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Impact of the Virtual Assistant's Interactive Dimensions in the Portuguese Young Adults' Customer Experience Expectations and Patronage Intentions, In the Retail Context

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Master in Management

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BUSINESS
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To all,

My sincere thanks.

SUMÁRIO

Ao longo dos tempos, tem-se vindo a testemunhar uma evolução na forma como o comércio é feito nos vários setores de atividade. As empresas têm de se reinventar constantemente para satisfazer as necessidades e expectativas dos consumidores, que resultam dos avanços tecnológicos. O mesmo acontece no setor do Retalho, que tem vindo a inovar, acompanhando a tecnologia e as tendências dos consumidores. Um exemplo disto é o aparecimento da uma nova forma de comércio, o comércio conversacional. Este combina a tendência de comunicação via mensagens instantâneas com o desenvolvimento da inteligência artificial, introduzindo assistentes virtuais neste setor.

O principal objetivo deste estudo prende-se com a investigação do impacto que a inclusão de um assistente virtual teria no setor do retalho interagindo com os jovens adultos portugueses. Para tal, procurou identificar-se quais as dimensões da interação com um assistente virtual – cognitiva, afetiva e comunicativa - que influenciariam as expectativas relativas à experiência de compra e consequentemente as intenções de uso e compra dos consumidores. Para a investigação foi utilizada uma metodologia quantitativa, com a criação de um chatbot informativo e de um questionário online, ao qual responderam 385 portugueses com idades desde os 18 até aos 35 anos, com acesso ao *Facebook Messenger*.

Neste estudo foi provado que as expectativas dos consumidores em relação à experiência de compra influenciam as suas intenções de uso (assistente virtual) e compra (retalhista). No entanto, apenas a dimensão cognitiva mostrou ter um impacto significativo na criação de expectativas relativas à experiência de compra.

Palavras-chave: Comércio Conversacional, Retalho, Inteligência Artificial, Assistente Virtual, Processo de tomada de decisão, Experiência de Compra

JEL Classification Codes: M150; M31

ABSTRACT

Throughout the times it has been witnessed a continuous evolution in the way people make business transactions, across sectors. This has been highly influenced by technological developments and the constant need for companies to adjust to their clients' needs and expectations. The retail sector has been no exception, evolving alongside innovation, and adapting to new trends. One of its results is the emergence of conversational commerce, a new form of commerce that combines the trend of communicating via instant messages and the use of artificial intelligence, introducing virtual assistants to the retail context.

The aim of this study is to better understand the potentialities virtual assistants have in the Portuguese retail context, amongst young adults. By identifying which of the dimensions of the interaction with a retailer virtual assistant - *Cognitive Perception, Affective Engagement, and Communication Quality* - have a significant impact on the expectation users create towards their customer experience and how this is determinant to their patronage intentions towards the retailer. A quantitative methodology was used to perform this investigation, with the development of an introductory chatbot and an online survey, completed by 385 individuals (Portuguese young adults, with ages ranging from 18 to 35, and that had access to the *Facebook Messenger* app).

The Customer Experience Expectation was proven to have a significant impact on the respondents' patronage intentions towards the virtual assistant and the retailer. However, only the cognitive dimension of the virtual assistant was confirmed to significantly impact the expectations on the customer experience.

Keywords: Conversational Commerce, Retail, Artificial Intelligence, Virtual Assistants, Decision-making process, Customer Experience

JEL Classification Codes: M150; M31

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GLOSSARY OF ACRONYMS

AI – Artificial Intelligence

CAT – Consumer Acceptance Technology

CRM – Customer Relationship Management

CX – Customer Experience

EFA – Exploratory Factor Analysis

PAD – Pleasure, Arousal, Dominance

TAM – Technology Acceptance Model

1. INTRODUCTION

1.1. Research Context & Problem Framing – Definition and relevance of the study

The way people do business has been in constant change throughout the times. In order to keep being relevant for the consumers, businesses have to reinvent themselves constantly, being up to date with the technological innovations and trying to meet the challenging consumers' needs, always changing and evolving.

The increasingly pace of technological developments have enabled new forms of commerce. It has been gaining new formats and different interactions with the clients, from the more traditional ones, contact with people in physical stores, to more technological and revolutionary ones, such as conversational commerce, an online interactive contact with virtual/ non-human assistants, like chatbots.

Phenomena like this gained more relevance with the increasingly accessibility to internet, mobile technology and technological developments, and is then shaping different aspects of the customers lives, as it defended in the Nielsen study *"Connected Commerce: a conectividade na origem da evolução dos estilos de vida,"* (2019).

Artificial Intelligence has been introduced into our daily lives in various ways, and therefore, it shows up, as expected, as a marketing trend. It complements the technological enhancements with its convenience and effort to ease people's life's. Conversational commerce is the result of this combination, through inserting either voice recognition assistants or chatbots in mobile messaging applications.

As this is a new trend, and brands, especially in Portugal are just now beginning to make this transition and creating their own chatbots (even though they might already have quite a significant presence in other countries) it is important to better understand how they work and what their role as an engagement tool between the organization and the public could be.

This issue it is expected to become more and more relevant to businesses as the time goes by, brands become more accessible for their clients, as it is easier to reach them, in this case through an already installed messaging app where customers can directly contact the brand.

Nowadays, in the pandemic context that is being lived, brands are forced to reinvent and adjust themselves to the new routines and lifestyles of their customers, at an even faster pace than they would normally have to. Consumer habits are shifting, according to the SIBS Analytics report "*100 Dias de Pandemia - Retrato das alterações nos hábitos de consumo dos*

Portugueses" (2020), the digital channels are the preferred ones by the Portuguese people, this choice is made out of need, as a response to the lockdown and as a preference for security. A 30% growth in e-commerce activities in October 2020 was noticed when compared to the same period last year, in line with the trend that has been verified over the year *(“Alterações nos hábitos de consumo dos portugueses,*” 2020).

The thematic of conversational commerce is then more pertinent than ever, alternatives to the traditional channels are now being pursued by the costumers, and the retail sector, as a major player in people’s daily life, should now look for innovative ways to meet customers’ needs. It can, therefore, be considered to be relevant to further study the impact virtual assistants have in the customer experience, which dimensions of their interaction are more important for the users, and should consequently, be integrated and developed when creating the chatbot.

Customers can, this way, communicate directly to the retail brand, be guided and have assistance throughout the entire decision-making process, in an intuitive and convenient conversation via instant messages.

Having that in mind, this thesis aims to study the impact conversational commerce, through the integration of a virtual assistant in the retail context, has in the perception of the Portuguese young adults Customer Experience and patronage intentions.

1.2. Investigation Objectives & Research Questions

The main objective of this thesis is to better understand in which way can a virtual assistant, specifically a chatbot integrated in a mobile messaging app, like the Facebook messenger app, can be used as a communication tool for retailers to interact with the Portuguese costumers:

Which dimensions of the interaction with a retailer virtual assistant will have a significant impact in the expectation users create towards their customer experience and how it will be determinant to their patronage intentions towards the retailer?

In this new technological era, brands must adjust its forms of commerce and communication in order to remain relevant for the consumer, the same applies in the retailing sector. It has a great importance in people’s lives and since it is part of their daily routines, every change in the way brands are able to reach their clients will impact, to a certain level, their perception of the brand itself and the entire customer experience.

In order to approach the main research question stated above, allied with the complexity and innovation inherent to the theme, it is also important to subdivide it into different issues that should be addressed:

· Understand the additional value given by costumers to the existence of a virtual assistant in the retail sector.

· Identify which dimensions of the virtual assistant have a higher impact in the interaction with the users and how they impact their customer experience.

· Detect the main attributes and features costumers consider to be essential to be incorporated into the virtual assistant.

· Analyse the impact that a positive customer experience expectation has on the users' patronage intentions.

· Identify on which stages of the shopping journey the customers consider the virtual assistant to be more valuable.

· Find what are the retail sectors where customers are more likely to interact with a virtual assistant.

· Understand what might be the barriers and concerns costumers have regarding the use of a chatbot.

· Identify best practices for the creation and integration of a virtual assistant into retail brands.

· Propose a set of attributes and approaches based on costumer's preferences for the development of a virtual assistant for retail.

This analysis intends to help retailers better comprehend how the young adults audience feel about the availability and usage of a retail brand chatbot, that would guide them through the entire shopping journey. It aims also to present them with a set of suggestions on which dimensions of the virtual assistant they should bet when developing the chatbot to meet customers' specific needs. Retail brands should then be more capable to create and develop a more complete marketing strategy that encompasses this conversational commerce tool, the virtual assistant.

1.3. Dissertation Structure

This dissertation is organized and divided into six Chapters, and the correspondent topics and subtopics. The first Chapter introduces the thematic that will be developed throughout the dissertation, framing the problematic in the specific context of the investigation and addressing its objectives and research questions that will be the starting point for the entire study.

The Chapter 2 comprises the literary review, enclosing previous studies and researches made in the thematic of the customer experience and new forms of commerce that emerged from technological developments, contextualizing it to the specificities of the retail sector. Leading to the hypotheses' formulation and the proposition of a conceptual model in Chapter 3.

In the Chapter 4 it will then be presented the methodology used for performing this investigation, from the definition of the universe under analysis to the methods used to collect the necessary data for the study of the research variables. The analysis of the results obtained from the methodology adopted will then be revealed and studied more in depth in Chapter 5.

Finally, Chapter 6 contains the relevant conclusions taken from the analysis of the collected data in this research, as well as the study's limitations and contributions for the future.

2. LITERATURE REVIEW

Considering previous researches and investigations on the thematic of this dissertation, this chapter intends to provide a better understanding of the evolution of the retail sector (1), especially in terms of the interaction and communication between businesses and its customers. Emphasizing, additionally, the importance of considering the customer experience (2) as a significant determinant for the business success, while tackling its role and implications throughout the customer shopping journey, and highlighting the relevance of retailers working towards meeting their clients' expectations.

In addition, it also aims to deconstruct an emerging form of commerce: conversational commerce (3), stressing the role of social media and messaging apps on its development and growth, and how technological developments and artificial intelligence contribute for it as well.

Moreover, it will be presented a more in-depth analysis of a form of artificial intelligence, the chatbots (4), that stands out in this new form of commerce. Its attractiveness for brands and part in the retail context will also be taken under consideration, while considering its implementation specificities and the impact it may have in the customer experience, leading to the hypotheses' formulation in the next chapter.

2.1. Retail sector

The Retail sector encompasses all the business activities related to the sale of goods and services made directly to the end consumer. It includes, therefore, a wide range of business areas and channels that include the direct interaction between the company and the end user (Lindon *et al*., 2013).

This sector has suffered some major changes throughout the times, especially in terms of the channels used to reach the customers, *"from the Industrial Age department stores to today's multi-channel, ubiquitous environments (...)"* (Diaz, *n.d*.), with the constant goal and effort to adapt to the continuous technological advancements in the industry.

Allied to this, there is the additional pressure on the businesses to keep innovating if they want to be successful "*in a highly dynamic and competitive customer-driven market*" (Diaz, *n.d.*). Resulting in a constant need to adapt the way the communication goes through, both internally, within the company, and externally, towards their customers, so that the businesses can meet the clients' constant changing expectations (Diaz, *n.d*.; O'Brien, 2019).

The businesses' communication can, then, be defined as the way they *"(...) inform, persuade, enlighten, teach, remind, and enrich the knowledge of their stakeholders about the brand, its strengths, values, fundamentals, and its offerings of products and services."* (Bhasin, 2019).

For a successful communication between brands and their costumers it is important that a communication strategy is defined, states Baynast *et al.*, (2018). One that considers the brand objectives, the targeted audience, the channels available and the mensage that is going to be transmited, they add.

One of the brand's communication objectives, amongst others, is the engagement of the consumer towards the brand, to encourage and improve their relationship, and therefore to lead to the ultimate goal of making a sale. This result is the intended outcome of the brand's communication strategy, and, to accomplish it, the more specific and detailed objectives that compose it, have to tackle the phases that preced it, leading the client to make the purchase (Baynast *et al.*, 2018).

Although being crucial to a brands success, its communication is not the only factor to take under consideration when defining a strategy to engage with the customers. It is, however, an integrated and highly important piece when creating and managing the Customer Experience. It is the starting point for this, since "*Communication breeds commitment."* as Franz (2012) summarizes. It instigates a relationship with all the stakeholders of honesty and trust, as well as *"(...) understanding and accountability, promotes participation, establishes a foundation for meaningful change, and leads to a successful outcome."* (Franz, 2012).

All the actions and decisions a brand makes have an impact on the customer's perception of the brand, as well as on their interaction with it and the overall shopping experience. Therefore, the investment retailers make on customer experience might be crucial for their success (Gentile *et al.*, 2007; Hyken, 2018; Verhoef *et al.*, 2009).

2.2. Customer Experience

As a key determinant in the success of a Retailer, it is extremely important to first, better understand the concept of Customer Experience, in what it consists of and which aspects influence it.

This concept was introduced in the mid-1980s, as part of the approach that started to perceive customers as rational decision makers, and developed from there to present days with the introduction of the importance of emotions in the customers behaviour, and later with the perception of it as an holistic experience of the customer with a company at different levels (Gentile *et al.*, 2007).

Across the literature, different and complementary definitions of customer experience have emerged throughout the years, representing the evolution described in the previous paragraph. For this study it will be taken under consideration some of the more consensual, and commonly accepted definitions.

An example of this is the emphasis on a multidimensional view of the concept, as it was defended by Schmitt (1999), where he *"(...) identifies five types of experiences: sensory (sense), affective (feel), cognitive (think), physical (act), and social-identity (relate) experiences."* (as cited in Lemon & Verhoef, 2016), that a costumer can experience throughout the sale.

According to Gentile *et al.* (2007):

> ''*The Customer Experience originates from a set of interactions between a customer and a product, a company, or part of its organization, which provoke a reaction. This experience is strictly personal and implies the customer's involvement at different levels (rational, emotional, sensorial, physical and spiritual)*" (p.397)

Meyer & Schwager (2007) consider that the Customer Experience should be defined as the individual and unique response of a customer to both direct and indirect interactions with the company. This definition complements the previous one with the distinction between direct and indirect contacts. The first *"(...) generally occurs in the course of purchase, use, and service and is usually initiated by the customer."*(Meyer & Schwager, 2007), whereas the indirect ones consist of all the unintentional contacts with the brand, its services and products, through different channels like *"(...) word-of-mouth recommendations or criticisms, advertising, news reports, reviews, and so forth."* (Meyer & Schwager, 2007).

Verhoef *et al.* (2009), contextualize the customer experience for the Retail sector and reinforce its multidimensional perspective and holistic nature, by incorporating the *"(...) cognitive, affective, emotional, social and physical responses (...)"* (Verhoef *et al.*, 2009) of the customers towards the retailers. And add to the definition, that the overall experience encompasses more than just what is under the retailer's control, as the atmosphere, product placement, its price and the service provided, but also factors and dimensions external to its control, exemplified by external influences on the customers and the reasons that led them to shop.

The idea that empirical features are a significant piece in the value proposition offered to customers was reinforced by Gentile *et al.* (2007). Despite the context they are inserted in, *"(...)*

customers want to live positive consumption experiences" Gentile *et al.* (2007), which can lead them to be emotionally connected with the brand and consequently tighten up this relation and increase their loyalty towards the brand.

In order to be able to measure the user experience on a attitudinal and behavioural scale, Rodden *et al*., (2010) developed the HEART framework, that stands for Happiness, the overall satisfaction with the Experience, Engagement, the frequency and intensity of the users' interactions, Adoption, addition of new users, Retention, maintaining users, and Task success, accomplishment of the task efficient and effectively.

Businesses are also able to measure the effects of a positive customer experience by the amount people are willing to pay for their products and services, according to Clarke & Kinghorn (2018), when customers feel valued they are more likely to spend more.

In addition, they are also more likely to return after having positive experiences with the brand and endorsing it to their family, friends, and nowadays even on social media. The authors also defend that customers will be more open to try new products and innovative services from brands who offer them a better customer experience. It is also important to highlight the need for this superior customer experience to be steady, as they found that one in three customers (in the US) will stop their relation with a brand after one bad experience with it. A good customer experience was also proven to be a decisive factor for clients when considering different purchasing alternatives (Clarke & Kinghorn, 2018).

The importance of businesses providing a good customer experience can be summarized with the advice from Clarke & Kinghorn (2018): *"Give customers a great experience, and they'll buy more, be more loyal and share their experience with friends.".*

Overall, it can be concluded that the Customer Experience incorporates the different dimensions of the interaction (*cognitive, affective, emotional, social and physical)* between the customer and the company throughout all the stages of the purchase journey. Meaning that, it englobes the entire experience, from the pre-purchase stages to the post-purchase ones and can include different retail channels (Grewal & Roggeveen, 2020; Lemon & Verhoef, 2016; Verhoef *et al*., 2009).

2.2.1. Consumer decision-making process

It will then be essential for businesses to understand how consumers behave , in order to be able to predict and influence their future decisions(Pizam *et al.*, 1999; Solomon *et al.*, 2010). Citing Stankevich (2017), based on other research articles, consumer behaviour can be defined by:

"the study of individuals, groups, or organizations and the processes they use to select, secure, use, and dispose of products, services, experiences, or ideas to satisfy needs and the impacts that these processes have on the consumer and society.".

The consumer behaviour is then subject to be influenced by different factors, varying from individual variables as needs, motivations, attitudes, personality, and lifestyle, to social and cultural variables, where others play a significant role. Additionally, variables like perceived risk and learning/experience will also play an important role in the decisions customers make across the shopping journey (Lindon *et al.*, 2013).

It is also crucial to understand the different steps that make the consumer decision-making process, understand which are the key elemements in each of them, and which role and reaction is expected from the target customer, so that the brand can plan and strategize accordingly (Stankevich, 2017).

Over time different perspectives of the decision-making process were developped. Solomon *et al.* (2010) organized this process according to the effort needed to make the decision each time, staring from routinary responses, that do not require much effort or that are not even counsciously made to extensive problem-solving, a more complex and thoughtful process.

In the same line of thought, decisional processes can be divided into four main types, according to Lindon *et al.* (2013):

- Routinary, when there is not required much effort or reflextion/planning;
- Limited decision, when there is the need to choose an option amongst a range of alternatives, but it does not require a lot of information search.
- Impulsive buy, this decisional process is not planned, it results from the arise of an unexpected need or pressure.
- Extensive decision, the costumer goes trough the entire process, it is more complex and thoughtful.

The level of detail considered to define each stage in this decision process may vary across the literature. Kotler & Keller (2012) defend that the consumer decision-making process comprehends 5 stages: the Need Recognition, Information Search, Evaluation of Alternatives, Purchase decision, and Post-purchase behavior (figure 2.1.).

Baynast *et al.* (2018) detailed the previous model into eight steps that consumers follow in their decision-making jouney: Need recognition; Problem Awareness; Search for information; Evaluation of alternatives; Decision; Buy; Evaluation and Reaction (figure 2.2.).

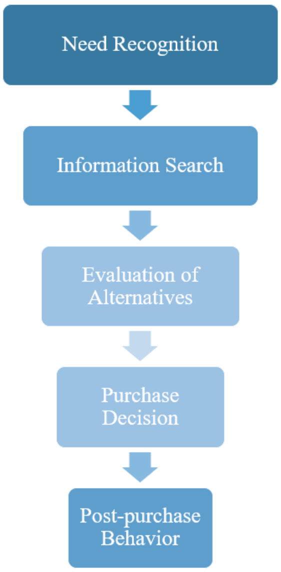

Figure 2.1: Decision-making process defined by Kotler & Keller (2012)

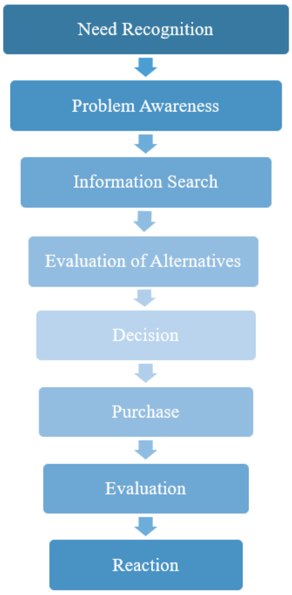

Figure 2.2: Decision-making process defined by Baynast et al. (2018)

A different vision for the consumer decision-making journey was presented by Court *et al.* (2009). They moved away from the idea of understanding this process as a funnel, as can be observed in the figures above. The previous described approaches started at a point from where there were a high number of potential brands to consider, and that were then gradually decreasing as consumers moved along the stages of the process, until there was only one brand left, the one they would choose to purchase from. Court *et al.* (2009) defended that the concept previously described did not consider *"(...)all the touch points and key buying factors resulting from the explosion of product choices and digital channels, coupled with the emergence of an increasingly discerning, well-informed consumer."* (Court *et al.*, 2009).

It was then proposed a new approach by Court *et al.* (2009), a circular one with four main stages (Figure 2.3.):

A. *Initial consideration*: In this starting point, consumers think about the set of brands they are already aware of.

B. *Active evaluation / Information gathering*: At this stage, consumers search for more information and might increase or reduce the set of brands previously considered, as they evaluate their options according to what they are looking for.

C. *Closure / Moment of purchase*: When the consumers select a brand at the moment of purchase, choosing a brand instead of others.

D. *Postpurchase*: At this stage the consumer will evaluate if the expectations he had for the product/service were met and, that, will impact future purchase journeys. In case the expectations are met a loyalty might be created for the next journey, where the consumer might skip the first two stages and go directly to the closure one.

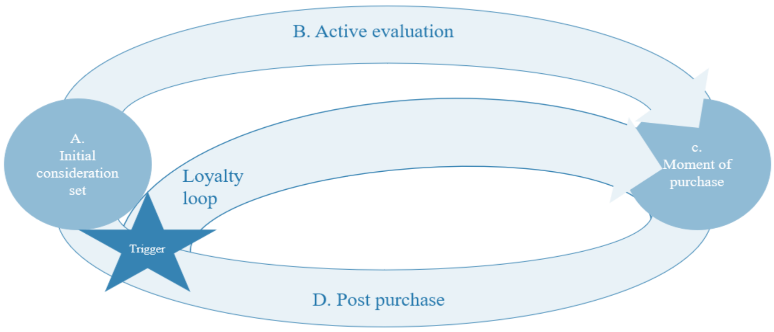

Figure 2.1: Proposed approach for consumer decision-making journey by Court et al. (2009).

Grewal & Roggeveen (2020), also take a nonlinear vision on the process, presenting also a circular version of this dynamic and iterative journey (figure 2.4.). They divided it into three main stages: pre-purchase, purchase, and post-purchase, and included the possibility of existing loops between them as current and future experiences are influenced by past ones. Additionally, "*each decision stage is represented as having cognitive, emotional, and behavioral elements*" (Grewal & Roggeveen, 2020). In this model, it is also taken under consideration external factors and influences, as it is the case of retail atmosphere, social, cultural and political contexts, and technology.

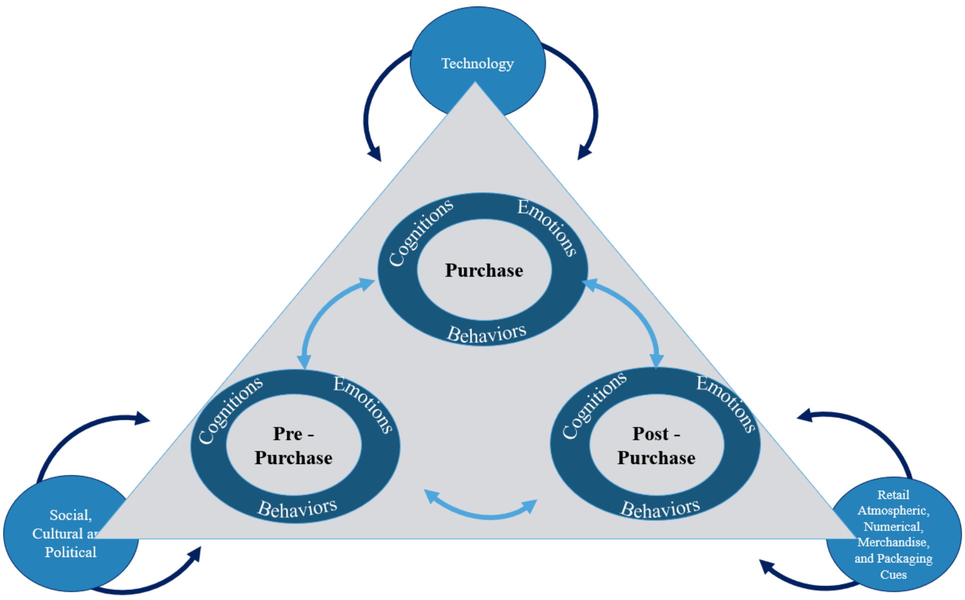

Figure 2.2: Retail experience and customer journey management model by Grewal & Roggeveen (2020).

2.2.2. Costumer Experience Expectation

Consumers' expectations are continuously changing, nowadays even more, as technology breakthroughs occur and new developments show up. Costumers are more and more demanding and retailers in response have to consider the trade-off between what the customers really want and need, and what they, as a business, can change in order to meet those needs (Sides & Swaminathan, 2020).

Clarke & Kinghorn (2018) warns for the exiting gap between the customers expectation and what they are actually getting in terms of the shopping experience, and the need for retailers to work on closing this gap. A path for this, they argue, is through the use of technology since it is believed to "(…) *have an impact on customer experience, and the majority of consumers are aware of that. But that impact could be positive, frustrating or a little bit of both."*(Clarke & Kinghorn, 2018). It will then be crucial, to be prepared for a successful implementation of such technologies so that customers are not disappointed.

Citing Lemon & Verhoef (2016):

> *"One key element of understanding and managing customer experience is the ability to measure and monitor customer reactions to firm offerings, especially customer attitudes and perceptions. (...) Satisfaction has primarily been conceptualized as resulting from a comparison of the actual delivered performance with customer expectations."* (p.71)

2.3. Conversational Commerce

There is no doubt that the consumers' habits have been changing throughout the years, and much due to the introduction of technology into people's lives. These technological enhancements have been, for the past years, enabling new forms of commerce in different sectors, as it is the case for Retail (Hernandez, 2017; Hou *et al.*, 2013; Martinez, 2018).

A great example of this, was the appearance of the Internet, that came to revolutionise the Retail sector, its marketing strategies and the way transactions were made. With e-commerce (electronic commerce) retailers had to change the way they operated, by integrating and providing customers with more channels, offering them the convenience to shop just by having an internet connection. Online sales and marketing initiatives are now a common reality, as most of the retailers have incorporated cross-channel strategies, being able to reach consumers simultaneously online and in physical stores (Diaz, *n.d.*; Lindon *et al.*, 2013).

Nowadays, the sector is still evolving and dealing with the continuous challenge of having to manage different channels, while trying to get closer to their customers by improving their engagement and overall experience with the brand, and keeping up to date with the latest technological improvements (Davenport *et al.*, 2020; Hou *et al.*, 2013; Passavanti *et al*., 2020).

It is the transformation from e-commerce to c-commerce (conversational commerce) that is now being witnessed, defends Darlington (2018). Conversational commerce results of the combination and "*integration of messaging apps and e-commerce*" (Van Eeuwen, 2017). "*The concept involves businesses interacting with their customers through messaging apps, chat, or voice technology to sell their products.*" (Carnett, 2018).

According to Messina (2015), conversational commerce can also be described as the way messaging apps bring the point of sale to the customer, by delivering convenience, personalization, and decision support to the customers in an era when people have barely no time to spare. The term can be used to "*describe how customers get in 'direct-contact' with businesses through messaging or voice technology.*"(Exalto *et al*., 2017).

In summary, conversational commerce can be defined as "*utilizing chat, messaging, or other natural language interfaces (i.e. voice) to interact with people, brands, or services and bots that heretofore have had no real place in the bidirectional, asynchronous messaging context*" Messina (2016).

2.3.1. Social Media and Messaging Apps

This new form of commerce emerged as a result of the existence of a clear preference for messaging as a way of communication in people's lives, states LoCascio (2018).

According to Darlington (2018), messaging apps overtook social networks when it comes to the number of monthly actively users on phones. This can be validated with the *The Messaging Apps Report* (2016), which presents that, in 2015, the "*combined user base of the top four chat apps is larger than the combined user base of the top four social networks.*" worldwide. This means that, globally, since the beginning of 2015, the big four messaging apps combined had more monthly active users than the total of the big four social networking apps.

The report also emphasizes the higher retention and usage rates of chat apps when compared to the rest of mobile apps. Clement (2019), on another Statista report, stated that the number of mobile phone messaging app users worldwide is expected to increase to 2.48 billion people by the year of 2021. In 2020, the **two most popular platforms globally are WhatsApp (with 2**

billion users) and Facebook Messenger (1.3 billion users), according to Clement (2019, 2020) and observed in the graph below (figure 2.5.).

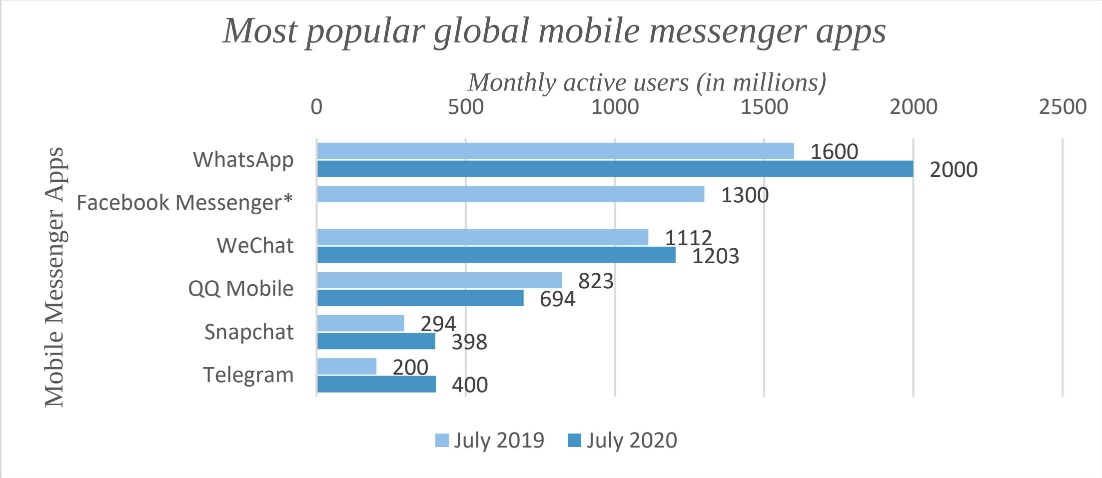

*Figure 2.3: Most popular global mobile messenger apps as of July 2019 and July 2020, based on number of monthly active users (in millions). * Facebook Messenger had no updated values up to the report publish date. Adapted: (Clement, 2019, 2020)*

It is also worth noting that an average of 21.47 minutes per day is spent on instant messaging apps among the people using these apps (Ask *et al*., 2016).

More recent numbers, provided in the "*Digital 2020: Portugal*" (2020) report, compiled by *Kepios*, *We Are Social*, and *Hootsuite*, showed that 4.54 Billion people across the world uses internet, and out of this 3.80 billion are active social media users. In January 2020, and only considering users with ages between 16 and 64 who have reportedly done an ecommerce activity in the month previous to the interview: *80% have looked online for a product / service* to buy; *90% visited an online retail store*; *74 % made an online purchase*; *36% made an online purchase via a laptop or desktop* computer; and *52% made an online purchase via a mobile device.*

With the pandemic outbreak the trend relative to e-commerce was also reinforced, leading more reluctant customers to try out this way of shopping, in response to the limitations and lockdowns imposed. Additionally, the specific trend of mobile online shopping, that was already becoming more popular in 2019, is accelerating and growing since the COVID-19 outbreak, with *"(…) its ease, portability and immediacy.(…) But the overarching trend will be towards an omnichannel experience, with consumer-facing companies needing to seamlessly integrate their offline and online experiences."*(Barr et al., 2020).

2.3.2. Portuguese Context

It is important to adapt the global reality of the internet, social media and messaging apps context to the Portuguese reality to better understand the environment where the study is being conducted. The global growing trend on the use of social media and messaging apps, is also verified in Portugal. According to Afonso (2019) the biggest growth in the adoption of social media was between the years of 2010 and 2012, and even though at a slower pace from there on, it has been continuously increasing every year.

In terms of the preferred social media platforms, for the Portuguese audience Falcão (2019) highlights five, based on a *Marktest* report: *Facebook, with 95% of the social media users accessing it, WhatsApp with 74.2%, Facebook Messenger with 70.8%, Instagram with 67.9%, and YouTube with 53.9%.*

It was presented in the *"Digital 2020: Portugal"* (2020), that in Portugal in January 2020, there were 8.52 Million internet users, which corresponds to 83% of the total population, and that the daily average of time spent on the internet independently of the device used was 6 hours and 38 minutes. When it comes to the mobile internet use, there were 7.82 Million users, and the daily average of users aged between 16 and 64 years old was of 2 hours and 45 minutes for the time spent on the internet through a mobile device.

Regarding the social media habits, also described in the *"Digital 2020: Portugal"* (2020), there were a total of *7 million active social media users* in January 2020, and an increase of 6.6% when compared to April 2019. *97% of the 7 million active users, access social media via mobile*. Focusing on the internet users with ages between 16 and 64 engagement with social media, they spent a daily average of 2 hours and 4 minutes on social media. Also 99% of the interviewed stated that have used a social network or messaging app in the previous month.

In the same period, there were a total of 6 Million people that can be reached with Facebook adverts, according to Facebook reports. The report also states that 96.5% of the Facebook users access this social media network via mobile phone, 3.5% access it via computer only, 37% via both computers and phones, and 59.5% only access it via mobile phones. Instagram reports to be able to reach 3.8 Million people with adverts on this social media, and Snapchat 1.1 Million ("*Digital 2020: Portugal*," 2020).

Also, included in the same report, it states that out of the internet users aged 16 to 64 who reportedly use mobile apps, *93% access messaging apps*, *94% social networking apps* and *60% shopping apps*. For the same age audience and comparing to the Global results already presented (Figure 2.6.), *88%* of the people who have reportedly performed any ecommerce activity in the previous month to the study, *searched online for a product* or service to buy, *81% visited an online retail store, 65% made an online purchase* and *33% made the purchase via a mobile device* ("*Digital 2020: Portugal*," 2020).

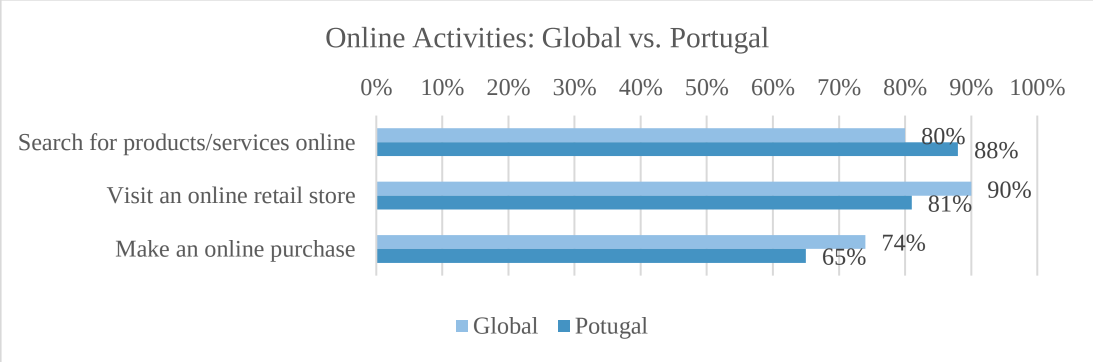

Figure 2.4: Survey Results for the comparison of activities performed online Globally vs. in Portugal Adapted:("Digital 2020: Portugal," 2020)

According to the survey from INE, *"Inquérito à Utilização de Tecnologias da Informação e da Comunicação pelas Famílias,"* (2019), in terms of the socio-demographic distribution of the Portuguese e-commerce, in 2019, male usage was higher than female (40.9% vs 36.7%), and it was also more frequent in younger age groups (71% of the users had ages between 25 and 34), for students (62.3%), and for people that had completed superior education (69.4%) or the high school (55.4%).

According to *Nielsen Connected Commerce Report 2018* (2019), 94% of the Portuguese consumers have made an online purchase at least once. And, the top 5 online purchases categories, in the Portuguese context, are: Travels, Fashion retail, Tickets to events, Books/Music/Stationery, and IT and mobile.

2.3.3. Artificial Intelligence

The unceasing technological developments, in which Artificial Intelligence (AI) can be highlighted as a relevant example, are offering industries new possibilities to adjust the way they operate and make businesses (Grewal *et al.*, 2020; Hernandez, 2017; Martinez, 2018).

Brands from various industries, such as retail, telecom, travel and financial services had to adjust their strategies in response to the structural changes caused by the enhancements developed in the AI context, providing ways for customers to communicate directly with them (Dale, 2016; Kannan & Bernoff, 2019; Kumar, Rajan, Venkatesan, & Lecinski, 2019; Wirth, 2018).

This broad term, that is AI, is defined by Copeland (2019) as "*the ability of a digital computer or computer-controlled robot to perform tasks commonly associated with intelligent beings*". It uses "*technology based on predictive analytics, machine and 'deep' learning, natural language processing*" (Martinez, 2018) amongst others, in an era where consumers "*want to connect with their preferred brands at a moment's notice*" (Hernandez, 2017).

It is then a major factor in redefining the way commerce is done, and the main booster for conversational commerce. It can adopt different forms of expression in this context: useful tools in predictive analytics and automation, to chatbots or voice assistants capable of making autonomous decisions and choices (Chao *et al.*, 2019; Hoffman & Novak, 2018; Martinez, 2018). The AI potentialities for commerce transformation and improvement are endless. In the retail sector, more specifically, it can be used in many ways: in automation, learning from past data and identifying behaviour patterns (Amato-McCoy, 2018), predicting customer behaviours (Martinez, 2018); supporting in logistics automation and supply chain management (Sides & Swaminathan, 2020), through *"(...)demand forecasting and customer intelligence(...)"* (Chao et al., 2019); *"(...)using machine learning for fraud prevention or tapping into customer data for personalisation(...)"*(McDonald, 2018), creating personalized marketing materials (Goldenberg, 2019).

2.4. Chatbots

Since the way people communicate has been changing, researchers identified that consumers will, therefore, expect to be able to do the same when it comes to brands: to reach them the same way they are used to communicate. They *"(...) have flipped convention on its head, demanding brands be available on their time and terms, via asynchronous communication through their channel of choice: i.e., messaging"*, citing LoCascio (2018).

This way, technology *"is bringing commerce into the familiar and personal context of messaging apps, transforming the customer experience by making it a whole lot more convenient for both businesses and their customer"* (B. Kumar, 2016). This convergence between the messaging world and artificial intelligence can be accomplished with the creation of messenger chatbots or conversational agents able to engage in natural language conversations with customers for commercial purposes (Van Eeuwen, 2017).

In this context it is important to clarify and define the concept of chatbots. According to Letheren & Glavas (2017) they were *"(...) created to mimic an interpersonal conversation, characterized by a high degree of personalization, both in the conversation as in potential* *offers, they can present to users."* (as cited in Van den Broeck *et al.*, 2019).

They are "*automated conversation systems*" (Kannan & Bernoff, 2019) able to engage and generate conversations using natural language, and automate certain tasks through the use of deep learning on messaging apps (Kannan & Bernoff, 2019; Przegalinska *et al.*, 2019).

According to Exon (2016), even though at an initial stage using and talking to a bot might feel awkward, the consecutive and repetitive style of conversations will become faster and more accurate.

These robots can collect and analyse a large amount of information retrieved from previous interactions and conversations, which will, ultimately, lead to a chatbot improvement as time goes by and as the consequently number of conversations with customers increase (C. Afonso, 2017; Carnett, 2018; Kannan & Bernoff, 2019; Martinez, 2018). This can be accomplished with the use of artificial intelligence. The chatbot, when created with this type of technology, is able to choose the best appropriate answer for a certain request. It will be commanded to search through its data source and generate new conversations using natural language (C. Afonso, 2017; Carnett, 2018).

Dale (2016) adds that the objective of using a chatbot is as simple as achieving a certain task and result through a conversation with a machine, using natural language. This result can be either informational or the resolution of a problem (Carnett, 2018).

Chatbots can be grouped into different categories according to their distinct functionalities. Mason (2017) identified three main types: support chatbots, skill chatbots and assistant chatbots. The first are "*built to master a single domain*"(Mason, 2017), being able to answer user questions regarding that domain and walk him "*through any major business processes*"(Mason, 2017). On the other hand, skill's chatbots do not have a personality as the support ones, but they work on by having a pre-defined set of specific commands that they can perform. Finally, the assistance chatbots can be defined as a combination of the previous two: they are entertaining conversational agents, that can work as intermediates between users and other types of bots as well. Preferentially, they should have knowledge in different topics so that they can answer to a wider range of questions (Mason, 2017).

Radziwill & Benton (2017) also felt the need to categorize chatbots according to its attributes. They retrieved and grouped a set of quality features for conversational agents, based on their similarities into different groups, and concluded that they were aligned with Abran's ISO 9241 concept of usability: "*The effectiveness, efficiency and satisfaction with which specified users achieve specified goals in particular environments*", citing Abran *et al*., (2003).

Considering this they have put together three main areas: for efficiency there were the attributes related to the performance of the chatbot, for effectiveness its functionality and humanity, and for satisfaction they were related to affect, ethics & behaviour, and accessibility.

Even though Phillips (2018) also identified three main groups of chatbots, he differentiated them accordingly to the technology involved for its development and the impact they have on the user experience. The simpler ones are the menu/button-based chatbots: they work on a menu basis with different options from which the user can select the one that better fits its needs. However, they have some limitations and may fall short to users' expectations in more complex questions. With more complexity, there are the keyword recognition-based chatbots: these can understand what the user writes and give an appropriate answer. They use AI and keywords to identify what is being requested, and to answer/act on it. Lastly, and more complex, there are contextual chatbots, which have the ability to self-improve over time, by saving previous conversations due to the combination of AI and machine learning (Dole *et al.*, 2015; Phillips, 2018).

In summary, it is extremely important for brands to be aware of which are the relevant factors for the chatbot's functionality, and which type of chatbot better fits their strategy, in order to make the investment in this technology a success.

Smiers (2017) divided chatbots functionalities into three main areas: interaction, intelligence and integration. And sub-divided each of them by three levels of maturity, as presented in table 2.1.. The first area, interaction, relates to the unique interacting experience provided by contacting with a chatbot in a social messaging app, and how it differs from the experience provided in a brand's website.

Table 2.1: Chatbot functionality factors. Adapted:(Smiers, 2017)

	Level 1	Level 2	Level 3
Interaction	• One Channel • One Language • Human to bot interaction	• Multi Channel • Multi Language • Human Handoff	• Multi person • Bot - to bot interaction
Intelligence	• Single Q&A • Menu based • Word based rules	• Line based intelligence • State machine • Mood detection • Context from channel • Training of NLP model	• Conversation listening • Conversation based intelligence • B2B conversation • Self learning
Integration	• API queries • Links for more information	• Bot initiates conversation • Event listening / producing • API transaction • API intelligent queries	• Case Process interaction

The intelligence of the chatbot refers to its ability to create and maintain a conversation with the end-user, by understanding what is being discussed and providing an appropriate answer. And the last area, the integration, includes the factors needed so that the chatbot can fully function and that will influence their ability to successfully perform. These factors depend on a back-end system and on how well the chatbot is integrated with it, allowing or not the end-user to reach other platforms and have access to additional information (Smiers, 2017).

Consumers, with this technology, provided by AI, instead of "*having to download a particular brand's app or visit its website,(…) can open up Facebook Messenger, type in the brand name and almost instantly are connected to a chatbot.*", remarks Darlington (2018).

2.4.1. Attractiveness for Brands

According to Ask *et al*. (2016), chatbots are so appealing to brands due to four main reasons. The first is based on the fact that mobile screens are the first screens consumers interact with, therefore it is extremely important for enterprises to try and borrow some of these mobile moments. This can be achieved with the help of messaging platforms, where the majority of these moments is spent on, allowing brands to "*extend their mobile presence beyond their own apps by using conversations to engage customers*"(Ask *et al.*, 2016).

The second relates to the high number of heavy users these types of platforms have. Then, is also because they "*promise a more convenient and natural user interface*"(Ask *et al*., 2016) than apps. The mobile apps are perceived as being a more forced way of interaction between brands and consumers, whereas conversations are a more natural form of contact.

The last reason stated highlights the high availability of the artificial intelligence tools for developers, with its readiness for use, that makes it easier and welcoming so that more and more people want to explore this area (Ask *et al*., 2016).

A common platform for chatbots is the Facebook Messenger. This platform, provides flexibility to chatbot builders as well as code simplicity. As a result, the number of chatbots being developed in this messaging app has been growing over the years (Eha, 2017; Hernandez, 2017).

2.4.2. Virtual Assistants' role in Retail

Alongside the gradual progresses and enhancements to the current systems and models, trends, like the use of chatbots in the retail world, are seen as the next obvious step. This occurs, especially, when it comes to the merge of both online and offline (physical stores) customers' experiences (Amato-McCoy, 2018; Cundiff, 2016; Johnston, 2018).

For the specific case of retailers, they continuously search for "*solutions that can improve operational efficiencies, better understand their customers preferences, and optimize the brick-and-mortar experience*" argues Amato-McCoy (2018). The author finalizes defending that such is accomplished with a wider offer of digital solutions developed towards the customer.

A pertinent way of accomplishing that, is through the use of virtual agents, generally considered the most prominent chatbots (Kannan & Bernoff, 2019).

Pearson (2017) also stresses the importance of retailers putting this virtual assistant technology into use and as a part of their strategies to better engage with customers. They will become, this way, more prepared, agile and consequently better positioned against their competitors. Additionally, by being easily reachable by their customers and connecting with them faster, customer indecision and loss of interest will be reduced, and customers will be retained and win over (O'Brien, 2019; Pearson, 2017).

According to Przegalinska *et al.* (2019) *"retail chatbots provide gamified ways to shop. Through a conversational interface, brands transform themselves into personal shopping assistants."*. They work on retaining the user focus and attention by *"(...) encouraging them to browse, providing responses about products or cross/upselling a purchase."*

Citing Goldenberg (2019):

> *"When AI is applied to CRM, the possibilities seem endless. AI-powered virtual assistants will automate sales and service tasks. Chatbots will help customers complete simple tasks. AI-powered content-generation tools will create one-to-one personalized marketing materials."*

LoCascio (2018), Martinez (2018), and Hoyer *et al.* (2020) stress the idea that chatbots can improve different areas of a business, and are essentially being implemented, in different industries, into the brands' customer services, marketing, and sales operations.

The advantages identified regarding the use of chatbots and virtual agents, more specifically, are numerous amongst researchers, for both brands and their clients. They can improve customer service, reduce costs and enhance efficiency for the company. When considering the customers point of view, they can also improve their experience by being ready for use at all times, answering questions in real-time and more rapidly than an human agent can most of the times, and offering a whole customized experience (Balasudarsun *et al.*, 2018;

Cundiff, 2016; Kannan & Bernoff, 2019; KLATT & GIBBER, 2018; LoCascio, 2018; McDonald, 2018).

2.4.2.1. Sales Automation

Virtual assistants should be able to take on the role of a sales associate. Through an engaging conversation their goal is to keep the customer interest and finalize the sale, meeting the client needs while increasing their overall shopping experience (Pearson, 2017).

Citing Klatt & Gibber (2018) chatbots by *"(...) reducing an inventory catalogue to the few most relevant items take the cognitive load out of shopping. When done through chat, it can create an intimate, highly personalized experience that grows brand loyalty and engagement while generating additional sales".*

According to Holzwarth *et al.* (2006), their interactions with customers can be compared *"(...) with real-world human agents for influencing purchase decisions, saving time, gathering advice, or gaining parasocial benefits."* (as cited in Chung *et al.*, 2018).

They can recommend specific products to the customer's unique desires, as well as deal with the user's transactions, providing a complementary experience, with the comfort and handiness of the online experience and the tailored service of shopping in a physical store (LoCascio, 2018).

2.4.2.2.Marketing Automation

Also with artificial intelligence, chatbots are able to collect data about the customer's purchasing history and behaviour: "*profile data as well as (...) data offered by the user during the in-chat experience*"(KLATT & GIBBER, 2018), that will make the brand better understand their customers individualities. This will allow for personalized recommendations and customized solutions that will better suit the customer's needs and requirements (Amato-McCoy, 2018; KLATT & GIBBER, 2018; LoCascio, 2018; Martinez, 2018; McDonald, 2018).

This two terms, personalization and customization play an important role for the marketing strategy of retailers. The personalization depends on the company, *"(...) when the firms decides, usually based on previously collected customer data, what marketing mix is suitable for the individual."* (Kumar *et al*., 2019), whereas the customization is more linked to the customer, in the sense that they are the ones making the decisions, when proactively choosing certain elements from the marketing mix (Kumar *et al.*, 2019).

Virtual assistants are powered with technology able to match customer preferences, based on previously collected data, to the range of products offered by the company, even anticipating customer searches, making the whole decision-making process a lot more efficient *(Kumar et al.*, 2019; O'Brien, 2019; Pearson, 2017).

The collected data can be obtained through different ways and formats, depending on how the chatbot is set up. Customers may provide access for the brand to see their basic information, demographics and interests from their profiles. The virtual assistant may have access to the buyer's previous purchasing history, matching the brand's current catalogue with customer's preferences. Or even asking a set of questions that will let the chatbot know exactly what the customer is looking for and then filtering the products available by the answers provided (Kumar *et al.*, 2019; McDonald, 2018; Przegalinska *et al.*, 2019; Van den Broeck *et al.*, 2019). The more data is obtained and the better analysis the retailers can do from it, better will be the accuracy and impact of the virtual assistant on the customer, and consequently better the customer experience (Chao *et al.*, 2019; Kumar *et al.*, 2019; Reshmi & Balakrishnan, 2018).

2.4.2.3.Customer Support Automation

Fuelled by artificial intelligence, virtual assistants can solve a wide range of customers inquiries and problems (Kannan & Bernoff, 2019). By detecting key words and having in storage frequently asked questions, chatbots are able to answer customer queries almost instantly. One of the main advantages of making a purchase through a conversation with a virtual assistant is the fact that any problem or doubt that may arise during the purchasing journey, can easily be asked and answered. The chatbots offer customer support throughout the different stages of this journey: working on avoiding customer indecision by presenting the best items to match their preferences, guiding them along the different stages, answering product and utilization related questions and offering any post-purchasing support and improve with the continuous learning for the following times (Chung *et al.*, 2018; Korzeniowski, 2020; Przegalinska *et al.*, 2019).

If needed the virtual assistant can redirect users to the company's website, or to an employee depending on the complexity of the support needed. They increase their efficiency as the time goes by. This is accomplished by the addition of previous conversations and procedures used before in their database, to then choose the best appropriate course of action in the following times (Carnett, 2018; O'Brien, 2019; Przegalinska *et al.*, 2019).

While dealing with repetitive requests they are able to replace employees that, this way, can be available to handle more difficult and complex tasks (LoCascio, 2018).

Complementing the 24/7 available support, virtual assistants can provide satisfaction surveys to the customers in order to evaluate the overall shopping experience as well as the product and service quality (K. E. Hoffman, 2017; Thompson, 2018).

2.4.3. Live Chatbots – Benchmarking

There are already different brands who have developed their own chatbots for messaging apps, and where is possible to identify some of the features and characteristics previously described.

2.4.3.1. Global Context

Brands like *H&M*, a Swedish fashion retailer, employ this type of technology in order to make personalized suggestions to their customers and even offer new outfit ideas. While *Sephora*, on the other hand, provides makeup tips and reviews (Cundiff, 2016). *Saks Fifth Avenue* Holiday Gift guide and *Ouai*, used the Facebook messenger platform and developed quizzes that would allow the brand to gain knowledge about their customers: their preferences and specific details. They would then suggest the best product from the store's inventory to match what they were looking for to offer as a gift or the best hair product for their type of hair, respectively (KLATT & GIBBER, 2018).

It is possible to enumerate other brands as examples of the different uses for the chatbot technology: *Nike*, for example, allows customers to design their own shoes based on a list of options, customers can this way customize the different parts of their sneakers. *Nike's* virtual assistant also shows and suggests different styles and outfits and direct users into the brand's website to know more about the products ("*Nike*," *n.d.*). Another example, is the brand *Covergirl* which "*created a chatbot of Kalani Hilliker, the 16-year-old dancer and television personality*" ("*COVERGIRL'S KALANI HILLIKER*," *n.d.*) and replicated her personality into the virtual assistant, that talks with the customer while promoting the brand's products.

The clothing brand *Uniqlo*, has a chatbot on Facebook messenger, named *IQ*. *IQ* incorporates emojis into its conversations to get a more friendly touch, while allowing the user to search for items and add them directly into the shopping cart ("*Uniqlo*," *n.d.*). *Unilever*, however, adopted a different approach when compared to the previously described, having a teaching context. The *Unilever's* Signal *Pepsodent* toothpaste, in partnership with the creative agency R/GA, created a Signal chatbot that "*tells a 21-part interactive video story called "The Adventures of Little Brush Big Brush," which entertains children while teaching them proper* *brushing techniques and habits*"("Unilever's Signal Pepsodent," *n.d.*), and promoting the brand.

2.4.3.2.Portuguese cases

In the Portuguese context the development of chatbots by brands in messaging app platforms has been developing more in recent years, and can still be considered in early stages. The majority of brands that adopted such technological innovation have been integrating it into their own website pages in most of the cases.

However, there are some Portuguese cases that can be highlighted. Both integrated in the companies' web pages, Anna and Sofia, are two virtual assistants from *IKEA* and *TAP*, respectively. Anna was created in 2007, with the aim to help customers, by answering their questions about the brand products, its prices, delivery and details about stores (like location and opening hours). Sofia, live since 2015, is able to help *TAP* customers throughout the entire process since they start planning their flight, by answering a wide range of customers about all the details from destinations, check-in options, baggage rules, and on boarding services. These two chatbots presented with avatars and human-like traits and personality to the users, are continuously improving and learning with each new interaction they made (Choi, *n.d.*).

In the messaging apps context, in Facebook Messenger more specifically, there are also some examples:

- *El Corte Inglés* Portugal has developed a chatbot to facilitate the interaction between brands and their customers as part of their digital strategy. At the start of the conversation the user can choose whether he wants to talk to a bot or to a human assistant. The chatbot is available 24/7, and has the ability to answer customer queries about the store and its services both online and offline (Costa, 2016);

- *Heineken*, integrated a chatbot in this platform to be where their customers are without having to download an additional app. This chatbot is mainly used for marketing effects, here the brand announces discounts and contests for their users. The main challenge before this development was to automate the download, read, and validation of contest and discount coupons which the chatbot helped out with. Even with some additional manual effort needed, the bot is able to read the coupons and reveal the prices to the winners ("*As 5 melhores características do chatbot da Heineken Portugal,*" 2018);

- *Knorr*, also used a chatbot as a tool for their marketing campaigns. The bot would have the role of reading the promotional codes and identifying proof of purchase for brand contests *(“A Knorr® Portugal acaba de lançar um Chatbot de Marketing!*,” 2018);

- *Milaneza*, more recently, added a chatbot to reach more easily to its customers. The goal is that the customers get to know their products and be able to see answered questions about them. To create a more interactive connection the bot also suggests recipes, with *Milaneza* products and ingredients that the users have at home *(“O Chatbot da Milaneza: O Sítio Certo para Receitas Incríveis*,” 2020).

Also, *WhatsApp* is preparing the integration of chatbots in its platform, developing new tools for brands to use. An example of a usage case is *Tranquilidade* an insurance company that transferred the bot they had on their website to this platform, for an easier accessibility for their customers *(“Tranquilidade coloca chatbot no WhatsApp,” 2020; “Visor.ai* Assistente Virtual *no WhatsApp da Tranquilidade,”* 2020).

2.4.4. Implementation Barriers

There are some challenges that retailers should keep in mind before adopting this digital solution. Some people might still argue that chatbots are not entirely ready to replace human beings in conversations and that are still dependent on some kind of human intervention (Ask *et al*., 2016). Consumers still prefer interacting with a human, or at least to have that option in case something goes wrong (Clarke & Kinghorn, 2018). It is also important to carefully consider privacy issues and data security, since users still don’t feel too comfortable sharing sensible and personal data in this context. Therefore, having a sense of security and protection will make them more willing to use this channel (Clarke & Kinghorn, 2018; Kannan & Bernoff, 2019).

Additional barriers to the implementation of this technology can be in terms of the available resources companies have, both financially, as expert knowledge is needed and the internal systems have to be adjusted, and by lacking technological expertise to implement, train employees, and take the most advantage from it by extracting only the needed data (McDonald, 2018; Thompson, 2018).

2.4.5. Drivers for a Successful Implementation

Trust is really important for a successful implementation, having customers trust that talking to a virtual assistant is secure, and that the data shared will be properly handled and not leaked, will be decisive for whether or not they will interact with it. Privacy and security concerns are probably the main obstacle identified to the use and making a purchase in the social media/messaging apps context. Consumers have to trust that their financial data is properly handled and that the environment they are in is secure, so that they can really feel comfortable interacting and making a purchase in these platforms (Inman & Nikolova, 2017; Przegalinska et al., 2019).

For a successful chatbot implementation, retailers must consider several factors. Adding an element like this carries some costs to the companies and is crucial that when introducing this type of technology it fits the overall brand's strategy (Kannan & Bernoff, 2019; McDonald, 2018). Kannan & Bernoff (2019) advocate that companies have to make sure they have a "*scale that makes this level of engineering worthwhile. Deployments are most likely to pay off in companies fielding thousands of customer chats or calls*".

Also, the dependency of the audience on messaging apps should be taken under consideration. Tsai & Men (2018) studied the antecedents and the relational outcomes of the organization – public engagement via a social messenger, and were able to conclude that the publics' social messenger dependency, and privacy perception of the medium, drive public engagement, and consequently enhances the organization-public relationships.

On the other hand, Araujo (2018) investigated how the presence of human-like cues on a chatbot, like its language style, name and the framing on which the consumer was introduced to the chatbot, influences the perception of social presence and mindful and mindless anthropomorphism. It was also studied the relevance of the perceived factors when it came to the company-related outcomes that the customers felt after interacting with the chatbot. Amongst other results Araujo (2018), found that there was a significant relation between the use of human-like cues and the emotional connection towards the company, and therefore it has a positive impact on the company – customer relationship.

The chosen strategy for the chatbot implementation should, thereby, try to minimize the risks and take the most advantage of the value added by the bot to the brand (Ask *et al.*, 2016). According to Andreoli *et al.*, (2017) there are six steps that should be followed to accomplish that. Even though these steps where thought for the financial services sector they can be considered as a reference point for the retail industry as well.

- 1st It is important to build/use specialized talent;
- 2nd To understand the technology;
- 3rd To take under consideration the user and its protection;
- 4th The brand should be transparent;
- 5th The brand should be consistent across channels;
- 6th The implementation should start with a hybrid/test model.

This progressive approach should be taken when it comes to all technological developments, start with a pilot chatbot, in this case, and backing it up with human intervention if needed. Over time that human factor might decrease as the bot becomes more effective and efficient, expanding its uses and functionalities (Ask *et al.*, 2016; Kannan & Bernoff, 2019).

2.4.6. Technology Adoption

Considering that the virtual assistant can impact different stages of the consumers' decision-making process, as described previously and according to the literature, it is relevant to better understand what are the main determinants for a successful interaction and which of them lead to a positive customer experience.

First of all, as being a technological development is important to take under consideration the user's acceptance and willingness to use such enhancement. The *Technology Acceptance Model* (TAM), is used in various domains as basis to test user acceptance of different technological enhancements (figure 2.7.). It was first presennted by Davis (1986) to test user acceptance processes of computer-based information systems (Van Eeuwen, 2017).

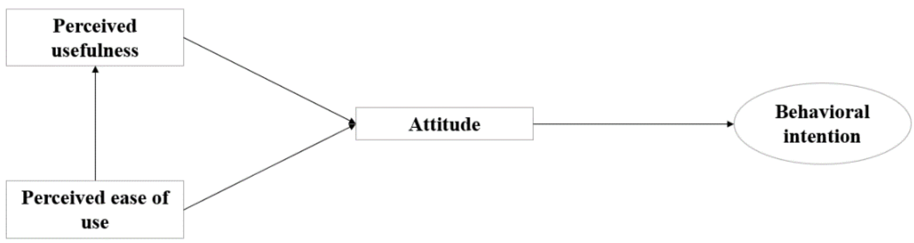

Figure 2.5: Technology Acceptance Model proposed by Davis (1986).

Davis (1986) proposed this model to better analyse these systems and so that it could serve as a theoretical basis for the evaluation of new systems prior to their implementation. The main goal was to identify which determinants would be able to explain the usage behaviour for technological innovations. The theory in study was that a person's intention to adopt a certain innovative technology was influenced by that individual's attitude to the use of technology

(Kulviwat *et al.*, 2007). The standardized TAM questionnaire measured this attitude using two determinants: the perceived usefulness and the perceived ease of use of the techonology under analysis. The first intended to evaluate up to which degree the user believed that the system would enhance his or her job performance. And the perceived ease of use was to measure up to which degree an individual thought that by using a certain system he would be free of any physical or mental effort (Davis, 1986).

However, this model only took under consideration cognitive aspects as determinants for the acceptance/usage of technological developments, failing to explain the impact of user's feelings on their willingness to adopt such innovations (Kulviwat *et al.*, 2007). As a result, there was literature that tried to fill this gap, as it was the case of Kulviwat *et al.* (2007), that considered both hedonic and utilitarian motivations, theorized by Childers *et al.* (2001), and added that fun could also have an effect on the attitude to adopt a technological product, as it was found by Bruner and Kumar (2005).

It was then concluded that the TAM model could be more complete, as there was the need to incorporate emotions in it, since they could affect and influence consumer adoption. Kulviwat *et al*. (2007) proposed, as a result of that conclusion, a new model (figure 2.8.): the Consumer Acceptance of Technology (CAT), as a replacement for TAM.

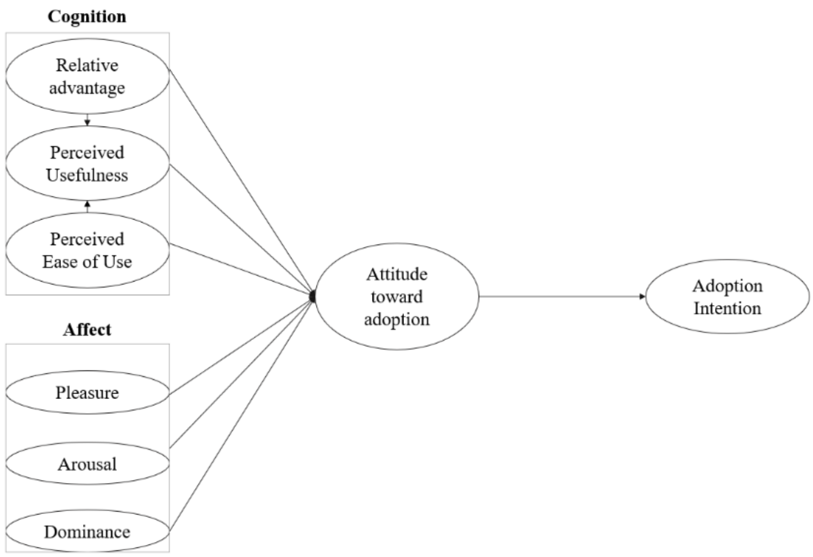

Figure 2.6: Consumer Acceptance of Technology model proposed by Kulviwat et al. (2007).

There, they included the two cognitive determinants from TAM: the perceived usefulness and perceived ease-of-use, and added relative advantage in the cognition area as well, and three affective determinants: pleasure, arousal, and dominance to also determine user's attitude towards adoption.

The relative advantage determinant was included because Kulviwat *et al.* (2007) believed that people would be more likely to adopt a product on which they found some advantage to its use than an alternative one that would not bring any or little additional benefits.

The inclusion of the three affective determinants was based on a previous psychological study from Mehrabian and Russell's (1974), the PAD theory. This theory *"(…) asserts that all emotional responses to physical and social environments can be captured with three dimensions of affect: pleasure, arousal, and dominance (PAD)"*, citing Kulviwat *et al.* (2007). Authors defended that these three dimensions would embody all human emotional responses to their surroundings, representing the user's feelings and influencing their behaviour. According to the literature, presented by Kulviwat *et al.* (2007), this theory has been used in several studies to analyse consumers reactions to the environment they are in, in the retail context their responses to the store's atmosphere, and in online contexts their shopping satisfaction.

2.4.7. Chatbots' Acceptance & Satisfaction, and Impact in the Attitude towards the brand and Patronage Intentions

Based on the CAT model, later on, Zarouali *et al.* (2018) proposed a model that combined three cognitive and three affective factors in order to determine the effectiveness of Facebook chatbots for brands. This adjusted model, differed from the Consumer Acceptance Technology one in three main aspects, replacing: the '*relative advantage*' determinant for '*perceived helpfulness'*, the analysis regarding the '*attitude toward the adoption of a new technology*' (from the CAT model) by considering the '*attitude toward the brand*' responsible for incorporating/developing that technology; and the '*adoption intention*' by the '*patronage intention*'.

Therefore, Zarouali *et al.* (2018) took under consideration both cognitive and affective consumer responses as predictors of their attitude towards the brand, and how it impacts patronage intention. The aforementioned model (figure 2.9.) integrates the PAD dimensions: pleasure, arousal and dominance, with the TAM model's rational and functional evaluation of innovations (Singh, 2018). Using for this three cognitive determinants: the perceived usefulness; the perceived ease-of-use and the perceived helpfulness (Zarouali *et al.*, 2018). The introduction of the last cognitive determinant is justified by the fact that is important to analyse the degree to which chatbot's replies are considered to be relevant to the user, and with the additional fact that the 'relative advantage' assumed a precursor, that being the chatbot an innovation would be less relevant to include that determinant than the perceived helpfulness (Zarouali *et al.*, 2018).

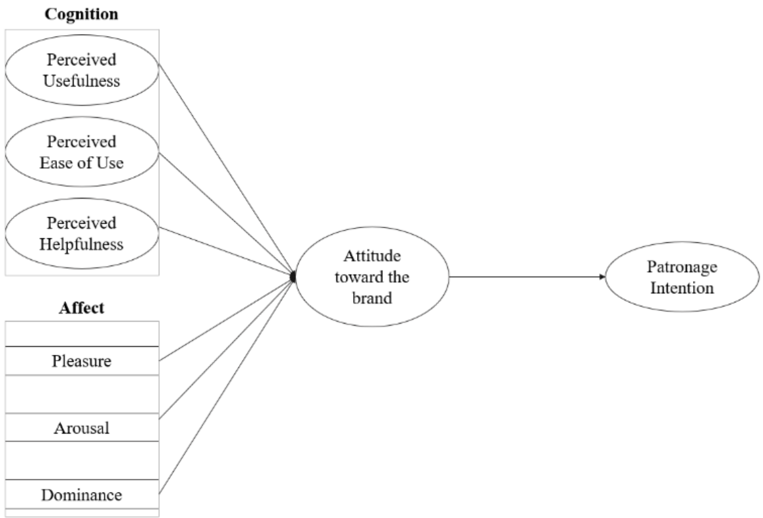

Figure 2.7: Model for the effectiveness of a chatbot on Facebook proposed by Zarouali et al. (2018).

This model would then study which factors from the chatbot interaction would have an impact on influencing the customer's attitude towards the brand, and consequently make them use again the chatbot or recommend it. Authors concluded that "*the perceived usefulness and the perceived helpfulness, are two cognitive predictors that are positively related to consumers' attitude toward the brand providing a chatbot.*"(Zarouali *et al.*, 2018); and that all of the affective predictors are positively related to the costumer's attitude towards the brand. Additionally, the patronage intention, in other words the likelihood for customers to use the chatbot and recommend it to others, can be significantly explained by the costumers' attitude towards the brand (Zarouali *et al.*, 2018).

With the aim to understand the impact of the interaction with chatbots in offering a personalized service to luxury brands clients, Chung *et al.* (2018) analysed "*how e-service agents' marketing efforts affect communication outcomes*", and consequently its impact in customer satisfaction. The authors defended that essential marketing efforts: as interaction, entertainment, trendiness, customization, and problem solving, could be delivered to the customers through the interaction with an e-service agent. The chatbot's quality of communication was defined by three determinants: its accuracy, credibility, and communication competence. The model proposed, as can be observed in the figure 2.10. below, that these service agents marketing efforts would also have an effect on the chatbot's communication quality, and impacting, therefore, the overall customer satisfaction.

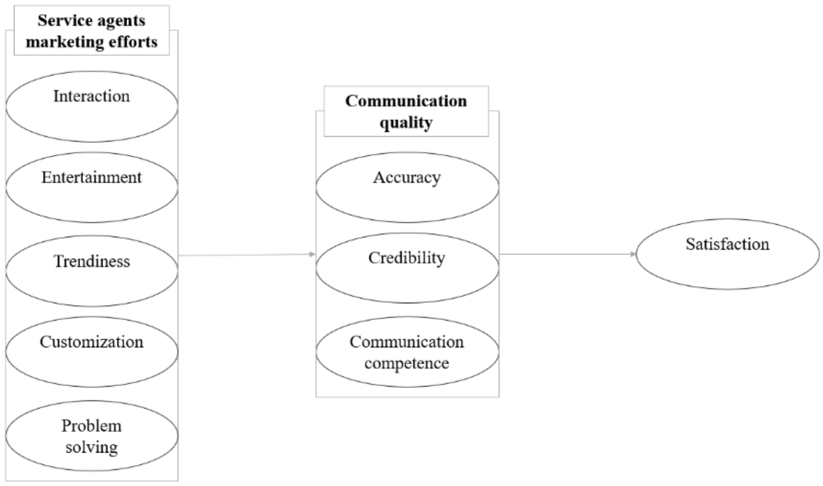

Figure 2.8: Model for the effects of e-service agents' marketing efforts in communication outcomes and satisfaction proposed by Chung et al. (2018).

It was concluded that for the customers to be satisfied with the luxury brand's e-service agent, the user must perceive the communication as having quality (it should be accurate and credible). However, the relationship between the customer and the agent can be improved even if the second does not show communication competence. It was also concluded that to "*strengthen online communications, fashion brands are advised to provide accurate and reliable information to ensure positive marketing efforts*" (Chung *et al.*, 2018).

Literature identified and studied, over the years, the changes and impact that technological developments have on businesses, consequently on the way they interact with their customers and how the different interactions throughout the purchasing journey affect their decision-making process and their customer experience as well as their overall satisfaction and patronage intention.

3. HYPOTHESES AND CONCEPTUAL MODEL

The fact that, in the Portuguese context, does not exist a large sample of virtual assistants being integrated in messaging apps and that the adoption of such technology for retail brands is still on early stages, allied with the lack of literature about the impact virtual assistants have in the customer experience of the Portuguese retail sector, made it relevant to adapt the investigation to this specific context.

The study aims to identify which interactive dimensions of a virtual assistant impact positively the customer experience, creating a positive expectation for it, and the effect that a positive customer experience expectation, in this online retail conversational context, will then have on user's patronage intention.

The literature review, presented before, resulted on the formulation of the study hypotheses described below, as well as on the conceptual model that can be observed in the end of the chapter, as a visual representation of the hypotheses.

3.1. Hypotheses Definition

Previous studies identified that the Customer Experience is a multidimensional concept that incorporates different levels of experiences (Grewal & Roggeveen, 2020; Lemon & Verhoef, 2016). These same dimensions have also been studied as having a significant role in the adoption of technological innovations and on the user's attitude towards brands (Chung *et al.*, 2018; Zarouali *et al.*, 2018) and can, thus, be embodied in the interaction between the virtual assistant and the customer to understand how they influence their customer experience.

As a starting point, it is important to identify which determinants should be included as part of each dimension– *Cognitive Perception, Affective Engagement, and Communication Quality* - of the Customer Experience and what will be their contribute for its definition.

For the first hypothesis, it is considered the possibility of creating a suitable measure for the *Cognitive Perception* dimension through the combination of cognitive determinants. It is then important to define which cognitive items from the literature review should be considered to embody the conceptual model.

According to Zarouali *et al*. (2018), and the adjustments made to the CAT-model, the cognitive dimension can be explained by three determinants:

- ***Perceived Usefulness***: It can be defined as the awareness of the likelihood of a certain technology to improve the user's productivity. For this case, in the consumer context, it can be understood as the perception of the customer, that by using a specific technology, interacting with the virtual assistant in this case, will benefit and improve the action of making a purchase and interacting with the brand. It is believed to be a significant determinant in terms of the use and adoption of technological innovations (Davis, 1986; Kulviwat *et al.*, 2007; Zarouali *et al.*, 2018);

- ***Perceived Ease-of-use:*** It refers to the perception that it will be simple to use a certain technology. The perception that the interaction with the virtual assistant will not require a lot of effort, being a simple process. Past studies have proven that this is an important factor for the user to decide to adopt such technology and that it improves his attitude toward the brand (Davis, 1986; Kulviwat *et al.*, 2007; Zarouali *et al.*, 2018). It is then expected that it will work as a predictor of a positive customer experience;
- ***Perceived Helpfulness:*** It is defined as the degree to which it is thought that the interaction with the virtual assistant will be relevant for the consumer to find all the information, details and assistance he is looking for. It has proven that if the costumer has the perception of a technology to helpful and provide the needed assistance that it will be beneficial to his attitude toward the brand and intention to use (Zarouali *et al.*, 2018). Expected to be translated into the feel of a good customer experience.

The main goal is to identify if the relation between the three items aforementioned and if they can be combined into defining the latent variable '*Cognitive Perception'*.

> **H1: The three cognitive determinants –*Ease of use, Usefulness, and Helpfulness* - can be combined for the creation of a suitable measure of the latent variable '*Cognitive Perception'*.**

Secondly, there was the need to define the affective-related dimension, considered to be a relevant part of the Customer Experience (Grewal & Roggeveen, 2020), and a significant predictor for the adoption of technological developments (Kulviwat *et al.*, 2007), influencing the customer's attitude towards the brand (Zarouali *et al.*, 2018).

To study this dimension, it was taken as basis the three affective predictors, considered in the CAT-model, the PAD- dimensions:

- ***Pleasure***: It is expected that hedonic feelings have considerable importance when it comes to the customer experience throughout the purchasing journey, that will then affect their consumption decision. This determinant refers to the level enjoyment and happiness felt during the experience, by being stimulated by external factors, in this case, the interaction with the virtual assistant (Chung *et al.*, 2018; Hou *et al.*, 2013; Kulviwat *et al.*, 2007; Zarouali *et al*., 2018);

- ***Arousal***: The level of excitement felt by the customers, also in response to an external factor stimulation. It is expected that consumers adoption to a certain technology is encouraged by the feeling of arousal in the interaction with that technology. It refers to the impact that the customers' mental stimulation during the interaction with the virtual assistant has on their experience (Hou *et al.*, 2013; Kulviwat *et al.*, 2007; Zarouali *et al*., 2018);
- ***Dominance***: This dimension measures the level of control and independence felt during the interaction with the virtual assistant. Explaining the importance of the user feeling like he is controlling the interaction instead of not being free to act accordingly his will (Kulviwat *et al*., 2007; Zarouali *et al*., 2018).

The aim is to understand which of these determinants significantly contribute for the definition of the *Affective Engagement* dimension.

H2: **The three affective determinants – *Pleasure, Arousal, and Dominance* - can be combined for the creation of a suitable measure of the latent variable '*Affective Engagement*'.**

Besides the two dimensions considered in the CAT-model, it was also felt the need to verify up to which extent does the communicative dimension of the virtual assistant impact the expectation of a good customer experience.

Similarly, to the study conducted by Chung *et al.* (2018), the communicative dimension of the virtual assistant, will also be divided into three determinants:

- ***Accuracy***: It is important that the information communicated to the customer is correct and updated for the users to feel like they can rely on the information being transmitted. This determinant will measure the importance of having updated and current information in the conversation with the virtual assistant for the customer experience (Chung *et al.*, 2018; Hayco, 2018);
- ***Credibility***: This factor relates to the chatbot's perceived trustworthiness as a result of the information shared being reliable, meaning that it is often correct and there is not the need of having to correct mistakes repeatedly. This will serve as a predictor the importance of having trustworthy information in the conversation with the virtual assistant for the customer experience (Chung *et al.*, 2018);

- ***Communication competence***: It refers to the virtual assistant's ability to transmit all the necessary information to the user, by being efficient and effective when performing the way, it was promised. It is believed that good and complete communication lead for customer's trust in the chatbot, resulting in a more positive experience (Chung *et al*., 2018; Przegalinska *et al*., 2019).

It will be important to verify which of these determinants have a significant contribution for the definition of the *Communication Quality* dimension.

> **H3**: **The three communicative determinants – *Accuracy, Credibility, and Communication Quality* - can be combined for the creation of a suitable measure of the latent variable '*Communication Quality*'.**

Before verifying the impact each of the previously presented dimensions have on the customer's expectation towards their shopping experience, it is important to identify which items can be helpful to predict and measure their behaviour and perceptions.

According to Kuo *et al.* (2009) and Lemon & Verhoef (2016), customer satisfaction is an important predictor of costumer behaviour. It will then be needed to deconstruct this concept into specific measures and metrics, in order to verify which of them play a significant role in the creation of an expectation.

Adjusting to the context of this study, the concept of *satisfaction*, complemented by Chung *et al.* (2018), with the integration of the *usage and enjoyment anticipation*, first presented by Davis (1986) , and the *attitudinal measures*, (Hassanein & Head, 2007; Hoyer *et al.*, 2020), as well as the various items used to define and evaluate them, it was obtained the following constructs:

- ***Interaction Appeal***, referring to what extent this possibility, of talking with a virtual assistant, would be attractive to the user;
- ***Comfortability***, to evaluate the users' state and feeling towards the opportunity of interacting with a virtual assistant;
- ***Experience Improvement***, the belief that such innovation would improve their customer experience;
- And the ***preferability***, to understand the users' preference for the idea of adopting the innovation compared to the existing alternatives.

These will be used to evaluate the satisfaction with the possibility of having a future interaction with a virtual assistant (innovation), instead of evaluating the interaction with a specific and already created chatbot.

The goal will then be to identify which of these can be used as measurements for the prediction of this multidimensional concept that is the customer experience.

H4: The four experience items – *Interaction Appeal, Comfortability, Experience Improvement, and Preferability* - can be combined for the creation of a suitable measure of the latent variable '*Customer Experience Expectation*'.

Additionally, the Patronage Intention variable will need to be defined. This concept, is described as the customer's willingness to use/buy and recommend the products (Hou *et al.*, 2013; Van den Broeck *et al.*, 2019; Zarouali *et al.*, 2018).

Adjusting to the virtual assistant context, it will be verified how the two items – the likelihood to interact with the virtual assistant at any stage of the decision-making process, and to recommend it to other people – help to define the latent variable '*Patronage Intention'*.

H5: **The two patronage determinants – *Usage* and *Recommendation* - can be combined for the creation of a suitable measure of the latent variable '*Patronage***

After the definition of the dimensions that are part, not only of the Customer Experience (Grewal & Roggeveen, 2020; Lemon & Verhoef, 2016; Verhoef *et al.*, 2009), but that are also determinants for the adoption of technological innovations (Chung *et al.*, 2018; Davis, 1986; Pantano & Di Pietro, 2012; Zarouali *et al*., 2018), as it is the case of a virtual assistant, it will be needed to verify the level of impact each dimension has for the creation of an expectation related to the customer experience, that results out of the possibility of interaction between potential customers and a brand's representative, the virtual assistant.

H6: The *Customer Experience Expectation* is positively influenced by:

H6a: *Cognitive Perception*,

H6b: *Affective Engagement*, and

H6c: *Communication Quality*.

Lastly, it will be studied the effect that the customer experience expectation has towards the patronage intention. It is important to verify up to which extent does the user consider that interacting with a virtual assistant will add value to and improve the overall experience. If they would be willing to use it, and in which phases of the decision-making process they would perceive it as being more relevant.

This results out of the combination and adaptation of previous studies, namely the ones performed by Van den Broeck *et al*. (2019); Zarouali *et al*. (2018), that analysed the impact different dimensions and perceptions of the customer experience have on patronage intentions.

H7: The *Patronage Intention* for the Virtual Assistant is positively influenced by the *Customer Experience Expectation* from its interaction.

3.2. Conceptual Model

In the scheme below, it is possible to observe the conceptual model proposed for this thesis. It considers evaluation of three dimensions from the virtual assistant's interaction with the user - cognitive, affective, communicative – and its impact on the overall customer experience expectation. Its impact will then be analysed in the customer's patronage intention context. Each dimension is being proposed to be defined out of the combination of three predictors for the effectiveness of the virtual assistant's interaction for the customer experience.

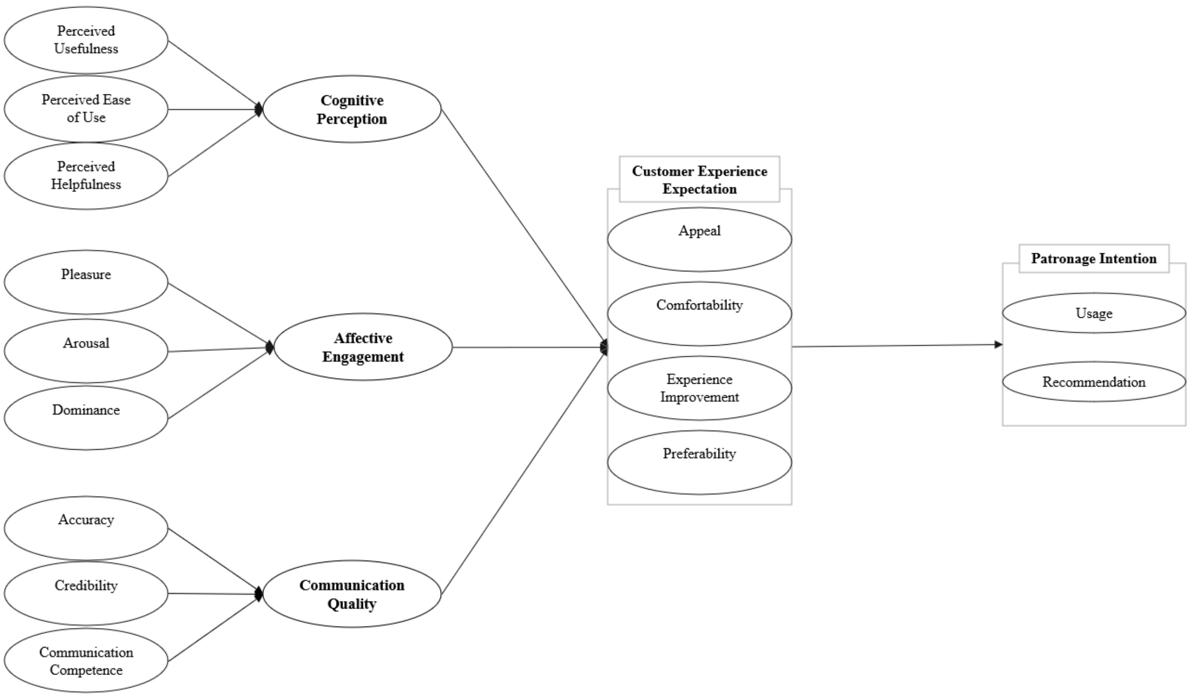

Figure 3.1: Proposed Conceptual model

4. METHODOLOGY

This chapter contains a detailed explanation of the study's research design, quantitative methodology (1), as well as the process followed to obtain the necessary data in order to test the previously theorized model and hypotheses. For this, a description of the Universe and Sample (2) for the study will be provided, with its context and targeted population definition as well as the criteria used for its selection.

It will then be followed by the process used to collect the necessary data (3), including its procedure, the tools and techniques applied for this stage. Complementing the above, it will also be presented a characterization of the research variables for the investigation and its measures (3), finalizing with the processing and analysis techniques that will be applied to the data collected, and further explored in the next chapter (5).

4.1. Research Design

This study, as an empiric investigation, will be based on observations to better understand the issue being investigated (Hill & Hill, 2016), the effectiveness of the interaction with a virtual assistant for the expectation of a better customer experience in the retail sector and for patronage intentions.

It will be an extension of studies previously described in the Literature Review, especially from Chung *et al*., (2018) and Zarouali *et al*., (2018), where a combination of research variables from both studies will be used as well as new hypotheses tested and applied to a new context, Portugal.

For the purpose of this study it will be used quantitative methodology. This type of methodology is considered to be the most objective as well as efficient in order to obtain a large amount of data in a limited time range.

To conduct this study, it will be used a primary quantitative research method: a cross-sectional survey research, that will be described in more detail throughout this chapter. This option was used as a tool to collect the necessary data to verify the hypotheses being tested, by gathering information from the targeted audience at a certain point in time. Its success is, however, dependent on the availability and honesty of the respondents when taking part of the study. Additionally, a chatbot, developed for the Facebook Messenger context, was created for this investigation. The interaction with it preceded the online survey, and will be described further ahead in this chapter.

4.2. Universe and Sample

4.2.1. Universe

The universe of a study consists of the set of all the cases from which we want to draw conclusions for the investigation. The size of the universe will then be the total number of elements that complete that group, either of people, objects or any other thing that can be measurable (Hill & Hill, 2016; Maroco, 2007).

For this investigation, the universe considered is all the Portuguese young adults, with ages between 18 and up to 35, that can access Facebook Messenger. This universe was adapted from previous studies to face the reality of Portugal, the country where the study was being conducted. The young adults were targeted because of their at ease to communicate through messaging apps and high representation in Facebook Messenger in Portugal as well as their potential to adopt new technology trends, as it is the case of the interaction with brands and making purchases via a virtual assistant. In line with the *Statista* report *"Portugal: Messenger users by age and gender 2020"* by Johnson (2020), and the calculations in Annex A (1), the considered universe for this investigation is the total of 2 066 316 individuals.

4.2.2. Sample

For this investigation, since the universe of the study is too large to completely analyse in light of the available time and resources, a sample was taken to perform the study on.

It was used a non-probabilistic sampling method: which means that the sample was taken without the existence of equal probability of everyone in the universe of the investigation to be selected; more specifically, a convenience sampling method, meaning that the elements that integrate the sample were in higher proximity of the researcher (Hill & Hill, 2016; Maroco, 2007), reached by social media connections. This will also mean, however, that the data and results provided by this sample cannot be extrapolated to the research universe.

In terms of the size of the sample, it was calculated as described in Annex A (2) where the value obtained was of 385 respondents needed for this investigation (Agranonik *et al.*, 2011; Israel, 1992).

The total number of answers obtained through the survey was of 400 responses. Out of these, only 385 were valid and relevant for the study, matching its universe criteria. The remaining 15 answers, that were excluded, belonged to individuals with ages out of the range selected (5), and that were immediately filtered out from the start of the survey, or to people with other nationalities (10) that were excluded before the analysis of the collected data.

4.3. Data Collection

4.3.1. Procedure

The procedure for collecting the needed data for this study can be divided in two phases:

1) The interaction with a chatbot on Facebook Messenger;
2) Filling out an online survey.

The purpose behind the creation of a chatbot for this study, and making it as a necessary first step, was to make people interact with it in order to have at least one experience with a chatbot before having to fill in the survey. To have an idea and feel of what a chatbot is, how it is to interact with an artificial being, and the potentialities it might have as a brand representative and shopping assistant in the retail sector.

As previously mentioned in the Portuguese context, and more specifically in the retailing one, brands are just starting to add virtual assistants as part of their strategies, and this can still be considered an innovation. It was then felt the need to provide the respondents with a feeling of how it would be to interact with a chatbot while presenting them different features and possibilities that can be incorporated into the interaction with the virtual assistant, instead of only mentioning them in the survey. The chatbot created is not intended, however, to be an example of a retail brand virtual assistant, but instead more informative, passing along the content to the users guiding them along the several areas of where a virtual assistant could impact the customer experience. This way, the user gets a taste of what is like to interact with a non-human agent, and gets access to information that the author felt important to share with the respondents before filling in the survey, about the potential of a virtual assistant, in a more interactive and engaging way.

Regarding the development of the chatbot, the chosen platform to integrate it was the Facebook Messenger, because of different factors: it combines both social media and messaging apps contexts; for each of these contexts there is a high representation of the targeted audience for the investigation in them; the tools and platforms, for the development of the chatbot in this app, are user friendly, there are lots of guidelines and tutorials to explain the process for its development and inclusion of specific features and attributes to meet the desired requirements; and it allowed an easier dissemination of the study in social media.

The chatbot was developed in a platform, called *Manychat*, that was perceived as the most user-friendly platform that simultaneously offered a free-user plan that matched the expectations and needs for the chatbot thought to be part of the study.

In this first stage, the direct link to a conversation with this chatbot, called '*Ró'*, was shared on social media leading people to interact with the bot. After opening the link and choosing to initiate the interaction, '*Ró'* while creating a connection with the users over an engaging conversation, guided them through the different areas of intervention that a virtual assistant can have when representing a brand in the retail sector.

The three main areas of action highlighted were:

1. Sales
2. Marketing: Personalization & Customization
3. Customer Support

In the Annex B can be found a table describing each of these areas presented by the chatbot, and an example of a conversation with it.

After the interaction with the chatbot, the respondents received a link to a survey where they were asked about their online and e-commerce habits, their expectations and evaluation of the different dimensions of a virtual assistant as well as their relative importance for the overall customer experience and patronage intentions.

4.3.2. Tool: Survey

As previously enunciated the data collection was made resorting to an online Survey. Taking into account the context, as well as the available resources, this tool was considered as being the most relevant to conduct the study on, because of following an online interaction (between the respondent and the chatbot created), and being easily shared across social media to reach a sample of the targeted universe. The Survey created can be observed in Annex C.

The main research purposes were presented in the conversation with the chatbot and at the beginning of the survey. There, it was explained the context in which the research was being conducted, that it had academic purpose as part of a master's thesis to measure and assess in which way an interaction with a virtual assistant would impact young adults' customer experience in retail.

The universe of the investigation was also highlighted in both phases, as well as a reassurance that even though respondents connected to the chatbot using their own social media accounts, all the answers and information disclosed in the survey would be anonymous and only used for academic purposes.

The survey had a total of 29 questions, divided into 10 sections. The first three focus on the consumer online habits, and on their attitude towards technology.

1) *Time spent online*. This section intended to characterize the audience in terms of their behaviour when they are online and in which ways or gadgets they choose to connect to the internet.

2) *E-commerce.* Aimed to analyse the habits of the respondents to make online purchases.

3) *Chatbot*. To understand the profile of the targeted audience when it comes to the adoption of new technologies and their previous awareness of what a chatbot is.

The structure of the survey also included the description of a hypothetical situation, where the respondent is asked to imagine he/she is considering to buy a product from a retail brand and there is a virtual assistant available from that brand to help him/her out. Some of the uses and applications of the virtual assistant's potentialities for retail are also described, before continuing the survey. The following five sections referred to the relative importance the different features and attributes, of a virtual assistant, have for the users as a way to enhance their customer experience. These will, then, compose the different dimensions of the interaction with a virtual assistant.

4) Ease of use

5) Usefulness

6) Helpfulness

7) Affective Engagement dimension: Pleasure, Arousal and Dominance

8) Communication Quality dimension: Accuracy, Credibility, Communication competence

After, respondents were asked to provide their overall perceptions on how interacting with a virtual assistant would influence their customer experience and patronage intention.

9) *Customer Experience Expectation* – Evaluation of the overall Satisfaction with the possibility of interacting with a retail virtual assistant. Intended also to understand their likelihood to interact with a virtual assistant that would represent a brand, and their patronage intention. Also, in which stages of the consumer decision-making process and for each retail sectors, this interaction would be relevant, in their opinion.

Finally, there will be collected data to characterize the survey audience and identify possible clusters.

10) Socio-demographic characterization.

As it is highlighted by Hill & Hill (2016), it was important to perform a test with a smaller sample before publishing and sharing the survey, to identify possible improvement areas or unclear questions, that could be revised. A sample of 8 people, using a convenience method (family and friends) took part on this phase, interacting with the chatbot and answering to the survey. As a result, the chatbot's communication was adjusted, correcting some spelling errors and made more informal. And in the survey questions, especially in the affective and communicative dimensions some adjustments were made, excluding specific items to measure each determinant, and measuring its overall importance for the customer experience instead. This, because the items were measuring the presence of certain attributes in the chatbot presented, and this was not the study' purpose. The chatbot developed has a merely informative purpose and to give a feel of how is the interaction with a chatbot, it is not intended to represent a specific brand's chatbot but only to present what functionalities that might have.

The survey was built mainly with resource to closed questions. This type of questions provide an easier and more sophisticated way to apply statistical analysis to the answers provided, since the respondent chooses the answer from a list of alternatives previously set by the researcher (Hill & Hill, 2016).

4.4. Research Variables

As mentioned, the survey contained closed questions where ordinal or nominal scales were used to define the alternative answers. Nominal scales measure variables using discrete categories, where an order can't be defined. In an ordinal scale, on the other hand, an order can be defined amongst the different alternatives/categories presented. Both this scales use mutually exclusive alternatives and are used for measuring qualitative variables (Maroco, 2007).

In this study, for each of the nine, previously defined, determinants it is measured the level of importance the respondents assign them, as part of the interaction with the virtual assistant, for their customer experience. Resulting, this way, in 15 observable variables (*Usefulness, Ease-of-use, Helpfulness, Pleasure, Arousal, Dominance, Accuracy, Credibility, and Communication competence*) that will be used to, later, infer the latent variables *Cognitive Perception*, *Affective Engagement*, and *Communication Quality*. For this, a five-point *Likert* scale, ranging from 1 (Not Important) to 5 (Very Important), will be used to measure the observable variables.

These variables were retrieved from previous studies, the first six, corresponding to the Cognitive and Affective dimensions of the interaction with the virtual assistant, from Zarouali *et al.* (2018) research, and the last three, related to the Communicative dimension of the interaction, from Chung *et al.* (2018) study. The variable measurement was adapted from 'level of agreement' to 'level of importance'.

For the first three determinants, there were also defined 13 items to measure them. The *Ease-of-use* was measured by 3 items, the *Usefulness* by 4 items, and the *Helpfulness* by 6 items. Each of these items represented different features and attributes of a virtual assistant that, according to the literature review, would be associated to that dimension of the interaction with the virtual assistant. For this specific case, the inclusion of these items would not be with the purpose to evaluate the presence of the features in the developed chatbot, but to understand the importance the user gives each of them. This would allow to check for a relation between the several features and the determinant, considering their importance to the customer experience. In the other hand it might mean that additional features should also be included to better analyse that cognitive determinant. The aim of this is essentially to identify which are the most important features and attributes for the customer experience, setting up best practices for future implementations of chatbots as retail brands' representatives.

Then, the perception of the customer experience including the interaction with the virtual assistant, is evaluated through the satisfaction with the possibility of interacting with a virtual assistant as a retail brand representative, to identify if this translates into a positive experience it is evaluated by 4 items – *Interaction Appeal, Comfortability, Experience Improvement*, and *Preferability* - measured on a five-point Likert scale, ranging from 1 (*Do not agree at all*) to 5 (*Totally agree*). The user patronage intention is also assessed by 4 items: two of them using the scale just mentioned before – *Usage* and *Recommendation* likelihood - and the other two will be using nominal scales to identify in which areas of the decision-making process the virtual assistant is more likely to be used as well in which sectors.

The nominal scales mentioned before on the chapter were used in the sections related to the respondent socio-demographic characterization, as well as in the first sections where the online, e-commerce habits and profile towards new technologies is being analysed. In these sections, when measuring the frequency of the habits ordinal scales are used.

4.5. Data Analysis

In the next chapter, the previously defined hypothesis will be tested through analysis on the data collected. To verify the hypothesis different types of analysis will be applied.

Both descriptive (mean, median, dispersion, skewness, and correlation) and inferential (parametric and non-parametric analysis accordingly) statistics will be used to analyse the data. Additionally, tests to the normality and correlation between the variables will also be applied, as preliminary steps for the reliability and factor analysis needed.

5. DATA ANALYSIS

Throughout this chapter, the characterization of the sample will be presented and described, socio-demographically (1), and in terms of its online (2) and e-commerce (3) habits, as well as for its innovativeness and technology adoption profile (4). Leading to the verification of the previously established conceptual model and research hypotheses (5).

5.1. Sample's Socio-demographic characterization

As mentioned before, the sample is composed by 385 Portuguese individuals. Out of these, *67% are female* and *33% are male*, as it can be observed in figure 5.1. When it comes to the analysis of the sample according to its age group, represented in figure 5.2., it is possible to verify that the majority of the respondents has ages *between 18 and 24 years old*, making *70.9%* of the total sample, and the remaining *29.1%* have ages *between 25 and 34 years old*.

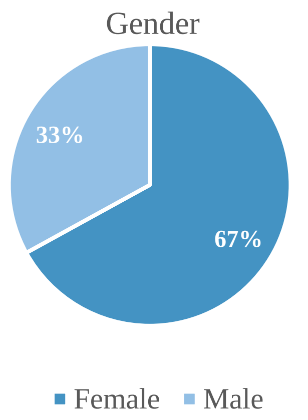

Figure 5.1: Sample Distribution by Gender

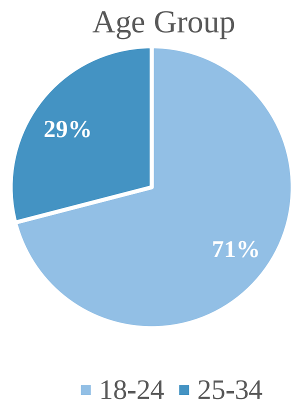

Figure 5.2: Sample Distribution by Age Group

In terms of the current employment situation, as it can be seen in figure 5.3., we have that the majority of the respondents are *employed*, representing *44.7%* of the sample, followed by *students*, that make *32.2%* of it. In 3rd place there is the *working students with 15.6%*. With less representation, there is the individuals *unemployed* (4.4%) and *self-employed* (3.1%). Complementing this and analysing the respondents' qualifications (last completed cycle of studies) it is observed, in figure 5.4. that *52.2% has a bachelor degree*, *28.8% a master's*, and *19% hasn't a college degree yet* (18,7% concluded high school and 0.3% elementary school).

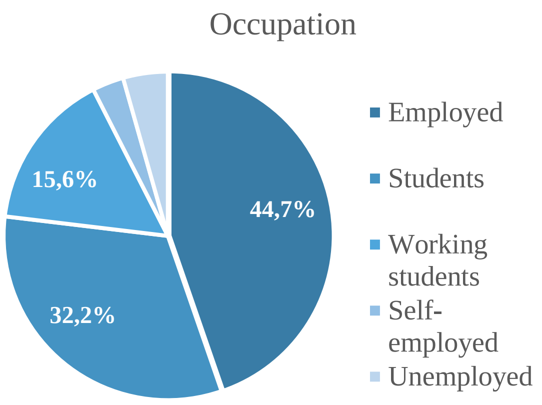

Figure 5.4: Sample Distribution by Occupation

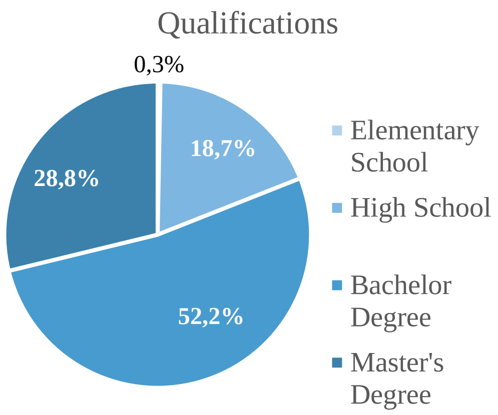

Figure 5.3: Sample Distribution by Qualifications

5.2. Online Habits

For the purpose of this investigation, it is important to also characterize the sample in terms of their online habits: understanding to which devices the respondents usually connect to the internet, how much time they are online and which are the main activities done in that case.

They were then, asked to rank the activities performed online according to the time spent on each of them, from the one where they spend more time to the one where less time is spent on. As a result, and in line with the figure 5.5., it was obtained the following overall ranking of activities:

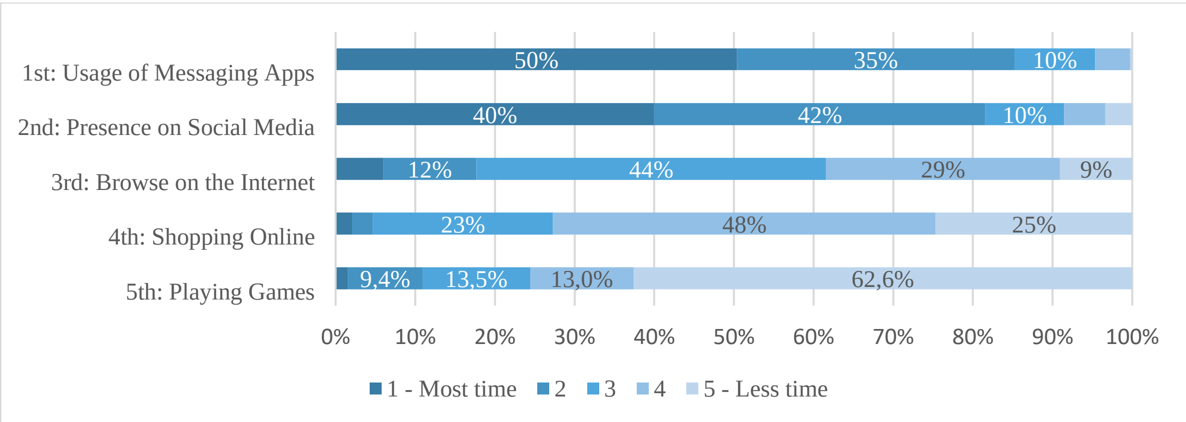

Figure 5.5: Activity Rank based on the Time Spent Online

The devices found to be used by the majority to connect to the internet, and perform the above tasks and activities were ***smartphones*** and **computers/laptops**, used by **99.5%** and **93.8%** of the respondents correspondently. When focusing, on the device stated to be the one where **most of the time online was spent**, the **smartphone** was the answer for the large majority (Annex D), with 85.5% of the sample answering this, followed by the computers with only 14% of it (figure 5.6.).

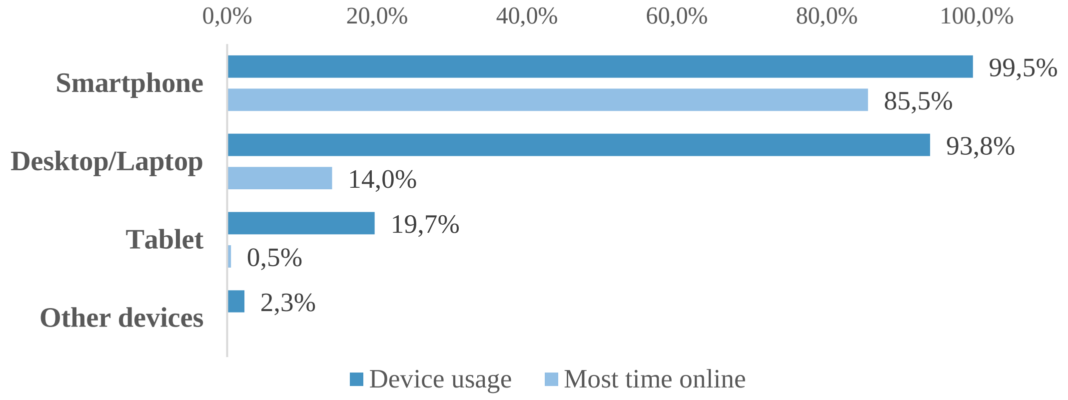

Figure 5.6: Internet access: devices used and where most time is spent on

In terms of the daily average of time spent online, **38% of the respondents stated spending over 4 hours connected to the internet on a daily basis**, excluding any labour related activity. This option was the most selected option by the respondents, and was transversal across both age groups and genders (Annex E). And it is possible to observe **that 63.9% of the total sample spend more than 3 hours online on a daily average** (figure 5.7.).

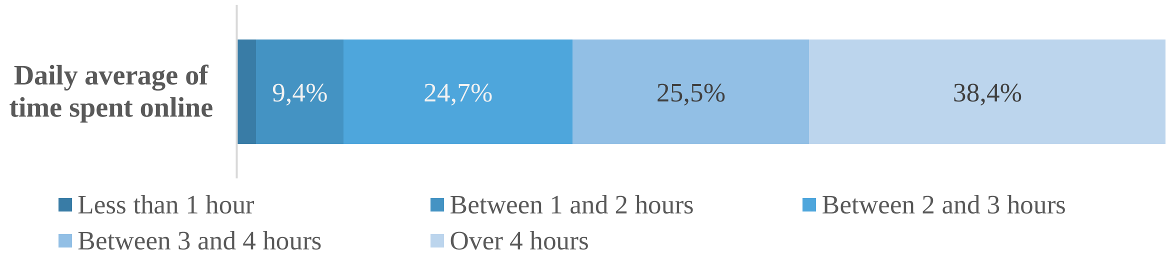

Figure 5.7: Online Time Daily Average

As it was observed previously, the main activity performed online was the usage and interaction with other people via Messaging Apps. Everyone who took part on this study confirmed using at least one messaging app, the Facebook Messenger. They were additionally asked which messaging apps they also used on a regular basis: the Facebook Messenger led the responses (used regularly by 95.1% of the sample) and was followed by the WhatsApp (used frequently by 91.2% of the sample). This means that the remaining 4.9% had access to the Facebook Messenger (still being relevant for the study) but used it more sporadically. The distribution of the sample in terms of the Messaging Apps used on a regular basis can be seen in figure 5.8., below.

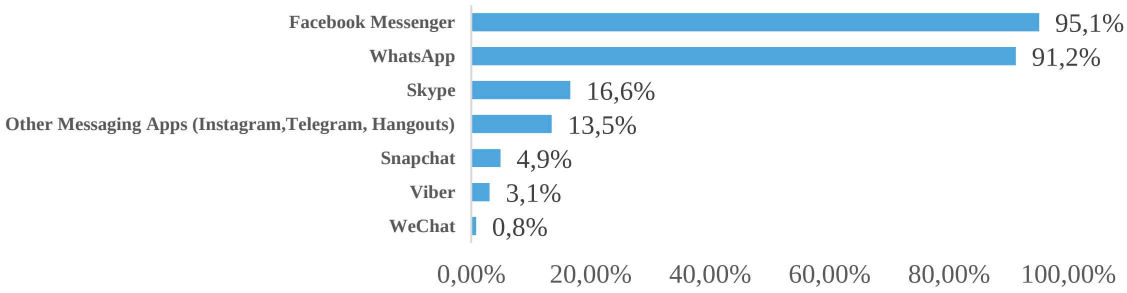

Figure 5.8: Messaging Apps used on a regular basis

5.3. E-commerce

Considering the purpose of this thesis it is also important to analyse the attitudes and behaviour towards online shopping. The internet can play different roles and be present in different phases of the consumer decision-making process. Considering the different steps that make up the 3 main stages of this journey: pre-purchase, purchase, and post-purchase, according to Chapter 2, the respondents selected the ones in which they usually use the internet, resulting in the following distribution (figure 5.9.):

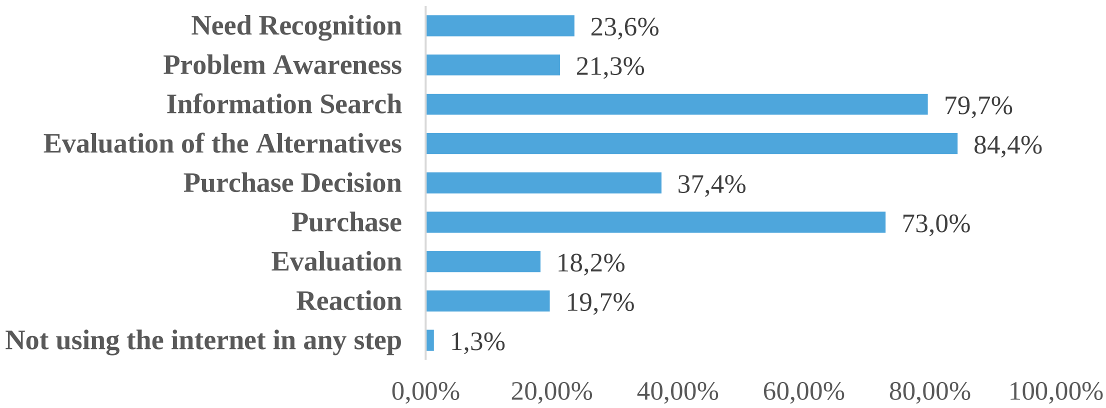

Figure 5.9: Internet usage in the decision-making process

It is relevant to highlight that only **1.3% of the respondents answered not using the Internet in any of the presented steps**, with lower percentages there are the post-purchase steps (Evaluation and Reaction), and that the majority of the sample claimed to use Internet on:

- **84.4%** of the sample stated to use the Internet to compare the existing offer of products/services – **evaluating the existing alternatives** (Pre-Purchase);
- Following close by, **79.7%** search on the Internet for **additional information** about the products they are looking for (Pre-Purchase);

- **73%** of the respondents claim to usually use it to make the actual **purchase** – shopping online (Purchase).

The online shopping frequency of the sample, it is distributed as presented in figure 5.10., stressing that: **69.3% of the respondents make online purchases at least once every three months**, **31.4% of the total sample shop online on a monthly basis**, and **12.2% of the total do it on a weekly basis**. On the other hand, 3.9% of the survey respondents do not make any online purchases.

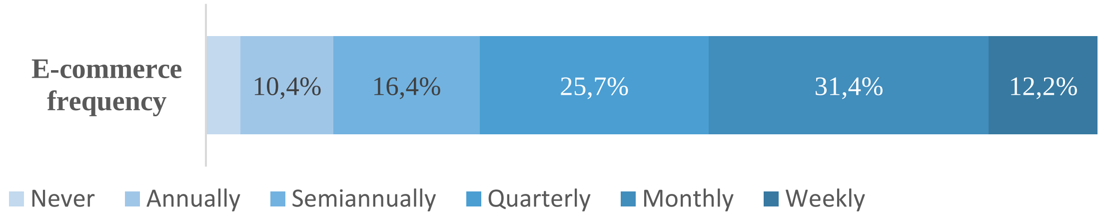

Figure 5.10: E-commerce Frequency

Excluding the 15 respondents that are not fans of online shopping, for the remaining 370 it was noticed that both smartphones and computers (desktop/laptops) were the respondents' most used devices for e-commerce (figure 5.11.).

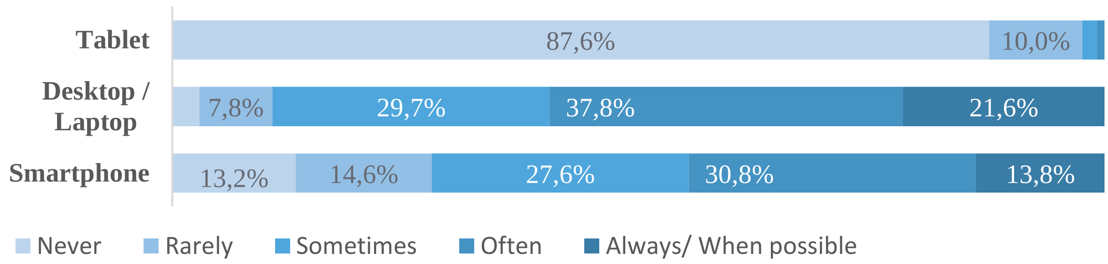

Figure 5.11: Devices used for E-commerce

For this sub-division of the sample, its characterization it is very similar to the overall sample both in terms of gender and age group division (Annex F).

In terms of the preferential sectors for performing the online purchase activity (figure 5.12.), complemented with the analysis in Annex G, the top 3 sectors identified for e-commerce were:

1) *the Fashion sector* - 73.8% of the respondents selected this as one of the sectors they already shop online for. In fact, 52.6% of the women in the sample answered that they already make online purchases in the fashion retail sector. Additionally, out of the 73.8% almost half (48.8%) were younger women (with ages between 18 and 24 years old).

2) *Cultural sector and Leisure activities* – identified by 61.6% of the sample as one of the sectors they do online shopping, where 52.6% of those were also were younger women (with ages between 18 and 24 years old).

3) *Tech sector* – 41.6% included this sector as one of the ones where they usually make online purchases. From the people selecting this sector, 70% were younger respondents (with ages between 18 and 24 years old). It is also relevant to highlight that more than half of the man in the sample, 66.4%, told stated that they have already made online purchases in the tech sector.

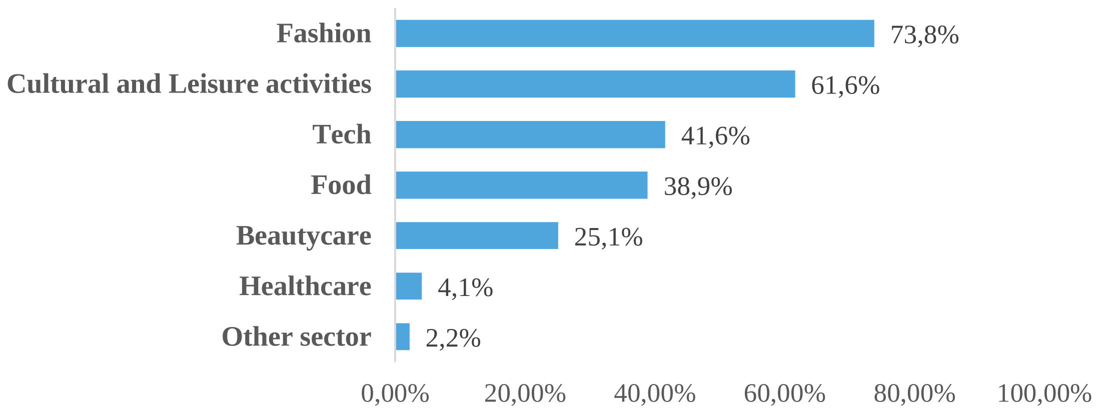

Figure 5.12: Sectors where online purchases were performed

5.4. Innovativeness Adoption Profiles

Depending on the way people react towards innovation they can be grouped into different categories. These categories take under consideration the willingness shown towards the acceptance and adoption of a novelty. Personality traits, age, communication behaviour and social-economic status are some factors that may influence the response individuals assume when facing innovativeness. Both psychological and demographic characteristics will, therefore, play a significant role in the division of the 5 categories identified by Rogers (2003): innovators, early adopters, early majority, late majority, and laggards (Annex H).

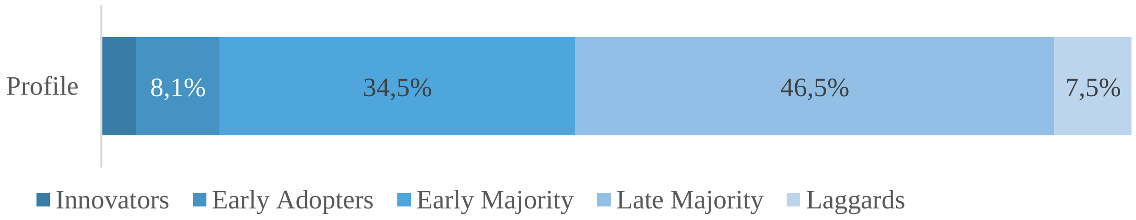

Figure 5.13: Sample Distribution according to Innovativeness Adoption Profiles

The main differentiator factor for the division into these 5 groups is the time taken by the individuals in the overall process of accepting and adopting innovations. Analysing more in depth each of the profiles, in figure 5.13. and Annex I, there are some data that can be highlighted:

1) ***Innovators*** – constitute 3.4% of the sample. With a higher representation of the younger audience (61.5%), but more closely distributed in terms of gender (53.8% of the innovators are female and 46.2% are males).

2) ***Early Adopters*** – this group represents 8.1% of the sample, distributed almost equally in terms of age groups, but composed mainly by female individuals (64.5%).

3) ***Early Majority*** – this category includes 34.5% of the respondents. Where high majority are young adults with ages between 18 and 24 years old. A big discrepancy was also verified in terms of genders, 72.9% of the early majority are female respondents.

4) ***Late Majority*** – with a representation of 46.5% of the individuals in the sample. Out of which 64.8% have ages between 18 and 24 years old, and the same percentage for females.

5) ***Laggards*** – making 7.5% of the sample. The majority of these individuals are students (41.4%) and 34.5% of all the respondents with this profile only have completed high school.

Thus, in the sample there are individuals with all 5 adopter profiles when it comes to innovativeness, with higher incidence in those that prefer to have some feedback prior to the adoption of the innovation, following trends already established and where the products have already been tested and validated for its usage and quality (late majority). This profile was selected by a higher percentage both across gender and age groups. It is also relevant to highlight that the majority of the self-employed individuals considered themselves as part of the early majority.

Taking into account the various profiles identified, it is pertinent to observe at which point it is applicable and correspond to their interaction and adoption with the object in study in this investigation, the chatbot. Understanding if the sample is aware of what a chatbot, as a technological innovation, is and if they had any previous contact with any chatbot and if so in which contexts.

Table 5.1: Crosstab between 'Chatbot prior knowledge' and 'Chatbot prior interaction'

		Have you had interacted with a chatbot before?		
		No	Yes	Total
Did you know what a chatbot was (prior to the interaction with the Ró-bot)?	No	24,7%	1,0%	25,7%
	Yes	35,6%	38,7%	74,3%
	Total	60,3%	39,7%	100,0%

It can be noticed on table 5.1. that **74.3% of the respondents knew what a chatbot was**, prior to this research, but when it came to having had a previous interaction with one, they were slipped almost in half: 52.1% of these **(38.7% of the total sample) have already had interacted with a chatbot before** whereas the remaining 47.9% **(35.6% of the total sample) had not.**

Even though, this technology is becoming more common across different sectors in the Portuguese context, **60.3% of the total respondents had not interacted with a chatbot before this study, and 41% of these did not know either what a chatbot was**. In addition to this, it is observed that **1% of the total sample claimed not knowing what a chatbot was**, but realizing then, at the time of the survey, **that they had already contacted with one** even though they did not know at the time what characterized a chatbot and what exactly it consisted of.

In terms of the socio-demographic characterization of both the previous knowledge and previous interaction with a chatbot it is very equally distributed for both positive and negative answers, as it can be observed in Annex J. For the first, the respondents that already knew what a chatbot was, were essentially employed (47.2% of them), with a bachelor degree (50.3%) females (68.9%) and with ages between 18 and 24 years old (72.7%). In terms of what matters the composition of the part of the sample that had a previous interaction with a chatbot, they similar characteristics to the previously described.

Crossing the data with the previously described adopter profiles (Table 5.2.), the majority of the individuals from each profile knew from before what a chatbot was, with the exception of the Laggards, as it can be expected since these were the ones with less interest for technology.

Table 5.2: Crosstab between 'Chatbot prior knowledge' and 'Innovativeness Adoption Profile'

		Profile				
		Innovators	Early Adopters	Early Majority	Late Majority	Laggards
Did you know what a chatbot was (prior to the interaction with the Ró-bot)?	No	23,1%	6,5%	15,0%	30,2%	**69,0%**
	Yes	**76,9%**	**93,5%**	**85,0%**	**69,8%**	31,0%

However, and unlike what could be anticipated **53.8% of the innovators had not yet interacted with a chatbot previously** (Table 5.3.). Excluding the Early Adopters, where 71% of the individuals with this profile declared having interacted with a chatbot before, the remaining profiles had the majority of their individuals stating not having contacted with one previously.

Table 5.3: Crosstab between 'Chatbot prior interaction' and 'Innovativeness Adoption Profile'

		Profile				
		Innovators	Early Adopters	Early Majority	Late Majority	Laggards
Have you had interacted with a chatbot before?	No	**53,8%**	29,0%	**50,4%**	**68,7%**	**89,7%**
	Yes	46,2%	**71,0%**	49,6%	31,3%	10,3%

In the cases where it existed a previous interaction with a chatbot, the contexts differed (figure 5.14.) from *online shopping* (with a high reference to the fashion retail sector), *contacting brands for customer assistance*, *travelling* (when booking flights and contacting with travel agencies), *entertainment* (with focus on betting sites and taking part in contests via a chatbot), *academic context* (from filling surveys to learning how to use and build chatbots), and to *banking*.

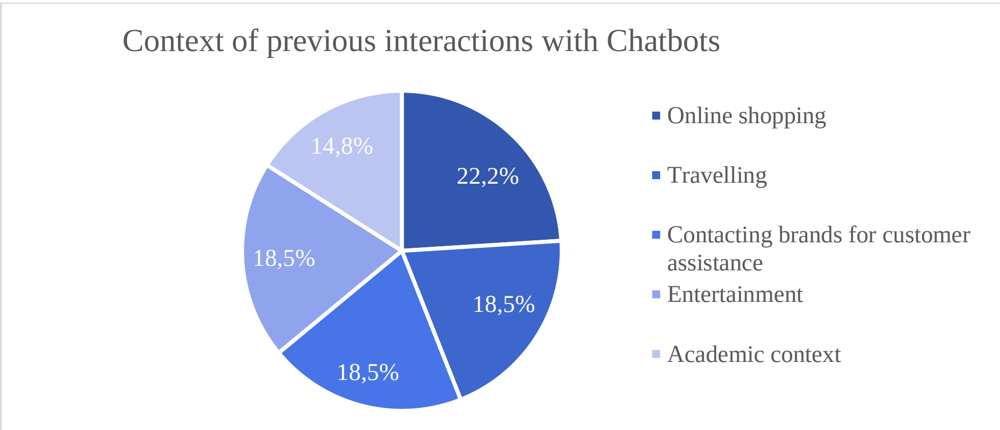

Figure 5.14: Contexts were chatbots were used in the past

5.5. Conceptual model and Hypothesis analysis

The proposed conceptual model and research hypotheses intend to verify the impact the three dimensions – Cognitive Perception, Affective Engagement, and Communication Quality - of the interaction between the user and the virtual assistant, have on the Customer Experience Expectation and how the last influences the Patronage Intention towards the Virtual Assistant.

5.5.1. Validity

When analysing the validity of the study it is very important to understand and evaluate both its internal and external validities.

Starting with the internal validity, it can be divided into four types:

- Content validity: The validity of the survey can be determined and accepted since it was constructed taking under consideration the findings presented in the literature review. This empirical data served as basis for the creation of the conceptual model and research hypothesis. Based on that, the survey was then developed.
- Construct validity: Since the variables under analysis in this investigation are latent variables, they will be measured by the combination and observation of other indicators. The validity of such measures can be verified since they've been identified on previous and relevant literature and the questions on the survey were developed considering this.
- Face validity: This type of validity can be proven because the survey developed met its goal in terms of identifying and evaluating the respondents' expectations on customer experience and patronage intentions items while integrating and considering the importance given to which interactive dimension.
- Criterion validity: this validity will be tested throughout this chapter when analysing the results obtained in the survey and then comparing them to what was expected from the literature review.

However, as previously mentioned, the external validity of this investigation is conditioned, because its results can't be generalized or extrapolated to its universe.

5.5.2. Preliminary Analysis

A preliminary analysis was performed, and is presented in the following sections. The aim of this analysis is to verify the assumptions needed in order to test the research hypotheses.

5.5.2.1. Tests of Normality

A preliminary analysis was done to test the normality of the distribution of the values of the 15 items, measured in a rating scale, and that will be the basis for the hypothesis testing – *the Virtual Assistant's: Ease of Use, Usefulness, Helpfulness, Pleasure, Arousal, Dominance, Accuracy, Credibility, and Communication Competence; the Interaction's Appeal, Comfortability, Experience Improvement, and Preferability for the interaction with the Virtual*

Assistant; and the Usage, and Recommendation likelihoods to use this innovation in the future. For this purpose, the author performed the Kolmogorov-Smirnov test (with Lilliefors significance correction) of normality (Annex K), which better suits big samples, on each of the items presented.

This test presents the null hypothesis that the variable being tested follows a normal distribution. For all tests performed there is a significance level for each item equal to 0.000. This can be translated into the decision of rejecting the null hypothesis for all the items, for the significance interval ranging from 0.05 to 0.01. In summary, none of the items being tested show a statistically significant level of following a normal distribution.

However, for some of the tests being performed on this investigation it is assumed the contrary. This assumption is made according to the *Central Limit Theorem*, which states that even when a certain population does not follow a normal distribution, the distribution of the data's average converges to a normal distribution as the size of the sample increases. The size of the sample under study, of 385 individuals, can be considered a big sample and therefore such assumption can be verified.

5.5.2.2. Correlations

For the first 5 hypothesis enunciated in previous chapters, and tested further ahead on this one, it is important to analyse the existence of a correlation between certain groups of items, in order to validate the choice for the tests performed.

As it was previously mentioned, all the items enunciated before were measured in a rating scale, the Likert scale more specifically. Over the next paragraphs it is possible to find the Spearman's correlation coefficient, a non-parametric measure of association between two variables, that are measured on a scale at least ordinal, which is the case. However, it is also important to note that non-parametric tests are considered to be less sensitive.

All the Spearman's correlation coefficients observed in the table 5.4. (and the correspondent correlation matrixes in Annex L) are statistically significant ($p<.001$) and positive.

Table 5.4: Spearman's correlation coefficients

	Spearman's rho	Sig. (2-tailed)
Ease of Use * Usefulness	0,456	0,000
Usefulness * Helpfulness	0,413	0,000
Ease of Use * Helpfulness	0,386	0,000
Pleasure * Arousal	0,529	0,000
Pleasure * Dominance	0,308	0,000
Arousal * Dominance	0,252	0,000
Accuracy * Communication Competence	0,607	0,000
Accuracy * Credibility	0,601	0,000
Credibility * Communication Competence	0,532	0,000
Interaction Appeal * Comfortability	0,614	0,000
Interaction Appeal * Experience Improvement	0,537	0,000
Comfortability * Experience Improvement	0,502	0,000
Comfortability * Preferability	0,480	0,000
Experience Improvement * Preferability	0,450	0,000
Interaction Appeal * Preferability	0,427	0,000
Usage * Recommendation	0,512	0,000

However, some of the identified correlations represent a weak association between the two items, as it is the case of the pairs Arousal * Dominance, Pleasure * Dominance.

And a high association can be identified between the pairs Accuracy and Communication Competence, and Accuracy and Credibility.

5.5.3. Hypothesis testing and verification

In order to verify the veracity of the defined research hypotheses, different tests were conducted, always taking under consideration the preliminary analysis already described.

H1: The three cognitive determinants can be combined for the creation of a suitable measure of the latent variable ‘Cognitive Perception’.

For each one of the cognitive items there were different features identified in the Literature Review that might be relevant for the user to have available when interacting with the Virtual Assistant.

In the following tables, there is the respondents’ evaluation of the importance each feature has in the interaction between the user and the virtual assistant. It is relevant to highlight that from the Ease of Use Features (table 5.5.), the *previous knowledge and prior contact with the* *platform/app where the chatbot is inserted* was considered to be the most important for it to be perceived as easy to use.

Table 5.5: Virtual Assistant's Ease of Use features

Virtual Assistant's features - Ease of Use	Mean
User's previous knowledge of the platform/app on which the Virtual Assistant is inserted.	**4,03**
Possibility of choosing different ways of communication in the same interaction. (Write text, select an option, …)	**3,53**
Introduction of the Virtual Assistant and of its services and functionalities at the beginning of the interaction.	**3,86**

** 1 Evaluated in a scale ranging from 1(Not Important) to 5(Highly Important)*

When it comes to the features that would make the virtual assistant more useful (table 5.6.), the ones that were considered to be the more important were that *the virtual assistant is able to provide a faster access to the information about the brand's products and characteristics*, and, *that would allow the user to interact directly with the brand.*

Table 5.6: Virtual Assistant's Useful features

Virtual Assistant's features - Usefulness	Mean
Provide faster access to the brand's product-related information and characteristics. (Price, dimensions, materials, usage instructions, exchange and return policies)	**4,41**
Suggest products considering the customer's profile and purchase history, and allowing product customization to make the interaction more effective.	**3,78**
Make interacting with a brand easier. Interact directly with the brand through instant messaging. (Possibility to ask questions about the brand's products and services)	**4,13**
Turn on notifications (for discounts, sales, new products, product availability), making the interaction more efficient.	3,24

** 2 Evaluated in a scale ranging from 1(Not Important) to 5(Highly Important)*

The most important features considered, in terms of helpfulness (table 5.7.), for the virtual assistant to have, were *its ability to answer customers' questions, the availability of product-related information,* and *redirect the conversation if needed to a brand employee*. The feature that was considered to be the least important to be included was the *chatbot's ability to start the conversation by sending notifications with product suggestions.*

Table 5.7:Virtual Assistant's Helpful features

Virtual Assistant's features - Helpfulness	Mean
Be able to answer customer questions.	**4,5**
Be available 24/7.	**3,81**
Redirect the conversation to a brand employee if needed.	**4,3**
Have available product-related information (brand catalogue and product characteristics).	**4,33**
Regular follow-ups with the customer, and making satisfaction surveys.	3,03
Anticipate customer contact with notifications with product suggestions.	2,88

** 3 Evaluated in a scale ranging from 1(Not Important) to 5(Highly Important)*

Overall, all the features where considered to be important to be included in the interaction. But, a more in-depth analysis is still relevant to prove that the three determinants can be combined into explaining the latent variable Cognitive Perception This will be verified next with the performance of a reliability (Annex M) and a factor analysis (Annex N).

To understand the relational structure between the items *Ease of Use, Usefulness, and Helpfulness* and how they describe the latent variable *Cognitive Perception* it was performed an Exploratory Factor Analysis (EFA) over their correlation matrix. For that, the Principal Axis Factoring method was used, advised by Hill & Hill (2016), since it maximizes the percentage of variance explained by the extracted factors. The retained factor was the one with an eigenvalue greater than 1 (following Kaiser's criterion), and also in line with the obtained from the Scree Plot, since as Maroco (2007) defends using only one criterion can lead to the retention of more/less factors than the ones that are actually relevant to describe the latent variable.

For the validation of the EFA the author analysed the Cronbach's Alpha (Annex M), that resulted out of the combination of the three items. It had the value of 0.744, which can be considered a reasonable alpha to measure the internal consistency of the variable ($\alpha > 0.6$), according to Hill & Hill (2016). Complementarily, it was used the Kaiser-Meyer-Olkin measure of sampling adequacy, KMO =0.684, a value that is considered to be acceptable to perform the factor analysis. The scores of each case for the retained factor were obtained using the regression method, and will then be used for the following analysis.

Following the Kaiser's criterion and the Scree plot (Annex N), it can be verified that the relational structure of the three cognitive items define only one factor, and that the measure's scale is unidimensional. In the table 5.8. it is presented the factorial weights of each item for the retained factor, its eigenvalue, the item's communalities, and the percentage of the variance explained by the factor.

Table 5.8: Exploratory Factor Analysis for the Cognitive Perception dimension

Item	Communalities	Factor Loadings
Ease of Use	0.453	0.673
Usefulness	0.598	0.773
Helpfulness	0.441	0.664
Eigenvalue		1.988
% of Variance Explained		66.3%

The retained factor, named *Cognitive Perception*, explains 66.28% of the total variance of the three cognitive items. These items have a relevant contribution for the definition of the factor. It can also be highlighted that the usefulness item is the one has a slightly higher value, and that therefore the contribution is not equal from all the items. The factor explains 59.8% of the variance of the usefulness item, 45.3% of the ease of use, and 44.1% of the helpfulness.

- The first hypothesis is validated. A suitable measure, unidimensional and with adequate internal consistency, for the latent variable 'Cognitive Perception' can be created through the combination of the three cognitive items – Ease of use, Usefulness, and Helpfulness.

H2: The three affective determinants can be combined for the creation of a suitable measure of the latent variable 'Affective Engagement'.

Intending to better understand the relational structure between the three affective items *Pleasure, Arousal, and Dominance* and how they describe the latent variable *Affective Engagement* it was performed a reliability analysis (Annex O) followed by an Exploratory Factor Analysis (EFA) over their correlation matrix (Annex P).

The reliability analysis shown that the Dominance item should be deleted, since the internal consistency of the new variable created through the combination of the affective items would increase without its presence.

The Exploratory Factor Analysis, was then performed considering only the *Pleasure*, and *Arousal* items. For that, the Principal Axis Factoring method was used, advised by Hill & Hill (2016), since it maximizes the percentage of variance explained by the extracted factors. The retained factor was the one with an eigenvalue greater than 1 (following Kaiser's criterion), also in line with the obtained from the Scree Plot and the percentage of the retained variance, because as it is stated by Maroco (2007) using only one criterion can lead to the retention of more/less factors than the ones that are actually relevant to describe the latent variable.

For the validation of the EFA the author analysed the Cronbach's Alpha (Annex O), that resulted out of the combination of the two items. It was obtained a value of 0.718, which is a reasonable alpha to measure the internal consistency of the variable ($\alpha > 0.6$), according to Hill & Hill (2016). Complementarily, it was used the Kaiser-Meyer-Olkin measure of sampling adequacy, KMO =0.500, the threshold of the acceptability to perform the factor analysis. This happens because there are only two items being considered for a factor analysis, which is the minimum for the creation of a new variable. However, this is not great, if there would be more items those could complement these two when defining the variable. The scores of each case for the retained factor were obtained using the regression method, and will then be used for the following analysis.

Following the Kaiser's criterion and the Scree plot (Annex P), it can be verified that the relational structure of the two affective items define only one factor, and that the measure's scale is unidimensional. In the table 5.9. it is presented the factorial weights of each item for the retained factor, its eigenvalue, the item's communalities, and the percentage of the variance explained by the factor.

Table 5.9: Exploratory Factor Analysis for the Affective Engagement dimension

Item	Communalities	Factor Loadings
Pleasure	0.568	0.753
Arousal	0.568	0.753
Eigenvalue		1,569
% of Variance Explained		78.4%

The retained factor, designated as *Patronage Intention*, explains 78.43% of the total variance of the two affective items. The two items have a relevant and equal contribution for the definition the factor. And it explains 56.8% of the variance of each item, *Pleasure* and *Arousal*.

➢ The second hypothesis is partially validated. There is statistical evidence that a suitable measure, unidimensional and with adequate internal consistency, for the latent variable '*Affective Engagement'* can be created by a linear combination of the two affective items – *Pleasure and Arousal.* However, the *Dominance* item should not be considered for the explanation of the latent variable.

H3: The three communicative determinants can be combined for the creation of a suitable measure of the latent variable ‘Communication Quality’.

For a better understanding of the relational structure between the items *Accuracy, Credibility, and Communication Competence* and how they describe the latent variable *Communication Quality* it was performed a reliability analysis (Annex Q) followed by an Exploratory Factor Analysis (EFA) over their correlation matrix (Annex R). For that, the Principal Axis Factoring method was used, advised by Hill & Hill (2016), since it maximizes the percentage of variance explained by the extracted factors. The retained factor was the one with an eigenvalue greater than 1 (following Kaiser’s criterion), also in line with the obtained from the Scree Plot and the percentage of the retained variance, since as it is defended by Maroco (2007) using only one criterion can lead to the retention of more/less factors than the ones that are actually relevant to describe the latent variable.

For the validation of the EFA the author analysed the Cronbach’s Alpha (Annex Q), that resulted out of the combination of the three items. It had the value of 0.837, which can be considered a good alpha to measure the internal consistency of the variable ($\alpha > 0.6$), according to Hill & Hill (2016). Complementarily, it was used the Kaiser-Meyer-Olkin measure of sampling adequacy, KMO =0.722, a value that is considered to be acceptable and good to perform the factor analysis. The scores of each case for the retained factor were obtained using the regression method, and will then be used for the following analysis.

Following the Kaiser’s criterion and the Scree plot (Annex R), it can be verified that the relational structure of the three communicative items define only one factor, and that the measure’s scale is unidimensional. In the table 5.10. it is presented the factorial weights of each item for the retained factor, its eigenvalue, the item’s communalities, and the percentage of the variance explained by the factor.

Table 5.10: Exploratory Factor Analysis for the Communication Quality dimension

Item	Communalities	Factor Loadings
Accuracy	0.706	0.840
Credibility	0.566	0.752
Communication Competence	0.633	0.795

Eigenvalue		2.267
% of Variance Explained		75.6%

The retained factor, designated as *Communication Quality*, explains 75.55% of the total variance of the three communicative items. These items have a relevant contribution for the definition of the factor. It can also be highlighted that the *accuracy* item is the one that has higher factor loading, and that therefore, is the one that more contributes for defining factor. The remaining factors even with slightly lower values also have an important contribution for the extracted factor. The factor explains 70.6% of the variance of the *accuracy* item, 63.3% of the *communication competence*, and 56.6% of the *credibility*.

- The third hypothesis is validated. A suitable measure, unidimensional and with adequate internal consistency, for the latent variable '*Communication Quality*' can be created through the combination of the three communicative items – *Accuracy*, *Credibility*, and *Communication Competence*.

H4: The four experience determinants can be combined for the creation of a suitable measure of the latent variable 'Customer Experience Expectation'.

To understand the relational structure between the items *Interaction Appeal, Interaction Comfortability, Experience Improvement, and Preferability* and how they describe the latent variable *Customer Experience Expectation,* a reliability analysis (Annex S) and an Exploratory Factor Analysis (EFA) over their correlation matrix (Annex T) were performed. For that, the Principal Axis Factoring method was used, advised by Hill & Hill (2016), since it maximizes the percentage of variance explained by the extracted factors. The retained factor was the one with an eigenvalue greater than 1 (following Kaiser's criterion), and also in line with the obtained from the Scree Plot, since as it is defended by Maroco (2007) using more than one criterion lessen the chances of retaining more/less factors than the ones that are actually relevant to describe the latent variable.

For the validation of the EFA the author analysed the Cronbach's Alpha (Annex S), that resulted out of the combination of the four items. It had the value of 0.822, which can be considered a good alpha to measure the internal consistency of the variable ($\alpha > 0.6$), according to Hill & Hill (2016). Complementarily, it was used the Kaiser-Meyer-Olkin measure of sampling adequacy, KMO =0.797, a value that is considered a good value for this statistic, meaning that the items correlations are adequate to perform the factor analysis. The scores of each case for the retained factor were obtained using the regression method, and will then be used for the following analysis.

Following the Kaiser's criterion and the Scree plot (Annex T), it can be verified that the relational structure of the four experience-related items define only one factor, and that the measure's scale is unidimensional. In the table 5.11. it is presented the factorial weights of each item for the retained factor, its eigenvalue, the item's communalities, and the percentage of the variance explained by the factor.

Table 5.11: Exploratory Factor Analysis for the Costumer Experience Expectation

Item	Communalities	Factor Loadings
Interaction Appeal	0,614	0,784
Interaction Comfortability	0,655	0,809
Experience Improvement	0,514	0,717
Preferability	0,424	0,651
Eigenvalue		2,644
% of Variance Explained		66,1%

The retained factor, designated as *Customer Experience Expectation*, explains 66.10% of the total variance of the four experience-related items. All these items have a relevant contribution for the definition of the factor. It can also be highlighted that the *satisfaction* item is the one that has a higher factor loading, and that therefore is the one that more contributes for the factor definition, and is complemented by the remaining three. The factor explains 65.5% of the variance of the *satisfaction* item, 61.4% of the *appeal for the interaction with the virtual assistant*, 51.4% of the *improvement in the experience*, and 42.2% of the *preference for the new interaction.*

- The fourth hypothesis is validated. There is statistical evidence that a suitable measure, unidimensional and with adequate internal consistency, for the latent variable '*Customer Experience Expectation'* can be created by a linear combination of the four experience-related items – *Appeal, Comfortability, Improvement, and Preference.*

H5: The two patronage determinants can be combined for the creation of a suitable measure of the latent variable 'Patronage Intention'.

To understand the relational structure between the items *Usage and Recommendation* and how they describe the latent variable *Patronage Intention*, a reliability analysis (Annex U) followed by an Exploratory Factor Analysis (EFA) over their correlation matrix (Annex V) were performed. For that, the Principal Axis Factoring method was used, advised by Hill & Hill (2016), since it maximizes the percentage of variance explained by the extracted factors. The retained factor was the one with an eigenvalue greater than 1 (following Kaiser's criterion), also in line with the obtained from the Scree Plot and the percentage of the retained variance, as it is argued by Maroco (2007) to use more than one criterion.

For the validation of the EFA the author analysed the Cronbach's Alpha (Annex U), that resulted out of the combination of the two items. It had the value of 0.748, which is a reasonable alpha to measure the internal consistency of the variable ($\alpha > 0.6$), according to Hill & Hill (2016). Complementarily, it was used the Kaiser-Meyer-Olkin measure of sampling adequacy, KMO =0.500, the threshold of the acceptability to perform the factor analysis. As observed previously, this happens because there are only two items being considered for a factor analysis, which is the minimum for the creation of a new variable. However, this is not great, if there would be more items those could complement these two for the definition of the variable. The scores of each case for the retained factor were obtained using the regression method, and will then be used for the following analysis.

Following the Kaiser's criterion and the Scree plot (Annex V), it can be verified that the relational structure of the two patronage items define only one factor, and that the measure's scale is unidimensional. In the table 5.12. it is presented the factorial weights of each item for the retained factor, its eigenvalue, the item's communalities, and the percentage of the variance explained by the factor.

Table 5.12: Exploratory Factor Analysis for the Patronage Intention

Item	Communalities	Factor Loadings
Usage	0.601	0.775
Recommendation	0.601	0.775
Eigenvalue		1,602
% of Variance Explained		80.1%

The retained factor, designated as *Patronage Intention*, explains 80.09% of the total variance of the two patronage items. The two items have a relevant and equal contribution for the definition the factor. And it explains 60.1% of the variance of each item, *Usage* and *Recommendation*.

- The fifth hypothesis is validated. There is statistical evidence that a suitable measure, unidimensional and with adequate internal consistency, for the latent variable '*Patronage Intention'* can be created by a linear combination of the two patronage items – *Usage and Recommendation.*

H6: The Customer Experience Expectation is positively influenced by:

H6a: Cognitive Perception,

H6b: Affective Engagement, and

H6c: Communication Quality.

As previously mentioned, the latent variables that resulted from the factor analysis were used to verify these hypotheses.

A preliminary exploratory analysis was performed to prove the existence of a linear relation between the dependent variable *Customer Experience Expectation* and the explanatory variables *Cognitive Perception, Affective Engagement, and Communication Quality*.

Table 5.13: Correlation Matrix between the explanatory variables 'Cognitive Perception', 'Affective Engagement', and the dependent variable 'Customer Experience Expectation'

Correlations

		Cognitive Perception	Affetive Engagement	Communication Quality	Customer Experience Expectation
Cognitive Perception	Pearson Correlation	1	,134**	,401**	,400**
	Sig. (2-tailed)		0,009	0,000	0,000
	N	385	385	385	385
Affetive Engagement	Pearson Correlation	,134**	1	,217**	,141**
	Sig. (2-tailed)	0,009		0,000	0,006
	N	385	385	385	385
Communication Quality	Pearson Correlation	,401**	,217**	1	,144**
	Sig. (2-tailed)	0,000	0,000		0,005
	N	385	385	385	385
Customer Experience Expectation	Pearson Correlation	,400**	,141**	,144**	1
	Sig. (2-tailed)	0,000	0,006	0,005	
	N	385	385	385	385

**. Correlation is significant at the 0.01 level (2-tailed).

As observed in the table 5.13. all the variables have positive and significant Pearson correlation coefficients ($p<0.01$). It can be highlighted that the Customer Experience Expectation has a higher correlation with the Cognitive Perception (weak/moderate linear association), than with the other two dimensions, that are considered as weak linear associations.

Even with the presence of some weak Pearson correlations between the dependent and explanatory variables, the author has decided to continue to the estimation of a Multiple Linear Regression Model, because the linear associations were confirmed by the Scatter plots in Annex W (1st assumption) where it was verified that the distribution was not non-linear.

This model was chosen since it helps in the understanding of the relation between a dependent variable and more than one explanatory variable, and it is also useful when the aim is to be able to make predictions and future decisions, which is also relevant when defying strategies for businesses. This method was also selected taking under consideration the nature of the variables, and the existence of a linear association between the variables (even if only two of them have a high and strong Pearson correlation).

The Multiple Linear Regression Model estimated to obtain a model able to predict the impact on *Customer Experience Expectation* by the influence of the independent variables (*Cognitive Perception*, *Affective Engagement*, and *Communication Quality*) used, on one side, the Stepwise method, and on the other, the Backward one, to select the variables that would make up the model.

The assumptions of the multiple linear regression model were verified, and can be found in the Annex W:

1. There is a linear relationship between the dependent variable and each of the explanatory variables;
2. The mean of the residual component of the model is 0;
3. The independent variables are not correlated with the residual terms;
4. There is no correlation among the residual terms;
5. The variance of the random term is constant;
6. The residuals follow a Normal distribution;
7. And, there is no correlation among the explanatory variables.

The Multiple Linear Regression Model identified (Annex X), as significant predictors of the Customer Experience Expectation, the variables Cognitive Perception ($\beta = 0.388$; $t(382)=8.247$; $p < 0.001$), and Affective Engagement ($\beta = 0.089$; $t(382) = 1.897$; $p=0.059$). The Affective Engagement variable is only marginally significant, and would be acceptable if the selection criteria were re-adjusted to $\alpha=0.1$, which would decrease the confidence interval to 90% (Maroco, 2007). The author chose to still consider this variable since the confidence interval would still be relevant and the Backward method also led to the choice of the model including the Affective Engagement variable.

The equation of the fitted regression model is: $\boldsymbol{Customer\ Exper\widehat{ience}\ Expectation} = \boldsymbol{0.409} * \boldsymbol{Cognitive\ Perception} + \boldsymbol{0.096} * \boldsymbol{Affective\ Engagement}$

This model is highly significant, but only explains 16.4% of the Customer Experience Expectation variation ($F(2,382) = 38.589$; $p <0.001$; $R_a^2 = 0.164$). Even though there is no statistical evidence that the constant term should be included in the equation model, it was kept as part of the regression model, because the two explanatory variables only explain a low percentage of the variation of the dependent variable and the constant term also captures the mean effects of additional variables that are not included in the model.

➢ The sixth hypothesis is partially validated. There is statistical evidence that the Cognitive Perception positively influences the Customer Experience Expectation (H6a). And by relaxing a little the confidence level it can also be observed a positive influence from the Affective Engagement dimension towards the dependent variable (H6b). Both these dimensions were included in the estimation of a Multiple Linear Regression Model to predict the Customer Experience Expectation. On the other hand, there is no statistical evidence that the Communication Quality dimension will have a significant impact on the dependent variable, and was, therefore, excluded from the estimated model (H6c).

H7: The Patronage Intention for the Virtual Assistant is positively influenced by the Customer Experience Expectation from its interaction.

A preliminary exploratory analysis was performed to prove the existence of a linear relation between the dependent variable *Patronage Intention* and the explanatory variable *Customer Experience Expectation*.

Table 5.14: Correlation Matrix between the independent variable 'Customer Experience Expectation' and the dependent variable 'Patronage Intention'

Correlations

		Customer Experience Expectation	**Patronage Intention**
Customer Experience Expectation	Pearson Correlation	1	**,703****
	Sig. (2-tailed)		0,000
	N	385	385
Patronage Intention	Pearson Correlation	,703**	1
	Sig. (2-tailed)	0,000	
	N	385	385

**. Correlation is significant at the 0.01 level (2-tailed).

As observed in the table 5.14. the Pearson correlation coefficient between the two variables is a high, positive and significant ($p < 0.001$) value.

The Simple Linear Regression Model estimated used the Enter method to obtain a model able to predict the impact on the Patronage Intention by the influence of the independent variable (Customer Experience Expectation).

The assumptions of the simple linear regression model were verified, and can be found in the Annex Y:

1. There is a linear relationship between the dependent variable and the explanatory variable;
2. The mean of the residual component of the model is 0;
3. The independent variable is not correlated with the residual terms;

4. The variance of the random term is constant;
5. And, the residuals follow a Normal distribution;

The Simple Linear Regression Model (Annex Z) identified the variable Customer Experience Expectation (β = 0.703; t(383)=19.344; p < 0.001) as a significant predictor of the Patronage Intention.

The equation of the fitted regression model is:

$$\widehat{\boldsymbol{Patronage\ Intention}} = \mathbf{0.664} * \boldsymbol{Customer\ Experience\ Expecctation}$$

This model is highly significant, but only explains 49.4% of the Customer Experience Expectation variation (F(1,383) = 374.191; p <0.001; $R^2 = 0.494$). Even though there is no statistical evidence that the constant term should be included in the equation model, it was kept as part of the regression model, because the explanatory variable only explains less than 50% of the variation of the dependent variable and the constant term also captures the mean effects of additional variables that are not included in the model.

➢ The seventh hypothesis is validated. There is statistical evidence that the Patronage Intention is positively influenced by the Customer Experience Expectation, proved by the estimation of a Simple Linear Regression Model.

5.6. Patronage Intention towards Retailers

Finally, when analysing the sample in terms of on which specific sector and stage of the customer decision-making process they would use and interact with a Virtual Assistant, it was observable that:

- The top 3 sectors where individuals perceive themselves utilizing this technology where the same as the ones where they already resort to Internet – with the switch of the Tech sector with the Cultural one. The Tech sector assumed now the second place, with 73% of the individuals choosing it as one of the sectors they would like to interact with a virtual assistant (figure 5.14.).
- The Fashion sector remained in the first position, since 83.1% of the sample selected this option as one of the sectors, they would be willing to interact with a virtual assistant.
- The Beauty care sector also suffered a high increase, when compared to the traditional usage of internet. Almost half of the sample (44.9%) selected this as one of the sectors they would use a Virtual Assistant.

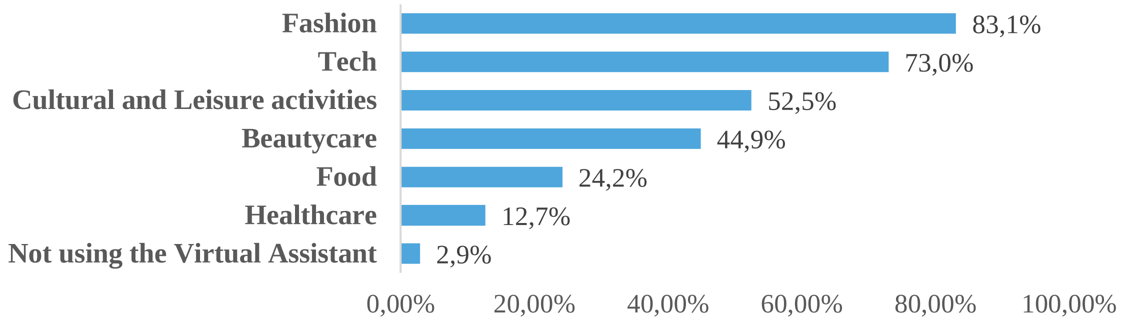

Figure 5.15: Sectors where a Virtual Assistant would be used

- The stage from the Customer journey where more respondents would resort to the interaction with a virtual assistant is to *Search for Information* about the products (65.7%). This was also one of the steps where the individuals already used Internet for.
- They could also perceive themselves as comparing and *Evaluating the different Alternatives* amongst the brand's catalogue with the help of a virtual assistant.

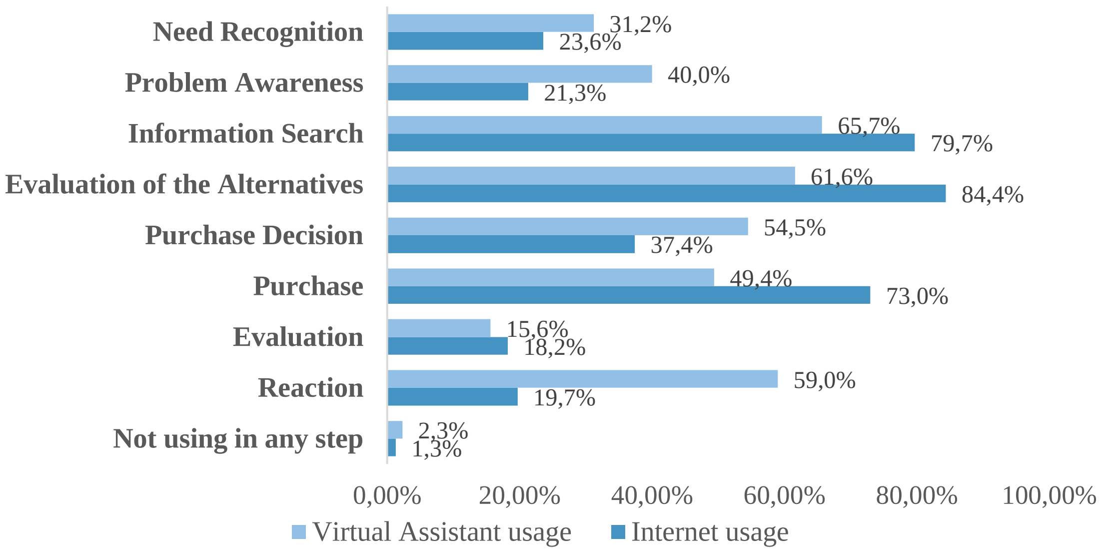

Figure 5.16: Internet and Virtual Assistant's Usage in Customer decision-making process

Comparing to the usage of the Internet (figure 5.15.), it can be highlighted that:

- The post-purchase step of *Reacting* is the step with a higher discrepancy. 59% of the sample stated they would interact with a virtual assistant to express their level of satisfaction and share their experience (after using the product in question), as opposed to the 19.7% that already do it through the use of internet.
- Besides that, the *Need Recognition*, *Problem Awareness*, and *Purchase Decision* steps were also selected by more people to be performed with the help of a Virtual Assistant than the ones that resort to internet in those stages of the customer journey;

- However, there are less people that would make the actual purchase via instant messaging with a Virtual Assistant than the ones that make online purchases by other platforms.
- It can also be highlighted that there is a lower discrepancy of the percentage's distribution towards the different steps for the interaction with a virtual assistant, when comparing to the Internet usage for them. This means that more people selected more options simultaneously, and that could see themselves utilizing the virtual assistant in more steps throughout the customer journey, instead of being a one-off operation.

5.7. Hypotheses' Decision Summary

Table 5.15: Hypotheses' Decision Summary

Hypotheses' Decision Summary
H1: The three cognitive determinants – *Ease of Use, Usefulness, and Helpfulness* - can be combined for the creation of a suitable measure of the latent variable 'Cognitive Perception'.
Validated. The Exploratory Factor Analysis proved that the cognitive dimension of the virtual assistant can be explained by the combination of the three cognitive determinants: Ease of Use, Usefulness, and Helpfulness.
These three determinants were proposed by Zarouali *et al*. (2018), when adjusting the Consumer Acceptance of Technology model, as components of the chatbots' cognitive dimension and it is now been proved that a suitable measure for this dimension can also be created by their combination.
H2: The three affective determinants – *Pleasure, Arousal, and Dominance* - can be combined for the creation of a suitable measure of the latent variable 'Affective Engagement'.
Partially validated. The combination of only two of the affective items – Pleasure and Arousal – shows internal consistency, and therefore, allows the creation of a suitable measure for the latent variable 'Affective Engagement'.
Only two of the determinants, initially presented by Mehrabian and Russell's (1974), in the PAD theory, also included in the CAT-model **(**Kulviwat et al. 2007) and when explaining the Customer Experience (Grewal & Roggeveen, 2020) and the chatbot's affective dimension (Zarouali *et al*. 2018) were proven to create a suitable measure for the virtual assistant Affective Engagement when combined.
H3: The three communicative determinants – *Accuracy, Credibility, and Communication Competence* - can be combined for the creation of a suitable measure of the latent variable 'Communication Quality'.
Validated**.** The Exploratory Factor Analysis proved that the cognitive dimension of the virtual assistant can be explained by the combination of the three communicative determinants: Accuracy, Credibility, and Communication Competence.

These three determinants were proposed by Chung *et al.* (2018), when defining a chatbot's communication quality and it was now been proved that a suitable measure for this dimension can also be created by their combination.

H4: The four experience determinants – *Interaction Appeal, Interaction Comfortability, Experience Improvement, and Preferability* - can be combined for the creation of a suitable measure of the latent variable '*Customer Experience Expectation*'.

Validated. The Exploratory Factor Analysis proved that a suitable measure for the *Customer Experience Expectation* variable was proven to be created out of the combination of the *Interaction Appeal, Interaction Comfortability, Experience Improvement, and Preferability* items.

The measures presented in the literature (Chung *et al.*, 2018; Clarke & Kinghorn, 2018; Davis, 1986; Hassanein & Head, 2007; Pantano & Di Pietro, 2012) to evaluate the customer experience and its expectations when adopting a new technological innovation were adjusted to measure the expectation created when being confronted with the possibility of interacting with a virtual assistant.

H5: The two patronage determinants – *Usage, and Recommendation* - can be combined for the creation of a suitable measure of the latent variable 'Patronage Intention'.

Validated. The Exploratory Factor Analysis proved that a suitable measure for the *Patronage Intention* variable was proven to be created out of the combination of the *Usage,* and *Recommendation* items.

This two items were considered in previous studies as being able to define the intentions users had either on adopting a certain innovation or purchasing a product, and on recommending it to others (Hou *et al.*, 2013; Van den Broeck *et al.*, 2019; Zarouali *et al.*, 2018). This study proved that a suitable measure can be created through their combination.

H6: The dependent variable *Customer Experience Expectation* is positively influenced by:

H6a: the explanatory variable *Cognitive Perception*

Validated. The *Cognitive Perception* variable was proved with significant statistical evidence that should be included in the Multiple Linear Regression Model as an explanatory variable to the *Customer Experience Expectation.*

The cognitive dimension was a considered as a component of both the customer experience (Grewal & Roggeveen, 2020; Lemon & Verhoef, 2016; Verhoef *et al.*, 2009) and of the interaction with chatbots (Zarouali *et al.*, 2018). It was this way proved that it also positively impacts the expectation users create towards the customer experience that results out of the interaction with a virtual assistant.

H6b: the explanatory variable *Affective Engagement*

Partially Validated. The *Affective Engagement* variable is only marginally significant, and can be included in the Multiple Linear Regression Model to explain the dependent variable *Customer Experience Expectation*.

The affective dimension was a considered as a component of both the customer experience (Grewal & Roggeveen, 2020; Lemon & Verhoef, 2016; Verhoef *et al.*, 2009) and

of the interaction with chatbots (Zarouali *et al*., 2018). It was proved that it also positively impacts the expectation users create towards the customer experience but only marginally.
H6c: the explanatory variable *Communication Quality*
Rejected. There is not statistical evidence for the presence of the explanatory variable Communication Quality in the Multiple Linear Regression Model to explain the dependent variable Customer Experience Expectation.
Even though the communicative dimension was considered as a component of both the customer experience, through behavioural influences (Grewal & Roggeveen, 2020; Lemon & Verhoef, 2016; Verhoef *et al.*, 2009) and of the interaction with chatbots (Chung *et al.*, 2018)), it was not proven to significantly impact the expectation users create towards the customer experience that results out of the interaction with a virtual assistant.
H7: The dependent variable *Patronage Intention* for the Virtual Assistant is positively influenced by the explanatory variable *Customer Experience Expectation* from its interaction.
Validated. A Simple Linear Regression model was created where the *Customer Experience Expectation* variable positively impacts the *Patronage Intention*.
Previous researchers analysed the impact the different dimensions of the technology adoption and of perceptions of the customer experience have on the users/customers patronage intentions (Van den Broeck *et al*.,2019; Zarouali *et al*., 2018). This study proved that the Customer experience expectation, acting as an intermediate construct of the different dimensions positively impacts the Patronage intention towards the virtual assistant.

6. CONCLUSIONS

This Chapter gathers the conclusions that could be retrieved from the analysis of the research findings, previously presented in Chapter 5. The main conclusions (1) described throughout the chapter will be complemented with the presentation of the limitations of the study (2), as well as its contributions (3), and impact on future researches (4).

6.1. Main Conclusions

From the analysis of the collected data it was possible to verify the previously described trends in terms of the increase of the distribution of the time spent online in messaging apps and social media by young adults, as well as their willingness and comfortability when making purchases online. The combination of both these contexts was then, taken under analysis with the study of the impact that the possibility of interacting with a virtual assistant (innovation) would have on the customers.

Even though the majority of the respondents already knew what a chatbot was, most of them had not interacted with one prior to this investigation. Complementing with the analysis on the innovativeness adoption profiles of the sample, classified, in most of the cases, as part of the Early and Late Majorities profiles, it was possible to conclude that they will tend to follow already established trends and are more cautious to initiate the use of a new technology. They tend to refer to existent feedback and validation from other users to get some prior knowledge of the new technology/product and make a conscious decision before its adoption and usage.

Out of the nine determinants, considered for the costumer - virtual assistant interaction analysis, eight of them were proven to be relevant for the construction of the three interactive dimensions that were being tested:

- *Cognitive Perception*: created combining the *Ease of Use, Usefulness, and Helpfulness* items, confirming Zarouali *et al*. (2018) when proposing that the three determinants could be set as components of a cognitive dimension on the interaction with chatbots.

- *Affective Engagement:* with the combination of the *Pleasure, and Arousal* items; That, even though, not proving entirely the PAD theory presented by Mehrabian and Russell's (1974), or posterior studies that based on it to evaluate the existance of an affective dimension as part of the multidimensional concept of customer experience (Grewal & Roggeveen, 2020) and as a predictor on the adoption of technological innovations (Kulviwat et al., 2007; Zarouali et al., 2018), proved that two of the affective determinants can create a suitable measure for this dimension.

- *Communication Quality*: through the combination of *Accuracy, Credibility, and Communication Competence*. Verifying that the three items, as proposed by Chung *et al.* (2018), can be components when defining the communicative dimension of the interaction with a chatbot.

The latent variables *Customer Experience Expectation* and *Patronage Intention* were also the result of the combination of other items. In the case of the first variable the items considered were based on the measured presented in the literature when evaluating and the customer experience, the different dimensions that make it up in order to measure expectations when adopting a new technological innovation (Chung *et al.*, 2018; Clarke & Kinghorn, 2018; Davis, 1986; Hassanein & Head, 2007; Pantano & Di Pietro, 2012). It was then verified that those dimensions - the *Interaction's Appeal* and *Comfortability*, the *Experience Improvement* (that the Virtual Assistant was expected to provide), and the *Preferability* (of this channel against the more traditional ones) created a suitable measure for the expectation created when being confronted with the possibility of interacting with a virtual assistant.

For the case of the *Patronage Intention* it was concluded to be created out of the combination of the likelihood to *Use*, and *Recommend* a virtual assistant as a way to interact with a retailer/brand. Confirming the relevance given to these items when defining the users' intentions either on adopting a certain innovation or purchasing a product, and on recommending it to others (Hou *et al.*, 2013; Van den Broeck *et al.*, 2019; Zarouali *et al.*, 2018).

However, not all of the dimensions were proven, with statistical evidence, to impact the *Customer Experience Expectation.* Only the *Cognitive Perception* associated to the interaction with the virtual assistant was proven to positively and significantly influence this variable, and the *Affective Engagement* variable was only marginally significant. Which comes in line with the investigations where it was considered the influence of cognitive and affective dimensions when explaining the variables of customer experience (Grewal & Roggeveen, 2020; Lemon & Verhoef, 2016; Verhoef *et al.*, 2009) and the influence on customer satisfaction for the interaction with chatbots (Zarouali *et al*., 2018).

However, unlike what would be predicted in terms of the influence the communication and behavioural dimension would have on the customer experience expectations of the consumers (Grewal & Roggeveen, 2020; Lemon & Verhoef, 2016; Verhoef *et al.*, 2009), and on the overall satisfaction when interacting with a virtual assistant, as proposed by Chung et al. (2018), it was not verified. The remaining dimension, *Communication Quality,* had a weak linear relation with the *Customer Experience Expectation* and did not have a significant impact on the last, becoming excluded of the Multiple Linear Regression Model, as an explanatory variable for the *Customer Experience Expectation.*

A possible explanation for that not being significantly verified for the Affective and Communicative dimensions, might have to do with the fact that the respondent did not fully understand the real features that both these dimensions would comprehend. This might have been the result of, in comparison to the Cognitive dimension, the lack of specific items and features that the respondent could evaluate in terms of importance, due to its high subjectivity. Making it harder for the respondent to have a concrete perception on what to expect for each of the determinants that are part of both the affective and communicative dimensions of the virtual assistant.

It was also possible to conclude that the expectation the users have of their Customer Experience via the interaction with a virtual assistant will also positively influence their patronage intentions. This conclusion was in line with the expectations since the explanatory variable was defined by experience related items evaluating the satisfaction with the possibility of a future interaction with a virtual assistant (Van den Broeck *et al*.,2019; Zarouali *et al*., 2018). These variables are correlated and a simple linear regression model could be estimated: a positive *customer experience expectation* will contribute to an increase of 0.664 on the *patronage intention* variable.

In terms of the steps of the customer decision-making process where the respondents would interact with the virtual assistant, it was verified that more individuals would use it in more steps throughout the process than the ones they would use internet on. The usage of the virtual assistant could then be perceived as a helper across the customer journey instead of being a one--off operation.

It was also verified that a higher percentage of the sample would use the virtual assistant in the stages of *Need Recognition*, *Problem Awareness*, and *Purchase Decision,* when compared to the one that already resort to the internet on these stages. These can be associated with some of the features the virtual assistant can have and show in the conversation with the user, and that were also considered to be important by the sample, as it is the case of: '*Suggest products considering the customer's profile and purchase history, and allowing product customization to make the interaction more effective.'*, '*Have available and provide faster access to product-related information (brand catalogue and product characteristics).'*, and '*Be able to answer* *customer questions.'*. The customer could then receive specific and personalized product recommendations, suggesting new options that he would not have considered before, while providing them access to all the product-related information and answering possible questions that might arise, helping this way to make the purchase decision. However, when it came to making the purchase the respondents showed less likelihood to do it directly in the conversation with the virtual assistant than they would on more traditional online channels.

On the other hand, a higher percentage of the sample would be more willing to react, express their opinions and level of satisfaction with the brand and the offered services via a conversation with a virtual assistant. This can be explained by the fact that the respondents considered to be important that the virtual assistant would *'Make interacting with a brand easier. Interact directly with the brand through instant messaging. (Possibility to ask questions about the brand's products and services)',* and have the possibility to *'Redirect the conversation to a brand employee if needed*.', and therefore would feel more comfortable communicating with the brand in a more convenient platform as it is the case of instant messaging, when compared to other options online.

6.2. Research Contributions

The study provided significant information regarding the importance of the presence of cognitive determinants in the interaction with the virtual assistant for the creation of a positive Customer Experience Expectation, leading, consequently users to interact with the virtual assistant in the future. The conclusions that could be retrieved from this were that the virtual assistant as a brand representative should be considered to be ease to use, useful, and helpful for the user to create a positive expectation for its purchase journey.

As a brand's representative, the virtual assistant was considered to be a helpful tool in different stages of the customer decision-making process, contributing to the research already being developed in the area, more specifically in the retail context. The study also proved that this technology can be used as an additional channel by the retail brands to reach out and communicate directly with their customers. It also leads the users to perceive the brand as more available and reachable to communicate and express their questions and feedback, since it can be integrated in platforms that the users already are familiar to and use regularly.

In conclusion, this research provides insights on which dimensions of the interaction with the virtual assistant have a significant and positive effect in the creation of a positive customer experience expectation, and on which steps of the decision-making process it would have a higher impact and would be perceived as being more useful to the customer. This was the case of the cognitive determinants, that can, therefore, serve as a starting point for brands in the retail context that want to implement such technology. In addition, there were also identified some pre-purchase and post-purchase steps where the chatbot would be used by the costumers. Even though the results cannot be extrapolated to the universe of the study, it can serve as basis for the creation of best practices and development in the area, when considering the cognitive perception as a relevant dimension to invest on, and the features and communication intended for the different stages of the costumer journey.

6.3. Management and Marketing Implications

From the businesses standing point, this investigation provided some useful insights for the management and marketing subjects in the retail context, highlighting the importance of the:

- Adjustment to the new reality: with an increasing need of more online solutions by the customers, without losing the level of experience and guidance throughout the shopping journey.
- Integration of the conversational commerce: as one of those solutions, and considering the major increase in the use of messaging apps and the change on the communication paradigm. Moving to a two-way communication stream, available at customers' choice. Adjusting the business strategy for a smooth integration of both online and offline contexts.
- Development of Virtual Assistants: as the result of the need to provide assistance in the shopping process and as conversational agents. Providing special attention to its cognitive dimension, the one found to be more relevant for the perception of a positive customer experience. Making sure it is easy to use, useful and helpful. Some recommendations for Managers for the development of this dimensions are to:
    - Integrate the virtual assistant in the most used messaging apps (in this case Facebook Messenger and WhatsApp);
    - Include an introduction on the use and potentialities of the virtual assistant at the start of the interaction;
    - Provide direct options to product related information;
    - While allowing the user to type questions and not only select amongst options;
    - Invest on data analysis to provide personalized suggestions;
    - Include the possibility to redirect the user to a human employee if requested for.

- Existence of data analysis expert talent and knowledge within the business to take the most advantage out of the virtual assistant and the data collected, so that it is possible to have all the features customers consider to be important available. To better understand which insights can be retrieved out of the conversations so that the virtual assistant can add more value to the entire experience.
- Understand the potentialities of the virtual assistant in each step of the shopping experience and the reasons behind the possibility of not completing the purchase in this channel (if it is for security and privacy concerns or if there are any additional barriers).

6.4. Research Limitations

It is important to also take under consideration all the limitations associated to the study and to the chosen methodology.

6.4.1 Sampling Method

Starting off with the sampling method, it represented a limitation since it was chosen a non-probabilistic method, done by convenience to the author. This means that not all the individuals in the universe of the study had an equal probability to be selected to take part in the study, the ones with higher proximity to the researcher had a higher probability to get in contact with the divulgation of the study and also to take part on it. This is mainly due to the fact that the author's social media were an important platform for sharing the survey, this way, the sample cannot be defined as representative.

It will not be possible, consequently, to extrapolate the results obtained in the study to its universe, and should only be considered for the analysis of the sample.

6.4.2. Research Variables & Conceptual Model

Another limitation, is the fact that only for the three cognitive determinants specific features for the virtual assistant were identified and presented to the respondents, and not for the remaining six determinants (affective and communicative). This happened due to the subjective content of the six determinants and the difficulty to translate them into best practices and specific features, since there was not a specific virtual assistant being analysed. This is perceived as a limitation, because for the cognitive determinants the users had more insights on what to expect and on what would be possible for the virtual assistant to accomplish. This limitation can, therefore, be one of the reasons for the weaker or non-existence impact of the affective (only marginally significant) and communicative (not significant) dimensions on the customer experience expectation, against what was predicted considering the literature review.

In addition, the study focused on the creation of an expectation on the customer experience, a hypothetic scenario, where it was not being tested an existing chatbot, so that people could evaluate its traits and features, and consider using it in the future. This is a limitation, since only a description of what the determinants consisted of was provided, allowing different interpretations of the same. Also, by not specifying a specific brand or sector within the retail context, it might make harder for the respondent to be certain of what to expect. This can also be very important in terms of the management of the users' expectations, since previous contacts with the brand might also influence it and might exist a pre-established type of service and communication associated with the brand/sector and expected by the user to be met.

6.5. Future Research

In order to gather more information related to the topic of this research and enrich the knowledge already available on it, some suggestions for future researches arouse and were identified as potential complementary topics: extension of the study to a larger universe, for other age groups (over 35 years old); inclusion of specific examples for the affective and communicative determinants in the survey; inclusion of other dimensions as trust and security as influencers for the customer experience expectation, and as possible explanations on the apprehension of using the virtual assistant to complete the purchase; adaptation of the study to a specific sector or brand, to test the viability of the virtual assistant for that exact case; more in-depth analysis of the influence the virtual assistant as in each of the steps of the customer decision-making process, to be able to develop certain features that would lead to a higher engagement with the customer; the application of a probabilistic sampling method, to be able to extrapolate the results for the universe of the study and be able to create best practices towards the development and implementation of the virtual assistant; and, complement the investigation with a qualitative approach, identifying other possible barriers and limitations to look out for but also other adoption drivers and insights, considering both the retailers' and the consumers' perspectives.

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ANNEXES

Annex A: Universe and Sample Size Calculation

1) Universe Size Calculation

To calculate the universe dimension, it was considered the *Statista* Report: *"Portugal: Messenger users by age and gender 2020"* (Johnson, 2020), where it could be observed the following distribution of the stated total 5 788 000 Facebook Messenger users in Portugal in June 2020:

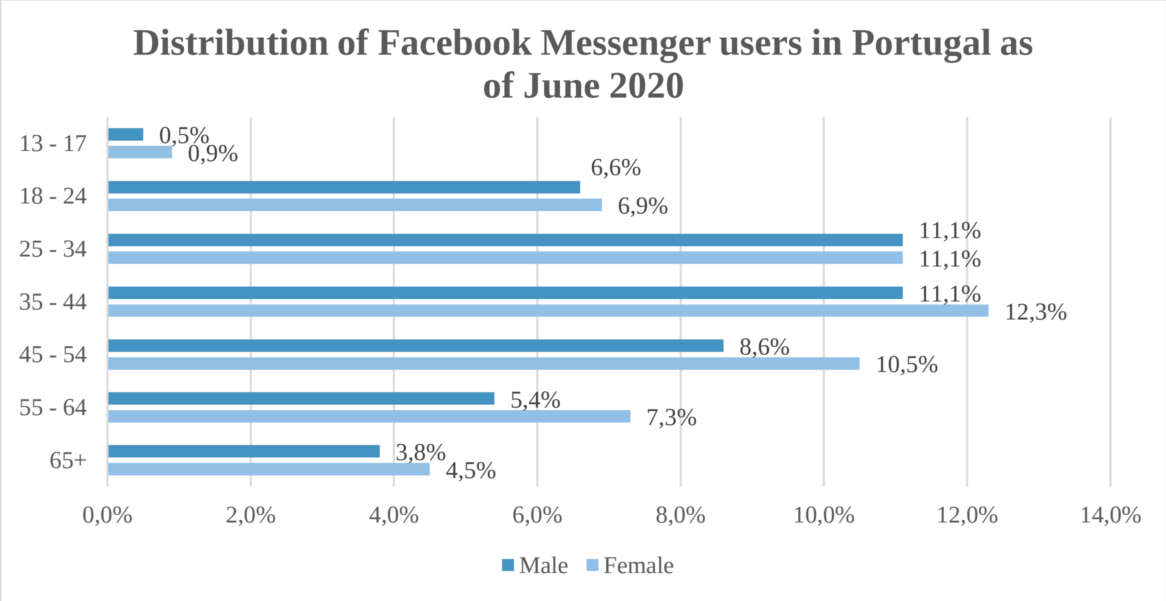


Figure 0.1:Distribution of Facebook Messenger users in Portugal as of June 2020 Source: Statista Report (2020)

The size of the universe was then obtained by calculating the absolute frequency of all the users between 18 and 34 presented in the figure above:

$$\begin{aligned} Universe\ size &= 5788000 * 0.066 + 5788000 * 0.069 + 5788000 * 0.111 + 5788000 * 0.111 \\ &= 2066316 \end{aligned}$$

As of June 2020, there were 2 066 316 Facebook Messenger users in Portugal, with ages ranging from 18 to 34, which will be considered the universe of this study.

2) Sample Size Calculation

To get the value for the sample size for this investigation it was used the formulas presented by (Agranonik et al., 2011; Israel, 1992):

$$n_0 = \frac{Z^2 p(1-p)}{\varepsilon^2}$$

Where:

n_0: is the sample size

Z: is the value for the normal distribution correspondent to the level of trust (obtained in the statistical tables)

p: is the estimated proportion of an attribute being present in the population

ε: is the desired level of precision

Resulting in:

$$n_0 = \frac{1.96^2 \cdot 0.5(1-0.5)}{0.05^2} = 384.16 \approx 385$$

Considering:

A 95% confidence level, corresponding to a Z of 1.96;

A 5% margin of error;

And a p of 0.5, since the variability in the population in unknown, maximum variability should be assumed (Israel, 1992).

Adjusting to the population size, of 2 066 316 Portuguese young adults using Facebook Messenger as presented in the *Statista* Report by Johnson (2020), the sample size can be confirmed with the following formula, where N is the population size, and n the sample size:

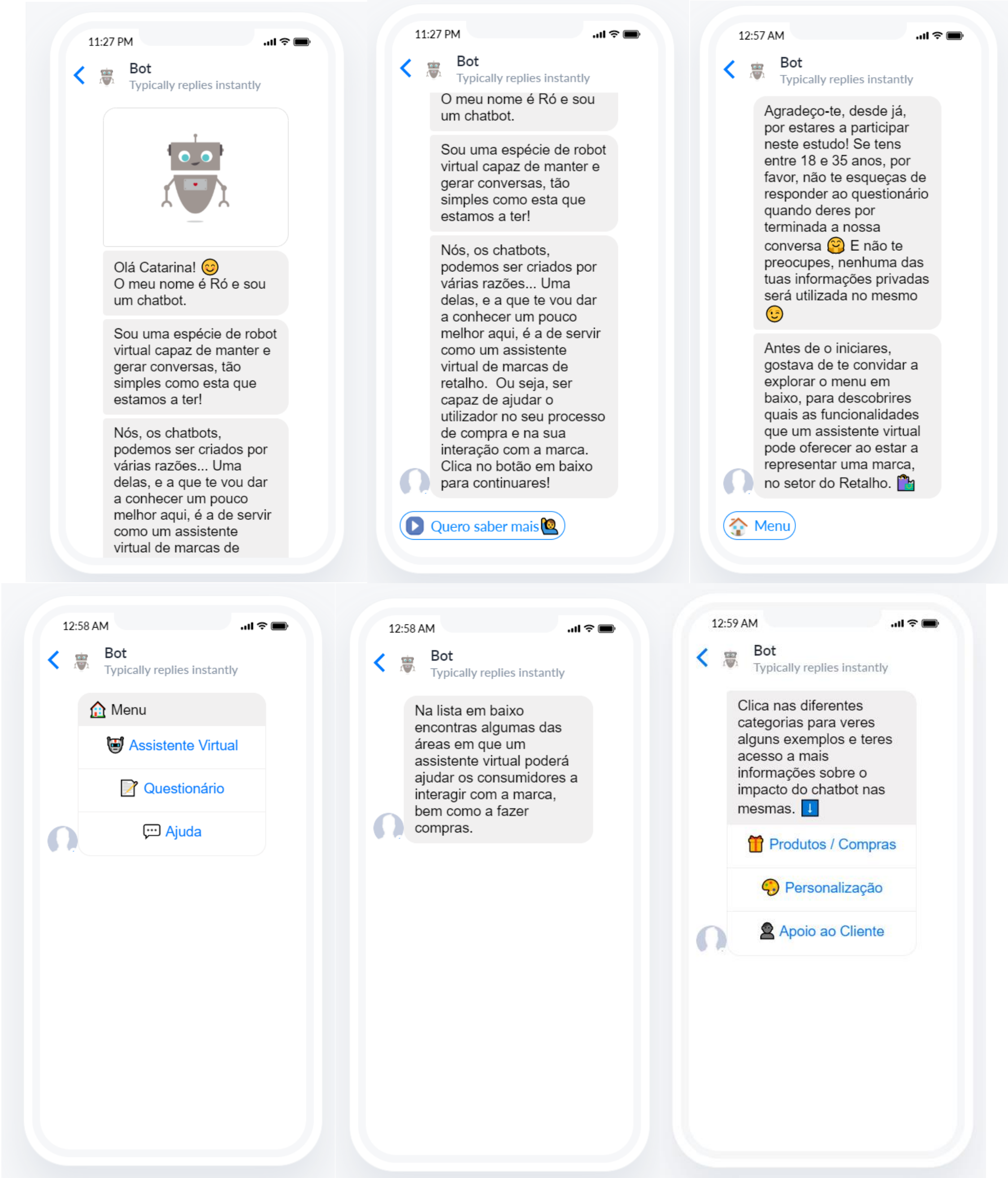
$$n = \frac{n_0}{1 + \frac{(n_0 - 1)}{N}}$$

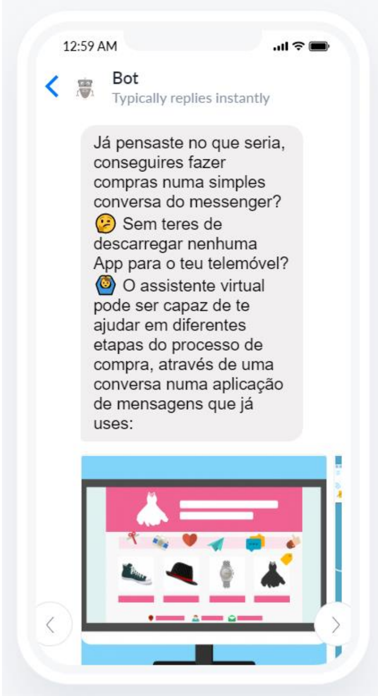
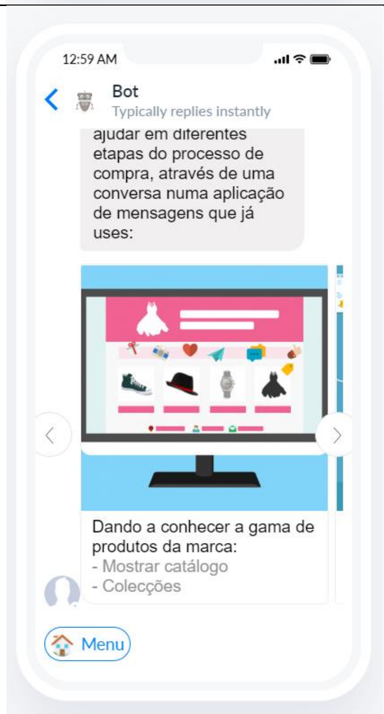
$$n = \frac{385}{1 + \frac{(385-1)}{2066316}} = 384.928 \approx 385$$

Annex B: Interaction with the Chatbot

Interaction with the Chatbot

Introduction

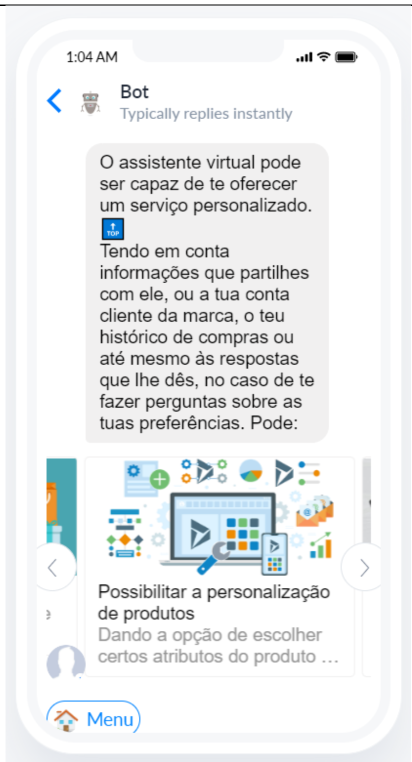


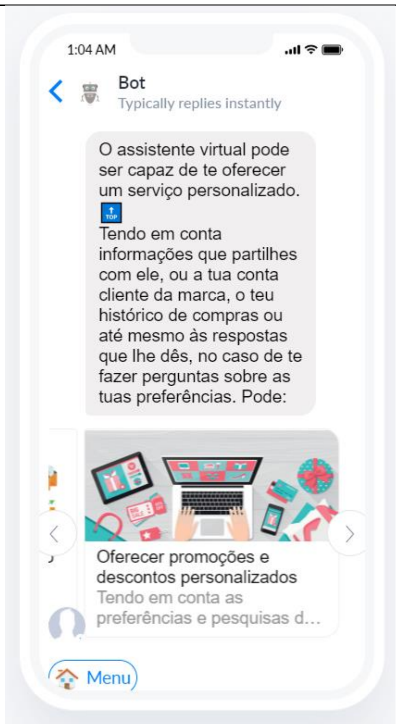
<table>
<tr><th colspan="2">Sales</th></tr>
<tr><td>The chatbot presented the different roles that a virtual assistant might assume throughout the consumer decision-making process, by integrating a messaging app. In the conversation started with the customer, the virtual assistant is able to:</td><td>
</td></tr>
<tr><td>- Show the products being sold by the brand, its catalogue, the existing collections and announce active campaigns;</td><td>
</td></tr>
</table>

- Allow the customer to search for a specific product, by selecting filters and choosing amongst options presented in the conversation, like gender, size and price range;	
- Give a preview of the product's specifications, letting the customer know more about the product features (e.g. size/dimensions, price, ways to use);	

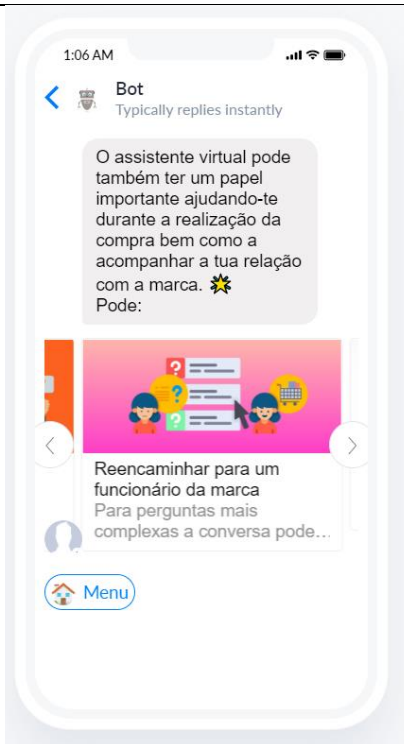
<table>
<tr>
<td>- Announce promotions and sales, by sending out to the customer notifications for specific campaigns;</td>
<td>
</td>
</tr>
<tr>
<td>- Save products to a customer list of favourites and being able to link it to his/her profile, for future reference and suggestions;</td>
<td>
</td>
</tr>
</table>

- Redirect the customer to the brand website if needed, by sharing its link for a specific page/information needed;	
- Allow for the sale to be done directly in the conversation, providing different payment methods, similar to an online sale, and sharing the invoice in the conversation.	

<table>
<tr><th colspan="2">Marketing: Personalization & Customization</th></tr>
<tr><td>A virtual assistant can offer a personalized service to whoever is interacting with it, whenever it is programmed that way. It can take under consideration and process data that the user shares, or even in case there are previous purchases, brands might set the chatbot up in a way that it analyses the purchase history. In order to better fit the customer needs, the chatbot can ask specific questions about the user preferences. With the all the data shared and that the user makes available through the chat, the virtual assistant can:</td><td rowspan="2">
</td></tr>
<tr><td>- Suggest products from the brand’s catalog that meet the requirements set by the customer;</td></tr>
<tr><td>- Let the customer customize products, when possible and when the product features allow it. If a brand offers the option to personalize a product in a certain way, by choosing from a range of features and settings available, this choice will can easily be done via the conversation with the chatbot.</td><td>
</td></tr>
</table>

- Offer discounts or notify whenever there is a campaign that meets the client's preferences and previous searches in the interaction.	

Customer Support	
The virtual assistant can also perform an important role when it comes to offering a relevant customer support, whether it refers to any support needed before, during or after the purchase. In the conversation on the messaging app where the virtual assistant is inserted, it can:	
- Answer questions from the potential customers, the more simple and common they are the more likely is the chatbot to be able to answer completely and accurately;	

- Redirect the customer to an employer of the brand. This will come more in hand for more complex questions, letting customers get in touch to a human employer.	
- Help in the post-purchase service. This can be done through surveys/ questions made by the bot for the client to evaluate on how was the purchase process, and to explain and clarify any doubts on the use of the product or their returning conditions.	

Annex C: Survey

Impacto da interação com Assistentes Virtuais na criação de expectativas relativas à Experiência de Compra

No setor do Retalho

O questionário que se segue pretende aferir de que forma a interação entre consumidores jovens e assistentes virtuais, como intermediários de marcas de retalho, impacta a experiência de compra dos primeiros. Ou seja, qual o contributo do assistente virtual para a experiência de compra do consumidor, e quais os aspetos mais valorizados neste para que a experiência seja positiva e o consumidor esteja satisfeito.

Este estudo destina-se apenas a jovens adultos com idades compreendidas entre os 18 e 35 anos.

Desde já agradeço a sua participação e peço que responda a todas as perguntas de forma mais sincera possível.

O presente estudo está a ser desenvolvido no âmbito da conclusão de uma Dissertação do Mestrado em Gestão, da ISCTE Business School.

Todas as informações obtidas neste questionário são anónimas e serão usadas apenas para fins académicos.

Qualquer dúvida ou questão que surja por favor contactar: cbcrs@iscte-iul.pt

Muito obrigada pela sua colaboração!

1. Idade *(pergunta de exclusão)*
    - o Até 18 anos
    - o 18-24
    - o 25-34
    - o Mais de 35 anos

- Muito obrigada pelo interesse demonstrado no presente estudo, no entanto este destina-se apenas a pessoas com idades compreendidas entre os 18 e os 35 anos.

Tempo online

Tendo em conta o tempo que passa online, excluindo contexto laboral, e a forma como esse tempo é distribuído, responda às seguintes questões:

2. Quais os aparelhos que utiliza para se ligar à Internet?

   Pode selecionar mais do que uma opção

   - Smartphone
   - Computador
   - Tablet
   - Outro:

3. Qual aquele em que passa mais tempo online?
   - Smartphone
   - Computador
   - Tablet
   - Outro:

4. No total, quanto tempo passa online diariamente?
   - Menos de 1 hora
   - Entre 1 a 2 horas
   - Entre 2 a 3 horas
   - Entre 3 a 4 horas
   - Mais de 4 horas

5. Ordene as seguintes opções tendo em conta o tempo que passa online em cada uma delas:

   Por ordem decrescente (daquela em que passa mais tempo para a que passa menos)

   - Compras
   - Aplicações de mensagens
   - Jogos
   - Redes sociais
   - Pesquisas

6. Quais as aplicações de mensagens que usa regularmente?

   Pode selecionar mais do que uma opção

   - Facebook Messenger
   - WhatsApp
   - Viber
   - WeChat
   - Skype
   - Snapchat
   - Nenhuma
   - Outro:

7. Selecione entre as seguintes hipóteses, todas as etapas do processo de compra em que geralmente usa a Internet:

   Pode selecionar mais do que uma opção:

   Exemplo: Comprar um par de luvas

   - o Identificar uma necessidade (ex. Ter frio)
   - o Definição do problema (ex.: Não ter luvas)
   - o Pesquisa de informação (ex.: Procurar marcas que vendam luvas)
   - o Comparação das várias alternativas existentes (ex.: Comparar preços e características das várias luvas)
   - o Tomar a decisão de comprar (ex.: Decidir comprar um par de luvas)
   - o Realizar a compra (ex.: Comprar as luvas escolhidas)
   - o Utilização / Consumo / Avaliação (ex.: Usar as luvas)
   - o Reação pós utilização (ex.: Satisfação com a compra / Resolução do problema)
   - o Nenhuma

<u>Comércio Eletrónico</u>

Entenda-se por compras online a aquisição de quaisquer produtos/bens realizada com recurso à internet (independentemente do dispositivo eletrónico utilizado).

8. Em média, qual a frequência com que faz compras online?
   - o Nunca faço
   - o Anualmente
   - o Semestralmente
   - o Trimestralmente
   - o Mensalmente
   - o Semanalmente
   - o Diariamente

9. Com que frequência usa os seguintes dispositivos para a realização de compras online?

	Nunca uso	É raro usar	Uso às vezes	Uso frequentemente	Uso sempre que possível
Smartphone	☐	☐	☐	☐	☐
Computador	☐	☐	☐	☐	☐
Tablet	☐	☐	☐	☐	☐

10. Quais os setores em que realiza compras online?
Pode selecionar mais do que uma opção.
    - Vestuário e calçado
    - Alimentação
    - Tecnológico
    - Cosmética
    - Saúde
    - Cultura e Lazer
    - Nenhum
    - Outro:

Chatbot

11. Relativamente à adoção de novas tecnologias, selecione entre as descrições em baixo aquela com que mais se identifica.
    - Geralmente sou dos primeiros a adquirir novos produtos e estou sempre a par das últimas inovações tecnológicas e novidades no mercado. Apesar das incertezas associadas a estes produtos não tenho medo de arriscar ao adquiri-los e testá-los.
    - Normalmente adquiro e experimento novos produtos/serviços antes da maioria das pessoas. Gosto de partilhar o meu feedback relativamente à minha experiência com os mesmos com as outras pessoas. Sinto que influencio outros e crio tendências.
    - Costumo seguir tendências já estabelecidas, após verificar o sucesso das mesmas. Gosto de ler algumas *reviews* acerca da experiência de utilizadores anteriores antes de tomar uma decisão. Costumo adquirir os produtos que estão na moda.
    - Sou mais ponderado relativamente à adoção de novas tecnologias e só tomo uma decisão relativamente à aquisição de um novo produto/serviço após este ter sido validado pela maioria das pessoas e estar bem consolidado no mercado. Valorizo as funcionalidades e utilidade do produto, mas não me sinto nem influenciado por campanhas de marketing nem a influenciar os outros. Sou bastante sensível a mudanças no preço.
    - Sou bastante cético relativamente a inovações tecnológicas. Geralmente sou dos últimos a adquirir um novo produto. Prefiro manter-me com as opções que conheço e com as quais estou familiarizado do que adotar mudanças, recorrendo às últimas apenas quando não tenho outra opção.

12. Antes de ter interagido com o Ró (-Bot), sabia o que era um chatbot?
    - Sim
    - Não
13. Já tinha interagido com um chatbot antes?
    - Sim
    - Não
14. Se Sim, em que contexto?

Antes de responder às próximas questões gostaria que pensasse num produto de uma marca de retalho não alimentar que gostasse/precisasse de comprar - um casaco, uma máquina fotográfica, um par de ténis, um creme, ou outro produto - mas que ainda não estivesse completamente decidido no modelo/gama a adquirir. Teria ainda de procurar conhecer mais sobre os produtos que essa marca oferece. Ou seja, quais as características, tamanhos e cores disponíveis, bem como quais as várias funcionalidades do mesmo, entre outros.

Imagine, agora, ter a possibilidade de ter acesso a todas essas informações através de uma conversa. Conversa, esta, com um assistente virtual da marca em questão, feita através de uma aplicação de mensagens instantâneas, acessível por isso a partir de qualquer aparelho eletrónico com esta aplicação instalada e ligação online.

Considerando todos os serviços apresentados anteriormente na sua interação com o Ró (-Bot), como:

- Conhecer a gama de produtos da marca (sendo capaz de aplicar filtros nos mesmos de forma a encontrar o que procura, bem como ter acesso às especificidades dos produtos oferecidos e às campanhas promocionais em vigor) e ser capaz de efetuar a compra através da interação com o assistente virtual;

- Possibilidade de ter um serviço personalizado (receber por parte do assistente virtual recomendações e promoções tendo em conta as suas preferências e compras anteriores bem como ser capaz de escolher certos elementos do produto, personalizando-o ao seu gosto);

- Usufruir de um serviço de apoio ao cliente mais alargado (obter resposta instantânea a perguntas mais frequentes disponível 24h, ter a possibilidade de entrar em contacto com um funcionário da marca para questões mais complexas, ter acesso a manuais de utilização dos produtos e ser capaz de avaliar a sua compra e relação com a marca).

Peço que responda então às seguintes perguntas.

Facilidade de Uso

15. Qual a relevância dos seguintes fatores para considerar o assistente virtual como sendo fácil de utilizar?

    Avalie de 1 a 5 cada um deles.

	1 Sem importância	2 Pouco importante	3 Razoavelmente importante	4 Importante	5 Muito importante
Conhecer a plataforma/aplicação onde o assistente virtual está inserido.	☐	☐	☐	☐	☐
Ter a possibilidade de escolher diferentes formas de comunicação com o assistente virtual numa mesma conversa (escrever mensagens ou selecionar opções pretendida num menu apresentado pelo assistente virtual)	☐	☐	☐	☐	☐
Existir uma apresentação do assistente virtual e explicação sobre as funcionalidades e apoio oferecidos no início da interação com o mesmo.	☐	☐	☐	☐	☐

16. De 1 a 5, quão importante é o assistente virtual ser fácil de utilizar para a sua experiência de compra?

    (Sendo 1- Não acho importante e 5- Considero muito importante)

    - 1
    - 2
    - 3
    - 4
    - 5

Utilidade

17. Qual a relevância das seguintes funcionalidades do assistente virtual para o considerar como sendo útil?

Avalie de 1 a 5 cada uma delas.

	1 Sem importância	2 Pouco importante	3 Razoavelmente importante	4 Importante	5 Muito importante
Possibilitar um acesso mais rápido a informações sobre os produtos da marca, como: preço, dimensões, composição, manual de instruções, condições de troca e devolução.	☐	☐	☐	☐	☐
Sugerir-me produtos tendo em conta o meu perfil enquanto consumidor da marca e histórico de compras e oferecer a possibilidade de personalizar produtos a meu gosto, sendo a interação mais eficaz.	☐	☐	☐	☐	☐
Facilitar o contacto com a marca, comunicando diretamente com a mesma através do envio de mensagens instantâneas (tendo a possibilidade de fazer questões/tirar dúvidas sobre os produtos da marca e serviços oferecidos)	☐	☐	☐	☐	☐

Ter a funcionalidade de ativar notificações, tornando a interação mais eficiente. (como por exemplo, avisando de promoções, novos produtos, ou disponibilidade dos mesmos)	☐	☐	☐	☐	☐

18. De 1 a 5, quão importante é o assistente virtual ser útil para a sua experiência de compra:
    (Sendo 1- Não acho importante e 5- Considero muito importante)
    - 1
    - 2
    - 3
    - 4
    - 5

Assistência

19. Qual a relevância das seguintes funcionalidades do assistente virtual para o considerar como sendo prestável?
    Avalie de 1 a 5 cada uma delas.

	1 Sem importância	2 Pouco importante	3 Razoavelmente importante	4 Importante	5 Muito importante
Ser capaz de responder a questões feitas pelo utilizador.	☐	☐	☐	☐	☐
Estar disponível 24h.	☐	☐	☐	☐	☐
Oferecer a possibilidade de redirecionar a conversa para um funcionário da marca, se necessário.	☐	☐	☐	☐	☐
Ter disponível informações sobre os produtos da marca, catálogo e características dos mesmos.	☐	☐	☐	☐	☐
Acompanhamento regular com o utilizador, e realização de inquéritos de satisfação.	☐	☐	☐	☐	☐
Antecipar o meu contacto e iniciar a conversa ao notificar-me com sugestões/recomendações de produtos.	☐	☐	☐	☐	☐

20. De 1 a 5, quão importante é o assistente virtual ser prestável para a sua experiência de compra:

    (Sendo 1- Não acho importante e 5- Considero muito importante)

    - 1
    - 2
    - 3
    - 4
    - 5

<u>Felicidade, Estímulo, Controlo</u>

21. Para a sua experiência de compra, quão importante é sentir que a interação com o assistente virtual é:

    Avalie cada sentimento de 1 a 5.

	1 Sem importância	2 Pouco importante	3 Razoavelmente importante	4 Importante	5 Muito importante
Agradável (Ou seja, sentir-se feliz/satisfeito ao conversar com o assistente virtual)	☐	☐	☐	☐	☐
Estimulante (A conversa ser entusiasmante)	☐	☐	☐	☐	☐
Controlada (O utilizador sentir que controla a conversa/ interação com o assistente virtual)	☐	☐	☐	☐	☐

Comunicação

22. Para a sua experiência de compra, qual a relevância dos seguintes fatores?
Avalie de 1 a 5 cada um deles.

	1 Sem importância	2 Pouco importante	3 Razoavelmente importante	4 Importante	5 Muito importante
A informação disponibilizada na conversa com o assistente virtual ser precisa (estar atualizada, correta e completa).	☐	☐	☐	☐	☐
O assistente virtual ser credível/fidedigno.	☐	☐	☐	☐	☐
A comunicação com o assistente virtual ser eficiente (ajudar o utilizador poupando-lhe tempo).	☐	☐	☐	☐	☐

Experiência de compra - Satisfação Global

23. Qual o seu nível de concordância com as seguintes afirmações relativamente à interação com o assistente virtual?

Indique de 1 a 5 o nível de concordância para cada uma delas.

	1 Discordo Totalmente	2 Discordo	3 Não Concordo Nem Discordo	4 Corcordo	5 Concordo Totalmente
A ideia de comunicar com uma marca através de um assistente virtual é apelativa.	☐	☐	☐	☐	☐
Sinto-me bem com a hipótese de interagir com uma marca através de um assistente virtual.	☐	☐	☐	☐	☐
Ter a possibilidade de poder comunicar com um assistente virtual melhoraria a minha experiência de compra.	☐	☐	☐	☐	☐
Preferiria uma marca que tivesse um assistente virtual disponível a uma do mesmo setor que não oferecesse este serviço.	☐	☐	☐	☐	☐
Interagiria com uma marca através de um assistente virtual.	☐	☐	☐	☐	☐
Recomendaria o uso do chatbot a familiares e amigos.	☐	☐	☐	☐	☐

24. Selecione entre as seguintes hipóteses, todas as etapas do processo de compra em que usaria um assistente virtual:

    Pode selecionar mais do que uma opção

    Exemplo: Comprar um par de luvas

    - Identificar uma necessidade (ex.: Ter frio)
    - Definição do problema (ex.: Não ter luvas)
    - Pesquisa de informação (ex.: Procurar marcas que vendam luvas)
    - Comparação das várias alternativas existentes (ex.: Comparar preços e características das várias luvas)
    - Tomar a decisão de comprar (ex.: Decidir comprar um par de luvas)
    - Realizar a compra (ex.: Comprar as luvas escolhidas)
    - Utilização / Consumo / Avaliação (ex.: Usar as luvas)
    - Reação pós utilização (ex.: Satisfação com a compra / Resolução do problema)
    - Nenhuma
25. Quais os setores em que se veria a usar um assistente virtual?
    - Vestuário e calçado
    - Alimentação
    - Tecnológico
    - Cosmética
    - Saúde
    - Cultura e Lazer
    - Nenhum
    - Outro:

<u>Caracterização</u>

26. Género
    - Feminino
    - Masculino
27. Nacionalidade
    - Portuguesa
    - Outra:
28. Ocupação
    - Estudante
    - Trabalhador – estudante
    - Trabalhador por conta própria
    - Trabalhador por conta de outrem
    - Desempregado
    - Reformado
29. Nível de EscolaridadePor favor indique o último nível concluído.
    - Ensino básico
    - Ensino secundário
    - Licenciatura
    - Mestrado
    - Doutoramento

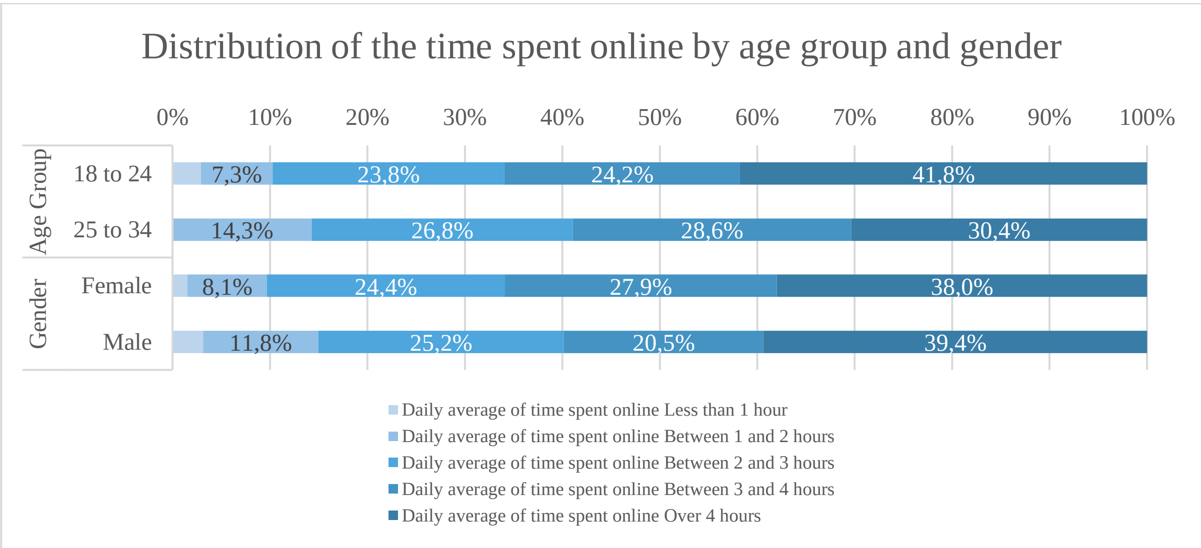
Annex D: Crosstabulation between the variables Device where most of the time online is spent on and Gender, and Age Group

			Age Group		**Gender**	
		Total	**18 to 24 years old**	**25 to 34 years old**	**Female**	**Male**
Device where most of the time online is spent on	**Smartphone**	85,5%	**86,8%**	**82,1%**	**91,5%**	**73,2%**
	Laptop/Desktop	14,0%	12,8%	17,0%	7,8%	26,8%
	Tablet	0,5%	0,4%	0,9%	0,8%	0,0%

		Device where most of the time online is spent on		
		Smartphone	**Laptop/Desktop**	**Tablet**
Gender	**Female**	**71,7%**	37,0%	100,0%
	Male	28,3%	**63,0%**	0,0%
Age Group	**18 to 24 years old**	72,0%	64,8%	50,0%
	25 to 34 years old	28,0%	35,2%	50,0%

Annex E: Crosstabulation between the Daily Average of Time Spent Online and Gender and Age Group

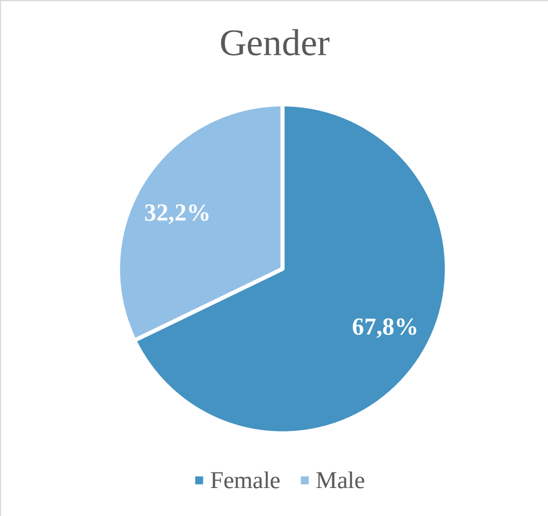
		Total	Age Group		Gender	
			18 to 24	**25 to 34**	**Female**	**Male**
Daily average of time spent online	**Less than 1 hour**	2,1%	2,9%	0,0%	1,6%	3,1%
	Between 1 and 2 hours	9,4%	7,3%	14,3%	8,1%	11,8%
	Between 2 and 3 hours	24,7%	23,8%	26,8%	24,4%	**25,2%**
	Between 3 and 4 hours	25,5%	**24,2%**	**28,6%**	**27,9%**	20,5%
	Over 4 hours	38,4%	**41,8%**	**30,4%**	**38,0%**	**39,4%**

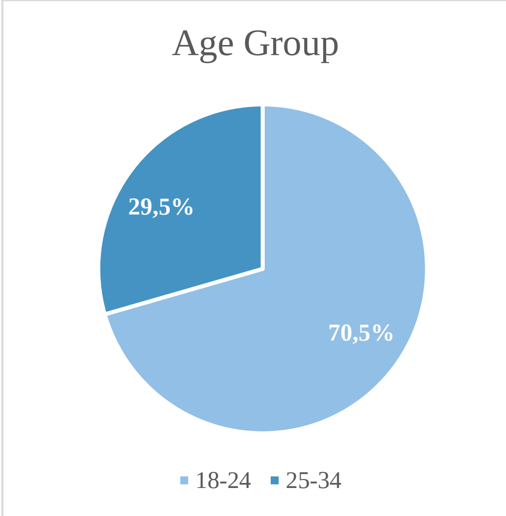


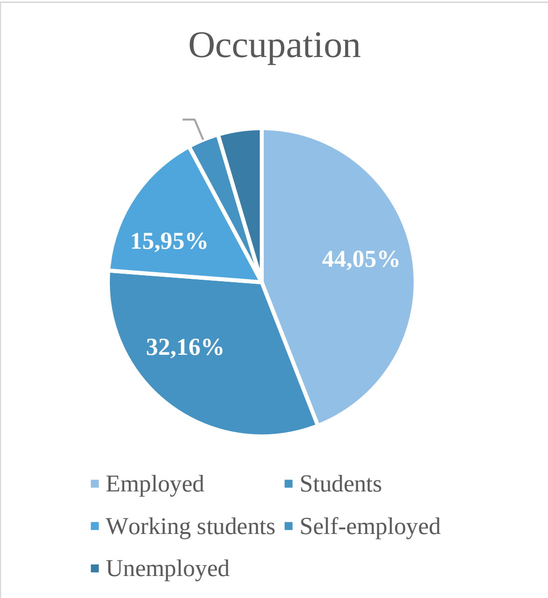
		Daily average of time spent online				
		Less than 1 hour	Between 1 and 2 hours	Between 2 and 3 hours	Between 3 and 4 hours	Over 4 hours
Gender	Female	50,0%	58,3%	66,3%	73,5%	66,2%
	Male	50,0%	41,7%	33,7%	26,5%	33,8%
Age Group	18 to 24	100,0%	55,6%	68,4%	67,3%	77,0%
	25 to 34	0,0%	44,4%	31,6%	36,7%	23,0%

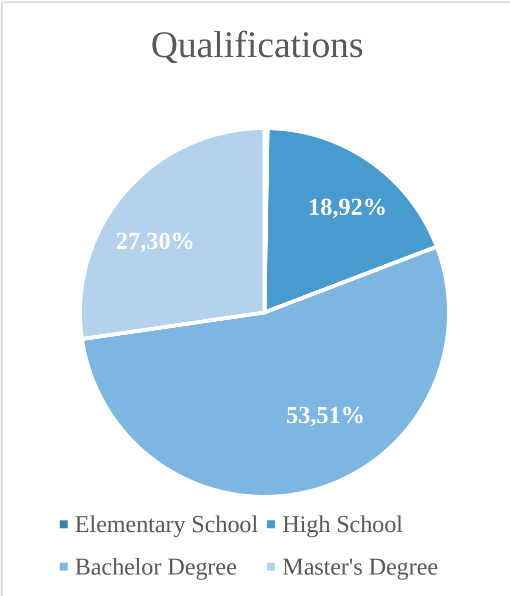
Annex F: E-commerce sub-division of the sample

- Characterization of the respondents that make online purchases:









Annex G: Crosstabulation between the Sectors where E-commerce activities are performed and the Gender and Age Group

		Fashion	Food	Tech	Beauty care	Healthcare	Cultural and Leisure activities	Other sectors
Gender	**Female**	**72,2%**	**75,0%**	48,7%	**93,5%**	**86,7%**	**68,9%**	37,5%
	Male	27,8%	25,0%	**51,3%**	6,5%	13,3%	31,1%	**62,5%**
Age Group	**18 to 24 years old**	**69,2%**	**64,6%**	**70,1%**	**64,5%**	46,7%	**78,5%**	**62,5%**
	25 to 34 years old	30,8%	35,4%	29,9%	35,5%	**53,3%**	21,5%	37,5%

	Gender		Age Group	
	Female	**Male**	**18 to 24 years old**	**25 to 34 years old**
Fashion	30,8%	27,6%	29,5%	30,7%
Food	16,9%	13,1%	14,5%	18,6%
Tech	11,7%	28,7%	16,8%	16,8%
Beauty care	13,6%	2,2%	9,4%	12,0%
Healthcare	2,0%	0,7%	1,1%	2,9%
Cultural and Leisure activities	24,5%	25,8%	27,9%	17,9%
Other sectors	0,5%	1,8%	0,8%	1,1%

__Annex H: Innovativeness Adoption Profiles__

According to Rogers (2003):

1) ***Innovators*** – **2.5% -** Individuals who selected this option identified themselves with the profile of being the first ones to adopt innovations, even though these bring along an associated risk with them. They usually are the younger and social ones, with a big interest for technology, not afraid of taking risks and with a high tolerance when dealing with failure.

2) ***Early Adopters*** – **13.5% -** It is characterized by individuals who also tend to experiment and adopt innovations quite easily. In addition to this favourable attitude towards change, they also have an important role as opinion makers and trend setters, influencing other people to follow their example and choices.

3) ***Early Majority*** – **34% -** These are individuals that usually follow trends, they are in contact with innovators and early adopters using their feedback to adopt trendy products/innovations. Their adoption process will, therefore, take a longer time than the previous categories.

4) ***Late Majority*** – **34% -** This category is the one where a higher percentage of the respondents perceived themselves as. They considered themselves as being more considerate and prudent when it comes to make the adoption decision of acquiring a certain product. The decision results of a previous validation of the innovation by other users and the thoughtful consideration of its features and overall quality, being price sensitive.

5) ***Laggards*** – **16% -** This category distinguish from the remaining for being the one with a longer adoption process. These individuals are the last to accept and embrace change and innovation. They present a higher level of scepticism towards technology, feel more comfortable with traditions and on maintaining their habits. They are also, usually, older individuals averse to risk and change that prefer to be on their comfort zone.

Annex I: Crosstabulation between the Innovativeness adoption profiles and the respondents Gender, Age Group, Occupation, and Qualifications

		Age Group		Gender	
		18 to 24 years old	**25 to 34 years old**	**Female**	**Male**
Profile	**Innovators**	2,9%	4,5%	2,7%	4,7%
	Early Adopters	5,9%	13,4%	7,8%	8,7%
	Early Majority	39,9%	21,4%	37,6%	28,3%
	Late Majority	**42,5%**	**56,3%**	**45,0%**	**49,6%**
	Laggards	8,8%	4,5%	7,0%	8,7%

		Occupation				
		Student	**Working Student**	**Self-employed**	**Employee**	**Unemployed**
Profile	**Innovators**	3,2%	3,3%	0,0%	4,1%	0,0%
	Early Adopters	8,9%	3,3%	8,3%	9,9%	0,0%
	Early Majority	31,5%	**41,7%**	**58,3%**	33,7%	23,5%
	Late Majority	**46,8%**	**41,7%**	33,3%	**49,4%**	**41,2%**
	Laggards	9,7%	10,0%	0,0%	2,9%	35,3%

		Qualifications			
		Elementary School	**High School**	**Bachelor**	**Master**
Profile	**Innovators**	0,0%	5,6%	4,0%	0,9%
	Early Adopters	0,0%	8,3%	8,5%	7,2%
	Early Majority	0,0%	**36,1%**	33,3%	36,0%
	Late Majority	0,0%	**36,1%**	**50,7%**	**45,9%**
	Laggards	**100,0%**	13,9%	3,5%	9,9%

		Profile				
		Innovators	Early Adopters	Early Majority	Late Majority	Laggards
Age Group	**18 to 24 years old**	**61,5%**	**51,6%**	**82,0%**	**64,8%**	**82,8%**
	25 to 34 years old	38,5%	48,4%	18,0%	35,2%	17,2%
Gender	**Female**	**53,8%**	**64,5%**	**72,9%**	**64,8%**	**62,1%**
	Male	46,2%	35,5%	27,1%	35,2%	37,9%

		Profile				
		Innovators	Early Adopters	Early Majority	Late Majority	Laggards
Occupation	**Student**	30,8%	35,5%	29,3%	32,4%	**41,4%**
	Working Student	15,4%	6,5%	18,8%	14,0%	20,7%
	Self-employed	0,0%	3,2%	5,3%	2,2%	0,0%
	Employee	**53,8%**	**54,8%**	**43,6%**	**47,5%**	17,2%
	Unemployed	0,0%	0,0%	3,0%	3,9%	20,7%
Qualifications	**Elementary School**	0,0%	0,0%	0,0%	0,0%	3,4%
	High School	30,8%	19,4%	19,5%	14,5%	**34,5%**
	Bachelor	**61,5%**	**54,8%**	**50,4%**	**57,0%**	24,1%
	Master	7,7%	25,8%	30,1%	28,5%	37,9%

Annex J: Crosstabulation between the variables:

1) *Chatbot Knowledge* and *Age Group*, *Occupation*, and *Qualifications*

		Age Group		Gender	
		18 to 24 years old	25 to 34 years old	Female	Male
Did you know what a chatbot was (prior to the interaction with the Ró-bot)?	**No**	23,8%	30,4%	23,6%	29,9%
	Yes	**76,2%**	**69,6%**	**76,4%**	**70,1%**

		Occupation				
		Student	Student worker	Self-employed	Employee	Unemployed
Did you know what a chatbot was (prior to the interaction with the Ró-bot)?	**No**	25,0%	35,0%	0,0%	21,5%	**58,8%**
	Yes	**75,0%**	**65,0%**	**100,0%**	**78,5%**	41,2%

		Qualifications			
		Elementary School	High School	Bachelor	Master
Did you know what a chatbot was (prior to the interaction with the Ró-bot)?	**No**	0,0%	27,8%	28,4%	19,8%
	Yes	**100,0%**	**72,2%**	**71,6%**	**80,2%**

		Did you know what a chatbot was (prior to the interaction with the Ró-bot)?	
		No	**Yes**
Age Group	**18 to 24 years old**	**65,7%**	**72,7%**
	25 to 34 years old	34,3%	27,3%
Gender	**Female**	**61,6%**	**68,9%**
	Male	38,4%	31,1%
Occupation	**Student**	31,3%	32,5%
	Student worker	21,2%	13,6%
	Self-employed	0,0%	4,2%
	Employee	**37,4%**	**47,2%**
	Unemployed	10,1%	2,4%
Qualifications	**Elementary School**	0,0%	0,3%
	High School	20,2%	18,2%
	Bachelor	**57,6%**	**50,3%**
	Master	22,2%	31,1%

2) Chatbot Interaction and Age Group, Occupation, and Qualifications

		Age Group		Gender	
		18 to 24 years old	25 to 34 years old	Female	Male
Have you had interacted with a chatbot before?	**No**	**57,1%**	**67,9%**	**62,0%**	**56,7%**
	Yes	42,9%	32,1%	38,0%	43,3%

		Occupation				
		Student	Student worker	Self-employed	Employee	Unemployed
Have you had interacted with a chatbot before?	**No**	**58,1%**	**65,0%**	**50,0%**	**59,3%**	**76,5%**
	Yes	41,9%	35,0%	**50,0%**	40,7%	23,5%

		Qualifications			
		Elementary School	High School	Bachelor	Master
Have you had interacted with a chatbot before?	**No**	**100,0%**	**69,4%**	**60,2%**	**54,1%**
	Yes	0,0%	30,6%	39,8%	45,9%

		Have you had interacted with a chatbot before?	
		No	**Yes**
Age Group	**18 to 24 years old**	**67,2%**	**76,5%**
	25 to 34 years old	32,8%	23,5%
Gender	**Female**	**69,0%**	**64,1%**
	Male	31,0%	35,9%
Occupation	**Student**	31,0%	34,0%
	Student worker	16,8%	13,7%
	Self-employed	2,6%	3,9%
	Employee	**44,0%**	**45,8%**
	Unemployed	5,6%	2,6%
Qualifications	**Elementary School**	0,4%	0,0%
	High School	21,6%	14,4%
	Bachelor	**52,2%**	**52,3%**
	Master	25,9%	33,3%

Annex K: Preliminary analysis - Normality tests

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Ease of Use	0,281	385	0,000	0,776	385	0,000
Usefulness	0,285	385	0,000	0,803	385	0,000
Helpfulness	0,285	385	0,000	0,783	385	0,000
Pleasure	0,291	385	0,000	0,859	385	0,000
Arousal	0,199	385	0,000	0,906	385	0,000
Dominance	0,217	385	0,000	0,883	385	0,000
Accuracy	0,419	385	0,000	0,609	385	0,000
Credibility	0,439	385	0,000	0,584	385	0,000
Communication Competence	0,397	385	0,000	0,657	385	0,000
Interaction Appeal	0,336	385	0,000	0,786	385	0,000
Interaction Comfortability	0,348	385	0,000	0,782	385	0,000
Experience Improvement	0,282	385	0,000	0,845	385	0,000
Preferability	0,238	385	0,000	0,887	385	0,000
Usage	0,366	385	0,000	0,712	385	0,000
Recommendation	0,255	385	0,000	0,841	385	0,000

a. Lilliefors Significance Correction

Annex L: Preliminary analysis - Correlations

Correlations

Spearman's rho		Ease of Use	Usefulness	Helpfulness
Ease of Use	**Correlation Coefficient**	**1,000**	**,456****	**,386****
	Sig. (2-tailed)		0,000	0,000
	N	385	385	385
Usefulness	**Correlation Coefficient**	**,456****	**1,000**	**,413****
	Sig. (2-tailed)	0,000		0,000
	N	385	385	385
Helpfulness	**Correlation Coefficient**	**,386****	**,413****	**1,000**
	Sig. (2-tailed)	0,000	0,000	
	N	385	385	385

**. Correlation is significant at the 0.01 level (2-tailed).

Correlations

Spearman's rho		Pleasure	Arousal	Dominance
Pleasure	**Correlation Coefficient**	**1,000**	**,529****	**,308****
	Sig. (2-tailed)		0,000	0,000
	N	385	385	385
Arousal	**Correlation Coefficient**	**,529****	**1,000**	**,252****
	Sig. (2-tailed)	0,000		0,000
	N	385	385	385
Dominance	**Correlation Coefficient**	**,308****	**,252****	**1,000**
	Sig. (2-tailed)	0,000	0,000	
	N	385	385	385

**. Correlation is significant at the 0.01 level (2-tailed).

Correlations

Spearman's rho		Accuracy	Credibility	Communication Competence
Accuracy	**Correlation Coefficient**	**1,000**	**,601****	**,607****
	Sig. (2-tailed)		0,000	0,000
	N	385	385	385
Credibility	**Correlation Coefficient**	**,601****	**1,000**	**,532****
	Sig. (2-tailed)	0,000		0,000
	N	385	385	385
Communication Competence	**Correlation Coefficient**	**,607****	**,532****	**1,000**
	Sig. (2-tailed)	0,000	0,000	
	N	385	385	385

**. Correlation is significant at the 0.01 level (2-tailed).

Correlations

Spearman's rho		Interaction Appeal	Interaction Contentment	Experience Improvement	Preferability
Interaction Appeal	**Correlation Coefficient**	**1,000**	**,614****	**,537****	**,427****
	Sig. (2-tailed)		0,000	0,000	0,000
	N	385	385	385	385
Interaction Comfortability	**Correlation Coefficient**	**,614****	**1,000**	**,502****	**,480****
	Sig. (2-tailed)	0,000		0,000	0,000
	N	385	385	385	385
Experience Improvement	**Correlation Coefficient**	**,537****	**,502****	**1,000**	**,450****
	Sig. (2-tailed)	0,000	0,000		0,000
	N	385	385	385	385
Preferability	**Correlation Coefficient**	**,427****	**,480****	**,450****	**1,000**
	Sig. (2-tailed)	0,000	0,000	0,000	
	N	385	385	385	385

**. Correlation is significant at the 0.01 level (2-tailed).

Correlations

Spearman's rho		Usage	Recommendation
Usage	**Correlation Coefficient**	**1,000**	**,512****
	Sig. (2-tailed)		0,000
	N	385	385
Recommendation	**Correlation Coefficient**	,512**	1,000
	Sig. (2-tailed)	0,000	
	N	385	385

**. Correlation is significant at the 0.01 level (2-tailed).

Annex M: H1 – Cognitive Perception - Reliability Analysis

Item Statistics

	Mean	Std. Deviation	N
Ease of Use	4,29	0,811	385
Usefulness	4,08	0,812	385
Helpfulness	4,16	0,717	385

Inter-Item Correlation Matrix

	Ease of Use	Usefulness	Helpfulness
Ease of Use	1,000	0,521	0,446
Usefulness	0,521	1,000	0,514
Helpfulness	0,446	0,514	1,000

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
12,53	3,635	1,907	3

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
Ease of Use	8,24	1,772	0,558	0,315	0,676
Usefulness	8,44	1,690	0,609	0,371	0,614
Helpfulness	8,37	2,004	0,550	0,308	0,685

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
0,744	0,745	3

Annex N: H1 – Cognitive Perception - Exploratory Factor Analysis

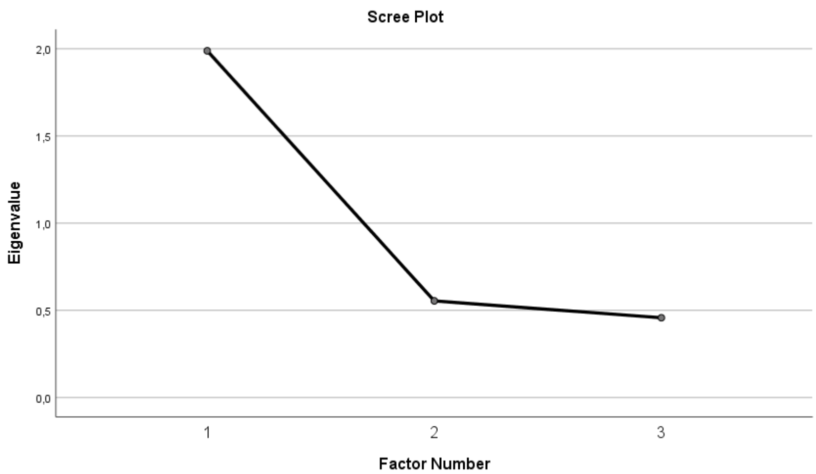
KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0,684
Bartlett's Test of Sphericity	**Approx. Chi-Square**	261,738
	df	3
	Sig.	0,000

Total Variance Explained

Factor	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	1,988	66,276	66,276	1,492	49,741	49,741
2	0,554	18,472	84,748			
3	0,458	15,252	100,000			

Extraction Method: Principal Axis Factoring.



Factor Matrix[a]

	Factor
	1
Ease of Use	0,673
Usefulness	0,773
Helpfulness	0,664

Extraction Method: Principal Axis Factoring.

a. 1 factors extracted. 11 iterations required.

Communalities

	Initial	Extraction
Ease of Use	0,315	0,453
Usefulness	0,371	0,598
Helpfulness	0,308	0,441

Extraction Method: Principal Axis Factoring.

Reproduced Correlations

		Ease of Use	Usefulness	Helpfulness
Reproduced Correlation	**Ease of Use**	,453[a]	0,521	0,447
	Usefulness	0,521	,598[a]	0,513
	Helpfulness	0,447	0,513	,441[a]
Residual[b]	**Ease of Use**		0,001	-0,001
	Usefulness	0,001		0,001
	Helpfulness	-0,001	0,001	

Extraction Method: Principal Axis Factoring.

a. Reproduced communalities

b. Residuals are computed between observed and reproduced correlations. There are 0 (0,0%) nonredundant residuals with absolute values greater than 0.05.

Factor Score Coefficient Matrix

	Factor
	1
Ease of Use	0,300
Usefulness	0,468
Helpfulness	0,289

Extraction Method: Principal Axis Factoring.

Factor Score Covariance Matrix

Factor	1
1	0,756

Extraction Method: Principal Axis Factoring.

Annex O: H2 – Affective Engagement - Reliability Analysis

Item Statistics

	Mean	Std. Deviation	N
Pleasure	3,67	0,865	385
Arousal	3,21	1,030	385
Dominance	3,62	1,030	385

Inter-Item Correlation Matrix

	Pleasure	Arousal	Dominance
Pleasure	1,000	0,569	0,341
Arousal	0,569	1,000	0,292
Dominance	0,341	0,292	1,000

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
10,49	5,110	2,261	3

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
Pleasure	6,82	2,740	0,566	0,357	0,452
Arousal	7,28	2,417	0,510	0,334	0,503
Dominance	6,88	2,823	0,355	0,131	0,718

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
0,658	0,667	3

Annex P: H2 – Affective Engagement - Exploratory Factor Analysis

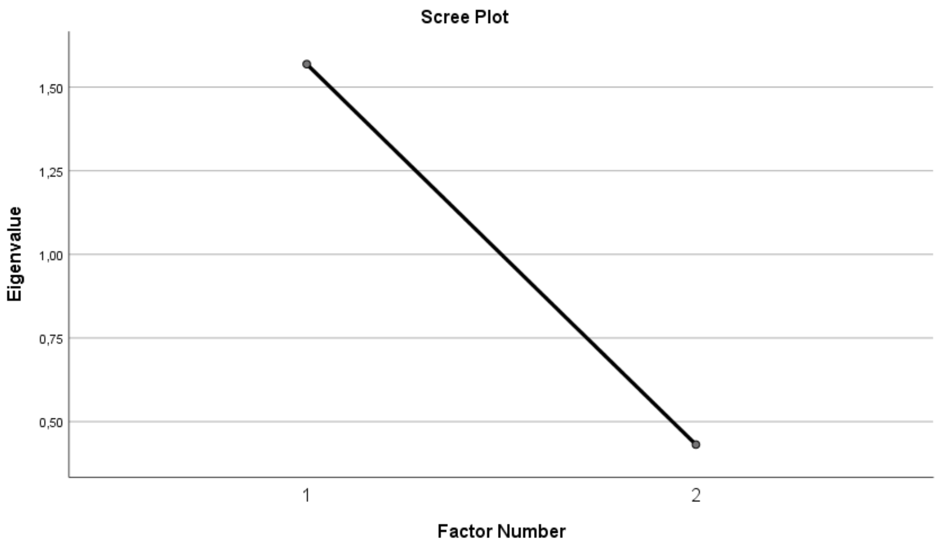
KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0,500
Bartlett's Test of Sphericity	**Approx. Chi-Square**	149,427
	df	1
	Sig.	0,000

Total Variance Explained

Factor	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	1,569	78,434	78,434	1,135	56,771	56,771
2	0,431	21,566	100,000			

Extraction Method: Principal Axis Factoring.



Factor Matrix[a]

	Factor
	1
Pleasure	0,753
Arousal	0,753

Extraction Method: Principal Axis Factoring.

a. 1 factors extracted. 8 iterations required.

Communalities

	Initial	Extraction
Pleasure	0,323	0,568
Arousal	0,323	0,568

Extraction Method: Principal Axis Factoring.

Reproduced Correlations

		Pleasure	Arousal
Reproduced Correlation	**Pleasure**	,568[a]	0,568
	Arousal	0,568	,568[a]
Residual[b]	**Pleasure**		0,001
	Arousal	0,001	

Extraction Method: Principal Axis Factoring.

a. Reproduced communalities

b. Residuals are computed between observed and reproduced correlations. There are 0 (0,0%) nonredundant residuals with absolute values greater than 0.05.

Factor Score Coefficient Matrix

	Factor
	1
Pleasure	0,480
Arousal	0,480

Extraction Method: Principal Axis Factoring.
Factor Scores Method: Regression.

Factor Score Covariance Matrix

Factor	1
1	0,724

Extraction Method: Principal Axis Factoring.
Factor Scores Method: Regression.

Annex Q: H3 – Communication Quality - Reliability Analysis

Item Statistics

	Mean	Std. Deviation	N
Accuracy	4,63	0,628	385
Credibility	4,69	0,551	385
Communication Competence	4,59	0,615	385

Inter-Item Correlation Matrix

	Accuracy	Credibility	Communication Competence
Accuracy	1,000	0,633	0,669
Credibility	0,633	1,000	0,598
Communication Competence	0,669	0,598	1,000

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
13,91	2,435	1,560	3

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
Accuracy	9,28	1,087	0,729	0,532	0,745
Credibility	9,22	1,289	0,674	0,455	0,801
Communication Competence	9,32	1,136	0,703	0,498	0,771

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
0,837	0,838	3

Annex R: H3 – Communication Quality - Exploratory Factor Analysis

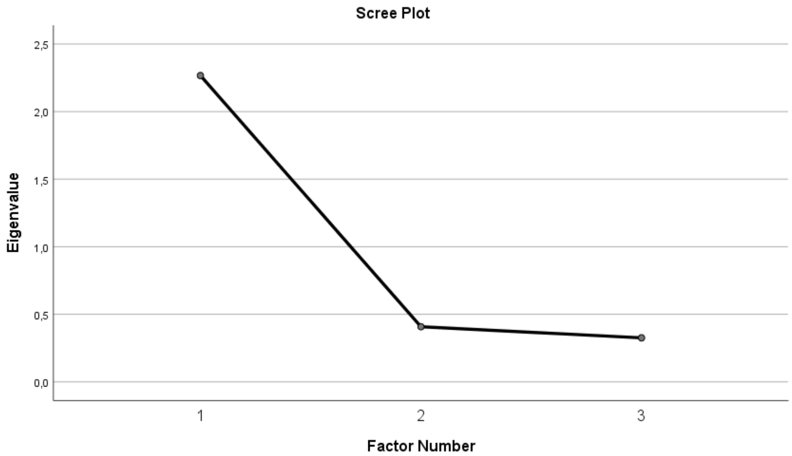
KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0,722
Bartlett's Test of Sphericity	**Approx. Chi-Square**	458,849
	df	3
	Sig.	0,000

Total Variance Explained

Factor	**Initial Eigenvalues**			**Extraction Sums of Squared Loadings**		
	Total	**% of Variance**	**Cumulative %**	**Total**	**% of Variance**	**Cumulative %**
1	2,267	75,552	75,552	1,905	63,495	63,495
2	0,408	13,593	89,145			
3	0,326	10,855	100,000			

Extraction Method: Principal Axis Factoring.



Factor Matrix[a]

	Factor
	1
Accuracy	0,840
Credibility	0,752
Communication Competence	0,795

Extraction Method: Principal Axis Factoring.

a. 1 factors extracted. 9 iterations required.

Communalities

	Initial	Extraction
Accuracy	0,532	0,706
Credibility	0,455	0,566
Communication Competence	0,498	0,633

Extraction Method: Principal Axis Factoring.

Reproduced Correlations

		Accuracy	Credibility	Communication Competence
Reproduced Correlation	Accuracy	,706[a]	0,632	0,668
	Credibility	0,632	,566[a]	0,598
	Communication Competence	0,668	0,598	,633[a]
Residual[b]	Accuracy		0,000	0,001
	Credibility	0,000		-0,001
	Communication Competence	0,001	-0,001	

Extraction Method: Principal Axis Factoring.

a. Reproduced communalities

b. Residuals are computed between observed and reproduced correlations. There are 0 (0,0%) nonredundant residuals with absolute values greater than 0.05.

Factor Score Coefficient Matrix

	Factor
	1
Accuracy	0,444
Credibility	0,270
Communication Competence	0,337

Extraction Method: Principal Axis Factoring.
Factor Scores Method: Regression.

Factor Score Covariance Matrix

Factor	1
1	0,844

Extraction Method: Principal Axis Factoring.

Factor Scores Method: Regression.

Annex S: H4 – Customer Experience Expectation -Reliability Analysis

Item Statistics

	Mean	Std. Deviation	N
Interaction Appeal	3,90	0,757	385
Comfortability	3,86	0,748	385
Experience Improvement	3,62	0,785	385
Preferability	3,34	0,930	385

Inter-Item Correlation Matrix

	Interaction Appeal	Comfortability	Experience Improvement	Preferability
Interaction Appeal	1,000	0,661	0,557	0,483
Comfortability	0,661	1,000	0,556	0,522
Experience Improvement	0,557	0,556	1,000	0,502
Preferability	0,483	0,522	0,502	1,000

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
14,72	6,812	2,610	4

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
Interaction Appeal	10,82	4,151	0,677	0,498	0,763
Comfortability	10,85	4,125	0,700	0,516	0,754
Experience Improvement	11,10	4,150	0,640	0,412	0,778
Preferability	11,38	3,810	0,589	0,350	0,812

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
0,822	0,828	4

Annex T: H4 – Customer Experience Expectation -Exploratory Factor Analysis

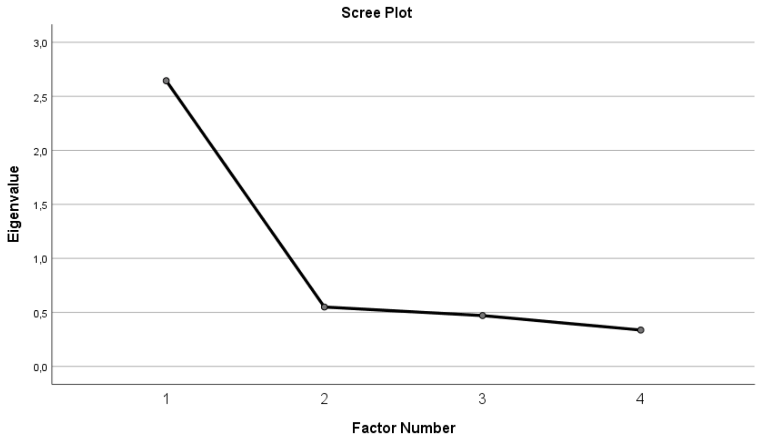
KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0,797
Bartlett's Test of Sphericity	**Approx. Chi-Square**	561,598
	df	6
	Sig.	0,000

Total Variance Explained

Factor	**Initial Eigenvalues**			**Extraction Sums of Squared Loadings**		
	Total	**% of Variance**	**Cumulative %**	**Total**	**% of Variance**	**Cumulative %**
1	2,644	66,101	66,101	2,207	55,168	55,168
2	0,549	13,733	79,834			
3	0,470	11,757	91,591			
4	0,336	8,409	100,000			

Extraction Method: Principal Axis Factoring.



Factor Matrix[a]

	Factor
	1
Interaction Appeal	0,784
Comfortability	0,809
Experience Improvement	0,717
Preferability	0,651

Extraction Method: Principal Axis Factoring.

a. 1 factors extracted. 7 iterations required.

Communalities

	Initial	Extraction
Interaction Appeal	0,498	0,614
Comfortability	0,516	0,655
Experience Improvement	0,412	0,514
Preferability	0,350	0,424

Extraction Method: Principal Axis Factoring.

Reproduced Correlations

		Interaction Appeal	Comfortability	Experience Improvement	Preferability
Reproduced Correlation	**Interaction Appeal**	,614[a]	0,634	0,562	0,510
	Comfortability	0,634	,655[a]	0,580	0,527
	Experience Improvement	0,562	0,580	,514[a]	0,467
	Preferability	0,510	0,527	0,467	,424[a]
Residual[b]	**Interaction Appeal**		0,026	-0,005	-0,027
	Comfortability	0,026		-0,024	-0,005
	Experience Improvement	-0,005	-0,024		0,035
	Preferability	-0,027	-0,005	0,035	

Extraction Method: Principal Axis Factoring.

a. Reproduced communalities

b. Residuals are computed between observed and reproduced correlations. There are 0 (0,0%) nonredundant residuals with absolute values greater than 0.05.

Factor Score Coefficient Matrix

	Factor
	1
Interaction Appeal	0,315
Comfortability	0,370
Experience Improvement	0,244
Preferability	0,184

Extraction Method: Principal Axis Factoring.
Factor Scores Method: Regression.

Factor Score Covariance Matrix

Factor	1
1	0,840

Extraction Method: Principal Axis Factoring.
Factor Scores Method: Regression.

Annex U: H5 – Patronage Intention - Reliability Analysis

Item Statistics

	Mean	Std. Deviation	N
Usage	4,01	0,679	385
Recommendation	3,58	0,767	385

Inter-Item Correlation Matrix

	Usage	Recommendation
Usage	1,000	0,602
Recommendation	0,602	1,000

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
7,59	1,675	1,294	2

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
Usage	3,58	0,588	0,602	0,362	
Recommendation	4,01	0,461	0,602	0,362	

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
0,748	0,751	2

Annex V: H5 – Patronage Intention - Exploratory Factor Analysis

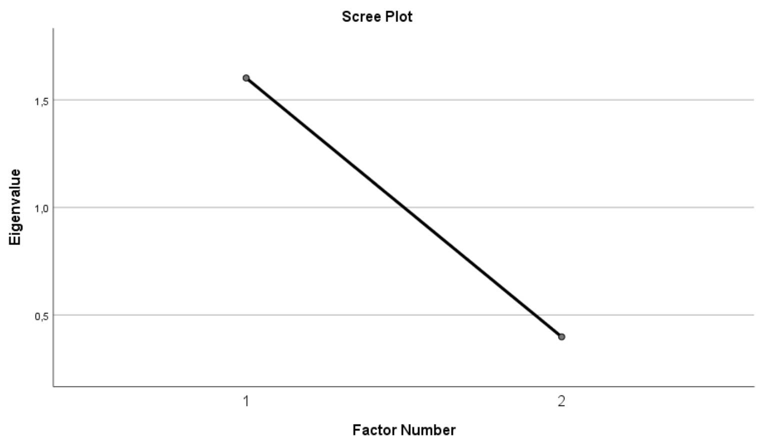
KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0,500
Bartlett's Test of Sphericity	**Approx. Chi-Square**	171,952
	df	1
	Sig.	0,000

Total Variance Explained

Factor	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	1,602	80,087	80,087	1,202	60,080	60,080
2	0,398	19,913	100,000			

Extraction Method: Principal Axis Factoring.



Factor Matrix[a]

	Factor
	1
Usage	0,775
Recommendation	0,775

Extraction Method: Principal Axis Factoring.

a. 1 factors extracted. 8 iterations required.

Communalities

	Initial	Extraction
Usage	0,362	0,601
Recommendation	0,362	0,601

Extraction Method: Principal Axis Factoring.

Reproduced Correlations

		Usage	Recommendation
Reproduced Correlation	**Usage**	,601[a]	0,601
	Recommendation	0,601	,601[a]
Residual[b]	**Usage**		0,001
	Recommendation	0,001	

Extraction Method: Principal Axis Factoring.

a. Reproduced communalities

b. Residuals are computed between observed and reproduced correlations. There are 0 (0,0%) nonredundant residuals with absolute values greater than 0.05.

Factor Score Coefficient Matrix

	Factor
	1
Usage	0,484
Recommendation	0,484

Extraction Method: Principal Axis Factoring.
Factor Scores Method: Regression.

Factor Score Covariance Matrix

Factor	1
1	0,750

Extraction Method: Principal Axis Factoring.

Factor Scores Method: Regression.

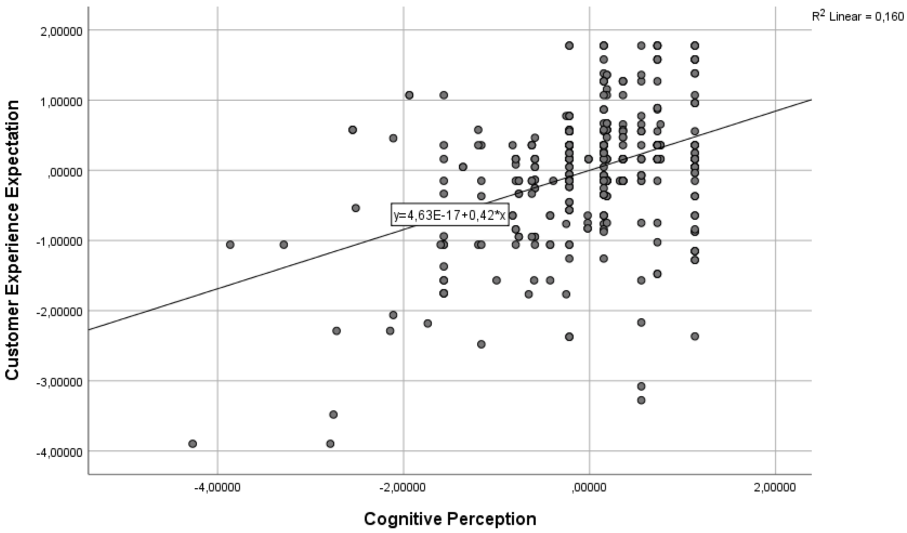
Annex W: H6 – Multiple Linear Regression Model Assumptions

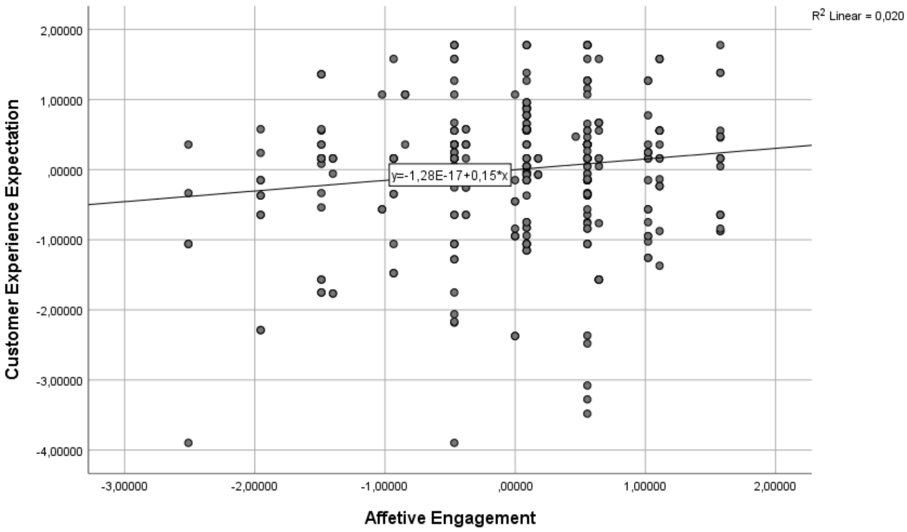
1) There is a linear relationship between the dependent variable and each of the explanatory variables: verified in the preliminary analysis.

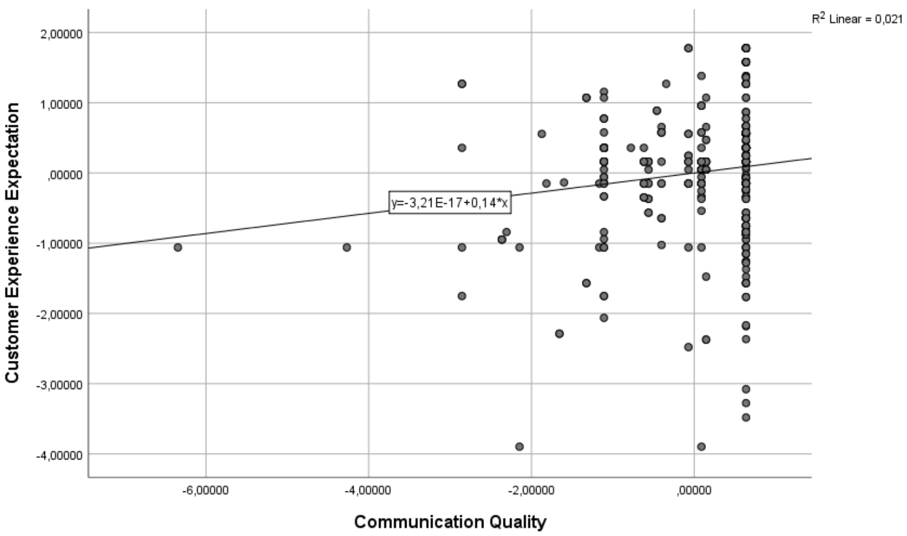
Correlations

		Cognitive Perception	Affective Engagement	Communication Quality	Customer Experience Expectation
Cognitive Perception	**Pearson Correlation**	1	**,134****	**,401****	**,400****
	Sig. (2-tailed)		0,009	0,000	0,000
	N	385	385	385	385
Affective Engagement	**Pearson Correlation**	,134**	1	**,217****	**,141****
	Sig. (2-tailed)	0,009		0,000	0,006
	N	385	385	385	385
Communication Quality	**Pearson Correlation**	,401**	,217**	1	**,144****
	Sig. (2-tailed)	0,000	0,000		0,005
	N	385	385	385	385
Customer Experience Expectation	**Pearson Correlation**	,400**	,141**	,144**	1
	Sig. (2-tailed)	0,000	0,006	0,005	
	N	385	385	385	385

**. Correlation is significant at the 0.01 level (2-tailed).


R2 Linear = 0,160
y=4,63E-17+0,42*x
Customer Experience Expectation
Cognitive Perception
2,00000
1,00000
,00000
-1,00000
-2,00000
-3,00000
-4,00000
-4,00000
-2,00000
,00000
2,00000


R2 Linear = 0,020
y=-1,28E-17+0,15*x
Customer Experience Expectation
Affetive Engagement
2,00000
1,00000
,00000
-1,00000
-2,00000
-3,00000
-4,00000
-3,00000
-2,00000
-1,00000
,00000
1,00000
2,00000


R2 Linear = 0,021
y=-3,21E-17+0,14*x
Customer Experience Expectation
Communication Quality
2,00000
1,00000
,00000
-1,00000
-2,00000
-3,00000
-4,00000
-6,00000
-4,00000
-2,00000
,00000

2) The mean of the residual component of the model is 0;

Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	-1,792	0,6153	0,0000000	0,376	385
Residual	-3,558	1,946	0,00000000	0,836	385
Std. Predicted Value	-4,769	1,637	0,000	1,000	385
Std. Residual	-4,244	2,321	0,000	0,997	385

a. Dependent Variable: Customer Experience (factor)

3) The independent variables are not correlated with the residual terms

Correlations

		Cognitive Perception	Affective Engagement	Unstandardized Residual
Cognitive Perception	**Pearson Correlation**	1	,134**	0,000
	Sig. (2-tailed)		0,009	1,000
	N	385	385	385
Affective Engagement	**Pearson Correlation**	,134**	1	0,000
	Sig. (2-tailed)	0,009		1,000
	N	385	385	385
Unstandardized Residual	**Pearson Correlation**	0,000	0,000	1
	Sig. (2-tailed)	1,000	1,000	
	N	385	385	385

**. Correlation is significant at the 0.01 level (2-tailed).

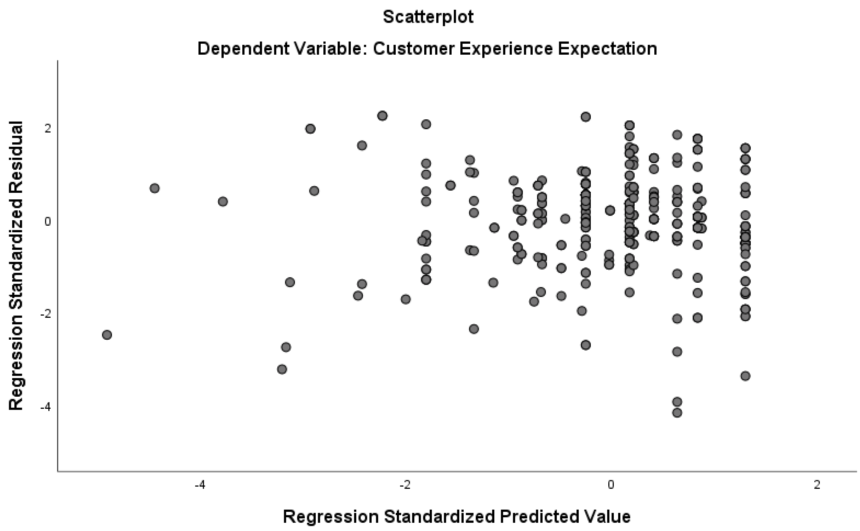
4) There is no correlation among the residual terms

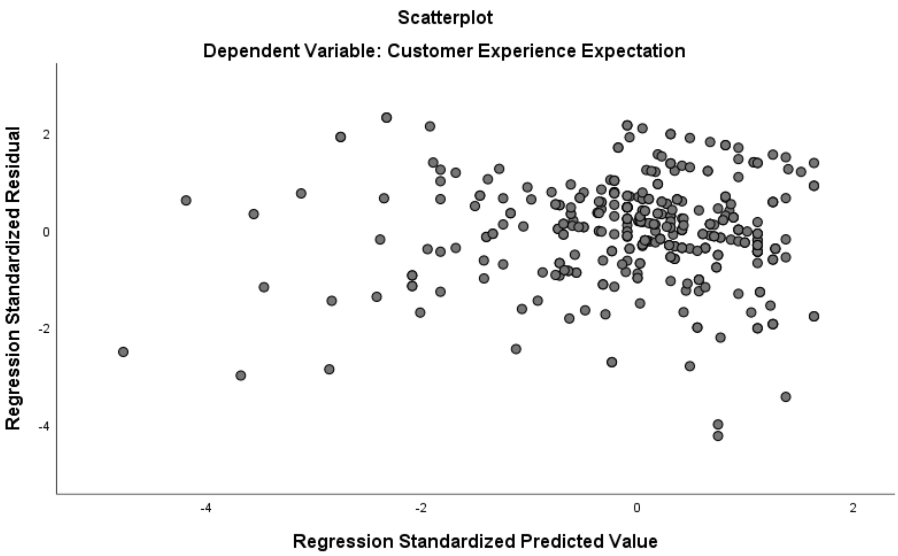
Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,410[a]	0,168	0,164	0,838	1,963

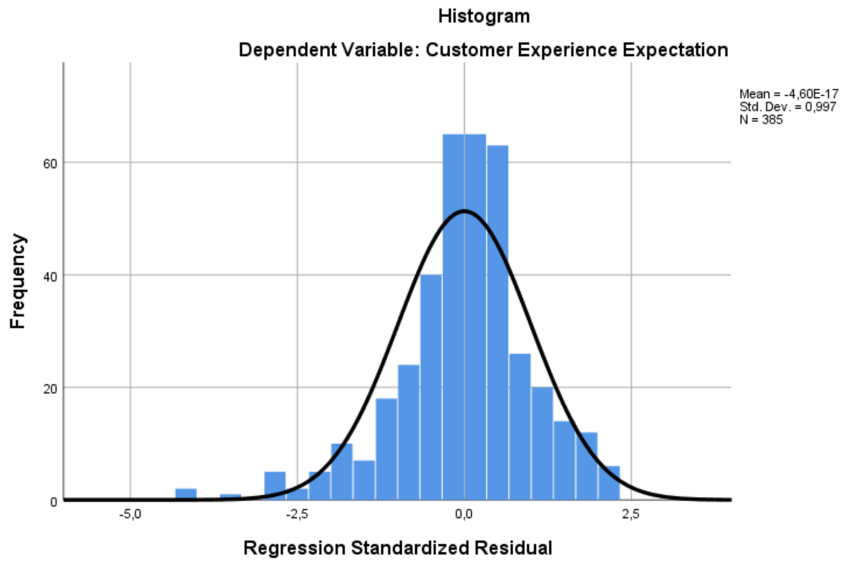
a. Predictors: (Constant), Affective Engagement, Cognitive Perception
b. Dependent Variable: Customer Experience (factor)

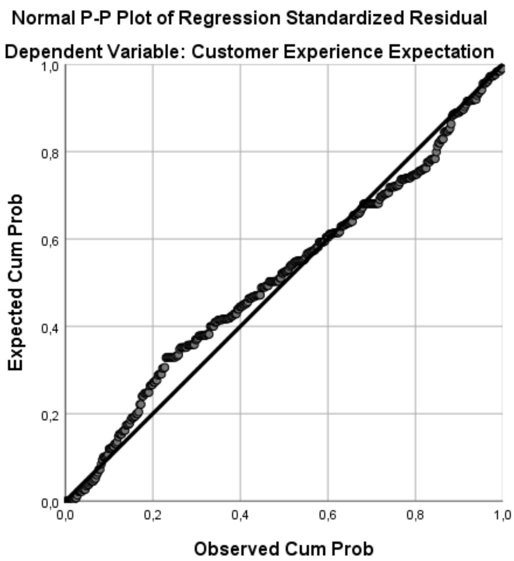
5) The variance of the random term is constant;





6) The residuals follow a Normal distribution;





7) And, there is no correlation among the explanatory variables.

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	7,525E-17	0,043		0,000	1,000		
	Cognitive Perception	0,409	0,050	0,388	8,247	0,000	0,982	1,018
	Affective Engagement	0,096	0,051	0,089	1,897	0,059	0,982	1,018

a. Dependent Variable: Customer Experience Expectation

Annex X: Estimated Multiple Linear Regression Model

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Affective Engagement, Cognitive Perception[b]		Enter

a. Dependent Variable: Customer Experience

b. All requested variables entered.

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,410[a]	0,168	0,164	0,838	1,963

a. Predictors: (Constant), Affective Engagement, Cognitive Perception

b. Dependent Variable: Customer Experience

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	54,234	2,000	27,117	38,589	,000[b]
	Residual	268,432	382,000	0,703		
	Total	322,665	384,000			

a. Dependent Variable: Customer Experience Expectation

b. Predictors: (Constant), Affective Engagement, Cognitive Perception

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	7,525E-17	0,043		0,000	1,000		
	Cognitive Perception	0,409	0,050	0,388	8,247	0,000	0,982	1,018
	Affective Engagement	0,096	0,051	0,089	1,897	0,059	0,982	1,018

a. Dependent Variable: Customer Experience Expectation

- **Stepwise Method:**

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Cognitive Perception		Stepwise (Criteria: Probability-of-F-to-enter <= ,050, Probability-of-F-to-remove >= ,100).

a. Dependent Variable: Customer Experience

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,400[a]	0,160	0,158	0,84111147

a. Predictors: (Constant), Cognitive Perception

b. Dependent Variable: Customer Experience

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	51,705	1	51,705	73,084	,000[b]
	Residual	270,960	383	0,707		
	Total	322,665	384			

a. Dependent Variable: Customer Experience

b. Predictors: (Constant), Cognitive Perception

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	8,561E-17	0,043		0,000	1,000
	Cognitive Perception	0,422	0,049	0,400	8,549	0,000

a. Dependent Variable: Customer Experience

Excluded Variables[a]

Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics
						Tolerance
1	Communication Quality	-,020[b]	-0,385	0,700	-0,020	0,839
	Affective Engagement	,089[b]	1,897	0,059	0,097	0,982

a. Dependent Variable: Customer Experience

b. Predictors in the Model: (Constant), Cognitive Perception

- **Backward Method:**

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Affective Engagement, Cognitive Perception, Communication Quality[b]		Enter
2		Communication Quality	Backward (criterion: Probability of F-to-remove >= ,100).

a. Dependent Variable: Customer Experience

b. All requested variables entered.

Model Summary[c]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,411[a]	0,169	0,163	0,83877138
2	,410[b]	0,168	0,164	0,83827263

a. Predictors: (Constant), Affective Engagement, Cognitive Perception, Communication Quality

b. Predictors: (Constant), Affective Engagement, Cognitive Perception

c. Dependent Variable: Customer Experience

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	54,618	3	18,206	25,878	,000[b]
	Residual	268,048	381	0,704		
	Total	322,665	384			
2	Regression	54,234	2	27,117	38,589	,000[c]
	Residual	268,432	382	0,703		
	Total	322,665	384			

a. Dependent Variable: Customer Experience

b. Predictors: (Constant), Affective Engagement, Cognitive Perception, Communication Quality

c. Predictors: (Constant), Affective Engagement, Cognitive Perception

Coefficients[a]

Model		Unstandardized Coefficients	Std. Error	Standardized Coefficients	t	Sig.
		B		Beta		
1	(Constant)	9,184E-17	0,043		0,000	1,000
	Cognitive Perception	0,425	0,054	0,403	7,893	0,000
	Communication Quality	-0,038	0,052	-0,038	-0,739	0,460
	Affective Engagement	0,103	0,052	0,096	1,998	0,046
2	(Constant)	7,525E-17	0,043		0,000	1,000
	Cognitive Perception	0,409	0,050	0,388	8,247	0,000
	Affective Engagement	0,096	0,051	0,089	1,897	0,059

a. Dependent Variable: Customer Experience

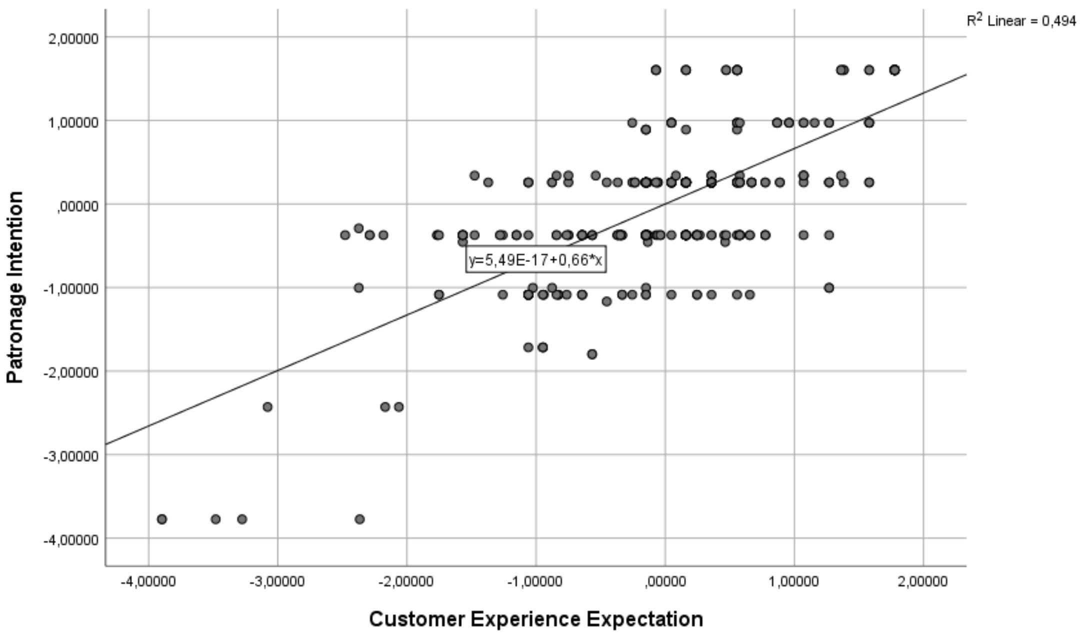
Annex Y: H7 – Simple Linear Regression Model Assumptions

1) There is a linear relationship between the dependent variable and the explanatory variable: verified in the preliminary analysis.

Correlations

		Customer Experience Expectation	Patronage Intention
Customer Experience Expectation	Pearson Correlation	1	**,703****
	Sig. (2-tailed)		0,000
	N	385	385
Patronage Intention	Pearson Correlation	,703**	1
	Sig. (2-tailed)	0,000	
	N	385	385

**. Correlation is significant at the 0.01 level (2-tailed).



2) The mean of the residual component of the model is 0;

Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	-2,589	1,180	0,0000000	0,609	385
Residual	-2,202	1,650	0,00000000	0,616	385
Std. Predicted Value	-4,252	1,938	0,000	1,000	385
Std. Residual	-3,570	2,675	0,000	0,999	385

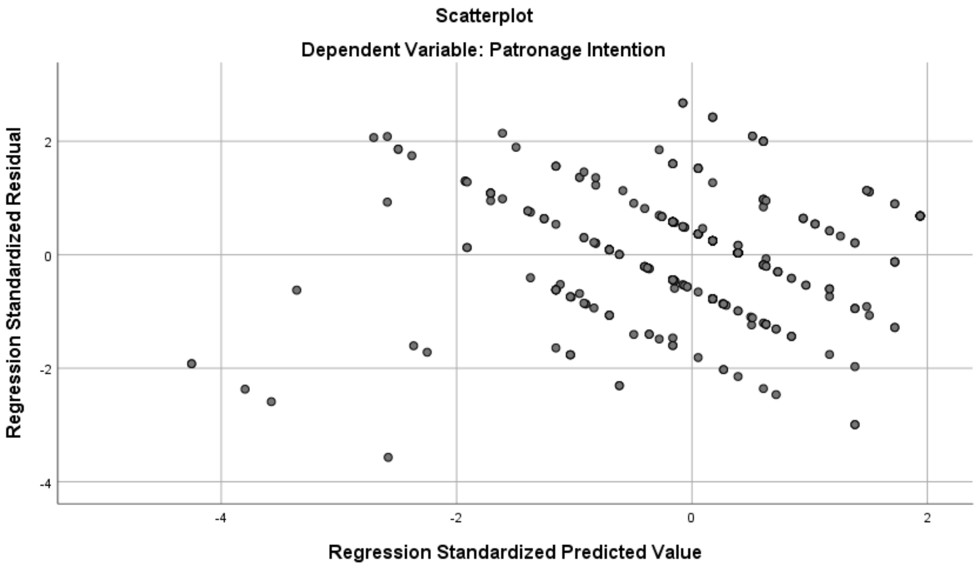
a. Dependent Variable: Patronage Intention (factor)

3) The independent variable is not correlated with the residual terms (Appendix);

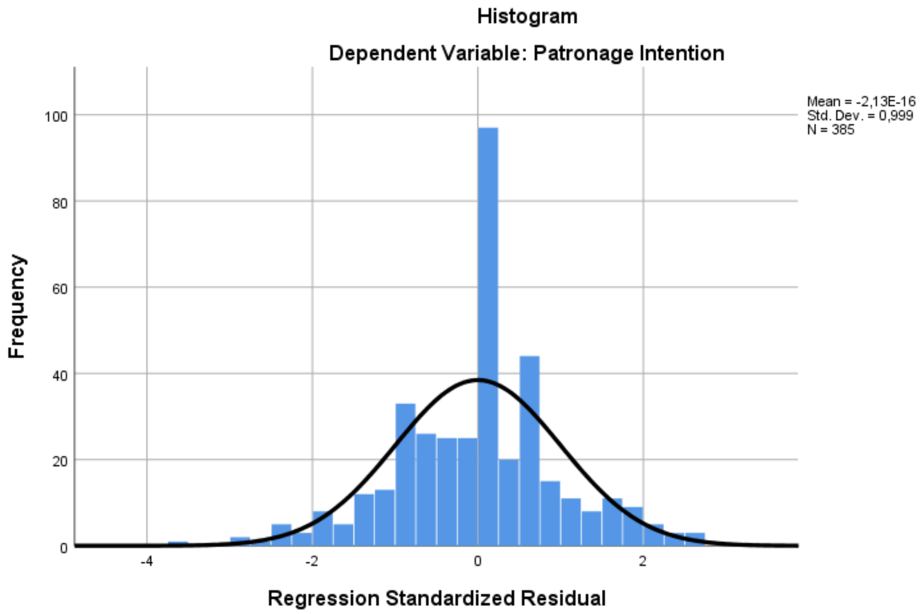
Correlations

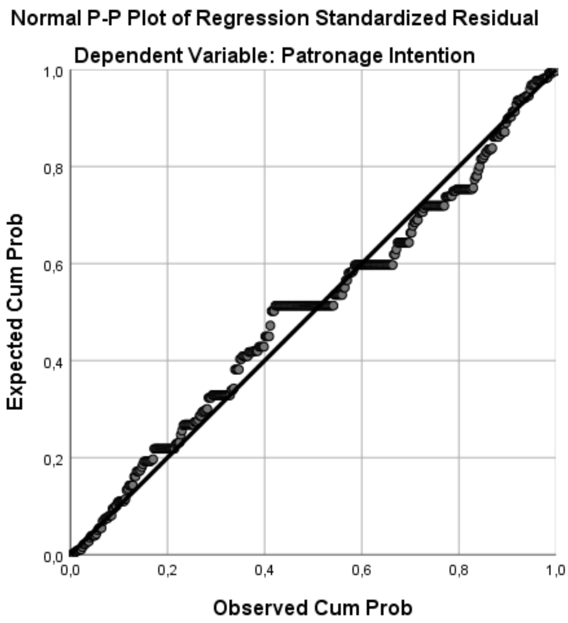
		Customer Experience Expectation	Unstandardized Residual
Customer Experience Expectation	Pearson Correlation	1	0,000
	Sig. (2-tailed)		1,000
	N	385	385
Unstandardized Residual	Pearson Correlation	0,000	1
	Sig. (2-tailed)	1,000	
	N	385	385

4) The variance of the random term is constant;



5) And, the residuals follow a Normal distribution;





Annex Z: H7 – Estimated Simple Linear Regression Model

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,703[a]	0,494	0,493	0,61680326

a. Predictors: (Constant), Customer Experience Expectation

b. Dependent Variable: Patronage Intention

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	142,360	1	142,360	374,191	,000[b]
	Residual	145,711	383	0,380		
	Total	288,071	384			

a. Dependent Variable: Patronage Intention

b. Predictors: (Constant), Customer Experience Expectation

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1,065E-16	0,031		0,000	1,000
	Customer Experience Expectation	0,664	0,034	0,703	19,344	0,000

a. Dependent Variable: Patronage Intention