Subriadi, 2020).

2.2.4 E-commerce Characterization

The main characterization of e-commerce is based on the nature of buyers and sellers and their position in the commercial value chain. Thus, it is possible to identify four types of relationships, which are:

- (i) Business-to-business, consists in electronic commerce related to transactions between companies;
- (ii) Business-to-consumer, embrace e-commerce between companies and consumers;
- (iii) Consumer-to-consumer, encompasses electronic transactions between individual consumers, typically through third-party platforms; and
- (iv) Consumer-to-Business occurs when an individual consumer posts products or services on dedicated blogs, forums or websites to be purchased or auctioned by companies (Moriset, 2018).

According to Suresh and Rani (2020), some of the areas of application of e-commerce are: personalized shopping experiences for online buyers, real time product targeting, visual search, AI based hiring process, voice powered search, assortment intelligence tool, conversational commerce, customer service, virtual personal shoppers, virtual assistants, AI fake reviews detection, AI based sales process and customer centric advertisements.

2.3 E-commerce and Artificial Intelligence

In the modern era, individuals are much closer to technology and expecting new and innovative things that make their work easier and save time.

According to Bawack et al., (2022), artificial intelligence is transforming e-commerce through its aptness to correctly interpret external data, to learn from such data, and to use the learnings to achieve specific goals and tasks through flexible adaptation (Kaplan & Haenlein, 2019). Depending on the context, AI could be a system, a tool, a technique, or an algorithm (Akter et al., 2021; Bawack et al., 2021; Benbya et al., 2021) to support activities related to buying and selling products or services over the internet (Bawack et al., 2022). In such manner,

firms have the opportunity to gain a competitive advantage by using big data to meet their customer's needs through personalised services (Deng et al., 2019; Kumar, V. et al., 2019b; Kumar, N. et al., 2019a).

Artificial intelligence can take several forms, such as:

- (1) Recommendations Tool or engine - Artificial intelligence through the use of an algorithm can analyse consumer behavior and large datasets, predicting in this way which products have the potential to attract customers. The algorithm is able to record key information of the searched product allowing the recommendation tool to generate the appropriate suggestions for the browser (Song, X. et al., 2019; Kumar, T, & Trakru, M., 2019; Pallathadka H, et al., 2021).
- (2) Visual and Voice Search - Artificial intelligence allow the implementation of visual and audio searches on websites, which are based on image and sound processing algorithms. In this way, customers can search for the product, using an image or voice, without the need to enter keywords (Kumar, T. & Trakru, M., 2019; Pallathadka H, et al., 2021).
- (3) Optimal Pricing - Artificial intelligence technology, with advanced deep machine learning algorithms, through big data process, can evaluate market dynamics continuously and change the competitive environment to solve the problem of optimal pricing (Song, X. et al., 2019).
- (4) Customer Relationship Management – Artificial Intelligence allow businesses to gather data from different channels in order to obtain information about their target customers, and respond to their needs and requirements in the best way, retaining customers and increasing sales. (Soni, V.D., 2020; Pallathadka H, et al., 2021).
- (5) Intelligent Logistics – Consists in a smart supply chain that generates real time information, excluding the need to have technical equipment controlled by people. Counterweight with traditional logistics mode, intelligent logistics can improve service quality and operation efficiency. Some examples of automated intelligent systems are Alibaba and JD intelligent logistics and warehousing (Song, X. et al., 2019).
- (6) Artificial Intelligence Assistants (Chatbots) – Chatbots, a type of software application, uses natural language processing system to conduct an online conversation via text or voice in order to respond to customer questions and requests, helping them find suitable products, check the order of products status, compare different products, and help consumers with their payments. Chatbots can also help consumers with complaints or questions, redirecting them to contact the adequate customer support (Kar, R., & Haldar R., 2016; Song, X. et al., 2019; Soni, V.D, 2020).

2.4 Chatbots

2.4.1 Chatbots Concept

Chatbots also known as Chatterbots or bots in generally (Kar R. & Haldar R., 2016) and can be defined as computers programs, existing most often within messenger applications, that emulate conversation with a human, either through text messages, navigation buttons or with a simulated voice to provide a particular service (Aleedy et al., 2019).

Chatbots uses Natural Language Processing (NLP) and sentiment analysis to communicate by text or oral speech with humans or also, with other chatbots (Khanna et al., 2015).

Chatbots are deployed on organizational websites, instant messaging apps, or social media, and can be easily accessed (McTear et al., 2016; Karri & Kumar, 2020). The way, chatbots mimic real-life interpersonal communication, make users to feel comfortable while in a conversation (Prasetya et al., 2018; Feine et al., 2019; Go & Sundar, 2019). Chatbots offer customers real-time information, feedback and fulfilment of their needs, alongside product recommendations or service consumption (Reinartz et al., 2019).

Chatbots can be classified in two approaches: chatbots that function based on rules, having the limitation of just being as smart as they are programmed, and chatbots that function on Artificial Intelligence, which give the impression of being “intelligent” as they are capable of understanding natural language, not merely pre-defined commands and have the capability to get smarter as they interact (Kar R. & Haldar R., 2016).

Besides imitating human interaction and amusing people, chatbots are useful in various other fields such as education, business, health, entertainment, e-commerce, among others (Shawar & Atwell, 2007). Productivity is the most important motivation for chatbot users, although different motivations include entertainment, social factors, and novelty interaction (Brandtzaeg & Følstad, 2017; R. Ranoliya et al., 2017).

Furthermore, there are two types of benefits that come from the interaction with a virtual assistant, which are functional (Yoon et al., 2013) and social (Holzwarth et al., 2006). The functional benefits are time saving and efficiency in the purchase decision, and the social benefits are the pleasure derived from the direct interaction with the firm, and the perception of being important for the company (Pantano & Pizzi, 2020).

2.4.2 Chatbots Evolution

As referred previously at the beginning of this chapter, the well-known question of Alan Turing, in 1950, originated the Turing Test and is by many, considered to be the generative idea of chatbots (Turing, 1950).

In 1966, the first chatbot named ELIZA was constructed, simulated a psychotherapist's operation, returning the user's sentences in the interrogative form (Weizenbaum, 1966). Its ability to communicate was limited, but it was a source of inspiration for the further development of other chatbots (Klopfenstein et al., 2017).

In 1972, emerged PARRY, which acted as a patient with schizophrenia (Colby et al., 1971). It was considered more advanced than ELIZA because it had a 'personality' and a better controlling structure. Its responses are based on a system of assumptions and 'emotional responses' activated by the change of weights in the user's utterances (Colby et al., 1972). In 1979, PARRY was used in an experiment, however the findings were not clear, since the sample was small and people with schizophrenia have a degree of incoherence in their speech (Heiser et al., 1979). In general, PARRY was considered a chatbot with low capabilities concerning language understanding and the ability to express emotions, and also had a low speed of responding, and couldn't learn from the conversation (Adamopoulou, E., & Moussiades, L., 2020).

In 1988, AI is firstly used in the domain of the chatbots with the construction of Jabberwacky, which was written in CleverScript, a language based on spreadsheets that facilitated the development of chatbots, and it used contextual pattern matching to respond based on previous discussions. Even so, could not reply to high speed and work with a massive number of users (Adamopoulou, E., & Moussiades, L., 2020).

In 1991, the term Chatterbot was first mentioned, it was a TINYMUD (multiplayer real-time virtual world) artificial player, whose primary function was to chat. It was observed that umpteen real human players seemed prefer talking with the Chatterbot than a real player (Mauldin, 1994).

In 1992, Dr. Sbaitso (Sound Blaster Artificial Intelligent Text to Speech Operator), a chatbot designed to display the digitized voices the sound cards were able to produce. It played the role of a psychologist without any sort of complicated interaction (Zemčík, 2019).

In 1995, was created ALICE (Artificial Linguistic Internet Computer Entity), the first chatbot inspired by ELIZA (Wallace, 2009), based on pattern-matching, without any actual perception of the whole conversation (Marietto et al., 2013) but with a discussion ability on the web that allowed longitude and included any topic. Some years after ALICE was improved

with the development of a new language Artificial Intelligence Markup Language (AIML), and won the title of the Loebner Prize of the best human-like computer program (Bradeško & Mladenović, 2012). In this way, ALICE's Knowledge Base consisted of about 41,000 templates and related patterns (Heller et al., 2005). However, ALICE did not have intelligent features and could not generate human-like answers expressing emotions or attitudes (Heller et al., 2005).

In 2001, was developed SmarterChild (Molnár & Zoltán, 2018), an evolution in chatbot technology. It was available on Messengers such as: America Online (AOL) and Microsoft (MSN) and had the capability to help people with practical daily tasks as it could retrieve information from databases about movie times, sports scores, stock prices, news, and weather. This ability marked a significant development in both the machine intelligence and human-computer interaction trajectories as information systems could be accessed through discussion with a chatbot (Adamopoulou, E., & Moussiades, L., 2020).

In recent years, Artificial Intelligence chatbots have taken a step forward with the development of smart personal voice assistants, which are built into smartphones or dedicated home speakers. These assistants understand voice commands, talk with digital voices, and can manage tasks like monitoring home automated devices, calendars, email and other (Adamopoulou, E., & Moussiades, L., 2020).

Siri, was developed by Apple in 2010, allows the users to make inquiries and have conversations using voice commands. Siri make recommendations and responds to user requests using various internet services and it includes integration with audio, video, and image files. However, Siri also has some weakness: requires an internet connection; besides being multilingual does not support some languages; when the interlocutor has a heavy accent or is in presence of noise, Siri has difficulties in understanding; and, the navigation instructions are only supported in English (Adamopoulou, E., & Moussiades, L., 2020).

In 2011, IBM built a chatbot called Watson. The natural language processing capabilities were qualified enough the Jeopardy quiz competition by successfully finding the correct questions for the information in the form of answers received. In addition, Watson Health was designed to help doctors in healthcare diagnose diseases, nevertheless, does not support other language than English (Adamopoulou, E., & Moussiades, L., 2020).

Google Now, developed in 2012, was designed to use contextual information such as time and location to present information to the user. Google Assistant, built in 2016 constitutes the next generation of Google Now. It has more advanced artificial intelligence features with a friendly and natural conversation interface and can predict user requirements. Although, it has

no personality and its questions may violate the user's privacy since it is linked directly to their Google Account (Adamopoulou, E., & Moussiades, L., 2020).

In 2014, a personal assistant named Cortana, was designed by Microsoft. It is a software that recognizes voice commands, perform tasks as track information as time and place, make reminders based on people, sends emails and texts, manages lists, play games and answer the users' requests. However, besides helping making the users daily lives easier, there were also serious security concerns, taking into account that has been reported is that, Cortana, can run a program that will install malware (Adamopoulou, E., & Moussiades, L., 2020).

In the same year, Alexa was created by Amazon. It is a voice assistant developed into devices for home automation and entertainment, performing different tasks on her behalf. A novelty is the introduction of the Alexa Skills Kit which allows programmers to develop and upload skills, along with games, apps and other content. Although, Alexa has also some security issues (Adamopoulou, E., & Moussiades, L., 2020).

Moreover, in 2014 was designed and implemented in China, XiaoIce, an empathetic social chatbots, by Microsoft. It was considered the most popular social chatbot in the world because was developed to be an AI companion in order to establish long-term emotional relationships with human users. XiaoIce has been shipped in five countries (China, Japan, US, India, and Indonesia) and had also attracted over 660 million active users (Zhou, L. et al., 2020).

Early in 2016, Artificial Intelligence Technology evolution changed drastically the way people communicate with manufacturers, in the manner of, social media platforms allowed developers to create chatbots for their service or brand in order to enable customers to perform specific daily actions within their messaging applications (Adamopoulou, E., & Moussiades, L., 2020).

2.4.3 Chatbots Categories

Table 2.4.3. Chatbots Categories, adapted from Adamopoulou, E., and Moussiades, L. (2020)

Chatbot Categories	Criterion	Definition
Knowledge Domain	Generic	Chatbots that can answer any user question from either domain (e.g., Chorus).
	Open Domain	Chatbots that operate in more than one domain (e.g., Guardian; CRQA).
	Close Domain	Chatbots that can only respond to questions concerning a particular knowledge domain (e.g., InstuctableCrowd, Legion: Mobile; SnapTravel).
Service Provided	Interpersonal	Chatbots that offer services without being a friendly companion
	Intrapersonal	Chatbots are close companions that live in the user's domain and understand his needs
	Inter-agent	Chatbots that can provide communication with other chatbots
Goals	Informative	Chatbots give specific information stored in a fixed source
	Chat-based/ Conversational	Chatbots hold a natural conversation with the user like a real person
	Task based	Chatbots handle different functions, such as room booking, requesting information and responding to the user appropriately
Response Generation Method	Rule based	Chatbots that match the user input to a rule pattern and select a predefined answer from a set of responses
	Retrieval based	Chatbots that use ANNs to assign scores and select the most likely response from a set of responses.
	Generative	Chatbots that use RNN (Recrual Neural Networks) are able to generate appropriate responses by combiing the context of the conversation and the given knowledge.
Human-aid	Human mediated	Chatbot utilizes human computation in at least one part of it.
	Autonomous	Chatbots overcome weaknesses by staff working to integrate intelligence into them.
Permissions	Open-source	The chatbot development platform make their code available, and the developer can have full control of the implementation.
	Commercial	The chatbot development platform do not give full control to developers, having costs involved in using it.
Communication Channel	Text	Chatbots can use all the communication channels (text, voice and image) at the same time.
	Voice	
	Image	

2.4.4 Chatbots on E-commerce

Chatbots are emerging forms of customer assistance in online retailing (Pantano & Pizzi, 2020), which use is influencing customer service (Suresh & Rani, 2020).

The technology advancements are mainly focusing on improving chatbot ability to automatically draw inferences on users starting from multiple data sources, and using consumers' knowledge adaptively in order to provide more customized solutions (Pantano & Pizzi, 2020).

Chatbots can reduce service costs and handle many costumers simultaneously. As well, chatbots are more friendly and appealing than the usually content search in frequently asked questions (FAQs) lists (Brandtzaeg & Følstad, 2017; R. Ranoliya, et al., 2017).

Customers likely prefer to interact with chatbots service agents who enable value creation through responsiveness and conversational tones (Verhoef et al., 2007; Rybalko & Seltzer, 2010; Fadhil & Schiavo, 2019). So, the ability to provide more engaging answers and direct responses to the customers, promotes post-consumption evaluation of chatbot services highly satisfactory (Suresh & Rani, 2020; Chung et al., 2020).

Signals of a humanlike interaction from chatbot dialogues, were found to enhance trust, social presence, customer satisfaction, positive attitudes toward organizations, long-term relationship with customers, as well as, purchase intention (Bickmore & Picard, 2005; Holzwarth et al., 2006; Verhagen et al., 2014; De Visser et al., 2016; Araujo, 2018; Chung et al., 2020; Liebrecht, Sander, & van Hooijdonk, 2020).

When customers are satisfied with organizations chatbot services, the customers response and acceptance can be determined (Chiang et al., 2017). In this way, customer engagement “refers to ‘a customer’s voluntary resource contribution to [an organization]’s marketing function, going beyond financial patronage” (Harmeling et al., 2017, p. 316).

Some examples of common voice-based AI in e-commerce for shopping activities are the intelligent personal assistants like Google’s Google Assistant, Amazon’s Alexa, and Apple’s Siri due to the fact that several retail organisations are making them an integral part of their e-commerce platforms (Bawack et al., 2022).

2.5 Past Studies regarding the adoption of AI based products in E-commerce

Past studies largely focused on how humans converse with robots (Hill et al., 2015; Mou and Xu, 2017), or how chatbots might replace human jobs (Huang and Rust, 2018). There are few studies related to consumer technology awareness and preference (Pantano & Pizzi, 2020).

However, it was possible to find some research about acceptance and adoption of artificial intelligence components, which may trigger a greater involvement with e-commerce, and consequently, a higher consumer perception of the use of AI on e-commerce websites.

One of the examples is the research accomplished by Pantano and Pizzi, (2020) with the purpose to provide a comprehensive understanding of the actual progresses in artificial intelligence, underlining chatbots as emerging forms of customer assistance in online retailing. Based the data on analysis of the chatbot patents in the paste twenty years, the results have shown that the increasing technology push towards the adoption of new conversational agents based on natural language. Also, there are research and development efforts seeking to improve artificial intelligence systems that characterize chatbots.

Farther, Suresh and Rani (2020) conducted a study, which had as a purpose to identify the consumer preferences towards the applications of AI in different areas of e-commerce. The findings showed that there is no relationship between usage and recompenses factors although there is significant relationship between the technique's factors. Also, it was possible to conclude that the most influencing areas of AI in e-commerce are real time product targeting, voice powered search and virtual personal shoppers.

Sohn and Known (2020), performed a comparative study in order to determine which models best explain consumer acceptance of AI-based intelligent products, as well as, which factors have the greatest impact in terms of purchase intention. It was appraised the utility of the Technology Acceptance Model (TAM), the Theory of Planned Behavior (TPB), the Unified Theory of Acceptance and Use of Technology (UTAUT), and the Value-based Adoption Model (VAM), modeling user acceptance in terms of behavioral intention to use AI-based intelligent products. Also were made analysis factor included in these models in terms of influence on purchase intention. VAM was the model considered to have the best performance, and enjoyment, followed by the subjective norms, was found to influence user purchase intention the most. It was possible to conclude that acceptance of highly innovative products with minimal practical value, such as AI-based intelligent products, are more influenced by interest in technology than in utilitarian aspects.

The study conducted by Haryanti and Subriadi (2020) aims to classify the journey of technology acceptance in e-commerce in order to show the driving factors for the acceptance of e-commerce in the future. This study uses a literature review approach to the use of UTAUT theory in e-commerce. The findings reveal that the technological dimension in solving humanity is an important factor in technology acceptance. Changes in the e-commerce phase play a role in determining the factors that drive their acceptance of the community.

2.6 Technological Acceptance Models

2.6.1 Theory of Reasoned Action (TRA)

The Theory of Reasoned Action (TRA) states that a person's performance of a specified behavior is determined by his or her behavioral intention to perform the behavior (Davis et al, 1989). TRA is a model from social psychology which focus in the determinants of consciously intended behaviors (Fishbein & Ajzen 1975; Ajzen & Fishbein 1980). The behavioral intention (BI) is determined by the person's attitude (A) as well by the subjective norm (SN), as is visible in Figure 2.6.1. (Davis et al, 1989).

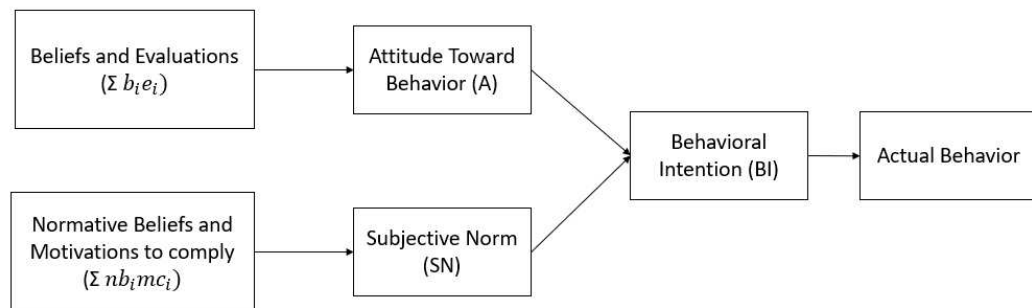


Figure 2.6.1. Theory of Reasoned Action, adapted from Davis et al. (1989)

According to Fishbein and Ajzen (1975, p.288), behavioral intention (BI) is “a measure of the strength of one’s intention to perform a specified behavior”. Attitude Toward Behavior (A) is settled as an individual’s positive or negative feeling about performing the target behavior (e.g., Fishbein & Ajzen 1975, p. 216). Subjective norm (SN) is considered “the person’s perception that most people who are important to him think he should or should not perform the behavior in question” (Fishbein & Ajzen 1975, p.302).

Thus, in line with the Theory of Reasoned Action, a person’s attitude towards a behavior is defined by his or her beliefs (b_i) about the consequences of performing the behavior multiplied by the evaluations (e_i) of those consequences. Beliefs (b_i) are “the individual’s subjective probability that performing the target behavior will result in consequence i ”. The evaluations (e_i) are “an implicit evaluative response” to the consequence (Fishbein & Ajzen 1975, p.29).

Also, TRA considers that a person’s subjective norm (SN) is determined by a multiplicative function of his or her normative beliefs (nb_i), which are, the “perceived

expectations of specific referent individuals or groups”, and his or her motivation to comply (mc_i) with those expectations. (Fishbein & Ajzen 1975, pg. 302).

According to Fishbein and Ajzen (1975), TRA model has a particularly aspect which is that, from an information systems perspective, any other factors that can influence behavior, will only have an indirect influence. Other variables, such as, system design, user and task characteristics, nature of the development or implementation process, political influences, organizational structure and among others, will be considered as external variables, implying in this way that TRA mediates the impact of uncontrollable environmental variables and controllable interventions on user behavior (Davis et al, 1989).

2.6.2 Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM), figure 2.6.2, was introduced by Davis (1996) is an adaptation of TRA, and was specifically tailored for modeling user acceptance of information systems (Davis et al, 1989).

According to Davis et al. (1989), the purpose of TAM is to provide an explanation of the determinants of computer acceptance, capable of explaining user behavior across a broad range of end-user computing technologies and user populations, while at the same time being both parsimonious and theoretically justified. Thus, TAM was developed not only for prediction, but also for explanation, enabling the researchers and practitioners to identify why a particular system may be unacceptable, and pursue appropriate corrective steps.

In this way, the goal of TAM is to provide a basis for tracing the impact of external factors on internal beliefs, attitudes, and intentions (Davis et al., 1989).

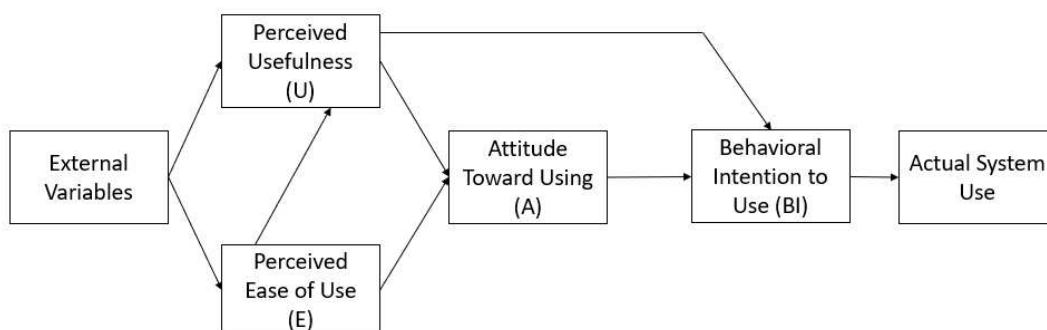


Figure 2.6.2. Technology Acceptance Model, adapted from Davis et al. (1989)

Thus, this model was formulated in order to identify a small number of fundamental variables suggested by previous research dealing with the cognitive and affective determinants of computer acceptance, and using the Theory of Reasoned Action for modeling the theoretical relationships among these variables (Davis et al., 1989).

TAM theorizes that the computer acceptance behaviors is based in two main ideologies: perceived usefulness (U) and perceived ease of use (EOU) (Davis et al., 1989; Venkatesh & Davis, 2000). Perceived usefulness (U) is defined as the individual's perception that using a specific application system will enhance his or her job performance within an organizational context. Perceived ease of use refers to the degree to which the individual expects the target system to be free of effort (Davis et al., 1989).

According to TAM, the effects of external variables, such as, system characteristics, development process and training, with the intention to use a specific application system are mediated by perceived usefulness and perceived ease of use. Also, perceived usefulness is influenced by perceived ease of use as well, in view of the fact that other things being equal, the easier the system is to use the more useful it can be (Venkatesh & Davis, 2000).

TAM is similar to TRA, the computer usage is determined by behavioral intention to use (BI), however according to TAM, BI is viewed as being determined by both, the person's attitude toward using the system (A) and perceived usefulness (U) (Davis et al., 1989).

Within TAM, the A – BI relationship implies that all being equal, individuals form intentions to perform behaviors toward which they have positive affect. This relationship is fundamental to TRA. Nevertheless, TAM contradicts TRA for the direct effect of a belief (such as U) on behavioral intention use (Davis et al., 1989).

Within organizational settings, the U – BI relationship, is grounded on the idea that people form intentions toward behaviors that they believe will increase their job performance, over and above whatsoever positive or negative feelings may be evoked toward the behavior per se (Davis et al., 1989). This occur due to the fact that enhanced performance is fundamental to achieving recompenses which are extrinsic to the content of the work itself, such as promotions and pay increases (e.g., Vroom, 1964).

According to Bagozzi (1982), Vallacher and Wegner (1985) the intentions which are form toward behaviors are theorized to be based on cognitive decision rules in order to improve performance, without, at each time, requiring a re-evaluation of how improved performance contributes to higher purposes and goals in individual's goal hierarchy, and thus without necessarily activating the positive affect associated with performance-contingent rewards.

Therefore, if affect is not fully activated when deciding whether to use a particular system, individual's attitude would not be expected to completely capture the impact of performance considerations on individual's intention (Davis et al., 1989).

Consequently, the U – BI relationship in TAM represents the resulting direct effect, hypothesizing that people form intentions toward using computer systems based largely on a cognitive appraisal of how it will improve their performance (Davis et al., 1989).

The subjective norm (SN) present in TRA is not included in TAM as determinant of behavioral intention. According to Fishbein and Ajzen (1975, pag.304), it is difficult to unravel the direct effects on subjective norm on behavioral intention from indirect effects via attitude toward using. Subjective norm influences behavioral intention indirectly via attitude toward using, as a result of internalization and identification processes, or influence behavioral intention directly via compliance (Kelman 1958; Warshaw 1980b).

Despite it is commonly believed that computer systems usage by professionals is mostly voluntary, because in some cases people may use a system in order to comply with their superior's orders, not because their own feelings and beliefs about the system usage (Robey 1979; DeSanctis 1983; Swanson 1987).

On the report of Warshaw (1980b), the standard measures of subjective norm do not appear to differentiate compliance from internationalization and identification, complicating matter further. Attitude toward using can influence subjective norm with a effect of false consensus, according to Oliver and Bearden (1985), because people project their own attitudes to others.

Taking into account the theoretical uncertainty, the subjective norm was not included in TAM (Davis et al., 1989).

TAM is the most widely used model to explain the behavior of consumers regarding technology adoption (Lee et al., 2003). Has been used in studies of the acceptance of various types of information technology (Subramanian, 1994; Adams et al., 1992; Karahanna & Straub, 1999; Kim & Shin, 2015). For instance, was used to explain the acceptance of wearable devices like the smart watch (Kim & Shin, 2015; Chuah et al., 2016; Yang et al., 2016), business intelligence systems (Wang, 2016), intelligent health monitoring systems (Tseng et al., 2013), intelligent tourism (Venkatesh & Davis, 2000), smart in-store technology (Kim et al., 2017), the smartphone credit card (Ooi & Tan, 2016), among others.

2.6.3 Theory of Planned Behavior (TPB)

The Theory of Planned Behavior (TPB) is an extension of the Theory of Reasoned Action (TRA) due to the original model limitations in dealing with behaviors over which people have incomplete volitional control (Ajzen, I., 1991).

Such as in theory of reasoned action (TRA), a central factor in the theory of planned behavior (TPB) is the individual's intention to perform a given behavior. Intentions are acknowledged to capture the motivational factors that influence a behavior, being indications of how hard people are willing to try and of how much of an effort they are planning to put in practice, in order to perform the behavior. Thus, the stronger the intention to engage in a behavior, the more likely should be its performance (Ajzen, I., 1991).

A behavioral intention can find expression in behavior merely if the behavior in question is under volitional control, in other words, if the individual can decide at will to perform or not perform the behavior (Ajzen, I., 1991).

According to Ajzen (1985) some behaviors meet the will to perform requirement, however, the performance also depends on non-motivational factors as availability of requisite opportunities and resources, such as, time, money, skills, cooperation of others, among others. So, these factors represent individual's actual control over the behavior. Insofar an individual has the required opportunities and resources and intends as well to perform the behavior, he or she should succeed in doing so (Ajzen, I., 1991).

Therefore, perceived behavioral control play an important role in the theory of planned behavior (TPB), differentiating, in this way, the actual model from the theory of reasoned action (TRA) (Ajzen, I., 1991), as it is possible to see in figure 2.6.3.

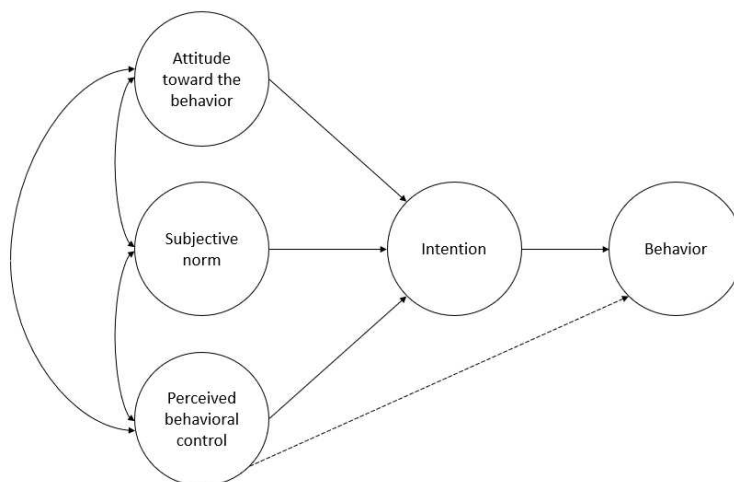


Figure 2.6.3. Theory of Planned Behavior, adapted from Ajzen, I. (1991)

The behavioral achievement is in certain way dictated by the resources and opportunities available to an individual. The perception of behavioral control and its impact on intentions and actions is due mostly from psychological interest than actual control (Ajzen, I., 1991).

In order to understand the present view of behavioral control, it is important to understand the Bandura's (1977, 1982) concept of perceived self-efficacy, whereby is concerned with judgements of "how well one can execute courses of action required to deal with prospective situations" (Bandura, 1982, p. 122).

The investigations resulting from the systematic research program of Bandura and his associates have demonstrated that an individual's behavior is mightily influenced by their confidence in their ability to perform it, in other words, by perceived behavioral control (Bandura, 1982).

According to Bandura (1982, 1991) self-efficacy beliefs can influence the choice of activities, the preparation for an activity, the effort expended during performance, as well as thought patterns and emotional reactions. The construct of self-efficacy belief or perceived behavioral control is placed within a more general framework of the relations among beliefs, attitudes, intentions, and behavior (Ajzen, I., 1991).

Thus, according to the theory of planned behavior, perceived behavioral control, together with behavioral intention, can be used directly to predict behavioral achievement. Two rationales can be presented in order to sustain this conjecture (Ajzen, 1985).

The first one is maintaining intention constant, the effort spent to lead a behavior to a successful conclusion is expected to increase with perceived behavioral control. So, if two individuals have the same strong intentions to learn how to ski, the individual who is reliant that he can master the activity is more likely to proceed than is the individual who doubt his own ability (Ajzen, 1985).

The second one is that perceived behavioral control can often be used as a substitute for a measure of actual control. Nevertheless, the possibility for a measure of perceived behavioral control can substitute a measure of actual control depends on the accuracy of the perceptions. So, when an individual has scarce information about the behavior, when requirements or available resources have changed, or when new and unfamiliar elements have entered into the circumstance, perceived behavioral control may not be particularly realistic. So, under those conditions, a measure of perceived behavioral control may contribute little to the accuracy of behavioral prediction. However, to the extent that perceived control is realistic, under accurate

perceptions, it can be used to predict the probability of a successful behavioral attempt (Ajzen, 1985).

The theory of planned behavior has been used in research to examining exogenous factors such as social influence, in order to explain acceptance of innovative products. Some examples were the acceptance of wearable devices (Basoglu et al., 2017; Lunney et al., 2016), smart home services (Yang et al., 2017), health cloud systems (Hsieh, 2015), mobile services (Yang and Jolly, 2009), and intelligent transport systems (Larue et al., 2015; Thorhauge et al., 2016).

2.6.4 Unified Theory of Acceptance and Use of Technology (UTAUT and UTAUT2)

The Unified Theory of Acceptance and Use of Technology (UTAUT) was developed by redefining representative technology acceptance theories, such as the TRA, TAM, and TPB, from an integrated perspective (Venkatesh et al., 2003).

UTAUT, figure 2.6.4, was formulated with four core determinants of intention and usage, and up to four moderators of key relationships. In this way UTAUT provides a useful tool to evaluate the probability of success for new technologies introductions and also to understand the drivers of acceptance in order to proactively design interventions targeted at individuals that may be less inclined to adopt and use new systems (Venkatesh et al, 2003).

In the formulation of the Unified Theory of Acceptance and Use of Technology (UTAUT) are included four constructs which play a significant role as direct determinants of user acceptance and usage behavior. The constructs are performance expectancy, effort expectancy, social influence, and facilitating conditions (Venkatesh et al., 2003).

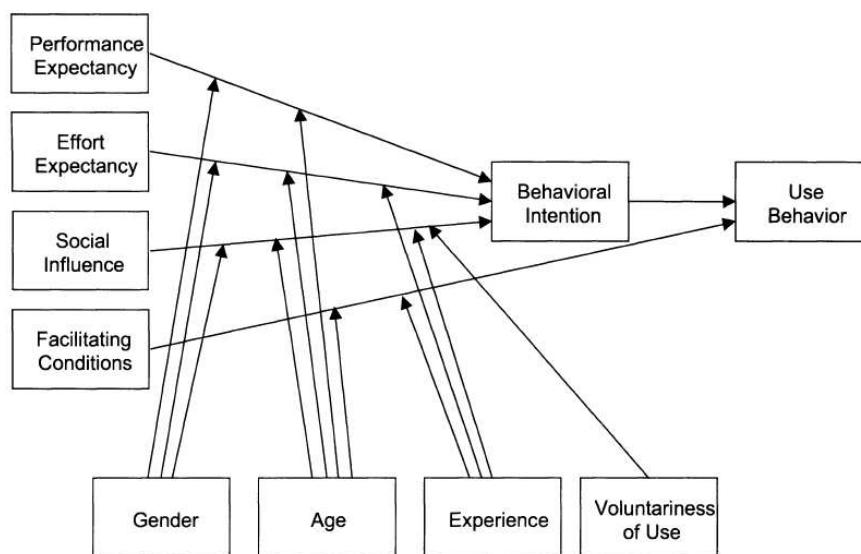


Figure 2.6.4. Unified Theory of Acceptance and Use of Technology, retrieved from Venkatesh et al. (2003)

Performance expectancy is determined as the degree to which an individual believes that using the system will help him or her to achieve gains in job performance (Venkatesh et al., 2003).

From a theoretical perspective, is expected that gender and age will moderate the relationship between performance expectancy and intention. According to Minton and Schneider (1980) men tend to be highly task-oriented, and in this way, performance expectancies, which focus on task accomplishment, are likely to be notable to men. On the report of the gender schema theory, is suggested that such differences stem from gender roles as well as from socialization processes reinforced from birth rather than biological gender per se (Bern & Allen 1974; Bern, 1981; Motowidlo, 1982; Lubinski et al., 1983; Kirchmeyer, 1997; Lynott & McCandless, 2000;). According to Porter (1963) and Hall and Mansfield (1995), younger workers may consider the extrinsic rewards more important. As stated by Levy (1988), regarding gender and age effects, the studies of gender differences can be misleading when there is no reference to age. An exemplification regarding the family-oriented responsibilities, given the traditional societal gender roles, the importance of job-related factors may change significantly for working women between the time they enter the labour force and the time they reach childrearing years (Barnett & Marshall, 1991).

Thus, is expected that the influence of performance expectancy on behavioral intention will be moderated by gender and age, such that the effect will be stronger for men and particularly for younger men (Venkatesh et al., 2003).

Effort Expectancy is established as the degree of ease associated with the use of the system. (Venkatesh et al., 2003). In the early stages of a new behavior, is expected that the effort-oriented constructs are more prominent, in view of the fact that is when process issues represent hurdles to be overcome (Davis et al., 1989; Szajna, 1996; Venkatesh, 1999).

Based on Bern and Allen (1974) and Bozionelos (1996), is proposed by Venkatesh and Morris (2000), that effort expectancy is more prominent for women than for men. As observed above, the gender differences predicted, may be driven by cognitions related to socially-constructed gender roles (Motowidlo, 1982; Wong et al., 1985; Lynott & McCandless, 2000). The age moderator has also influence in the relationship between effort expectancy and behavioral intention. Has been demonstrated that increased age is associated with difficulty in processing complex stimuli and in allocating attention to information on the job, which are required for software systems usage (Plude & Hoyer, 1985). Venkatesh and Morris (2000) state that constructs related to effort expectancy will be stronger determinants of individuals' intention for women and for older workers.

According to Levy (1988), in the context of performance expectancy is expected that gender, age and experience to work together. Therefore, it is expected that the influence of effort expectancy on behavioral intention will be moderated by gender, age, and experience, such that the effect will be stronger for women, particularly older women, and particularly at early stages of experience (Venkatesh et al., 2003).

Social Influence is designated as the degree to which an individual perceives that, important others, believe he or she should use the new system (Venkatesh et al., 2003).

According to Venkatesh and Davis (2000), the social influence construct, operates by influencing perceptions about the technology and is not significant in voluntary context, however becomes significant when use is mandated. The authors suggested that “such effect could be attributed to compliance in mandatory contexts that causes social influences to have a direct effect on intention”. In mandatory settings, social influence appears to be significant only in early stages of individual experience with the technology becoming nonsignificant with sustained usage.

Miller (1976) and Venkatesh et al. (2000) theorizes that women tend to be more sensitive to others’ opinions and in such manner social influence is noted to be more prominent when forming an intention to use new technology, which tends to decrease with experience (Venkatesh & Morris, 2000).

According to meta-analytic review of age effects by Rhodes' (1983), affiliation needs increase with age, suggesting that older workers are more likely to place increased projection on social influences, which declines with experience (Morris & Venkatesh, 2000).

Hence the influence of social influence on behavioral intention will be moderated by gender, age, voluntariness, and experience, such that the effect will be stronger for women, particularly older women, particularly in mandatory settings in the early stages of experience. (Venkatesh et al., 2003).

Facilitating Conditions are settled as the degree to which an individual believes that an organizational and technical infrastructure exists in order to support use of the system (Venkatesh et al., 2003).

According to Venkatesh (2000), there is support for full mediation of the effect of facilitating conditions on intention by effort expectancy. Evidently, if effort expectancy is not present in the model as is the case with TPB as example, then would be expected that facilitating conditions become predictive of intention. Although, when both constructs, performance expectancy and effort expectancy, are present, facilitating conditions becomes

nonsignificant in predicting intention. Therefore, facilitating conditions will not have a significant influence on behavioral intention (Venkatesh et al., 2003).

In line with the empirical results, facilitating conditions do have a direct influence on usage other than that explained solo by behavioral intentions. Consistent with TPB mentioned above, facilitating conditions are not fully mediated by intention, they are also mediated as a direct precursor of usage (Venkatesh et al., 2003). It is awaited that the effect increases with experience as users of technology find multiple approaches for help and support throughout the organization, thus removing barriers to sustained usage (Bergeron et al., 1990). It is recognized by organizational psychologists that older workers attribute more importance to receiving help and assistance on the job (Hall and Mansfield 1995). Then, the influence of facilitating conditions on usage will be moderated by age and experience, which effect will be stronger for older workers, particularly with increasing experience. (Venkatesh et al., 2003).

UTAUT is used as a base model for the study of different technologies both in organizational and non-organizational contexts, it was extended to focus only on the non-organizational context, a strand turned to the consumer use, resulting in a similar model known by The Unified Theory of Acceptance and Use of Technology 2 (UTAUT2). The UTAUT 2 presented in figure 2.6.5, aims to understand the use of systems by users in a non-organizational context, having incorporated three new constructs, which are Hedonic Motivation, Price Value and Habit (Venkatesh et al., 2012).

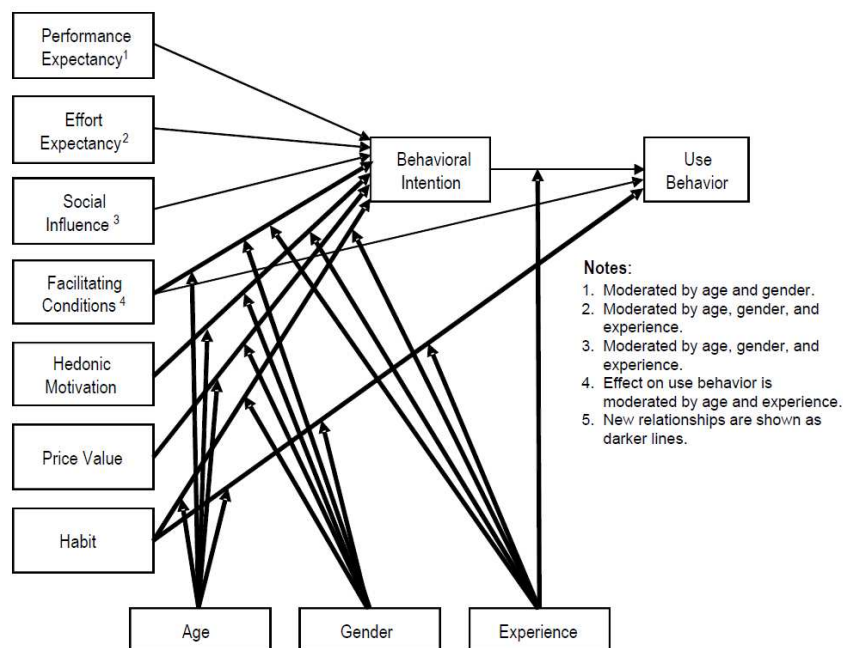


Figure 2.6.5. Unified Theory of Acceptance and Use of Technology 2, retrieved from Venkatesh et al. (2012)

Additionally, changes were made at the level of relationships, the volunteering of use variable was eliminated and a relationship between Facilitator Conditions and Behavior Intention was added (Venkatesh et al., 2012).

Hedonic motivation is defined as the fun or pleasure derived from using a technology, and play an important role in determining technology acceptance and use (Brown & Venkatesh, 2005). Has been found that hedonic motivation (conceptualized as perceived enjoyment), influence technology acceptance and use directly (van der Heijden 2004; Thong et al., 2006). Also, in the consumer context, hedonic motivation has appeared to be an important determinant of technology, acceptance and use (Childers et al., 2001; Brown & Venkatesh 2005). Therefore, hedonic motivation was added as a predictor of consumers' behavioral intention to use a technology (Venkatesh et al., 2012).

The cost and pricing structure may have a significant impact on consumers' technology use when compared to the organizational use, because consumers usually bear the monetary cost of such use whereas employees do not. The monetary cost/price is usually conceptualized together with the quality of products or services to determine the perceived value of such products or services (Zeithaml, 1988). In this way, according to Dodds et al. (1991), price value is defined as "consumers' cognitive trade-off between the perceived benefits of the applications and the monetary cost for using them". So, when the benefits of using a technology are perceived to be greater than the monetary cost, the price value has a positive impact on intention. Thereby, price value was added as a predictor of behavioral intention to use a technology (Venkatesh et al., 2012).

The last construct being added to UTAUT was habit. In order to understand the habit concept it is important to understand the experience concept, because although being distinct constructs, they are both related. Experience "reflects an opportunity to use a target technology and is typically operationalized as the passage of time from the initial use of a technology by an individual" (e.g., Venkatesh et al., 2003; Kim & Malhotra, 2005). According to Limayem et al. (2007) habit has been defined as "the extent to which people tend to perform behaviors automatically because of learning", along with Kim et al. (2005) equate habit with "automaticity". Research was conducted and was inferred that habit is a perceptual construct that reflects the results of prior experiences. This way, related to the operationalization of habit as a prior use, it was found by Kim and Malhotra (2005) that prior use was a strong predictor of future technology use. Also, according to Limayem et al. (2007) research, which encompassed a survey and perceptions based approach to the measurement of habit, has been

shown that an operationalization of habit have a direct effect of intention and also moderate the effect of intention on technology use such that intention is less important with increasing habit.

The Unified Theory of Acceptance and Use of Technology was used to explain acceptance of intelligent healthcare systems (Gao et al., 2015; Hsieh, 2016; Fan et al., 2018), wearable devices (Gu et al., 2016; Adapa et al., 2018), systems of recommendations (Oechslein et al., 2014; Wang et al., 2015), other intelligent systems (Williams et al., 2015) as well as virtual reality education systems (Setiawan et al., 2019).

Chapter III – Theoretical Approach

3.1 Objectives and Research Questions

Following the literature review prepared in chapter II of the present dissertation there were several points of view presented by the authors studied. As a result of such investigation, a research question has emerged to which we propose to answer in order to achieve the aim. In such manner, for the main goal we begin to try to understand the factors that influence the use of artificial intelligence technologies in the e-commerce area, more specifically chatbots.

Therefrom, indicators were considered in the present study based on technology acceptance theories, TRA (Davis et al., 1989), TAM (Davis et al., 1989), TPB (Ajzen, I., 1991), UTAUT (Venkatesh et al., 2003) and UTAUT2 (Venkatesh et al., 2012), in order to achieve the objective – *Understanding consumers' acceptance of AI based intelligent products on e-commerce with a particular focus on chatbots* (Suresh & Rani, 2020; Pantano & Pizzi, 2020; Sohn & Known, 2020). This opens the path for the Research Question:

RQ – Which factors influence the intention to use and the effective use of chatbots on e-commerce?

In the following Table 3.1, are presented the RQ, along with the hypotheses derived by them, as well as the bibliography used to compare results. The hypotheses will be mentioned in another section where we show the conceptual model used for the RQ.

Finally in order to answer the research question, a quantitative data collection method, an online survey, will be performed as well as hypotheses confirmation through surveys statistical analysis, which will be presented in the following section of the present dissertation.

Table 3.1. Theoretical Approach

Research Question	Hypotheses	References
1. Which factors influence the use of chatbots on e-commerce?	H1 – <i>Behavioral Intention to Use positively influences the Use Behavior of Chatbots in E-commerce</i>	Fishbein and Ajzen (1975); Ajzen, I. (1985); Davis et al (1989); Ajzen, I. (1991); Venkatesh and Davis (2000); Venkatesh and Morris (2000); Venkatesh et al. (2003); Brown and Venkatesh (2005); Venkatesh et al. (2012)
	H2a – <i>Automaticity positively influences the Use Behavior of Chatbots in E-commerce</i>	Venkatesh et al. (2003); Kim and Malhotra (2005); Kim et al. (2005); Limayem et al. (2007)
	H2b – <i>Automaticity positively influences the Behavioral Intention to Use Chatbots in E-commerce</i>	Venkatesh et al. (2003); Kim and Malhotra (2005); Kim et al. (2005); Limayem et al. (2007)
	H3 – <i>Automaticity moderates the effect of Behavioral Intention to Use on the Effective Use Behavior of Chatbots in E-commerce</i>	Limayem et al. (2007)

Author's Elaboration

Chapter IV – Methodology

4.1 Research Model

The present research is based on a set of primary sources, with the use of questions, and secondary sources, through bibliographic research and information treatment, such as the systematized studies developed in books, journals, and scientific articles. Considering in this way, the research classification criteria of Vergara (2006) and Vilelas (2009) where the methodology applied to research can be classified as to ends and as to means (Vergara, 2006; Vilelas, 2009). On these terms the ends refer to applied and exploratory research, whilst the means are related to field study and bibliographic research.

Following the Literature Review undertaken in the present dissertation, hypotheses were structured for the Research Question. To answer the Research Question, was used a quantitative methodology, consisting in an online survey. In order to analyse the answers obtained in the survey, was used a Structural Equations Model (SEM) which establish the relationship between measurement model and structural model, based upon the assumptions supported by the theory. SEM allows questions to be answered, involving multiple regression analyses of factors (Ullman & Bentler, 2012).

The first step when performing a SEM analysis is specification of a model, being in this way a confirmatory rather than an exploratory technique. Afterwards, the model is estimated, evaluated, and perhaps modified. The goal of the analysis can be to test a model to test specific hypotheses about a model, to modify an existing model, or to test a set of related models (Ullman & Bentler, 2012). In such manner, since the purpose of the survey research in the present dissertation is to verify the veracity of the hypotheses derived from the Literature Review, the SEM analysis was used.

SEM analysis enable the measurement of the relationships free of measurement error, since it estimates it and removes it. Moreover, the use of diagrams in which the researcher's proposed relationships between variables are easily understood, attest the utility of this technique (Tarka, 2018).

Additionally, as stated by Tarka (2018), SEM is important for analyses which require a certain background knowledge of topics, as it aids in the model's estimation procedures. SEM models, enable to conduct a complex and multidimensional analysis of empirical data in which theoretical constructs are considered, as well as, aspects of the examined reality or even abstract concepts.

Lastly, the software chosen to analyse the data from the surveys was SmartPLS. SmartPLS uses a data analysis technique, Partial Least Squares (PLS). PLS is part of the Structural Equation Model (SEM), which examines the relationship between variables reciprocally (Sholihin & Ratmono, 2013). Also, PLS was introduced to overcome the limitations of ordinary least square regression. When the number of data samples is small, there are missing values, and data is abnormally distributed with multicollinearity (Kock, 2015). The conceptual model along with the hypotheses defined, can be found in the next section of the dissertation.

4.2 Conceptual Model

4.2.1 Conceptual Model – Research Question

Hypotheses for the Research Question - **Which factors influence the use of chatbots on e-commerce?**

H1 – Behavioral Intention to Use positively influences the Effective Use Behavior of Chatbots in E-commerce

H2a – Automaticity positively influences the Effective Use Behavior of Chatbots in E-commerce

H2b – Automaticity positively influences the Behavioral Intention to Use Chatbots in E-commerce

H3 – Automaticity moderates the effect of Behavioral Intention to Use on the Effective Use Behavior of Chatbots in E-commerce

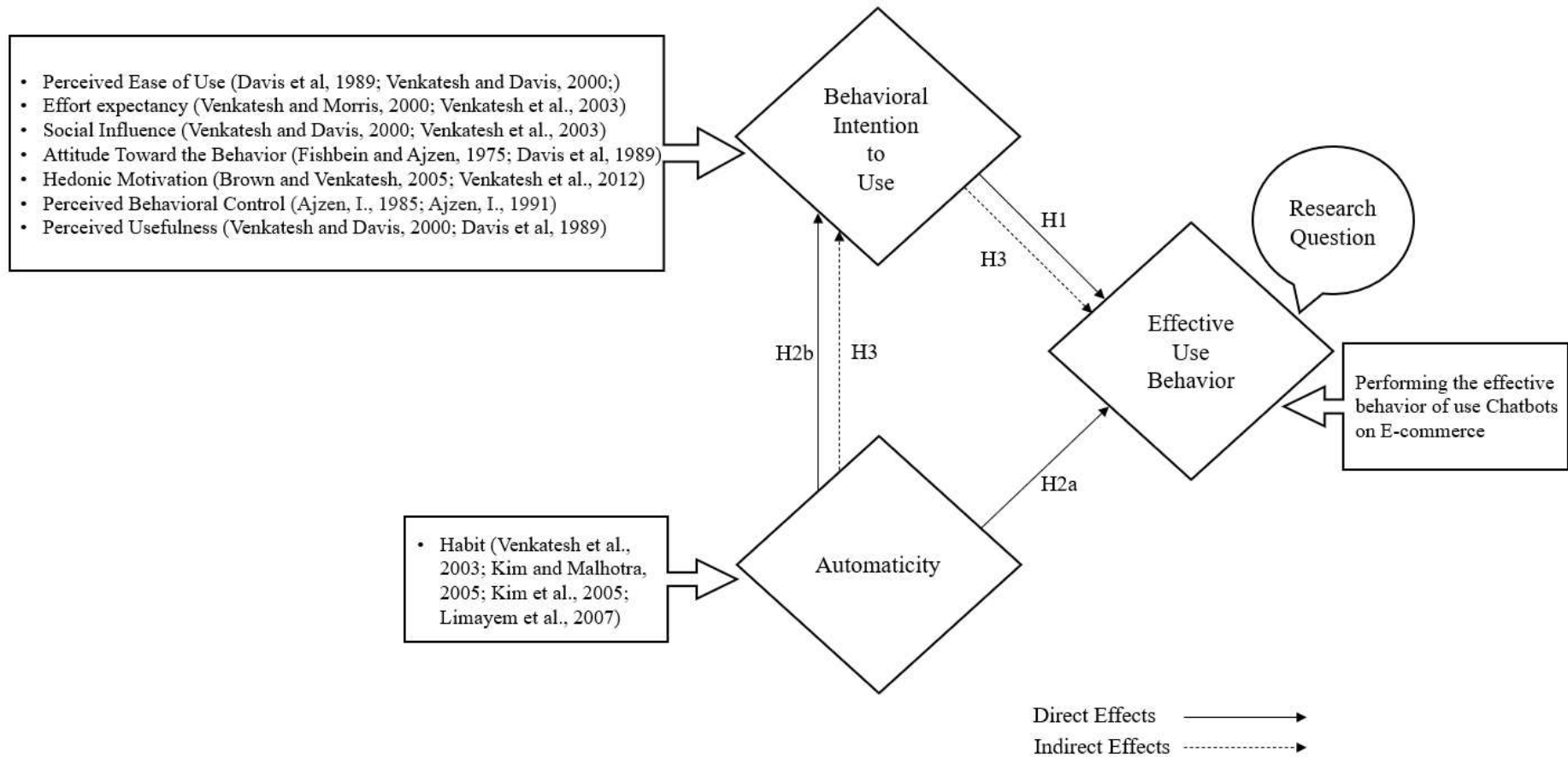


Figure 4.2. Conceptual Model

Author's Elaboration

Table 4.2. RQ, Variables, Indicators and Questions

1. Which factors influence the use of chatbots on e-commerce?		
Independent Variable	Indicator	Questionnaire Questions
Behavioral Intention to Use	Perceived Ease of Use (Davis et al, 1989; Venkatesh and Davis, 2000;)	Learning to operate with chatbots in e-commerce is easy for me.
		I find chatbots easy to use.
	Effort expectancy (Venkatesh and Morris, 2000; Venkatesh et al., 2003)	Learning how to use chatbots is easy for me.
		I find chatbots flexible to interact with.
		My interaction with chatbots is clear and understandable.
	Social Influence (Venkatesh and Davis, 2000; Venkatesh et al., 2003)	People who influence my behavior think I should use chatbots.
		People who are important to me think I should use chatbots.
		I use chatbots because of the proportion of friends/family who use chatbots.
	Attitude Toward the Behavior (Fishbein and Ajzen, 1975; Davis et al, 1989)	Using chatbots is a good idea.
		Using chatbots is a wise idea.
		I like the idea of using chatbots.
	Hedonic Motivation (Brown and Venkatesh, 2005; Venkatesh et al., 2012)	I find using chatbots to be enjoyable.
		The actual process of using chatbots is pleasant.
		I have fun using chatbots.
	Perceived Behavioral Control (Ajzen, I., 1985; Ajzen, I., 1991)	I have the knowledge necessary to use chatbots.
		I have control over using chatbots.
		I have the resources necessary to use chatbots.
	Perceived Usefulness (Venkatesh and Davis, 2000; Davis et al, 1989)	I feel confident when I use chatbots.
		Using chatbots improves the quality of service.
		I find using chatbots useful.
Automaticity	Habit (Venkatesh et al., 2003; Kim and Malhotra, 2005; Kim et al., 2005; Limayem et al., 2007)	Using chatbots enable me to accomplish tasks more quickly.
		Using chatbots optimize my customer experience.
		Using chatbots make it easier to shop online.
Dependent Variable	Indicator	Questionnaire Questions
Use Behavior	Performing the effective behavior of use Chatbots on E-commerce	I regularly use chatbots.
		When I use an e-commerce website, I automatically use chatbots.
		When using an e-commerce website, I use chatbots.

Author's Elaboration

4.3 Sample Description

Personal information of every respondent was asked at the beginning of the questionnaire, regarding Age, Gender and Education. The surveys are fully anonymous and this information is useful to understand if the samples are sufficiently heterogeneous for the results validity.

The present sample includes 117 individuals. Regarding the respondent's age, 1 (1%) was "Under 18", 37 (32%) were "Between 18 and 25", 62 (53%) were "Between 26 and 35", 12 (10%) were "Between 36 and 50", and 5 (4%) were "Over 50". The following figure 4.3 shows the age distribution:

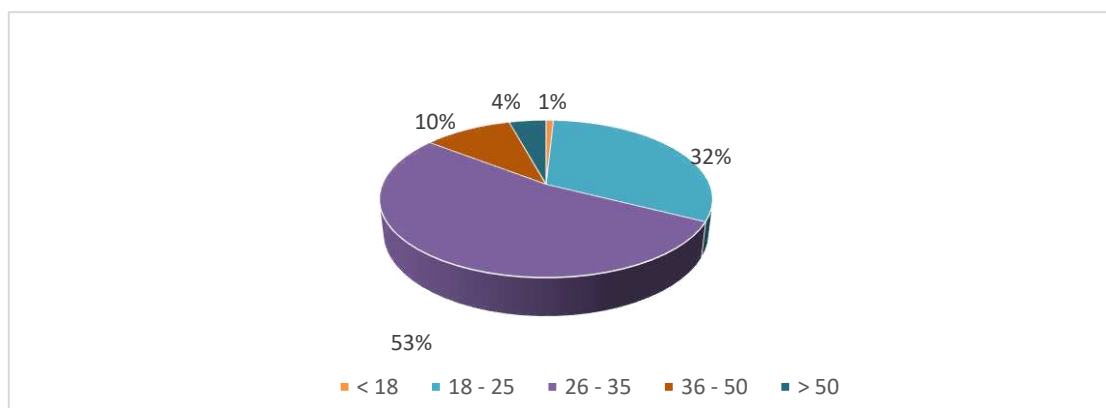


Figure 4.3. Survey's Age Distribution

Author's Elaboration

Regarding the gender distribution, 38 (32%) were female and 79 (68%) were male. The following figure 4.4 shows the gender distribution:

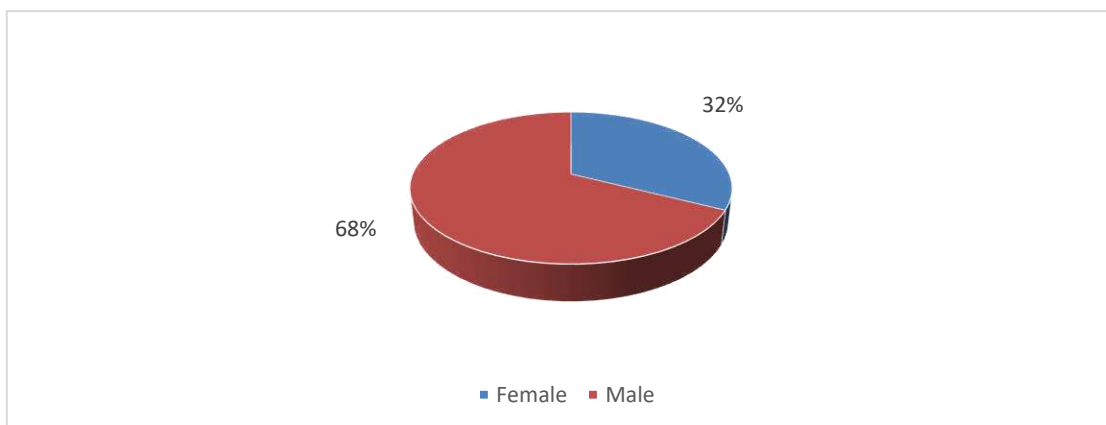


Figure 4.4. Survey's Gender Distribution

Author's Elaboration

Regarding education, 2 (2%) had Basic Education, 26 (22%) had Secondary Education, 26 (22%) had a Bachelor's Degree, 11 (9%) had a Post-graduate Degree, 49 (42%) had a Master's Degree, and 3 (3%) had a PhD. The following figure 4.5 shows the educational distribution:

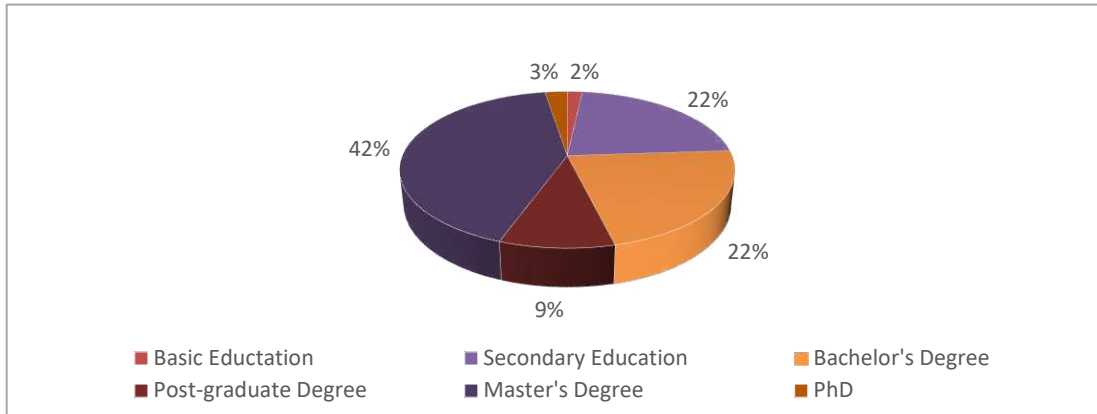


Figure 4.5. Survey's Educational Distribution

Author's Elaboration

Chapter V – Results Presentation and Discussion

The analysis and interpretation of the results of the research question followed a two-step approach. First, the reliability and validity of the measurement model were evaluated, then the structural model was examined. To assess the quality of the measurement model, individual reliability indicators, convergent validity, internal consistency reliability and discriminant validity were examined (Hair et al., 2017).

Once reliability is a condition for validity, indicator reliability is first checked to ensure the associated indicators have as much in common as what is captured by the latent. On the first try of this project, after examining the outer loadings for all latent variables, there were five constructs supporting the variable “Behavioral Intention to use” which were removed, (“aprender_chatbots_facil”, “pessoas_influenciam_comport”, “pessoas_importantes”, “proporcao_amigos” and “gosto_ideia_usar_chatbots”) because the respective outer loadings were lower than the 0.6 threshold level, in this way, the indicator “Social Influence” which was supported by the constructs (“pessoas_influenciam_comport”, “pessoas_importantes”, “proporcao_amigos”) was removed as well. The PLS algorithm was re-run and the resulting path Model estimation is presented in Figure 5.1.

5.1 Model Results Presentation

The figure below (Figure 5.1), is a PLS-SEM diagram which represents the present research’s model. The number in the circles (0.438 and 0.702) shows how much the variance of the latent variables are being explained by the others latent variables. The numbers on the arrows are called the path coefficients and explain how strong the effect of one variable is on another variable. The weight of different path coefficients enables to rank their relative statistical importance.

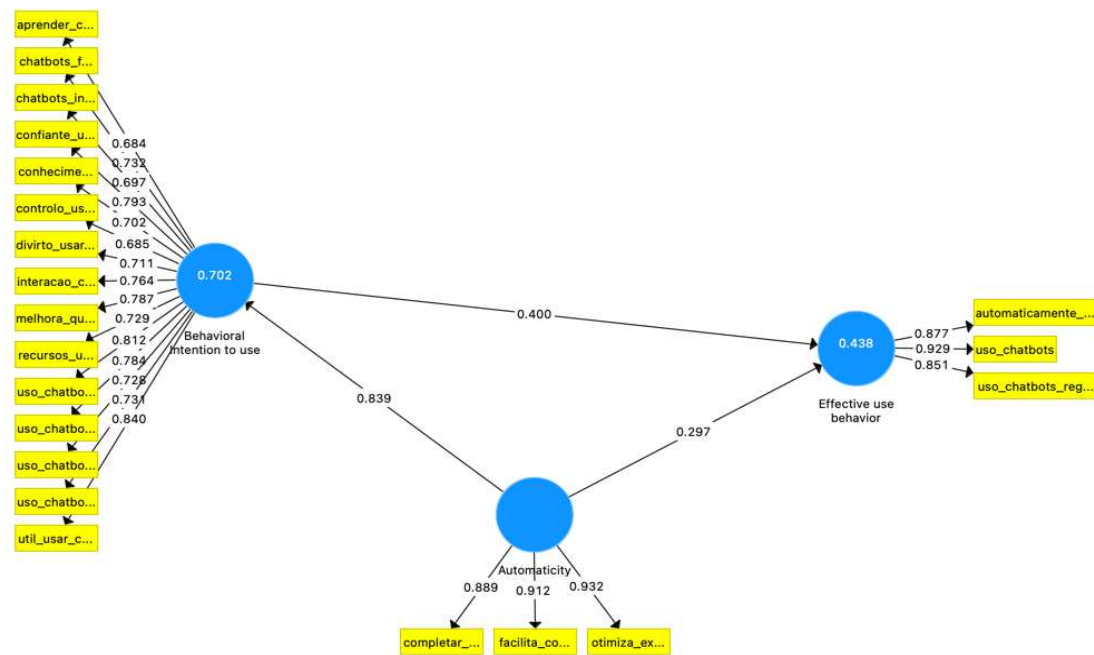


Figure 5.1. Path Model

Source: PLS Software

5.1.1 Measurement Model Assessment

Resembling all statistical methods, PLS-SEM, requires several choices that, if not made correctly, can lead to improper findings, interpretations and conclusions (Hair et al., 2012).

Measurement model specification requires the consideration of the nature of the relationship between constructs and measures. Latent variable measurement is relative to the process of ensuring that local independence is satisfied for a selected set of observed variables or indicators, via the use of a model such as a common factor model (Oodhue et al., 2012). The two types of measurement models are: reflective and formative (Hreats, Becker & Ringle, 2013), which are the two currently accepted ways of specifying the relationship between latent constructs and observed variables that are causally related to them (Aguirre-urreta & Marakas, 2012).

The present study, introduces three latent variables (Behavioral Intention to Use, Automaticity and Effective Behavior). The first latent variable is made up of fifteen observed indicators and the last two are made up of three indicators.

The confirmatory tetrad analysis technique (CTA-PLS), developed by Gudergan, Ringle, Wende and Will (2008), that has been used, by some researchers, to determine if the measurement model is formative or reflective, cannot be applied to the “Automaticity” and “Effective Behavior” variables, because it can only check latent variables that have at least 4

associated indicators. In this way, due to the pointed limitation of CTA-PLS considering the number of indicators, this technique will not be applied to any variable, and the decision “reflective vs formative” should be based on theoretical considerations.

If the indicators are highly correlated and interchangeable among themselves, one has a reflective measurement model. If not, it suggests a formative measurement model (Wong, 2013).

In tables below, 5.1.1, 5.1.2 and 5.1.3, it is possible to observe the correlation between the observable indicators of each latent variable. All of them suggest a moderate positive correlation, so the latent variables are made up of correlated measures. As such, a reflective measurement scale is used throughout this research, with the causality direction going from the blue colour latent variable to the yellow colour indicators in Figure 5.1.

Table 5.1.1. Correlation (Behavioral Intention to Use)

Behavioral Intention to Use	aprende_r_operar_chatbots_facil	chatbots_faceis_usar	chatbots_interacao_flexivel	interacao_chatbots_clara_compre	uso_chatbots_boa_ideia	uso_chatbots_ideia_sabia	uso_chatbots_agradavel	uso_chatbots_prazeroso	divirtu_usar_chatbots	conhecimento_usar_chatbots	controle_uso_chatbots	recursos_usar_chatbots	confiante_uso_chatbots	melhora_qualidade_servico	util_usar_chatbots
aprender_operar_chatbots_facil	1.000														
chatbots_faceis_usar	0.837	1.000													
chatbots_interacao_flexivel	0.379	0.482	1.000												
interacao_chatbots_clara_compre	0.645	0.696	0.722	1.000											
uso_chatbots_boa_ideia	0.383	0.450	0.478	0.513	1.000										
uso_chatbots_ideia_sabia	0.319	0.383	0.445	0.452	0.783	1.000									
uso_chatbots_agradavel	0.417	0.496	0.516	0.529	0.705	0.662	1.000								
uso_chatbots_prazeroso	0.283	0.372	0.444	0.388	0.567	0.578	0.746	1.000							
divirtu_usar_chatbots	0.312	0.363	0.440	0.441	0.525	0.511	0.685	0.772	1.000						
conhecimento_usar_chatbots	0.607	0.628	0.409	0.559	0.463	0.398	0.386	0.347	0.359	1.000					
controle_uso_chatbots	0.612	0.594	0.445	0.551	0.345	0.216	0.412	0.457	0.453	0.748	1.000				
recursos_usar_chatbots	0.646	0.657	0.509	0.581	0.455	0.470	0.416	0.310	0.330	0.731	0.677	1.000			
confiante_uso_chatbots	0.497	0.541	0.492	0.557	0.542	0.476	0.544	0.546	0.532	0.564	0.676	0.626	1.000		
melhora_qualidade_servico	0.448	0.515	0.515	0.542	0.675	0.596	0.635	0.520	0.522	0.390	0.354	0.462	0.610	1.000	
util_usar_chatbots	0.505	0.560	0.508	0.555	0.638	0.601	0.706	0.601	0.529	0.583	0.495	0.592	0.649	0.728	1.000

Source: PLS Software

Table 5.1.2. Correlation (Automaticity)

Automaticity	completar_tarefas_rapidamente	otimiza_experiencia_consumidor	facilita_comprar_online
completar_tarefas_rapidamente	1.000		
otimiza_experiencia_consumidor	0.725	1.000	
facilita_comprar_online	0.686	0.825	1.000

Source: PLS Software

Table 5.1.3. Correlation (Effective Use Behavior)

Effective Use Behavior	uso_chatbots_regularmente	automaticamente_uso_chatbots	uso_chatbots
uso_chatbots_regularmente	1.000		
automaticamente_uso_chatbots	0.556	1.000	
uso_chatbots	0.645	0.840	1.000

Source: PLS Software

5.1.2 Reliability Indicator

The Reliability Indicator can be assessed through the factor loading estimates. As factor loading estimates are standardized in PLS-PM, the squared factor loading estimate equals the estimated reliability indicator. It is generally advisable for factor loadings to be 0.707 or above since that number squared equals 0.5, indicating that more than 50% of the variance in a single indicator can be explained by the corresponding latent variable.

Table 5.1.4. Reliability

Constructs (latent Variables)	Outer loadings	Reliability met?
Behavioral Intention to Use		
aprender_operar_chatbots_facil	0.684	yes
chatbots_faceis_usar	0.732	yes
chatbots_interacao_flexivel	0.697	yes
confiante_uso_chatbots	0.793	yes
conhecimento_usar_chatbots	0.702	yes
controle_uso_chatbots	0.685	yes
divirto_usar_chatbots	0.711	yes
interacao_chatbots_clara_compre	0.764	yes
melhora_qualidade_servico	0.787	yes
recursos_usar_chatbots	0.729	yes
uso_chatbots_boa_ideia	0.812	yes
uso_chatbots_ideia_sabia	0.784	yes
uso_chatbots_agradavel	0.728	yes
uso_chatbots_prazeroso	0.731	yes
util_usar_chatbots	0.840	yes
Automaticity		
completar_tarefas_rapidamente	0.889	yes
facilita_comprar_online	0.912	yes
otimiza_experiencia_consumidor	0.932	yes
Effective use behavior		
automaticamente_uso_chatbots	0.877	yes
uso_chatbots	0.929	yes
uso_chatbots_regularmente	0.851	yes

Source: PLS Software

Indicators which have loadings between 0.4 to 0.7, require a loading relevance test, since, as it is possible to see in Table 5.1.4, there are no loadings below 0.65, there is no need to perform relevance tests, in order to assess whether or not they should be retained in the model.

5.1.3 Internal Consistency Reliability

The next step is assessing internal consistency reliability, most often using Jöreskog's (1971) composite reliability indicator. Higher values generally indicate higher levels of reliability. For example, reliability values between 0.60 and 0.70 are considered “*acceptable in exploratory research*,” values between 0.70 and 0.90 range from “*satisfactory to good*”. Values of 0.95 and higher are problematic, as they indicate that the items are redundant, thereby reducing construct validity (Diamantopoulos *et al.*, 2012;)

Prior research suggests that a threshold level of 0.6 or higher is required to demonstrate a satisfactory composite reliability in exploratory research (Bagozzi & Yi, 1988) but not exceeding a 0.95 level (Hair *et al.*, 2013).

Composite Reliability is used to measure the Model's internal consistency reliability, because it takes into consideration the different outer loadings of the indicators (Werts, Linn & Joreskog, 1974). On the present research, as shown in Table 5.1.5, the composite reliability for constructs Automaticity, Behavioral Intention to Use and Effective use behavior are 0.936, 0.950 and 0.917 respectively, indicating high levels of internal consistency reliability.

Table 5.1.5. Composite Reliability

	Composite Reliability	Average Variance Extracted (AVE)
Automaticity	0.936	0.830
Behavioral Intention to use	0.950	0.558
Effective use behavior	0.917	0.786

Source: PLS Software

Cronbach's alpha is another measure of internal consistency reliability that assumes similar thresholds, but produces lower values than composite reliability. However, Cronbach's alpha is a less precise measure of reliability, as the items are unweighted. In contrast, with composite reliability, the items are weighted based on the construct indicators' individual loadings and, hence, this reliability is higher than Cronbach's alpha, so for that reason in this study is only analysed the Composite Reliability.

5.1.4 Convergent Validity

The following step of the reflective measurement model assessment addresses the convergent validity of each construct measure. Convergent validity is the extent to which the indicators of a latent variable actually measure the same construct. To check convergent validity, each latent variable's Average Variance Extracted (AVE) is evaluated, which indicates how much of the indicators' variance can be explained by the latent variable. An AVE higher than 0.5 has been suggested (Bagozzi & Yi, 1988) to provide empirical evidence for convergent validity, as the

corresponding latent variable explains more than half of the variance in the respective indicators, and consequently, all other latent variables explain less than half.

As seen in the Table 5.1.5 all constructs exceeded this level. The AVE for the latent construct Automaticity, Behavioral Intention to Use and Effective use Behavior are 0.830, 0.558 and 0.786, respectively. The AVE of these three dimensions ranged from 0.55 to 0.83, hence indicating convergent validity. Therefore, the measures of the three reflective constructs can be said to have moderate levels of convergent validity

5.1.5 Discriminant Validity

Discriminant validity ensures that a construct measure is empirically unique and represents phenomena of interest, that other measures in a structural equation model do not capture (Hair et al. 2010). Technically, discriminant validity requires that “*a test not correlate too highly with measures from which it is supposed to differ*” (Campbell, 1960). If discriminant validity is not established, “*constructs have an influence on the variation of more than just the observed variables to which they are theoretically related*” (Henseler, J., Ringle C., Sarstedt M., 2015).

On this research, discriminant validity is assessed by the criterion of Heterotrait-Monotrait ratio (Hair et al., 2013).

According to Henseler et al. (2015) proposed the Heterotrait-Monotrait (HTMT) ratio of the correlations (Voorhees, C., Brady. M., Calantone, R., 2016). Discriminant validity problems are present when HTMT values are high. Using the Heterotrait-Monotrait ratio (HTMT) as a criterion involves comparing it to a predefined threshold. If the value of the HTMT is higher than this threshold, one can conclude that there is a lack of discriminant validity. However, the exact threshold level of the HTMT is debatable. Some authors suggest a threshold of 0.85 (Clark & Watson, 1995; Kline, 2011), which has an average sensitivity rate of 99.90%, whereas others propose a value of 0.90 (eg. Gold et al., 2001) which has a sensitivity rate of 99.45%. HTMT should be lower than 0.85 (stricter threshold) or 0.90 (more lenient threshold) or significantly lower than 1 (Voorhees et al., 2016), in consideration the fact that all three HTMT approaches detect discriminant validity issues reliably (Henseler et al., 2015). In this study, all HTMT values are below the threshold value of 0.9, providing additional evidence of discriminating validity (Table 5.1.6).

Table 5.1.6. Heterotrait-Monotrait Ratio

	Automaticity	Behavioral Intention to use	Effective use behavior
Automaticity			
Behavioral Intention to use	0.885		
Effective use behavior	0.708	0.679	

Source: PLS Software

5.1.6 Collinearity Assessment

In addition to checking the measurement model, the structural model must be properly evaluated before drawing up any conclusion. Collinearity must be checked to make sure it does not generate any bias on the regression results. This process is similar to assessing formative measurement models, but latent variable scores of the predictor constructs in a partial regression are used to calculate the VIF values (Table 5.1.7).

Table 5.1.7. Collinearity

Constructs	VIF	Colinearity problem? (VIF >5)
aprender_chatbots_facil	3.566	No
automaticamente_uso_chatbots	3.395	No
chatbots_faceis_usar	3.525	No
chatbots_interacao_flexivel	2.432	No
completar_tarefas_rapidamente	2.223	No
confiante_uso_chatbots	2.924	No
conhecimento_usar_chatbots	3.744	No
controle_uso_chatbots	4.460	No
divirto_usar_chatbots	2.887	No
facilita_comprar_online	3.296	No
interacao_chatbots_clara_compre	3.499	No
melhora_qualidade_servico	3.014	No
otimiza_experiencia_consumidor	3.684	No
recursos_usar_chatbots	3.545	No
uso_chatbots	4.019	No
uso_chatbots_agradavel	3.908	No
uso_chatbots_boa_ideia	3.616	No
uso_chatbots_ideia_sabia	3.680	No
uso_chatbots_prazeroso	3.872	No
uso_chatbots_regularmente	1.715	No
util_usar_chatbots	3.744	No

Source: PLS Software

VIF values above 5 are indicative of probable collinearity issues among the predictor constructs (Mason & Perreault, 1991; Becker et al., 2013). The collinearity assessment results can be seen on the table above, suggesting that there is no indicative of collinearity between each set of variables, where all VIF values are lower than 5.

When the measurement model assessment is satisfactory, the next step in evaluating PLS-SEM results is assessing the structural model. Standard assessment criteria to be considered, include the coefficient of determination (R^2), the blindfolding-based cross-validated redundancy measure (Q^2), and the statistical significance and relevance of the path coefficients. In addition, it is assessed model's out-of-sample predictive power by using the PLS predict procedure (Shmueli *et al.*, 2016).

5.1.7 Coefficient of Determination (R^2)

Once the measurement model is deemed to be of sufficient quality, one can proceed to assess the structural model. If OLS is used for the structural model, the endogenous construct's R^2 value is the point of departure. It indicates the percentage of variability accounted for by the precursor constructs in the model. The adjusted R^2 value takes into account model complexity and sample size and is thus helpful to compare different models, or the explanatory power of a model, across different data sets.

The assessment of coefficient of determination (R^2), is an important part of structural model evaluation in this research, Effective Use Behavior is the main construct of interest. However, it is important to analyse in addition, the coefficient of determination (R^2) for the Behavioral Intention to Use, once it is also explained by the third latent variable Automaticity.

According to Hair *et al.* (2013) threshold value, 0.25, 0.5 and 0.7 marks are used to describe a weak, moderate and strong coefficient of Determination.

From the PLS path model estimation diagram (Figure 5.1), as can be seen in the Table 5.1.8, the coefficient of determination, R^2 , is 0.704 for the endogenous latent variable Behavioral Intention to Use and is 0.447 for the endogenous latent variable Effective Use Behavior. This means that the latent variable Automaticity strongly explain 70.4% of the variance of Behavioral Intention to Use and the two latent variables (Behavioral Intention to Use and Automaticity) moderately explain 44.7% of the variance of Effective Use Behavior.

Table 5.1.8. Coefficient of Determination (R^2)

	R Square	R Square Adjusted
Behavioral Intention to use	0.704	0.702
Effective use behavior	0.447	0.438

Source: PLS Software

5.1.8 Predictive Relevance (Q^2)

An assessment of Stone Geisser's predictive relevance (Q^2) is important because it checks if the data points of indicators in the reflective measurement model of the endogenous construct can be predicted accurately. Table 5.2.9 shows that the proposed model has a good predictive relevance (0.329) for the endogenous variable (Effective Use Behavioral). The Q^2 value for the endogenous variable (Behavioral Intention to Use) is above zero (0.367), as well as, the Q^2 value for the endogenous (Effective Use Behavior) is above zero (0.329), which indicates the predictive relevance of the model (Chin., 1998; Hair et al., 2017).

Table 5.1.9. Predictive Relevance (Q^2)

	SSO	SSE	$Q^2 (=1-SSE/SSO)$
Automaticity	351.000	351.000	
Behavioral Intention to use	1755.000	1110.594	0.367
Effective use behavior	351.000	235.480	0.329

Source: PLS Software

5.1.9 Path Coefficients

On this project, the relationships between constructs are determined by examining their path coefficients and related t statistics via a bootstrapping procedure. Table 5.1.10 shows that all of the structural model relationships are significant ($P \text{ Value} < 0.05$). The path coefficient estimates for the hypothesized relationships included in this research range from 0.295 to 0.844 and are all at a 5% significance level. A path coefficient estimate is considered as statistically significant, if different from zero at a 5% significance level, when its p-value is below 0.05, or when the 95% bootstrap percentile confidence interval constructed around the estimate does not cover zero.

P value test: To conduct a test of the hypothesis that β (original sample "O") > 0 , at the 0.05 significance level (i.e., 1-95%), we calculate the one-tailed P value associated with the path coefficient. Generally speaking, this quantity could be interpreted as the probability that β belongs to a distribution with mean of zero and standard deviation of σ (STDEV). It can be calculated as the area under the curve shown on the left side of the figure 9, considering the total area to be 1. If $P \leq 0.05$ the hypothesis is accepted, otherwise it is rejected.

The T ratio test (or T statistics) can be seen as a variation of this test, where the T ratio (a.k.a. T value, T statistic, and t-statistic), calculated as β/σ , is used instead of the corresponding P value for comparison against a threshold such as 1.64 (to be significant at 90%), 1.96 (to be significant at 95%) or 2.57 (to be significant at 99%). If the values are higher than 3.29, which

is the case of the first two paths, on the present research (table 18), it means they are significant at 99.9% (Chin, Marcolin & Newsted, 2003).

Table 5.1.10. Path Coefficients

Path:	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (O/STDEV)	P Values
Automaticity -> Behavioral Intention to use	0.839	0.844	0.025	34.211	0.000
Automaticity -> Effective use behavior	0.297	0.295	0.147	2.025	0.043
Behavioral Intention to use -> Effective use behavior	0.400	0.403	0.137	2.920	0.004

Source: PLS Software

The results according to table 5.1.10, highlight that Automaticity positively influences the Effective Use Behavior ($\beta=0.839$, $p<0.05$), supporting hypothesis H2a. Likewise Automaticity positively influences the Behavioral Intention to Use ($\beta=0.297$, $p<0.05$), supporting hypothesis H2b.

Moreover, the results highlight that Behavioral Intention to Use positively influences the Effective Use Behavior ($\beta=0.400$, $p<0.05$), supporting hypothesis H1.

To test the mediation hypothesis (H2b), the recommendations of Hair et al. (2017) were followed. Thus, a bootstrapping procedure was applied to test the significance of indirect effects through the mediator. Table 5.1.9.2 presents de results of the mediation effects.

Table 5.1.11. Bootstrap results for indirect effects

Path	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (O/STDEV)	P Values
Automaticity -> Behavioral Intention to use -> Effective use behavior	0.336	0.340	0.114	2.938	0.003

Source: PLS Software

The indirect effect of Automaticity on Effective Use Behavior via the mediator of Behavioral Intention to Use was significant ($\beta=0.336$, $p<0.05$), thus verifying the mediation hypothesis H2b.

Following the results from the analysis, it is possible to verify which of the hypotheses of the research model were accepted. Table 5.1.11 presents the hypotheses of the study, in addition to the value of β and its statistical significance, that will support the decision of rejecting or accepting the hypothesis presented.

Table 5.1.12. Hypotheses testing

Hypotheses	β	P-value	Accepted/Rejected
H1: Behavioral Intention to Use positively influences the Use Behavior of Chatbots in E-commerce	0.400	0.004	Accepted
H2a: Automaticity positively influences the Use Behavior of Chatbots in E-commerce	0.297	0.043	Accepted
H2b: Automaticity positively influences the Behavioral Intention to Use Chatbots in E-commerce	0.839	0.000	Accepted
H3 – Automaticity moderates the effect of Behavioral Intention to Use on the Effective Use Behavior of Chatbots in E-commerce	0.336	0.003	Accepted

Author's Elaboration

From the analysis of hierarchical regressions, all hypothesis were accepted. Hence it is possible to infer that Behavioral Intention to Use and Automaticity influence the Effective Use Behavior of chatbots on e-commerce, and Automaticity influences Behavioral Intention Use and moderates the effect of Behavioral Intention to Use on the Effective Behavior.

5.2 Discussion

In this subchapter, the results of the empirical data are critically compared with the findings explored throughout the Literature Review Chapter.

The main purpose of this study was to understand consumers' acceptance of AI based intelligent products on e-commerce with a particular focus on chatbots. So, for this purpose, the model intended to answer the Research Question *Which factors influence the use of chatbots on e-commerce?* In order to do so, the model identified two main factors which were based on the Literature Review conducted for the dissertation.

The two factors are 1) Behavioral Intention to Use (Fishbein & Ajzen, 1975; Ajzen, I., 1985; Davis et al., 1989; Ajzen, I., 1991; Venkatesh & Davis, 2000; Venkatesh & Morris, 2000; Venkatesh et al., 2003; Brown & Venkatesh, 2005; Venkatesh et al., 2012) and 2) Automaticity (Venkatesh et al., 2003; Kim & Malhotra, 2005; Kim et al., 2005; Limayem et al., 2007).

The validity of the model is shown in the previous section, ultimately aiming to understand the acceptance of chatbots, consumers have been enquired.

Several indicators were used for each variable. Regarding Behavioral Intention to Use, the used indicators were “Attitude Toward Behavior” (Fishbein & Ajzen, 1975; Davis et al., 1989), “Perceived Ease of Use” (Davis et al., 1989; Venkatesh & Davis, 2000), “Perceived Usefulness” (Davis et al., 1989; Venkatesh & Davis, 2000), “Perceived Behavioral Control” (Ajzen, I., 1985; Ajzen, I., 1991), “Effort Expectancy” (Venkatesh & Morris, 2000; Venkatesh et al., 2003), “Hedonic Motivation” (Brown & Venkatesh, 2005; Venkatesh et al., 2012), and “Social Influence” (Venkatesh & Davis, 2000; Venkatesh et al., 2003).

These indicators, retrieved from the literature review intend to represent intentions to perform behaviors toward which they have positive effect. The questions asked in the survey show that, the first six indicators have a strong influence on the Behavioral Intention to Use factor. However, regarding the last indicator, “Social Influence” (Venkatesh & Davis, 2000; Venkatesh et al., 2003) it was excluded from the analyses, since the constructs that were supporting the indicator were removed because the respective outer loadings were lower than the 0.6 threshold level. In this way, “Social Influence” does not have a positive effect on the variable Behavioral Intention to Use, what comply with the literature review, since this indicator, does not have a significant effect in a voluntary context (Venkatesh & Davis, 2000).

Regarding the Automaticity, the used indicator was “Habit” (Venkatesh et al., 2003; Kim and Malhotra, 2005; Kim et al., 2005; Limayem et al., 2007) intended to explain the extent to which a person tend to perform a behavior automatically because of learning. The questions asked in the online survey, regarding this indicator show that this indicator has a strong influence on the Behavioral Intention to Use, as well as, on the Effective Use of chatbots.

After identifying the main factors that may contribute to the intention to use and the effective intention to use of chatbots on e-commerce the previously formed hypotheses were tested. As shown before, the two direct effects proved significant, as well as, the indirect effect. Starting by showing that Behavioral Intention to Use positively influences the Use Behavior of Chatbots in E-commerce, supporting hypothesis H1. This is in line with the literature review, that identify behavioral intention as a measure of the strength of a person’s intention to perform a specified behavior (Fishbein & Ajzen, 1975).

Also supported by the model, is the hypothesis H2a, which state that Automaticity positively influences the Use Behavior of Chatbots in E-commerce. The literature suggests that related to the operationalization of habit as a prior use (Kim & Malhotra, 2005), that prior use is a strong predictor of future technology use. Hypothesis H2b was also supported by the results

in the model, stating that Automaticity positively influences the Behavioral Intention to Use Chatbots in E-commerce. Literature suggests also, according to Limayem et al. (2007) that an operationalization of habit have a direct effect of intention and also moderate the effect of intention on technology use such that intention is less important with increasing habit.

Regarding the indirect effects it was possible to verify that Automaticity moderates the effect of Behavioral Intention to Use on the Effective Use Behavior of Chatbots in E-commerce, supporting hypothesis H3. This is in line with the literature review, that considers the operationalization of habit have a direct effect of intention and also moderate the effect of intention on technology use (Limayem et al., 2007).

Finally, the results obtained through the model, are supported by the literature review, showing that Behavioral Intention to Use and Automaticity have positive influence in the Effective Use of Chatbots in E-Commerce, and also, the indirect effect of Automaticity is verified.

Chapter VI – Conclusions

The use of AI based intelligent products, has gained a greater presence in our daily lives. The aim of this investigation was to analyse which factors influence the use of chatbots on e-commerce. To analyse the problem statement, a quantitative online survey was conducted to gain insights regarding consumers' acceptance perspectives of the perceived value of chatbots in e-commerce.

Two variables were selected considering the scientific findings highlighted in the bibliographic review of the present dissertation: Behavioral Intention to Use (Fishbein & Ajzen, 1975; Ajzen, I., 1985; Davis et al., 1989; Ajzen, I., 1991; Venkatesh & Davis, 2000; Venkatesh & Morris, 2000; Venkatesh et al., 2003; Brown & Venkatesh, 2005; Venkatesh et al., 2012) and Automaticity (Venkatesh et al., 2003; Kim & Malhotra, 2005; Kim et al., 2005; Limayem et al., 2007).

Analysing the current psychological motivations for Portuguese consumers' acceptance of AI based intelligent products through quantitative analysis, it was concluded that both variables positively influence the Effective Use Behavior of Chatbots in E-commerce, as well as, Automaticity positively influence the Behavioral Intention to Use and moderate the effect of Behavioral Intention to Use on the Effective Behavior.

More specifically, the hypotheses formulated for the research question (*Which factors influence the use of chatbots on e-commerce?*) tried to verify if there are significant positive relations between the psychological motivations selected through the literature and the Effective Use Behavior of Chatbots in E-commerce. What is shown by the analysis of the survey's responses is that, these relations exist, and therefore is possible to recognize which are the psychological motivations for the Portuguese consumers to use chatbots in e-commerce.

To conclude, the factors identified are: "Attitude Toward Behavior", "Perceived Ease of Use", "Perceived Usefulness", "Perceived Behavioral Control", "Effort Expectancy", "Hedonic Motivation" and "Habit" as supported by the literature review.

Ultimately, it is important to consider that AI is a technology still in current development. It is expected that, in the following years, AI based intelligent products improve and become more used, what in turn will impact the consumers perception of customers about the use of chatbots in e-commerce.

Over the years, the area of artificial intelligence related to the e-commerce sector has gained greater relevance. This phenomenon, is explained by the new habits of consumers, and the adaptation of the industry to the new needs and expectations of its customers.

In such manner, this study makes it possibly to add even more value to the scientific area of artificial intelligence based intelligent products, especially in the field of the consumers acceptance of chatbots usage in e-commerce. In the Portuguese case, there is a small number of studies on the acceptance of AI based products on e-commerce with a particular focus on chatbots, which highlights the importance of this study in this country.

In this way, the project presented, not only enriches the scientific area, but also allows future studies to draw conclusions from it. Generating even more significant results for understanding consumers' acceptance of AI based intelligent products on e-commerce with a particular focus on chatbots.

In this investigation, it was possible to see that in the last years e-commerce sector is evolving in the way that is continuously exploring new digital strategies to optimize the interaction between consumers and companies.

It is possible to verify a digital transformation, as well as the change in their business' strategies. In this way, this study makes it possible to understand the consumers' acceptance of AI based intelligent products on e-commerce with a particular focus on chatbots, and as well as, the psychological motivation factors that influence the intention to use and the effective use of chatbots on e-commerce for consumers. Making possible to understand that the strategies that the companies are adopting makes sense from the perspective of consumers.

This study was performed resorting to literature and a quantitative analysis of survey answers. As such, some limitations were found. The nature of AI based intelligent products is understandably complex, e-commerce is a growing sector and chatbots on e-commerce is a recent topic. As such, studies regarding the consumer's perception on e-commerce chatbots are scarce. Further studies would be favourable for this study.

Regarding the survey, the limitations mostly concern the fact that the targeted population was strictly Portuguese and that the sample are relatively small, and the overall lack.

For future works, the following proposals are presented: focus the study on targets groups such as Millennials, to get detailed information about their perception, attitude and usage behavior of chatbots on e-commerce; try to detect which are the obstacles in the use of AI based intelligent products, allowing to understand whether the investment made by companies in this technology is justified by consumers; and also, extend this study to other countries in order to analyse the difference regarding psychological motivations to use chatbots on e-commerce.

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Annexes

Annex A – Survey

The consumers perception about the use of Artificial Intelligence in the area of e-commerce with emphasis on chatbots

O presente questionário integra o projeto de investigação final no âmbito do mestrado em Gestão realizado no ISCTE Business School. O mesmo tem como objetivo, a análise da perceção do consumidor dos fatores que influenciam o uso de Inteligência Artificial no e-commerce, com especial destaque no uso de chatbots.

Ao longo do questionário são apresentadas afirmações relativas ao uso dos chatbots, peço que avalie a sua concordância com cada afirmação.

Todas as questões serão tratadas anonimamente.

Agradeço desde já a disponibilidade.

Informação Pessoal

1. Idade *

Selecione apenas uma opção

☐ < 18

☐ 18 - 25

☐ 26 - 35

☐ 36 - 50

☐ > 50

2. Gênero *

Selecione apenas uma opção

- ☐ Feminino
- ☐ Masculino
- ☐ Outra opção...

3. Escolaridade *

Selecione apenas uma opção

- ☐ Ensino Básico
- ☐ Ensino Secundário
- ☐ Licenciatura
- ☐ Pós-graduação
- ☐ Mestrado
- ☐ Doutoramento

Chatbots



Chatbots, também denominados de assistentes virtuais de e-commerce, são um agente de software especializado em serviços de suporte a negócios e serviços técnicos para comércio conversacional. Os chatbots interagem com os consumidores para dar ao mesmo, um atendimento personalizado. Por favor, selecione a opção que mais se adequa à sua percepção relativa ao uso dos chatbots, considerando 1 como "Discordo plenamente" e 7 como "Concordo plenamente".

4. Aprender a operar com chatbots no e-commerce é fácil para mim *

	1	2	3	4	5	6	7	
Discordo plenamente	☐	☐	☐	☐	☐	☐	☐	Concordo plenamente

5. Eu acho os chatbots fáceis de usar *

	1	2	3	4	5	6	7	
Discordo plenamente	☐	☐	☐	☐	☐	☐	☐	Concordo plenamente

6. Aprender a usar chatbots é fácil para mim *

	1	2	3	4	5	6	7	
Discordo plenamente	☐	☐	☐	☐	☐	☐	☐	Concordo plenamente

7. Considero os chatbots de interação flexível *

	1	2	3	4	5	6	7	
Discordo plenamente	☐	☐	☐	☐	☐	☐	☐	Concordo plenamente

8. A minha interação com os chatbots é clara e compreensível *

	1	2	3	4	5	6	7	
Discordo plenamente	☐	☐	☐	☐	☐	☐	☐	Concordo plenamente

9. As pessoas que influenciam o meu comportamento acham que eu deveria usar chatbots *

	1	2	3	4	5	6	7	
Discordo plenamente	☐	☐	☐	☐	☐	☐	☐	Concordo plenamente

10. As pessoas que são importantes para mim acham que eu deveria usar chatbots *

	1	2	3	4	5	6	7	
Discordo plenamente	☐	☐	☐	☐	☐	☐	☐	Concordo plenamente

11. Eu uso chatbots devido à proporção de amigos/familiares que usam chatbots *

	1	2	3	4	5	6	7	
Discordo plenamente	☐	☐	☐	☐	☐	☐	☐	Concordo plenamente

12. O uso de chatbots é uma boa ideia *

	1	2	3	4	5	6	7	
Discordo plenamente	☐	☐	☐	☐	☐	☐	☐	Concordo plenamente

13. O uso de chatbots é uma ideia sábia *

	1	2	3	4	5	6	7	
Discordo plenamente	☐	☐	☐	☐	☐	☐	☐	Concordo plenamente

14. Eu gosto da ideia de usar chatbots *

	1	2	3	4	5	6	7	
Discordo plenamente	☐	☐	☐	☐	☐	☐	☐	Concordo plenamente

15. Eu acho o uso de chatbots agradável *

	1	2	3	4	5	6	7	
Discordo plenamente	☐	☐	☐	☐	☐	☐	☐	Concordo plenamente

16. O uso de chatbots é prazeroso *

	1	2	3	4	5	6	7	
Discordo plenamente	☐	☐	☐	☐	☐	☐	☐	Concordo plenamente

17. Eu divirto-me a usar chatbots *

	1	2	3	4	5	6	7	
Discordo plenamente	☐	☐	☐	☐	☐	☐	☐	Concordo plenamente

18. Eu tenho o conhecimento necessário para usar chatbots *

	1	2	3	4	5	6	7	
Discordo plenamente	☐	☐	☐	☐	☐	☐	☐	Concordo plenamente

19. Eu tenho controlo sobre o uso de chatbots *

	1	2	3	4	5	6	7	
Discordo plenamente	☐	☐	☐	☐	☐	☐	☐	Concordo plenamente

20. Eu tenho os recursos necessários para usar chatbots *

	1	2	3	4	5	6	7	
Discordo plenamente	☐	☐	☐	☐	☐	☐	☐	Concordo plenamente

21. Sinto-me confiante quando uso chatbots *

	1	2	3	4	5	6	7	
Discordo plenamente	☐	☐	☐	☐	☐	☐	☐	Concordo plenamente

22. O uso de chatbots permite-me completar tarefas mais rapidamente *

	1	2	3	4	5	6	7	
Discordo plenamente	☐	☐	☐	☐	☐	☐	☐	Concordo plenamente

23. O uso de chatbots melhora a qualidade do serviço *

	1	2	3	4	5	6	7	
Discordo plenamente	☐	☐	☐	☐	☐	☐	☐	Concordo plenamente

24. O uso de chatbots otimiza a minha experiência de consumidor *

	1	2	3	4	5	6	7	
Discordo plenamente	☐	☐	☐	☐	☐	☐	☐	Concordo plenamente

25. O uso de chatbots facilita comprar online *

	1	2	3	4	5	6	7	
Discordo plenamente	☐	☐	☐	☐	☐	☐	☐	Concordo plenamente

26. Eu acho útil usar chatbots *

	1	2	3	4	5	6	7	
Discordo plenamente	☐	☐	☐	☐	☐	☐	☐	Concordo plenamente

27. Eu uso chatbots regularmente *

	1	2	3	4	5	6	7	
Discordo plenamente	☐	☐	☐	☐	☐	☐	☐	Concordo plenamente

28. Quando uso um site de e-commerce, automaticamente uso chatbots *

	1	2	3	4	5	6	7	
Discordo plenamente	☐	☐	☐	☐	☐	☐	☐	Concordo plenamente

29. Quando uso um site de e-commerce uso chatbots *

	1	2	3	4	5	6	7	
Discordo plenamente	☐	☐	☐	☐	☐	☐	☐	Concordo plenamente