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**Influence of brand awareness methods on consumer
engagement: Online Retail Industry**

Diogo Oliveira Silvestre Amaro

Master Thesis

presented as partial requirement for obtaining a Master's Degree in Data-Driven Marketing with a specialization in Digital Marketing & Analytics

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

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by

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Supervised by

Jorge Carrola Rodrigues, PhD, Universidade Nova de Lisboa

July, 2024

STATEMENT OF INTEGRITY

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

Lisbon, July 2024

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ABSTRACT

This research aims to discover the brand awareness marketing methods that promote more efficiency in engaging the consumer on the online retail industry. The main research methodology approach involves a questionnaire that consists of surveying online retail consumers and understand the effectiveness of the different marketing strategies towards their engagement within the brand. Additionally, there is also a text mining and sentiment analysis approach by analyzing online reviews from a Portuguese company of the sector: Prozis. The marketing strategies concepts considered were Social Influence, existing e-WOM and Consumer Experience. The questionnaire got 188 answers and was only answered by Portuguese residents. The 28.283 reviews extracted from Trustpilot were from the period of April 2015 to April 2024 (9 years). The main findings of this research indicates that Social Influence has not statistically significance on Consumer Engagement, but E-WOM and Consumer Experience are two marketing concepts that impacts positively Consumer Engagement.

KEYWORDS

Brand awareness; Consumer engagement; Consumer experience; E-wom; Online retail; Sentiment analysis; Social influence

Sustainable Development Goals (SDG):



TABLE OF CONTENTS

1. Introduction	1
2. Literature review	3
2.1. Influence of Others	3
2.1.1. Social Media	3
2.1.2. Influencer Marketing.....	4
2.2. Existing e-WOM.....	5
2.3. Consumer Experience Optimization.....	7
2.3.1. Artificial intelligence (AI)	7
2.3.2. Vertical Engagement (VE).....	8
2.4. Consumer Engagement	9
3. Conceptual Model and Hypothesis	11
3.1. Conceptual Model	11
3.2. Hypotheses	13
4. Methodology	15
5. Data Collection	17
5.1. Data Preparation	17
5.1.1. Questionnaire.....	17
5.1.2. Online Reviews.....	17
6. Results	19
6.1. Questionnaire.....	19
6.1.1. Sample Results	19
6.1.2. Measurement Model Results.....	22
6.2. Online Reviews	26
7. Discussion	31
8. Limitations and Future Work.....	33
9. Conclusion	34
Annexes	43

LIST OF FIGURES

Figure 1 – Conceptual Model	11
Figure 2 - Data Preparation Steps	18
Figure 3 - Professional Situation	20
Figure 4 - Employment Regime.....	20
Figure 5 - Path Model with Path Coefficient.....	25
Figure 6 - Reviews overall Sentiment Analysis.....	27
Figure 7 - Data Distribution Boxplot.....	28
Figure 8 - Keywords Sentiment Analysis	30

LIST OF TABLES

Table 1 - Model Constructs and Items	12
Table 2 - Gender, Age, Education Level and Civil Status	19
Table 3 - Region.....	21
Table 4 - Frequency of Online Purchases.....	21
Table 5 - Relation between Age and FP	22
Table 6 - Outer Loadings & Cross Loadings.....	23
Table 7 - The Fornell-Larcker criterion.....	23
Table 8 - AVE, CR and Cronbach's alpha	24
Table 9 - Variance Inflation Factor (VIF).....	25
Table 10 - P-values	26
Table 11 - Sentiment per Review Star Rating.....	27
Table 12 - Data Distribution	28
Table 13 - Frequency Analysis: Top-25.....	29

LIST OF ABBREVIATIONS AND ACRONYMS

AI	Artificial Intelligence
AVE	Average Variance Extracted
CEB	Customer Engagement Behavior
CR	Compose Reliability
CXO	Customer Experience Optimization
DV	Dependent Variable
E-WOM	Electronic Word-of-Mouth
FP	Frequency of Purchases (per month)
IV	Independent Variable
PLS	Partial Least Squares
PEU	Perceived Ease of Use
SM	Social Media
VADER	Valence Aware Dictionary for sEntiment Reasoner
VE	Vertical Engagement

1. INTRODUCTION

The online retail industry is fiercely competitive and brand awareness methods play a pivotal role in attracting and retaining customers (Phong et al., 2020). Due to this market competitiveness, the concept of brand presence is at the same time fundamental and challenging. Commerce is growing exponentially year on year and the trend is set to continue. A Forbes study projects that, by 2024, online transactions will represent 20% of all retail purchases. Retailers are increasingly implementing diverse digital technologies to engage with their customers and maintain competitiveness in the industry (Grewal, 2017). As the business volume on the online retail industry is increasing, it is essential to understand the most effective brand awareness methods so that it consequently results on more sales and greater engagement of the consumers. Indeed, consumer brand perception creates value for an organization (Phong et al., 2020), and establishing effective brand awareness marketing methods plays a key role in enhancing the awareness of the brand. This study seeks to determine which specific brand awareness methods have the strongest relation with consumer engagement on the online retail industry.

Although some studies consider brand awareness an antecedent of online retail trust (Das, 2016) there is a research gap concerning the relative impact or influence of various brand awareness methods on consumer engagement. Bowden & Mirzaei (2021) suggests research about the connection between self-brand with brand awareness to enhance consumers engagement. This study aims to address this gap. The research question of this research is: "What is the influence of different brand awareness methods on consumer engagement for online retail enterprises striving to thrive in highly competitive markets?"

The fact that social media networks are making online commerce increasingly widespread, makes the research both trendy and challenging. Therefore, the research has a social media approach since, according to Dolega (2021), it plays an essential role in promoting brand awareness as well as it is considered an important tool to engage with the clients, digitally.

The main research method involves a quantitative study that consists of surveying online retail consumers through a questionnaire, to understand the different brand awareness methods influence on their engagement, taking into consideration the brand awareness methods collected in the existing literature. Another main motivation for carrying out this study was the availability of a lot of secondary data. Additionally, there is also a text mining and sentiment analysis approach by analyzing consumer feedback via online reviews on a particular online retail company. This analysis add value to the research results, since can identify the consumer sentiment within the brand and identify the main consumer engagement causes, by performing text analysis.

The aim of this research is to analyze the relation between brand awareness methods and consumer engagement metrics to determine which methods are most influential in driving engagement on the online retail sector. The findings provide valuable insights for retailers and

marketers, helping them tailor their marketing strategies to boost engagement with its customers and ultimately drive business growth on the online retail industry.

This study is divided into 9 chapters to make it easy to read, straightforward and organized. The first chapter, Introduction, is included in this section and covers the context of the topic, the research motivation and presents the thesis flow and structure. The second chapter is the Literature Review, which presents a theoretical overview about the main brand awareness methods that influences consumer engagement on the online retail industry, supported by quality references in the research field. This chapter is the pillar of the research as it is used to formulate the conceptual model and the hypothesis. The third chapter presents the conceptual model with all the variables (independents and dependent), as well as formalize the various hypotheses that will be tested in the next chapter. The next phase is about the methodology used. Fifth chapter presents the data collection of the two data sources presented on this dissertation. The sixth chapter outlines the results, which are analyzed in the seventh chapter. The eighth chapter addresses the study's limitations and suggests areas for future research, while the ninth chapter presents the conclusion of the research.

2. LITERATURE REVIEW

2.1. INFLUENCE OF OTHERS

“Opinions of others influence consumers’ purchasing intent” (M. K. O. Lee et al., 2011). Decisions are part of life and are an intrinsic attribute of the human condition, which begins with a friction between reason and feelings. Although we assume that decisions are driven by human rationality, the truth is that they are shaped by a variety of influencing factors. The human being is not a robot that bases its actions purely on rationality/intelligence, but rather on past experiences, emotions, social contexts, and even subconscious impulses. All these factors influence our daily decisions. Society's opinion, as well as the entire context in which we live, exert emotional pressure on the daily choices we make. For example, according to X. Zhang et al. (2014), shopping with friends is likely to increase the amount that customers spend. All these variables shape decision-making process as well as influence us subconsciously, and for that reason the sentence: “We reflect our surroundings” makes complete sense.

Argo & Dahl (2019) argues that influence can be categorized into active and passive. Active influence involves direct verbal or physical interactions that both parties notice and share. A practical example is a sales employee in a store trying to persuade a customer to buy a product, saying things that the consumer wants to hear in order to sell. Passive influence involves a one-way social experience where the consumer is influenced by the actor without existing any interaction or by the social information present. A practical example of this approach is a customer seeing a queue of people lining up to enter a restaurant without the owner of the restaurant being present. In this hypothetical scenario, the consumer can make two choices: either he joins the queue because he believes the restaurant is good due to its demand, or he chooses another one because he must wait a long time to get a table. In both scenarios the consumer has been passively influenced.

According to M. K. O. Lee et al. (2011), positive social influence contributes to the strengthening of the attitude towards online shopping as well as the relation between attitude and intention to shop.

2.1.1. SOCIAL MEDIA

Social media (SM) has contributed to the expansion of the online retail market (Hyun et al., 2022) as is an excellent tool for companies to express their values and mission. Furthermore, SM has become an essential digital marketing platform to promote goods, aiming to maximize company’s profits (Dolega et al., 2021) and engage with the customers (Vithayathil, 2020). By developing a good social media marketing strategy, brands can cause positive engagement with the consumers and consequently brand awareness in the digital environment, by

providing product visibility to new customers, customer support and customer acquisition (Mary J. Culnan & Patrick McHugh, 2010).

In the marketing field, brand recognition is primordial. Research has shown that, the more known the brand is, the more people buy and recommend its products or services to other people (Horng et al., 2012), and as Barreda et al. (2015) proved, not only SM increase the brand awareness but also enhance positive electronic word-of-mouth (e-WOM). Social Media strategies are a great opportunity to enhance brand reputation across borders and an effective way of reaching people all over the world (Nieto et al., 2014). From a market growth perspective, a positive e-WOM metric is relevant, since building strong brand awareness is one of the main objectives of any marketer, besides it's an organic way of building trust without investment.

Kumar (2016) has shown that social media marketing has a positive impact on consumer spending, especially among those who are digitally and technologically savvy. Another important aspect is the capability of social media to enhance relationships with ongoing and future clients and create communities of people with the same interests that can contribute in a positive way for the company, since their collaboration by itself can identify company problems and find solutions (Tsimonis & Dimitriadis, 2014).

2.1.2. INFLUENCER MARKETING

Social media influencers are known as individuals who have a considerable number of people following them on social media (De Veirman, 2017), that have the power to directly influence their followers' purchasing intentions (Lee & Watkins, 2016) as they are considered a reliable source of information (De Veirman, 2017). These influencers are considered branding experts on the various digital platforms (Khamis, 2017) as they are seen as a trustworthy personality in one or more digital niches (De Veirman, 2017).

Influencer marketing has emerged as a critical element of brands' digital marketing strategies (Leung, 2022a). This concept consists of a communication strategy in which a company pays influencers to promote the firm's offering (Leung, 2022b); (De Veirman, 2017).

To gauge the success of influencer marketing campaigns, it is important to understand the trustworthiness characteristics of an influencer. Since digital influencers are moving from being just information providers to developing relationships with followers (Ismagilova et al., 2020c) the similarity/homophily metric needs to be pointed out. This metric refers to the similarity of values, attitudes, attributes or preferences between the follower and the influencer (Jin, 2019). A study conducted by Schouten, (2020) concluded that social media influencers have a greater persuasive factor than celebrities and that a consumer can easily trust an influencer more than a celebrity.

Influencer Marketing strategy often promotes higher credible e-WOM compared to paid advertising, as the publicity side is camouflaged with the digital content these influencers post every day (Abidin, 2016).

Other recent concept related to Influencer Marketing environment is the adoption of Virtual influencers. This recent technology is described as an entity that operates through artificial intelligence and is visually represented as an interactive, real-time rendered character in a digital environment (Sands, 2022). It's a 100% digital character that makes its imaginary life and personality very realistic, which generate a strong connection with its audience. Several luxury brands have already joined in, for example Dior created "Noonouri" and Prada, "Candy". According to a study carried out by Allal-Chérif (2024), the fact that a virtual influencer is not human is advantageous: its imaginary story is more important than the appearance in terms of engagement; it contributes to an improvement in digital marketing campaigns and finally concludes that it appears to be more authentic than human influencers.

Source credibility is considered a crucial factor when weighing e-WOM communications (Akyüz, 2013). According to Ismagilova et al. (2020a), when conducting this consideration, there are several relevant factors, including expertise, trustworthiness, credentials and attractiveness. Yang (2015) found that information derived from a credible source positively affects intention to buy.

2.2. EXISTING E-WOM

Electronic Word of Mouth (e-WOM) is defined as an exchange of information between users regarding a product, service, brand, or company, via the Internet (Ismagilova, 2020b).

Nowadays, e-WOM is a crucial consideration factor for consumers when making online purchases (Dwi Santy & Andriani, 2023), and from a business point of view is one of the most valuable digital marketing dimension for any organization (Akbari et al., 2022).

By building a community where consumers communicate with each other, spreading feedback and endorsing the brand through e-WOM, individual purchasing behavior may be influenced and a domino effect is created as people are induced to purchase similar products from other users within that community (Kim & Ko, 2012). By building strong consumer relationships, companies are encouraging consumers to engage in e-WOM activities (Barreto, 2014).

It has already been acknowledged in marketing/consumer behavior literature that e-WOM exerts greater influence on consumer decision-making compared to traditional advertising methods. (Goldsmith & Clark, 2008). This brand awareness method should be carefully planned as negative reputation across the web can be spread quickly or sometimes faster than positive. This means that the consumer loyalty to a brand can quickly end. As already stated, e-WOM influence consumer purchase decision and therefore monitoring consumer

sentiments and perception is an excellent way to achieve continuous improvement to provide a superior online service (Duarte et al., 2018).

A well-known e-WOM is through online reviews. This is a way of letting people freely discuss the brand or their experience, exposing it positively or negatively. Recent studies by *Podium* show that 93% of online consumers indicates that online reviews have influence in their purchase decisions. A study conducted by K. Z. K. Zhang (2014) shows that source credibility and perceived volume of reviews are two heuristic factors impacting purchase intention, positively. The volume of reviews is considered a crucial factor to increase firms' sales according to the literature. P.-Y. Chen (2004) studied 610 different books feedback on Amazon and demonstrated that the number of online reviews of each book were positively associated with number of sales, and also concluded that the volume of reviews converts more customers on less-popular books than more-popular books.

Tata et al. (2020) studies concluded that positive reviews on the retail industry have greater influence than negative reviews on both attitude and purchase intentions. Although some studies found that positive reviews provide the customer confidence and credibility, other researchers found it to be the opposite. Teng et al., 2017 studies reveal that negative online reviews are more credible and reliable than positive ones. In the same page, Y. Chen (2011) studies revealed that negative e-WOM has a greater impact on product sales than positive one. As a result, consumers are heavily influenced by the valence of the reviews and generally avoid products that have received negative feedback. These discrepant results could be attributed to the different contexts the studies were conducted. For example, Mauri & Minazzi (2013) conducted a study that found that positive online reviews comments on the hotel industry increase intention to book. Chih et al. (2013) found that site reputation, source credibility and social orientation through positively e-WOM, influences purchase intentions in an online community.

As previously mentioned, source credibility plays an important role in online reviews. Nowadays with the raise of social media platforms, the process of evaluating authentic product reviews is challenging (Chakraborty, 2019). Source credibility refers to the degree to which the receiver relies in a specific information source. It is considered a way of questioning the veracity of the message.

The digital market is becoming trendier and more challenging and all the dimensions of e-WOM are important. The dimension "time" also needs to be considered on online reviews. People search for all aspects before intending to buy something online. "The timeliness of the message concerns whether the messages are current, timely, and up to date" (Sa'ait). In the hotel sector, Zhao (2015) concluded that timeliness reviews have a positive impact on online booking intention. The more up to date the online reviews are, the more chance the customers intend to book a hotel room.

2.3. CONSUMER EXPERIENCE OPTIMIZATION

Consumer Experience Optimization (CXO) refers to the process of enhancing and improving the customer journey experience when interacting with a product, service, or a brand. It involves analyzing the various customer journey touchpoints to ensure a satisfying customer experience which according to Cuesta-Valiño et al. (2022), is considered one of the most important variable to increase companies' profits. Although this process does not correspond to a direct brand awareness method to promote engagement in the obvious sense (such as advertising or marketing campaigns), it surely influences consumer engagement within the brand. Gavrilă et al. (2023) concluded that task optimization within the internal company processes generates positive consumer expectations, which presupposes a positive impact on customer loyalty and engagement during the purchasing process, and of course on the business results. As stated, CXO enhance and improve customer engagement, here's how: By providing a positive experience thought the service, customers are more likely to share it with other people through e-WOM by writing positive comments and give positive ratings on social media platforms. This organic sharing increases brand visibility among potential customers and could bring competitive advantage within the online retail industry.

In their recent study, Vila et al. (2021) analyzed the factors that enhance the user experience in the tourism e-commerce industry. The main results unveil "usability" and "branding" as the principal engagement metrics of the sector. The author considered usability as how easy the user interface feels to the user and how easily the user can interact with it, and branding as the whole presence of the brand in the digital, not only on the search engines but also in social media and online communities.

In 1989 Davis created one of the most influential models of technology acceptance, TAM model, that explains how to encourage users to accept and utilize a new technology. This model includes the perceived ease of use variable which is considered the "degree to which a person believes that using a particular system would be free from effort". A user-friendly website (easy to use) can result in behavioral engagement consequences, such as purchasing or enhancing brand awareness.

A crucial tool to improve CXO is through Artificial Intelligence.

2.3.1. ARTIFICIAL INTELLIGENCE (AI)

In recent years we have seen technological growth in various industries. One of the game-changer technologies is Artificial Intelligence (AI). AI represents knowledge, expertise, and intuition to solve problems (Poole & Mackworth, 2010). AI can have several definitions, but the most recognizable refers to a computer system that can act intelligently (Poole & Mackworth, 2010) through the ability to interpret and learn external data correctly to accomplish tasks through fast and flexible adaption (Kaplan & Haenlein, 2019).

These tasks include visual perception, speech recognition, decision making, fast and smart translation, among others according to the Oxford Dictionary. Many retailers are using this tool to engage with their customers (Morgan, 2019) as AI can enhance marketing functions across the marketing planning process (Campbell et al., 2019).

Today, any ad video can be edited in minutes using AI. For example, through the content of the video, the algorithm perceives and interprets it using editing techniques adapted to the context of the video. Inserting subtitles based on the audio, as well as simulating and transforming people's voices or facial features are some of the techniques that AI could perform in this digital marketing format.

Various authors consider the adoption of AI on the retail sector a huge competitive advance in the retail industry. The adoption of AI technologies on the retail value chain are predominantly focused on the customer journey (Oosthuizen et al., 2021), enabling a better customer service. The main objective with that is to build customer trust by providing personalized experiences through all the customer online path, such as product recommendations or chatbot assistance (Oosthuizen et al., 2021). Chatbots are considered a helpful tool because has the capacity to learn from past data and provide recommendations to the consumers, using machine learning algorithms (Pallathadka et al., 2023). This technology is a perfect tool to help customers finding a certain product or to provide alternative similar products to the consumer (cross-selling), enhancing the proximity with the client. According to a study from Sung et al. (2021) AI technologies boosts consumer engagement, leading to unpaid brand endorsement (WOM) and consequently increases purchase intentions.

2.3.2. VERTICAL ENGAGEMENT (VE)

As social media contributes in a significant slice to firms digital marketing strategy success, it becomes important to study the media formats that provide the most interest and engagement for consumers. An important touchpoint of the consumer journey is the consumption of video media content not only on social media but also on the others digital channels. According to Sedej (2019), video marketing strategy is moving to the core of strategic marketing planning as is a marketing tool that engage with people emotions and appeal to their needs. We've always been used to consuming digital content in a horizontal format, mostly due to the influence of the television or a computer. Due to the pandemic, digital content consumption has increased significantly, and a new screen format has been trended: The vertical screen format. Mulier (2021) has demonstrated that vertical video ad format is more effective in increasing consumer interest and engagement compared to the horizontal default format as users process vertical video more fluently and experience less effort watching it. The movement of changing the natural position of a smartphone to a horizontal position requires effort from the average mobile user. In 2017, Martin Erik J.

concluded that less than 30% of the users do this movement and the ones who do, only consume 14% of the content. The trend is set to continue with the vertical format content consumption ruling, and marketers need to track and rethink their content marketing strategies (Sedej, 2019) to keep updated. There are already industries that are restyling their services as a way of keeping up with this trend. For example, the movie industry is exploring vertical film festivals (Canella, 2018). This is considered a recent phenomenon in the context of CXO.

2.4. CONSUMER ENGAGEMENT

The concept of "consumer engagement" has been widely discussed and represents a pillar subject in this research. Consumer engagement can be stated as consumers disposition to engage with a firm (Sim et al., 2022), manifesting this intention in non-transactional behaviors such as writing reviews or giving recommendations to others. This consumer manifestations can lead to higher retention, loyalty, and profitability. Lay & Bowden (2009) views this concept as a psychological process involving both cognitive and emotional aspects. His conceptual model suggests that the engagement process journey starts in customer satisfaction and culminates in customer loyalty. New customers' commitment mostly involves thinking and hesitation ("calculative commitment" in the model), while repeat customers rely more on emotional bond ("affective commitment" in the model) when engaging with the brand. For Rappaport (2007), consumer engagement focusses on two key ideas: the high relevance of the brand for the customers and the development of emotional connection between the brand and the customer. Brands that develop a clear narrative where their consumers can quickly connect to an experience, are more likely to be selected (Harrigan et al., 2018) since the key points of this narrative are triggered by the cognitive system through thoughts and memories.

Beyond these emotional and psychological aspects associated with consumer engagement, there are also notable cross-cutting behaviors resulting from this concept. In their article, van Doorn (2010) defined these behaviors as "customers' manifestations or actions toward a brand, beyond purchase, resulting from motivational drivers". These consumer attitudes include a vast range of behaviors including word-of-mouth activities, recommendations, writing reviews or even social media engagement. Although we might think it in a positive way, consumer engagement can also be demonstrated negatively (Azer & Alexander, 2020) when for example, boycotting a firm after a public scandal. Their conceptual model includes the antecedents and the consequents of Consumer Engagement Behavior (CEB). From the antecedents that the authors mention in the article, *Identity* and *Resources* stand out as two unusual dimensions in this context of consumer engagement, which will be considered further in this section.

The consumer engagement dimension in which this study is focused but not exclusively is the behavioral one, the type of engagement where the consumer actually demonstrates an intention or an attitude. As written before, these behaviors include not only purchasing products but also brand's endorsement actions. Regarding brand endorsement, a positive consumer experience directly influences the likelihood of recommendation to other consumers and also could lead to social media engagement (by liking, commenting, and sharing).

Consumer resources have an impact on the consumer engagement activities. Before an engagement activity, consumers evaluate the cost, time, and effort of doing it. Individuals with low income may avoid money donation to a brand-related charity for example, but in the other hand people who are taking a bachelor course, or a part-time job tend to be more likely to engage with the brand via social media communities or forums due to time freedom.

Customer engagement can also be influenced by individual customer traits and characteristics. For example, people with higher moral identity are more likely to help other consumers, providing them recommendations/ suggestions leading to a brand promotion through word-of-mouth.

In addition to the cognitive and behavioral aspects, according to Dessart (2017), consumer engagement can also have an affective dimension. The degree of enjoyment, enthusiasm and social connection with the brand generates a positive impact for the customer and for the company. By participating in brand related events, customers can experience emotional benefits. For example, the fact that a brand sponsors a football team can lead to a lot of enjoyment and positive effects to the fans as well as provide more engaging activities. In many cases, the simplicity of just buying a product brings enthusiasm to the consumer. The successful the CEB antecedents' efforts are, the more intense and frequently the customers engage affectively.

3. CONCEPTUAL MODEL AND HYPOTHESIS

In this section of the dissertation, the Conceptual Model of the research is presented. The main objective of this chapter is to present the conceptual model (Figure 1) with the main marketing variables (constructs) that contribute to Consumer Engagement within a brand on the online retail industry. Given the findings covered in the literature review, the independent variables (IV) considered are Social Influence, Existing E-WOM and Online Consumer Experience and the dependent variable (DV) considered is Consumer Engagement. Also, hypotheses were formulated to study the relation between the variables in the following chapters.

3.1. CONCEPTUAL MODEL

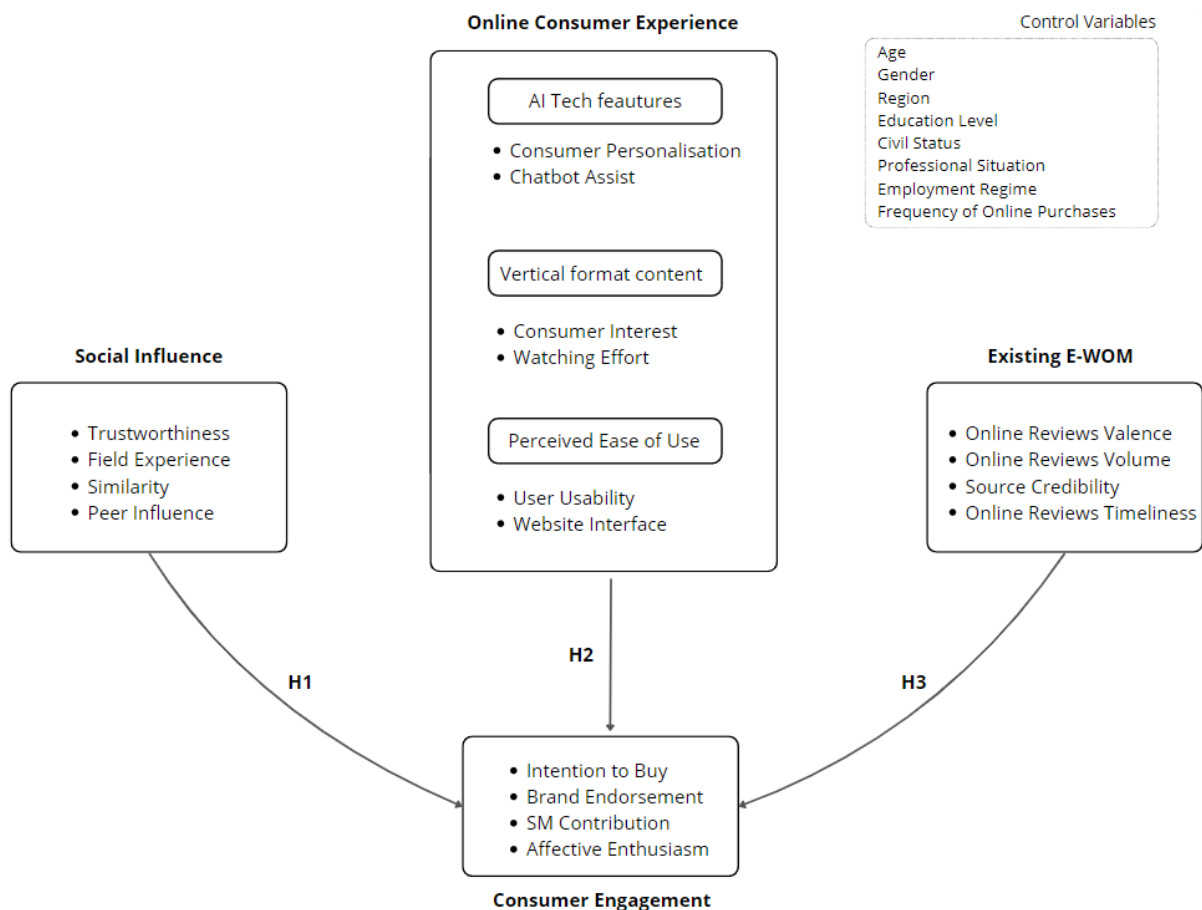


Figure 1 – Conceptual Model

In the conceptual model, the Customer Engagement construct is primarily guided by the principles of behavioral engagement as written in the section 2.4. Additionally, drawing upon the research of Sung et al. (2021), who similarly incorporates these behavioral intentions into their model, the measures of the construct include Purchase Intention and Brand Endorsement. Brand Endorsement construct is focused on the behavior of recommendation the service to others. Also, the conceptual model follows Schivinski et al. (2016) framework

construct “Contribution”, which refers to the consumer social media contribution to the brand. The Affective Enthusiasm suggested by Dessart (2017) in their studies, is also considered in the study since the deepening of the topic in the literature review section.

The control variables of the conceptual model are age, gender, region, education level, civil status, professional situation, employment regime and frequency of online purchases per month (FP).

Table 1 presents the model constructs and measures to be studied. To facilitate further analysis, a code was assigned to each item.

Construct	Item	Item Description	Source
Social Influence	SI1	Peer Influence	M. K. O. Lee (2011)
	SI2	Similarity	Jin (2019)
	SI3	Trustworthiness	Ismagilova (2020a)
	SI4	Field Expertise	
Existing E-WOM	EE1	Online Reviews Volume	Tata (2020)
	EE2	Online Reviews Valence	Ismagilova (2020a)
	EE3	Source Credibility	Chakraborty (2019)
	EE4	Online Reviews Timeliness	Zhao (2015)
Consumer Experience	UX1	Chatbot Assist	Oosthuizen et al. (2021)
	UX2	Customer Personalization	
	UX3	Consumer Interest	Mulier et al. (2021)
	UX4	Watching Effort	
	UX5	User Usability	Davis, 1989
	UX6	Website Interface	Vila et al. (2021)
Consumer Engagement	CE1	Purchase Intention	Sung et al. (2021)
	CE2	Brand Endorsement	
	CE3	SM Contribution	Schivinski et al. (2016)
	CE4	Affective Enthusiasm	Dessart (2017)

Table 1 - Model Constructs and Items

3.2. HYPOTHESES

Social influence plays a significant role in consumer engagement in the context of online retail. Both peer recommendations by friends and digital influencers play a crucial role in this subject. These social interactions shape purchasing decisions, directly influencing consumer behavior as seen in *section 2.1*. Digital influencers have a major impact, as they have the power to reach large audiences and set consumer trends. Their ability to build authentic relationships with their followers, increases their trust and drives consumer engagement within the brands. To study how strong is this influence on the consumer behavioral engagement, the principal measures include Trustworthiness, similarity, and field expertise (Ismagilova et al., 2020a). The main premise of the model is to validate the idea that the messenger is more influential than the message itself. That said, the following hypotheses was formulated:

H1: Social Influence affects Consumer Engagement on the online retail context.

There are tools that could improve the customer experience journey in the online environment. In the literature review there was acknowledge elements that enhance consumer engagement such as AI, the vertical video format and website usability.

AI features customize the user experience by providing accurate and personalized recommendations, which increases purchase intention by targeting relevant products. The vertical video format optimizes the digital consumption on mobile devices (Mulier et al., 2021), improving consumer interest and retention. Effective website usability, including intuitive navigation and user-friendly interface, enhances the user experience, increasing the likelihood of engaging with the website. That said, the following hypotheses was formulated:

H2: Online Consumer Experience affects Consumer Engagement on the online retail context.

In the realm of e-commerce, the impact of e-WOM is crucial for consumer engagement as seen before (*section 2.2*). Online reviews directly influence consumers' purchase intent, shaping their purchasing decisions. Specifically, the valence of reviews (whether positive or negative) plays a considerable role in brand perception and the purchasing decision. (Y. Chen, 2011; Tata, 2020; Teng, 2017; K. Z. K. Zhang, 2014). Positive reviews can strengthen brand endorsement, while negative reviews can discourage consumers from buying firm products/service. The volume of the online reviews is also a factor when considering a brand (P.-Y. Chen, 2004; K. Z. K. Zhang, 2014). The credibility of the source (Chakraborty, 2019) as

well as the timeliness (Zhao et al., 2015) are also dimensions that affects online decision making. That said, the following hypotheses was formulated:

H3: Existing E-WOM affects Consumer Engagement on the online retail context.

4. METHODOLOGY

The research methodology approach is consumer centered. The study involves a quantitative questionnaire that consists of surveying consumers from the online retail industry to understand the effectiveness of different marketing strategies towards their engagement within the brand. With that said, the main methodology is Natural Science. Natural Science is tied with the scientific method which is based on observation and formulation of hypothesis (An Gulinck, 2022). This approach involves a research model with the hypotheses associated within the constructs. This method allows the validation of this associations through the survey respondents results. Oliveira (2016) points some benefits of using survey as the research method, such as reducing the risk of distortion due to the researcher's lack of influence; reaching a larger number of people/ geographic area; allowing the complete anonymity of the respondents.

To supplement the research, there is also a text mining approach in analyzing online reviews. This extra research method is focused on the Perceived Ease of Use sub-construct (Usability and Interface as the items of it). The main goal with this approach is to analyze the relation between the content of online reviews and the user engagement on the online retail industry. By analyzing secondary data from online reviews, it is possible to identify underlying patterns trends and sentiments, providing a deeper understanding of consumer experience within the brand, and understand the most valued characteristics by the users in their online journey. Unlike surveys, which depend on participants' self-retrospective evaluations and could be susceptible to biases answers, online reviews contain the raw writer sentiments which leads to honest results.

The text mining approach was performed in online reviews from Prozis consumers on TrustPilot (<https://www.trustpilot.com/review/www.prozis.com>). Prozis was chosen for this analysis due to its relevance in the Portuguese market and in specific for this approach because they have a strong online presence. As the study is focused on the Portuguese market, the only reviews considered were the Portuguese ones (approximately 30.000 reviews).

Vader (Valence Aware Dictionary and sEntiment Reasoner) was used as the main sentiment analysis tool as it has the ability to detect the polarity of sentiment of a given text. This tool analyzes text's sentiment using a dictionary of words and guidelines. One of the benefits of using *Vader* is that it performs exceptionally well in the social media domain compared to other traditional sentiment lexicons as it is more sensitive on dealing with text in this field. Also, compared to other sentiment analysis tools, *Vader* had been considered the one with the highest quality and performance, according to their creators (Gilbert & Hutto, 2014). *Vader* uses *polarity_scores()* method to determine the sentiment of a sentence. This method gets 4 different results with 2 different scales:

- “*neu*”: scale from 0 to 1 -> how neutral the text was.
- “*neg*”: scale from 0 to 1 -> how negative the text was.
- “*pos*”: scale from 0 to 1 -> how positive the text was.
- “*compound*”: scale -1 to 1 -> the overall sentiment of the text (being negative values, negative sentiments, 0 a neutral sentiment and positive values, positive sentiments).

5. DATA COLLECTION

5.1. DATA PREPARATION

5.1.1. QUESTIONNAIRE

The questionnaire was launched initially with all the items presented in the Table 1. A pilot study was performed, using 20 random responses through the Smart-PLS software, in order to assess the feasibility of the questionnaire as well as to identify potential issues before conducting the large-scale questionnaire. The results showed that there were items that were performing very poor in the model, so the decision was to take them out.

After the results the items considered were SL1, SL2, EE1, EE3, EE4, UX2, UX5, UX6, CE1, CE2. The original questionnaire also suffered alterations, as the questions of the items removed were also taken out.

The large-scale questionnaire had 10 quantitative variables plus 8 control variables (age, gender, region, education level, civil status, professional situation, employment regime and frequency of online purchases) and was active from 4th April to 25th May. The variables got measured on a Likert interval Scale from 1 to 5, being 1 – “Totally Disagree” and 5- “Totally Agree”.

The answers got collected and exported to Excel and had to go through a “cleaning” process as there was some answers with missing values. There were also people that answered “5 – Totally Agree” on all the questions. These observations were not considered as it were considered biased answers (20 answers).

The survey got 188 complete and valid answers and the sample size goal got reached, as it must be ten times greater than the number of the items considered for the research. After all this process, a descriptive analysis was done to demonstrate the sample characteristics, followed by the inclusion of the results on the PLS Program.

5.1.2. ONLINE REVIEWS

All the Portuguese reviews were extracted to an Excel document using Python, more specifically with *Beautiful Soup*, a powerful tool to perform web scrapping. *Beautiful Soup* is a Python library that can parse HTML content of a website. The sections extracted from the Trustpilot website were the name of the person, the total number of reviews of the person, the location, the review date, the review rating, and the text of the review. The reviews scrapped covered the period from April 2015 to April 2024 (9 years), being 2015 the year of the first review recorded on Trustpilot. With all this information scrapped, the main data considered for the analysis was the review text itself.

With that said, the next step was to clear all the raw data extracted. As the text of the review was scrapped with the date of the review appended, the first step was to eliminate the date

of the review as it was not necessary for the sentiment analysis later on (step 1). At this stage, all the text presented on the reviews (30.627) were clean and correct.

The next step was to select only the reviews with the location set as “PT” (step 2) since the research is focused on the Portuguese territory. With this filter the number of the reviews went from 30.627 to 28.823 as there was approximately 2.000 reviews that, although were in Portuguese, the location was different from Portugal.

The next phase involved preprocessing the data. With all the reviews scrapped correctly, this phase had the importance of preparing the data for the sentiment analysis. The process started with the removal of stop words and numbers from the reviews text (step 3). These words and numbers were not relevant for the sentiment analysis as they did not transmit much sentiment. Eliminating this set of words lead to a better result.

Following that, all the data got converted into lower case letters to normalize all the words and avoid conflicts (step 4), as it is considered a good practice of preprocessing data before performing sentiment analysis. The final step before moving to Vader to perform the sentiment analysis was to convert all the reviews to English (step 5). Vader only works on English texts. Figure 2 shows all the steps summarized, from the raw data to the data processed, ready to be analyzed.

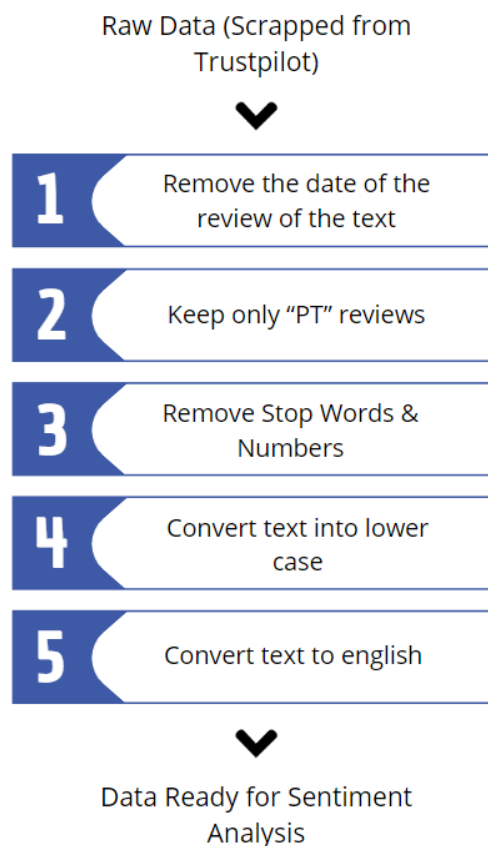


Figure 2 - Data Preparation Steps

6. RESULTS

6.1. QUESTIONNAIRE

6.1.1. SAMPLE RESULTS

From the 188 valid observations, the most frequent gender was female, corresponding to 60% of the sample with 113 answers. Unlike gender, there was a predominant age range that highlights from the others in a clear and obvious way. There was 101 people from 15-25 years old (corresponding to 54% of the sample), 21 people from 26-36 years old (11%), 18 people from 37-47 years old (10%), 39 people from 48-58 years old (21%) and only 9 people from 59-69 years old (5%).

Regarding the education level characteristics, Bachelor level represented the most frequent answer, with a representation of 48%. Following that, the Master got 27% of the responses, <12^o grade represented 22%, primary school got 3% and there was only 1 people from the sample collected that had a Doctorate.

The civil status was also a control variable considered in this study. 67% of the observations were from single people, 28% of the total observations were from married people and only 5% were in the Divorced/Widower category. Table 2 presents the complete sample characteristics regarding these 4 control variables: *Gender, Age, Education Level* and *Civil Status*.

Control Variable		Frequency	(%)
<i>Gender</i>	Female	113	60%
	Male	75	40%
<i>Age</i>	[15-25]	101	54%
	[26-36]	21	11%
	[37-47]	18	10%
	[48-58]	39	21%
	[59-69]	9	5%
<i>Education Level</i>	Primary School	6	3%
	<12 ^o grade	41	22%
	Bachelor	90	48%
	Master	50	27%
	Doctorate	1	1%
<i>Civil Status</i>	Single	126	67%
	Married	52	28%
	Divorced/Widower	10	5%

Table 2 - Gender, Age, Education Level and Civil Status

The most part of the respondents were Employed people (76 observations, corresponding to 40% of the sample) and Students (64 observations, corresponding to 34%). The survey also got 34 answers from Student-Workers (18%), 10 from unemployed people (5%) and only 4 retired people (see Figure 3).

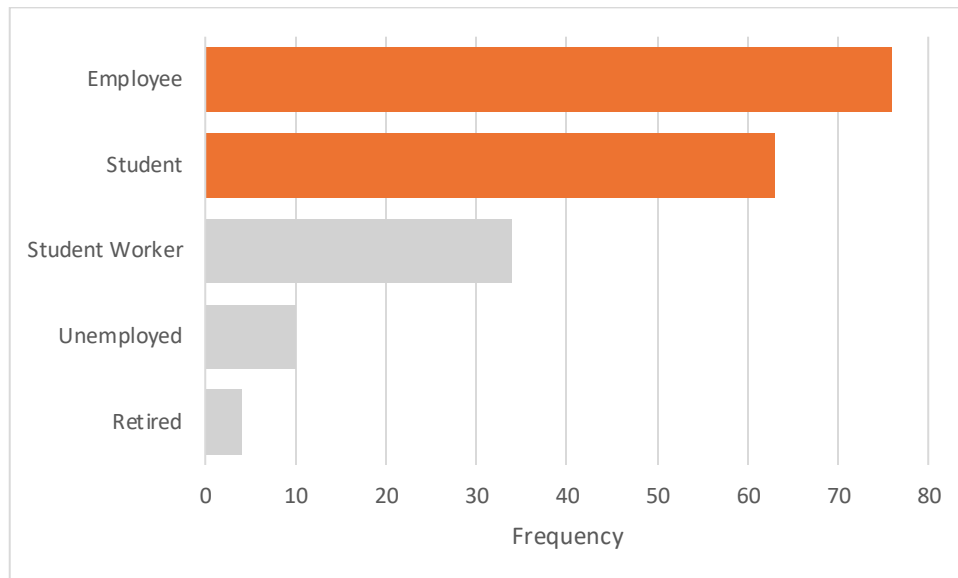


Figure 3 - Professional Situation

There was also considered the regime in which employed/student people work/studies. For this analysis, unemployed people were excluded as they are not able to be categorized under any of the options. This aspect was considered in the questionnaire in order to ensure questions coherence: if respondents indicated that they were unemployed, the subsequent question about work regime did not appear. The most part of the respondents were in a presential system regime (55%). Following that, the sample got 38% in hybrid regime and only 7% were in a full remote regime.

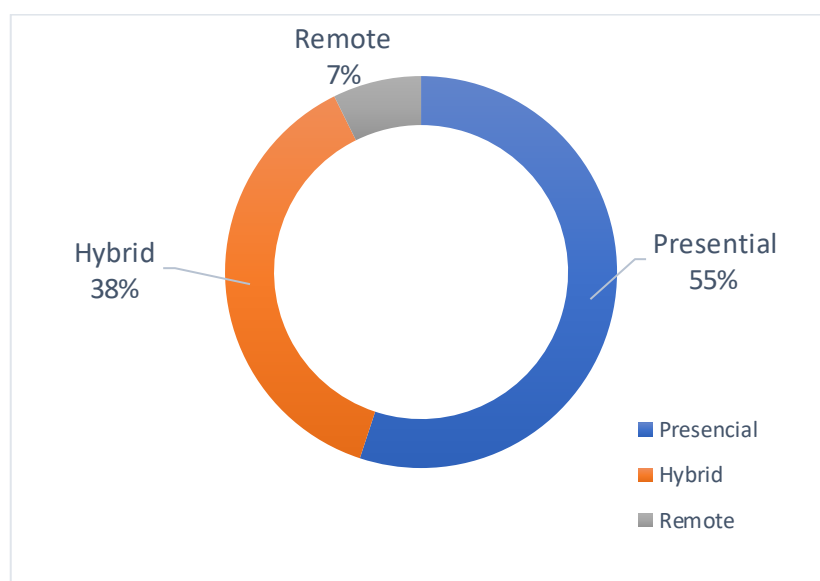


Figure 4 - Employment Regime

Region analysis was also considered in this research. As the study is limited to the Portugal habitants, the district where each respondent live was studied. From the results presented below, there is a clear winning district. Lisbon got 130 answers, representing 69% of the sample region, followed by Setúbal with 23 respondents (12%). The other 16 districts, plus the islands (Madeira and Azores) represents in the total only 19% of the sample (Table 3).

Control Variable		Frequency	(%)
<i>Region</i>	Lisboa	130	69%
	Setúbal	23	12%
	Santarém	6	3%
	Porto	6	3%
	Leiria	6	3%
	Faro	4	2%
	Aveiro	3	2%
	Coimbra	2	1%
	Évora	2	1%
	Beja	1	1%
	Vila Real	1	1%
	Viana do Castelo	1	1%
	Braga	1	1%
	Castelo Branco	1	1%
	Portalegre	1	1%

Table 3 - Region

As the research is focused on the online retail industry, it was considered fundamental to analyze the frequency of online purchases per month from the respondents of the survey. Most of the observations were the 1-5 range (85%), followed by 6-11 range (12%). The table below (Table 4) shows the frequency of all the observations as well as the representative percentage of it on all the sample size.

Control Variable		Frequency	(%)
<i>Frequency of online purchases</i>	[1-5]	159	85%
	[6-11]	23	12%
	[12-17]	2	1%
	[+18]	4	2%

Table 4 - Frequency of Online Purchases

Lastly, it was performed a descriptive analysis relating the age range with the frequency of online purchases per month (FP). It was concluded that the most common FP range (1-5 online

purchases) were from young people (58%) as well as on the 6-11 range (39%). On the higher categories of online purchases (12-17 and +18) there was not any relation with the 15-25, 26-36 and 59-69 age ranges (see Table 5).

	<i>FP</i>			
	[1-5]	[6-11]	[12-17]	[+18]
<i>Age</i>				
[15-25]	58%	39%		
[26-36]	11%	17%		
[37-47]	8%	13%		50%
[48-58]	19%	22%	100%	50%
[59-69]	4%	9%		
Frequency	159	23	2	4

Table 5 - Relation between Age and FP

The data from the questionnaire was inserted into the Smart-PLS Software in order to perform model analysis and understand which constructs were more important/ explained better in the model.

Before taking any premature conclusions, the results got thought a validation (discriminant and convergent) and reliability check. Convergent validity refers to the degree in which a group of indicators of the same latent construct is correlated with. On the other hand, Discriminant validity checks if a latent construct is truly distinct from the others in the model. According to (Henseler et al., 2015), the most common methods for assessing discriminant validity are the Fornell-Larcker criterion and cross-loading analysis.

6.1.2. MEASUREMENT MODEL RESULTS

Discriminant Validity

In order to verify the discriminant validity of the performance results, it was performed the comparison between outer loadings and cross loadings (Table 6). This analysis is fundamental to validate if the items have a stronger relation with their own construct rather than with the others in the model.

Before this comparison, the verification of each outer loading value was considered and studied, confirming if there were indicators below 0.7. There were 2 indicators that were below this value, so the decision was to take them out of the research (*EE4* and *UX2*). Outer loadings must be visibly higher than the cross loadings values, which is verified in the model.

	Consumer Engagement	Consumer Experience	E-WOM	Social Influence
CE1	0.911	0.427	0.212	0.165
CE2	0.836	0.232	0.206	0.030
EE1	0.228	0.163	0.917	0.182
EE3	0.202	0.255	0.892	0.353
SL1	0.111	0.159	0.224	0.869
SL2	0.089	0.273	0.262	0.786
UX5	0.337	0.859	0.189	0.264
UX6	0.332	0.854	0.201	0.167

Table 6 - Outer Loadings & Cross Loadings

Fornell-Larcker's criterion was chosen as the second discriminant validity criterion. The correlations between each construct and the other ones in the model are assessed using this method, which uses the square root of the Average Variance Extracted (AVE) of each construct. According to Fornell & Larcker (1981) AVE quantifies the amount of variance that a latent construct captures from its indicators. According to Garson (2016) this value must be greater than the correlation with any other latent variable to show that each construct is unique and that its own items share more variation with it than with other constructs. All the latent constructs of the model meet this condition as indicated in the table below (Table 7).

	Consumer Engagement	Consumer Experience	E-WOM	Social Influence
Consumer Engagement	0.874			
Consumer Experience	0.390	0.856		
E-WOM	0.238	0.228	0.905	
Social Influence	0.122	0.252	0.290	0.828

Table 7 - The Fornell-Larcker criterion

Convergent Validity

AVE was considered to verify the model's internal coherence and convergent validity. To guarantee the consistency of the model, AVE value ought to be higher than 0.5 (Höck, M., & Ringle, C. M., 2006), which indicates that the construct explains more than half of the variance of its respective items (Garson, 2016). All the latent constructs of the model meet this condition.

Two additional approaches were considered beyond the AVE to evaluate the convergent validity: the factor loading of the indicators (seen before) and the composite reliability, as according to J. Hair, M. Hult, M. Ringle (2014), these are three fundamental practices on partial least squares (PLS) modeling.

In PLS-based research, composite reliability (CR), which assesses the internal consistency of a group of items representing a latent construct, is frequently chosen over Cronbach's alpha. Similar to Cronbach's alpha, composite reliability typically yields higher estimates of genuine dependability and adheres to the same acceptable cutoff conditions (Garson, 2016). According to J. Hair, M. Hult, M. Ringle (2014) CR is a more accurate indicator of internal consistency than Cronbach's alpha.

An adequate model, for confirmatory purposes, should have composite reliability values greater than 0.7. (Jorg, 2012) indicating that the construct is measured with an acceptable level of reliability, as well as the items are representing the underlying construct. All the latent constructs of the model meet this condition as well. Cronbach's Alpha was also evaluated, as it measures also the internal consistency or reliability of the model (Cronbach, 1951). The closer to 1, the more consistent the model is. Above 0.7 is considered acceptable and between 0.6 and 0.7 is considered questionable (George & Mallery, 2003). Social Influence construct had a poor performance in this field (0.546). E-WOM construct appears as the one that performed better (0.779). Consumer Engagement was also considered "acceptable" as it was very near to 0.7 (0.697). Consumer Experience got a "questionable" result (0.637). This result leads to conclude that the model has a satisfactory internal consistency.

Table 8 shows the AVE, Composite Reliability and Cronbach's alpha values of each construct.

	Average variance extracted (AVE)	Composite reliability (rho_c)	Cronbach's alpha
Consumer Engagement	0.764	0.866	0.697
Consumer Experience	0.734	0.846	0.637
E-WOM	0.818	0.900	0.779
Social Influence	0.686	0.813	0.546

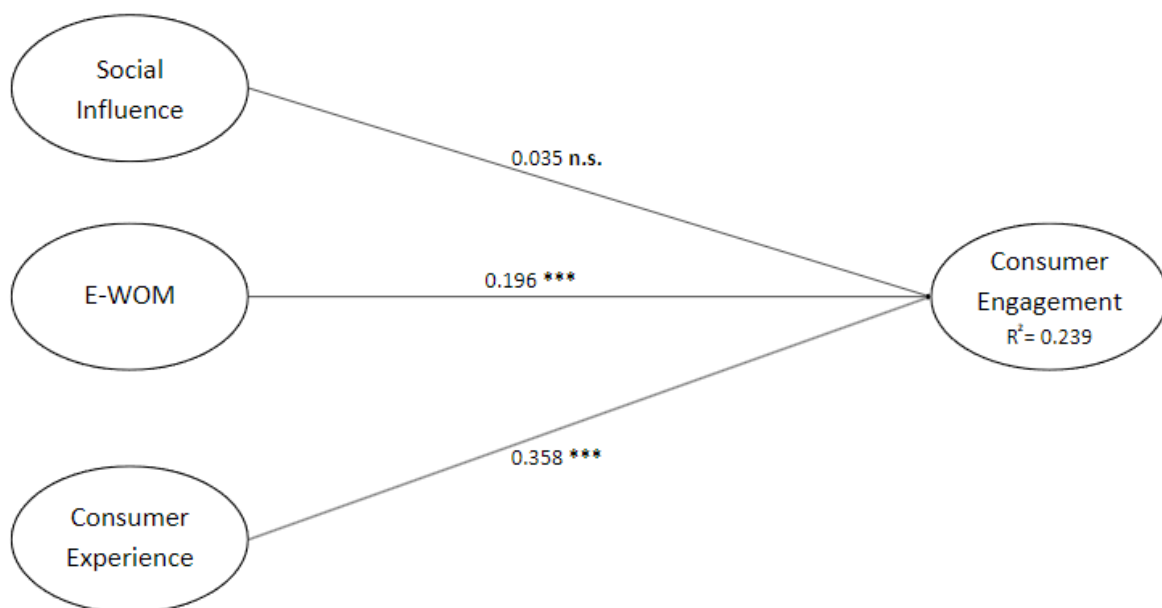
Table 8 - AVE, CR and Cronbach's alpha

To determine if there were issues with data multicollinearity, the Variance Inflation Factor (VIF) was also evaluated. Values under 2 are considered acceptable, and it indicates that the multicollinearity among the variables within the model is minimal. All the values meet this condition. The table below shows the VIF results that the model got.

	VIF
Consumer Experience -> Customer Engagement	1.099
E-WOM -> Consumer Engagement	1.157
Social Influence -> Consumer Engagement	1.194

Table 9 - Variance Inflation Factor (VIF)

The figure below shows the Path Model as well as the Path Coefficients (β). Path coefficients range from -1 to +1, with values closer to absolute 1 indicating a stronger relationship between the constructs.



Notes: n.s. = non-significant; *** p<0.01

Figure 5 - Path Model with Path Coefficient

The results showed that not all the variables relation were statistically significant. From the three independent variables, the one which explained/related better with “Consumer Engagement” was “Consumer Experience” with $\beta = 0.358$ ($p < 0.01$). This leads to the conclusion that customer experience has a positive effect on customer engagement on the online retail industry (H2 got confirmed). Although less impactful, “E-WOM” latent variable

also had a positive impact on the dependent construct with a $\beta = 0.196$ ($p < 0.01$). This result suggests that E-WOM contributes positively to customer engagement on the online retail industry (H3 got confirmed). Alternatively, “Social Influence” variable did not have statistical effect on customer engagement with a result of $\beta = 0.035$ ($p > 0.05$). Thus, the H1 did not get confirmed. The table below summarizes all the values discussed.

Relation between Constructs	Original sample	Sample mean	Standard deviation	P-Values
Consumer Experience -> Consumer Engagement	0.358	0.360	0.079	0.000
E-WOM -> Consumer Engagement	0.196	0.195	0.069	0.005
Social Influence -> Consumer Engagement	0.035	0.044	0.072	0.629

Table 10 - P-values

It was also analyzed the R-Square (R^2) value which indicates how well the independent variables in the model explain the variability in the dependent variable. (Chicco, 2021). Consumer Engagement construct got a R^2 of 0.239 which means that the model explains 23.9% of the variance of the construct “Consumer Engagement”. The R^2 value quality is relative to the research field (Garson, 2016). For example, Höck & Ringle (2006) considers a value below 0.33 a “moderate” result. Ozili (2022) research shows that a low R^2 is not necessarily bad in the context of social science research, as this one. The author considers that the goal of this type of studies is not to predict human behavior but rather access whether explanatory variables are statistically significant and argues that, in the context of the social science subject, an acceptable R^2 score ranges between 0.1 and 0.5.

6.2. ONLINE REVIEWS

A quick descriptive analysis of all the reviews demonstrated that the most part of the reviews were classified with 5 stars rating. Out of a total of 28.283 reviews scrapped from Trustpilot, 25.645 (89%) were 5 stars rated, 1.809 (6%) were 4 stars rated, 558 (2%) were 3 stars rated, 305 (1%) were 2 stars rated and 506 (2%) were 1 star rated. It was also measured the average sentiment presented on each star rating group. As expected, the overall average sentiment score was directly proportional to the review rating, as it increases as the review rating increases. The 1 star-rated reviews got an average sentiment (compound) of -0.13, the reviews classified with 2 stars of rating got an average sentiment slightly negative (-0.06), the 3 stars-rated reviews got 0.12, the 4 stars-rated reviews got 0.4 and lastly the 5 stars-rated reviews

got 0.4. The value of the standard deviation indicates that as the average sentiment score increases, the data becomes less disperse, more consistent, indicating that the values are more tightly clustered around the mean. This align with the idea that lower-rated reviews (1,2 and 3 stars) have a broader range of sentiments and higher-rated reviews (4 and 5 stars) are more uniformly positive (see Table 11).

Star Rating	# of Reviews	% of Reviews	Average Sentiment	Standard Deviation
1	506	2%	-0.13	0.48
2	305	1%	-0.06	0.47
3	558	2%	0.12	0.47
4	1809	6%	0.4	0.38
5	25645	89%	0.48	0.34

Table 11 - Sentiment per Review Star Rating

From this analysis, it is intended that the most part of the reviews were positive, and only a few were negative. In order to get more details regarding this conclusion, it was performed sentiment analysis for all the reviews collected and it was observed that almost 73% express positive sentiments, 24% got classified as neutral and only 4% got the negative sentiment associated with (see Figure 6).

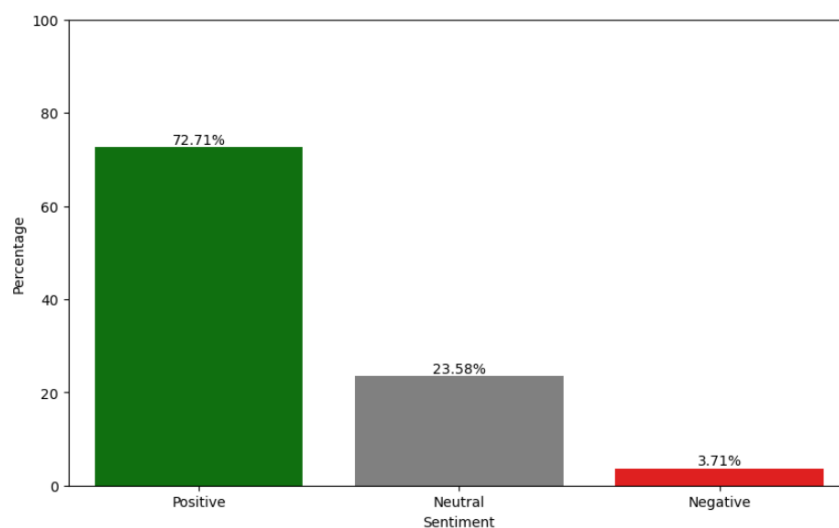


Figure 6 - Reviews overall Sentiment Analysis

To understand better the distribution of the results got previously and to get a clear visualization of the data, it was performed more descriptive statistics analysis. Table 12 shows the distribution of the dataset based on quartiles (Q1, Q3) and on the median of each stars rating group.

Star Rating	Average Sentiment	Q1 (25%)	Q3 (75%)	Median
1	-0.13	-0.5267	0.1531	-0.01
2	-0.06	-0.4228	0.2732	0
3	0.12	-0.1962	0.5106	0
4	0.4	(---)	0.7184	0.44
5	0.48	(---)	0.7717	0.57

Table 12 - Data Distribution

On the 1 star-rated group, the median was slightly negative (-0,01) demonstrating that the most part of that reviews had a sentiment below 0, although the distribution of the results showed that some reviews were neutral or even slightly positive (Q3). 2 and 3 stars-rated reviews got a median of exactly 0 (most frequent result sorting the results in an ascending way).

On the other side, 4- and 5-stars' reviews got a median of 0.44 and 0.57, respectively, and there were no values on Q1 which indicates that all the users were completely satisfied, and all expressed a positive sentiment review.

On the boxplot presented below, is it possible to see these results graphically (Figure 7). Each box represents the distribution of the results, being que Q1 the bottom of the box, the black line inside the box, the median and the top of the box the third quartile (Q3).

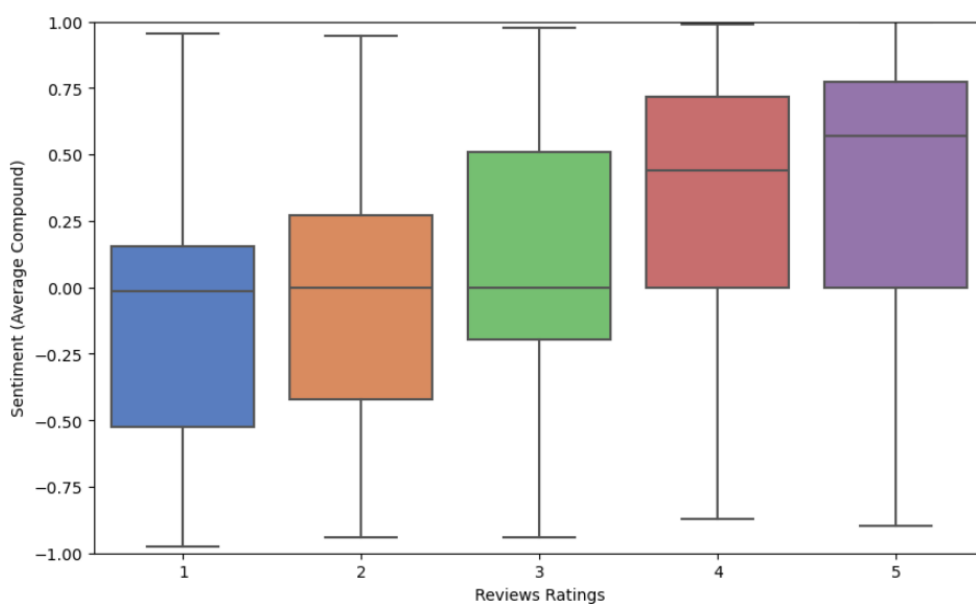


Figure 7 - Data Distribution Boxplot

Beyond these overall and stars group rating sentiment analysis performed above, it was measured the sentiment for specific keywords that are related to the main goal of the research on the online reviews that is to understand how consumer experience, more particularly the usability of a website affects the 2 dimensions of engagement considered in the research: *Intention to Buy* and *Brand Endorsement* (particularly the tendency to recommend the brand to others). First of all, it was performed frequency analysis to see the most common words written by users on the reviews. On this top-25 most common words, 5 were analyzed in detail since were keywords related to the study and could identify relevant results. The words highlighted were: *serviço*, *compra*, *recomendo*, *site* and *experiencia*.

Keyword	Count
<i>entrega</i>	13064
<i>produtos</i>	9328
<i>qualidade</i>	5882
<i>rápida</i>	5869
<i>rapidez</i>	4786
<i>rápido</i>	4364
<i>encomenda</i>	4362
<i>super</i>	4108
<i>tudo</i>	3774
<i>serviço</i>	3264
<i>excelente</i>	2855
<i>bem</i>	2850
<i>prozis</i>	2330
<i>sempre</i>	2328
<i>bom</i>	2314
<i>produto</i>	2210
<i>dia</i>	1987
<i>boa</i>	1642
<i>compra</i>	1536
<i>rápidos</i>	1491
<i>bons</i>	1472
<i>chegou</i>	1469
<i>recomendo</i>	1150
<i>site</i>	1053
<i>experiência</i>	1021

Table 13 - Frequency Analysis: Top-25

The figure below (Figure 8) shows the average sentiment (compound) for the 5 keywords considered to the analysis. The blue color words (*experience*, *website*, *service*) represent

keywords associated with the *Perceived ease of use* subconstruct and the green ones (*purchase* and *recommend*) represent the *Consumer Engagement* construct. All the words selected got positive sentiments associated (compound scale: -1 to 1). From all these keywords, the one with the highest average sentiment was “*recommend*” with a score of 0.71, indicating that was the one linked to the most positive sentiment on the reviews. As it was considered clearly positive, it was concluded that there is a proportional relation between the satisfaction/sentiment of the user and the tendency to recommend the experience to others. The second top word within this short list appeared with a score of 0.63 and was the word “*experience*”. *Prozis* user experience within a purchase seems to be also really positive. The next words got similar results as “*Website*” got 0.57, “*service*” got 0.54 and “*purchase*” got 0.52. That suggests that the website, the service, and the purchase are variables that weight on customer satisfaction.

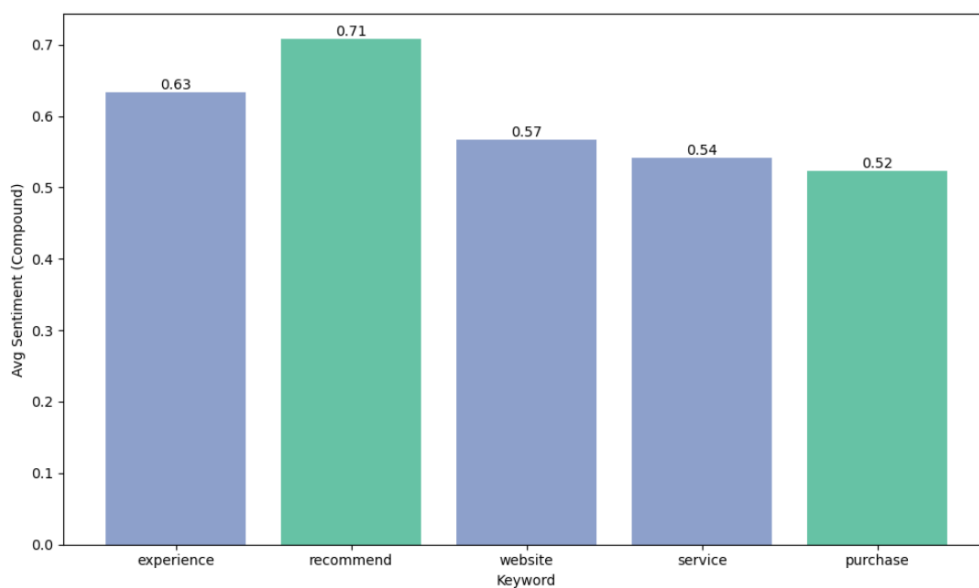


Figure 8 - Keywords Sentiment Analysis

7. DISCUSSION

The global results showed that not all the proposed hypotheses got confirmed. **H1:** Social Influence affects Consumer Engagement on the online retail context did not get confirmed, but **H2:** Online Consumer Experience affects Consumer Engagement on the online retail context and **H3:** Existing E-WOM affects Consumer Engagement on the online retail context did. This research indicates that Social Influence does not influence Consumer Engagement on the online retail industry, taking into consideration the sample characteristics. In the other hand, E-WOM and Consumer Experience influences positively Consumer Engagement. Consumer Experience was the variable which had the strongest positive relation with Consumer Engagement from the ones considered.

Although there was a weak positive relation between Social Influence and Consumer engagement constructs in this study, there was not statistically significance on the results, so the conclusion was to not consider relevant nor reliable. Initially the research involved four measures on this field, but there was only considered two (SL1 - Peer Influence and SL2 - Similarity) of them to the evaluation of this construct. This conclusion does not match with M. K. O. Lee et al. (2011) research, which defends that social influence affects intention to shop and the attitude towards online shopping. These contrasting values could be influenced by the sample context, as his study focused only on Chinese students with a “collectivistic culture”, which could bias the results, as well as the fact that the majority of the research sample (40%) corresponds to workers. The questionnaire results confirmed this discussion as the answers from this construct score an average (although positive) of 3.6 out of 5, which is not worthy of great conclusions.

The results showed that E-WOM influences Consumer Engagement positively on the online retail context (H2 confirmed), based on the measures considered for this construct. Not all the items initially proposed were considered for the research because of poor performance on the pilot step verification. The variables considered for this construct were EE1 (Online reviews volume) and EE3 (Source Credibility). The respondents of the survey consider the volume of online reviews and the credibility of the reviews two important factors when considering an online purchase. The average response on the questionnaire for these two items was 4.2 out of 5. The research shows that online shopping customers feels tempted to buy or recommend the product when there are a considered number of online reviews, and those reviews transmits security to them by the credibility of the messenger.

The global conclusion is in line with the literature references cited. According to (K. Z. K. Zhang, 2014), the perceived quantity of reviews as well as source credibility have direct impact on purchase intention. Also Chih (2013) and Yang (2015) recognize that credible sources enhance the intention to buy.

Consumer Experience construct appears to be the variable with the strongest relation with the consumer engagement construct. The criteria of keeping only the items that performed

good on the pilot test was also considered to this latent construct. According to the results, this construct got the highest score mean in the survey launched (4.5 out 5). The items kept for the study focused on the importance of the usability of a digital product as well as the way the information is presented on a website interface where the customer interacts with (UX5, UX6).

The descriptive data analysis of the survey indicates that 85% of the respondents make 1-5 online purchases per month and within this group, the most common age range was from 15 to 25 years old (58%). As expected, people from 58 to 69 years old represents the group that makes less online purchases. The majority of the results were from Lisbon residents (69%).

From the text mining analysis, it is possible to conclude that the website of a company is an excellent opportunity to engage with the customers positively. According to the results and to the literature cited, user usability enhances customer experience (Vila et al., 2021). The results showed that customers write reviews about the website when they are satisfied with the service, being this element important to their engagement with the company, and that the online experience ignite a feeling of positive sentiment.

Although this usability enhances customer satisfaction, there was one keyword that highlighted from the others on the frequency analysis. The keyword with the most positive sentiment associated was “recommend”. Overall, the main conclusion to take from this result is that a positive online experience boosts the likelihood of recommendation to others, which provides an edge to the company in a highly competitive market. Results also demonstrated that positive online reviews are related with the purchase itself. The fact that a customer feel satisfied in the whole online journey, confers a better opportunity to the customer consider the purchase.

Sentiment analysis and text mining approach lead to confirm the proposed H3 hypothesis: Consumer Experience affects Consumer Engagement on the online retail context as all the measures from the two constructs were presented and evaluated on this analysis (UX5, UX6, CE1, CE2).

8. LIMITATIONS AND FUTURE WORK

Throughout this study, several limitations have been identified. There was identified limitations related to the questionnaire results quality, as is a source of data that depends on the respondent willingness to cooperate.

On some cases, respondents may answer in a biased way, which can skew the outcomes. Some respondents may worry about the privacy, security issues and the way the questionnaire can be used, which can compromise the truth and generate dishonesty results (Evans & Mathur, 2005).

Additionally, sentiment analysis faced a limitation due to the necessity of translating text from Portuguese to English before using *VADER*. This tool does not analyze Portuguese words sentiment so there was the necessity to do this translation first. This setup may have introduced a few inaccuracies as the translation might not fully capture the linguistic nuances and contextual subtleties present in the original text, thereby affecting the accuracy of the analyses conducted.

The study was based exclusively on the Portuguese territory. Online business gives the opportunity to the companies to explore and sell to other territories and not stick to only one market. In a future extension of this work, the expansion of the territory to other countries/continents could give the possibility of segmenting the marketing strategies that influence consumer engagement by territory. Likewise, retailers can target their marketing concepts according to the characteristics of the market and invest better on the most effective strategies to promote engagement within their customers.

9. CONCLUSION

The objective of this study was to address the gap initially identified. This study follows the suggestion of Bowden & Mirzaei (2021) which is trying to understand the relative impact of various brand awareness methods on consumer engagement. The methods considered were based on three major subjects: Social influence, E-WOM and Consumer experience. The relationship between these subjects and consumer engagement was examined in order to evaluate if there was a positive relation between the independent variables and the dependent one, as indicated in the literature review section.

The questionnaire launched got 188 responses and was targeted to the Portuguese residents as the study is limited to the Portuguese market. The most respondents were aged between 15 and 25 years old (54%), and a significant part of the participants were from Lisbon (69%). The questionnaire data results indicate that the majority of participants reported making 1-5 online purchases per month (85%). Also, the gender distribution was 60% female and 40% male.

The conclusion of the study indicates that Social Influence does not influence Consumer Engagement on the online retail industry. In the other hand, E-WOM and Consumer Experience influences positively Consumer Engagement. Consumer Engagement is the variable which had the strongest positive relation with Consumer Engagement from the ones considered. Regarding E-WOM, respondents agreed that the volume of online reviews and the credibility of these reviews are factors when considering an online purchase, as stated by the literature (Chih, 2013; Yang, 2015; K. Z. K. Zhang, 2014). From the point of view of consumer experience, the results confirmed what the literature indicated: The usability of a digital product, as well as a well-structured website, enhances consumer experience (Vila et al., 2021) as generates a positive sentiment on the consumers, which incentive the intention to buy and the recommendation of the service to other people.

The findings provide valuable insights for Portuguese retailers and marketers, helping them tailor their marketing strategies to enhance engagement with its customers and ultimately drive business growth on the online retail industry. The three marketing concepts considered and evaluated were Social Influence, E-WOM and Consumer Experience.

Therefore, the goal of this research was reached as there was identified marketing strategies that enhance consumer engagement on the online retail industry to help Portuguese companies defining their strategy on the digital. The gap considered on the beginning of the thesis got addressed as written before, and the research question "What is the influence of different brand awareness methods on consumer engagement for online retail enterprises striving to thrive in highly competitive markets?" got answered. The key conclusion of this research was that E-WOM and Consumer Experience are two marketing concepts that impacts positively Consumer Engagement

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ANNEXES

Annex 1 – Questionnaire

[PT]

Este questionário é uma componente integral para a obtenção do grau de Mestre em "Digital Marketing & Analytics" e tem fins meramente académicos. O questionário tem a duração de **3 minutos** e as respostas são anónimas e totalmente confidenciais.

Objetivo: Analisar a influência de várias estratégias de Marketing no engajamento do consumidor, no contexto do retalho online.

Idade

15-25

26-35

37-47

48-58

59-69

Género

Masculino

Feminino

Região

Nível de Educação

Ensino Básico

Ensino Secundário

Licenciatura

Mestrado

Doutoramento

Estado Civil

Solteiro(a)

Casado(a)

Divorçado(a) / Viúvo(a)

Situação Profissional

Desempregado

Estudante

Trabalhador-Estudante

Trabalhador

Reformado

Regime de Trabalho / Aulas

Presencial

Híbrido

Remoto

Frequência de compras online (mês)

1-5

6-11

12-17

+18

Num contexto de comércio online, a tomada de decisão muitas vezes é influenciada por uma série de fatores. Para alguns, a opinião de família/amigos desempenha um papel importante, enquanto outros são mais tentados a confiar em pessoas que partilham os mesmos valores ou gostos. Tendo isso em consideração, responda às seguintes questões:

As recomendações de família/amigos influenciam as suas decisões de compra online.

1 - Discordo Totalmente

2

3

4

5 - Concordo Totalmente

Identifica-se com pessoas que partilham características semelhantes às suas ao decidir sobre uma compra online.

1 - Discordo Totalmente

2

3

4

5 - Concordo Totalmente

Para outros, as avaliações online desempenham um papel essencial ao decidir fazer uma compra online. Alguns confrom na credibilidade das experiências partilhadas por outros utilizadores, enquanto outros valorizam a diversidade de opiniões que podem encontrar. Reconhecendo a importância desses aspetos, responda às seguintes questões:

O número das avaliações online influencia a sua tomada de decisão online.

1 - Discordo Totalmente

2

3

4

5 - Concordo Totalmente

A credibilidade das avaliações online influencia a sua tomada de decisão.

1 - Discordo Totalmente

2

3

4

5 - Concordo Totalmente

Valoriza mais avaliações online recentes face às mais antigas, quando considera uma compra online.

1 - Discordo Totalmente

2

3

4

5 - Concordo Totalmente

As considerações de uma compra online, uma série de fatores pode influenciar a decisão do consumidor como introduzido anteriormente. Desde a eficácia da publicidade digital da marca até à usabilidade do website, cada aspeto desempenha um papel crucial na experiência de compra do utilizador. Tendo isso em consideração, responda às seguintes questões:

O fornecimento de ofertas direcionadas e descontos personalizadas com base nas suas preferências de compra faz-se sentir valorizado como cliente.

1 - Discordo Totalmente

2

3

4

5 - Concordo Totalmente

A rapidez e facilidade com que consegue encontrar o que procura num website influencia positivamente a sua experiência de compra online.

1 - Discordo Totalmente

2

3

4

5 - Concordo Totalmente

A aparência visual limpa e organizada de um website influencia a sua experiência de compra online.

1 - Discordo Totalmente

2

3

4

5 - Concordo Totalmente

Quando tem uma experiência online positiva, a sua intenção de compra aumenta.

1 - Discordo Totalmente

2

3

4

5 - Concordo Totalmente

Quando tem uma experiência online positiva, tende a recomendar a marca a terceiros.

1 - Discordo Totalmente

2

3

4

5 - Concordo Totalmente

Annex 2 – Ethics Committee Approval

RE: NOVA IMS | Ethics Committee - NEED REVIEW

1 mensagem

Ethics Committee <ethicscommittee@novaims.unl.pt>

quinta, 11/07/2024 à(s) 09:53

Para: Diogo Oliveira Silvestre Amaro <r20191194@novaims.unl.pt>, Jorge Carrola Rodrigues <jcarrola@novaims.unl.pt>

Cc: Ethics Committee <ethicscommittee@novaims.unl.pt>

Dear Diogo Amaro,
Dear Professor Jorge Carrola,

Thank you for filling in the Research Ethics Checklist. After reviewing your request, you can proceed with the study we do not foresee any major ethical concerns with the project.

Project No.: **DDMKT2024-7-13291**

Project Title: **Influence of brand awareness methods on consumer engagement: Online Retail Industry**

Principal Researcher: **Diogo Amaro**

according to the regulations of the Ethics Committee of NOVA IMS and MagIC Research Center this project was considered to meet the requirements of the NOVA IMS Internal Review Board, being considered **APPROVED** on 11/07/2024.

It is the Principal Researcher's responsibility to ensure that all researchers and stakeholders associated with this project are aware of the conditions of approval and which documents have been approved.

The Principal Researcher is required to notify the Ethics Committee, via amendment or progress report, of

- Any significant change to the project and the reason for that change;
- Any unforeseen events or unexpected developments that merit notification;
- The inability of the Principal Researcher to continue in that role or any other change in research personnel involved in the project.

Lisbon, 11/07/2024

NOVA IMS Ethics Committee

ethicscommittee@novaims.unl.pt

Cristina Oliveira

Gestora executiva do centro de investigação MagIC | *Executive manager of the Information Management Research Center (MagIC)*

Find out more about our research at <https://magic.novaims.unl.pt/en/>

Vice-chair of BESTPRAC - EARMA Thematic Group

Team member of RM Roadmap - Co-creating the future of Research Management (<https://rmroadmap.eu/>)

<https://orcid.org/0000-0002-0887-7961>



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

Universidade Nova de Lisboa