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Investigating the factors of brand loyalty in e-commerce through brand engagement and brand switching behavior

Renske Marije ten Have

Master of Science in Marketing

Supervisor:
Ricardo Godinho Bilro,
Assistant professor,
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BUSINESS
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Dedication and acknowledgements

Writing this dissertation was challenging at times and there are some people that I would like to thank for supporting me throughout this journey.

Firstly, I would like to thank my family, who have shown their support time and time again by giving me motivational speeches when I was low and sharing my survey with their networks repeatedly to help get me the necessary number of respondents. I could not have received as many respondents if it were not for their help.

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Lastly, I would like to thank Dr. Ricardo Bilro for his guidance throughout the writing of this dissertation. The provided feedback for the research topic, questionnaire structure and for the final draft were greatly appreciated and inspired me to improve the dissertation further.

Abstract

This study examines the influence of customer characteristics on brand loyalty within the Fast-Moving-Consumer-Goods (FMCG) industry's online environment. As omnichannel shopping gains prominence, online brand loyalty research lags, neglecting the impact of this shift on consumer behavior. Previous studies vary in their brand loyalty measurement approaches, some emphasizing repeat purchases, while others assess cognitive, affective, and behavioral aspects. To address this, this study combines Hollebeek's Customer Brand Engagement (CBE) scale and Liao's Push-Pull-Mooring (PPM) model of brand switching behavior (BSB). The relationship between customer attributes (age, gender, education, income, residence type, nationality) and brand loyalty using the CBE and BSB scales is examined. Gathering 230 valid responses through an online questionnaire, the study reveals that consumers engage more emotionally and actively with brands rather than cognitively. Findings indicate that factors such as youth, income, and the type of residence influence brand engagement and subsequently, brand loyalty. Contradicting to previous research, no significant relation between the CBE and BSB scores are found, implying a disconnect between brand engagement and brand switching behavior. Despite engagement, consumers still exhibit brand switching tendencies. This study contributes to understanding online brand loyalty in the FMCG industry, underscoring the importance of emotional connections and engagement in fostering loyalty. It also calls for further exploration of evolving consumer behavior in the omnichannel shopping landscape.

Keywords: brand loyalty, consumer brand engagement, brand switching behavior, FMCG, eCommerce, omnichannel

Resumo

Este estudo examina como as características dos clientes afetam a fidelidade à marca na indústria de Bens de Rápido Consumo (FMCG) em um contexto de comércio eletrônico. Com o aumento notável das compras online em diversos canais, a pesquisa sobre a lealdade do consumidor frequentemente fica defasada em relação às mudanças no comportamento. Integrando a escala de Envolvimento da Marca pelo Consumidor (CBE) de Hollebeek com o modelo Push-Pull-Mooring (PPM) de Liao relacionado ao Comportamento de Troca de Marcas (BSB), este estudo examina a relação entre as características dos clientes (idade, gênero, educação, renda, tipo de residência e nacionalidade) e a fidelidade do consumidor. Foram coletadas 230 respostas válidas por meio de um questionário online. Os resultados indicam que os consumidores tendem a se envolver emocionalmente com as marcas em vez de apenas cognitivamente. Fatores como idade, renda e tipo de residência influenciam o comportamento do consumidor e, por consequência, a fidelidade à marca. No entanto, é importante ressaltar que não foi encontrada uma correlação significativa entre as pontuações da escala CBE e BSB, sugerindo que, mesmo com alto envolvimento emocional, os consumidores ainda podem estar dispostos a mudar de marca. Esse estudo contribui para a compreensão da lealdade do consumidor no ambiente de e-commerce na indústria FMCG, destacando a importância das conexões emocionais para promover a fidelização. Além disso, enfatiza a necessidade de investigar mais profundamente o comportamento dos consumidores em um cenário de compras omnicanal em constante evolução.

Keywords: Fidelidade à marca, engajamento da marca do consumidor, comportamento de mudança de marca, Bens de consumo rápido, omnicanal

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Glossary of tables

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Glossary of Abbreviations

Activation – ACT
Affective – AFF
Brand Engagement – BE
Brand Inertia – BI
Brand Loyalty – BL
Brand Switching – BS
Brand Switching Behavior – BSB
Cognitive Processing – CP
Consumer Brand Engagement – CBE
Fast Moving Consumer Goods – FMCG
MOO – Mooring
Standard Deviation – SD
Statistical Package for the Social Sciences – SPSS
Social Exchange Theory – SET
Push-Pull-Mooring – PPM
PUS – Push
PUL – Pull

Introduction

In the fast-moving-consumer-goods (FMCG) market, consumers are faced with a large range of product substitutes offered by different brands that compete with one another. Due to this large selection of options, there is high competition among companies, with brands facing a continuous threat of substitution. A common competitive strategy for brands to minimize costs and better their position themselves in the market is to focus on consumer retention, and thus brand loyalty (BL) (Aboagye & Abdullah, 2013). Loyal consumers have shown to be less price sensitive and provide firms with valuable extra time in case of competitive counter actions. (Dekimpe et al., 1997). In fact, research performed by Rosenberg & Czepiel (1983) suggests that retaining existing consumers is six times more cost-efficient than acquiring new ones. Yet, several concerning studies (Dawes et al., 2015); (Dekimpe et al., 1997); (Yim & Kannan, 1999; Casteran et al., 2019); (Nagar, 2009) suggest that BL may be declining over time. The underlying reasons for this decrease in loyalty is indicated to be the fragmentation of the market, increased cynicism among consumers and tightening economic situations. These studies, which attempted to statistically confirm or decline the notion of eroding BL, however, yield contradicting results. Despite the inconsistent results, a broad inference can be made that the most significant influence on BL was the tightening economic conditions, notably the 2008 economic crisis. With the current crisis looming, it can be inferred that this may cause a shift in consumer behavior and could result in a reduction in BL once again (Tepper, 2022).

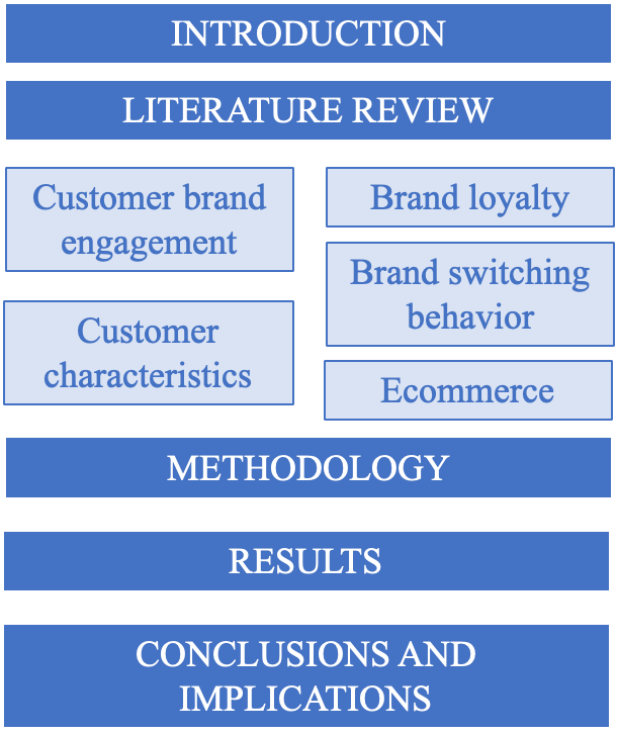
Another major trend that drastically changed consumer behavior is the switch to e-commerce. This shift was expedited by the COVID-19 crisis that occurred from 2019 to 2021. In the Netherlands, there was a 16% rise in e-commerce sales in FMCG between 2020 and 2021 (Deloitte, 2022). Moreover, research by Nielsen GFK suggests that by 2030, 11% of total sales in this industry will be driven by e-commerce (Singh, 2018). Considering this trend towards e-Commerce, it is imperative for managers to reassess their competitive strategies. As far as I am aware, the current studies on the erosion of BL in the FMCG market solely focusses on the offline sales and dismisses this consumer shift to an omnichannel behavior. Considering that the online and offline consumer journey differs through its different touchpoints and channels, one cannot assume that BL is impacted in the same way that it is offline. The suggested decline in BL may not be as severe online as it is offline and therefore research must be performed for managers to make informed decisions about their marketing strategies. This research is relevant for if managers rely on the assumption that BL is declining, then they are prone to apply more aggressive strategies which would only cause further disruption in the market (Casteran et al.,

2019). When creating a marketing strategy, the first step is to segment the company's audience into different groups so that each audience can be targeted accordingly (Martin, 2011); (Kotler, 2010). As BL has only been observed offline, the objective of this study is to determine the segmentation factors of BL online.

Although many researchers have attempted to measure BL, the specific method to do so is still heavily debated. All studies agree that for consumer to feel BL, a balance of affective, behavioral, and attitudinal dimensions need to be considered. (Ishak & Ghani, 2013). Most studies performed to assess BL among brands focus on its behavioral aspect, measuring it in terms of repeat purchases (Meyer-Waarden et al., 2015); (Dekimpe et al., 1997); (Koll et al., 2022); (Yim et al., 1999); (Casteran et al. 2019); (Dawes et al., 2022); (Montazeri et al., 2022); (Danaher et al., 2003); (Touzani et al., 2009); (Chu et al., 2010). However, Howard & Sheth (1969) suggest that repeat purchases are not necessarily linked to brand commitment (BC) but rather to Brand Inertia (BI). This is when one repeatedly purchases the same brand due to habit or situational factors, often in frequently purchased, low-priced product categories. This behavior may lead to switching if alternatives are available, and hence has little to do with the in-depth benefits of BL. Consumer Brand Engagement (CBE) and Brand Switching Behavior (BSB) were chosen as scales to measure BL, as these reinforce one another in a loop and take into consideration both the relational aspect of BL as well as the attitudinal aspect (Fernandes & Moreira, 2019); (Hollebeek et al., 2014), (Helme-Guizon, & Magnoni, 2019). This research aims to *identify which customer characteristic impact brand loyalty measured through Hollebeek's customer brand engagement scale and Liao's Push-Pull-Moore BSB scale.* By doing so, this research will address the knowledge gap of consumer characteristics impact on BL in an online environment in the FMCG industry.

To address the research objectives, this dissertation is structured into four major parts, excluding the introduction. The first part consists of a literature review which will contextualize the research problem and explain in depth the different concepts that are relevant to the research. Then, the methodology section will present the research conceptual model with hypotheses and the method for data collection. In the third section, the collected date will be represented, analyzed, and discussed which will create the basis for the final conclusions and implications that will be drawn from this study. This final part will also include limitations of the study as well as suggestions for future research.

Figure 1 – Structure of the dissertation



Source: Own elaboration

1. Literature review

To provide context to the research problem and achieve a comprehensive perspective, various relevant concepts were defined and analyzed. Firstly, brand loyalty was defined in terms of market relevance, and its measurements were examined. Subsequently, the concepts of CBE and BSB were defined, with their relevance to BL being explained, along with the depiction of their measurement scales. Lastly, a brief discussion was conducted on consumer segmentation and e-commerce.

1.1 Brand loyalty

Brand loyalty (BL), as defined by DeKimpe et al. (1996), is a "biased behavioral response expressed over a period of time." It refers to consumers' positive affection and attitude towards a brand, leading them to repurchase from the same brand repeatedly. A brand is defined as a name, term, sign symbol (or a combination of these) that identifies the maker or seller of the product (Kotler & Keller, 1980). Multiple factors contribute to BL, encompassing affective, behavioral, and attitudinal dimensions (Ishak & Ghani, 2013). A clear brand image plays a crucial role in fostering BL as it assists consumers in locating, identifying, evaluating the product's quality, and shaping their expectations (Pelsmacker et al., 2001). The significance of BL is evident from its utilization as a measure to evaluate brand marketing strategies and brand equity (Knox & Walker, 2010). Over the years, it has become an essential focus of company's growth strategies and cost reductions. The awareness and positive affection for brands significantly influence consumers' purchasing decisions and even impact their perceived risk evaluation and level of confidence in their buying decisions (Aboagye & Abdullah, 2013).

Today, when choosing a product, consumers are faced with an abundance of nearly identical product substitutes, making BL more crucial than ever before. However, studies (Dawes et al., 2015); (Dekimpe et al., 1997); (Yim & Kannan, 1999); (Casteran et al., 2019); (Nagar, 2009) have shown that in fact, BL is eroding. This trend is particularly prominent in the Fast-Moving Consumer Goods (FMCG) industry, where product substitution is at its highest and brand value, quality and brand purpose have started playing a bigger role in the eyes of the consumer (McKinsey & Company, 2020). Research conducted by Dawes et al. (2015) reveals that consumers exhibit less loyalty when presented with a range of identical products. If their preferred product is unavailable, they readily switch to an alternative. This phenomenon has been examined worldwide, yielding conflicting results. Meyer-Waarden & Driesener's (2015) study suggests a marginal, natural decrease in BL, with consumers remaining loyal to only a

small repertoire of brands. Similarly, Dekimpe et al. (1997) find only short-term variability in BL, which mostly affects the market-share leaders. On the other hand, Casteran et al. (2019) observe that BL erosion is happening but is only significant in food and perishable goods products within the FMCG category. The brands that see a decrease in loyalty often have a wider product category with a higher share of private labels, suggesting that strategies aimed to increase penetration might in fact be eroding BL further. This is, assuming the penetration strategies imply increasing product shelf visibility through an increased product assortment. Managers must recognize the importance of BL, as its erosion may lead them to employ aggressive penetration strategies which only result in further decreased loyalty but also has environmental and over consumption implications (Sharp, 2010). When managers rely on the assumption that BL is declining, they tend to apply more aggressive strategies such as market penetration through the implementation of new products. These strategies, however, have only proven to further disrupt the market and contribute to the decline in BL. (Casteran et al.,2019).

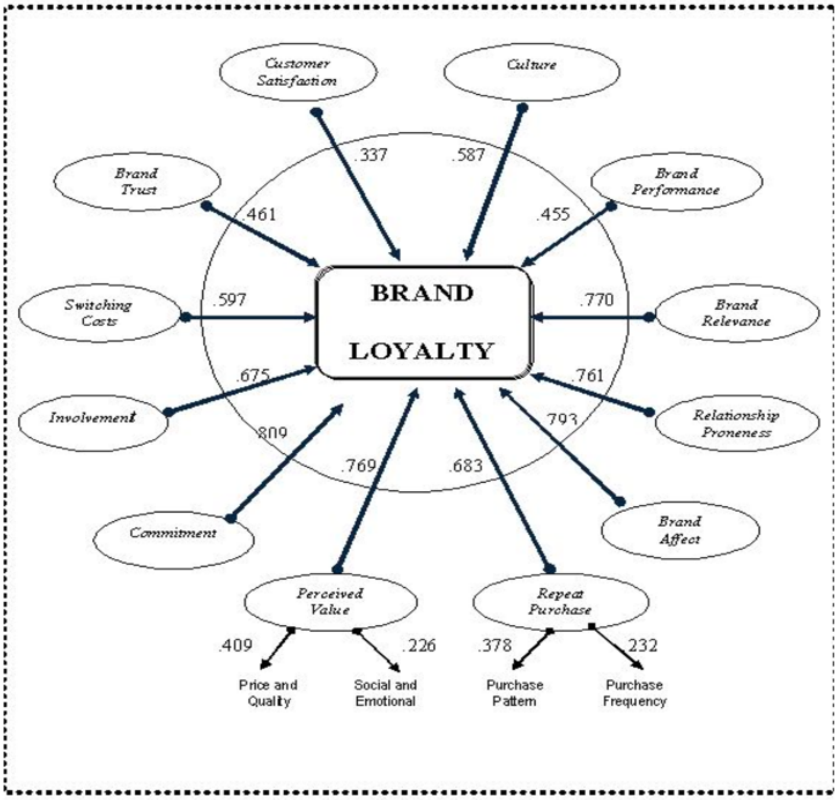
Although the findings of these articles are somewhat contradicting (please refer to appendix 2 for an overview of drawn conclusions), their assumptions as to the underlying causes for this change in BL remains the same: fragmentation of the market, increased cynicism among consumers and decreased consumer spending due to economic recessions. As we are heading into yet another economic recession because of COVID-19, the war between Russia and Ukraine and growing inflation rates, managers can expect a change in consumer behavior where consumer are more price sensitive and less brand loyal than before (Varasteh et al., 2019).

Although many researchers studied BL, its definition in terms of measurement remains complex (Dawes et al., 2015); (Dekimpe et al., 1997); (Yim & Kannan, 1999); (Casteran et al., 2019); (Nagar, 2009). Knox & Walker (2001), indicate that BL can be measured using a stochastic model or a deterministic model. The stochastic view is a way of looking at consumer behavior that uses basic information about consumers and how often they make purchases on average. However, it assumes that the market situation does not change much over time and that the market does not affect how consumers behave. According to this view, consumer behavior can be calculated with a mathematical formula, which would be ideal. However, the market does have an impact on consumer behavior, making the model unrealistic and unreliable. The deterministic model, however, proposes that repeat purchases are caused by a few causal variables that can assist in predicting consumer behavior. The model eliminates randomness and uncertainty by arguing that only a few variables of the market will influence consumer behavior in repeat purchases. In their study they conclude that Jacoby and Chestnut's definition is the amplest one to measure BL as it is considering all its variables:

"*The biased (i.e. non-random), behavioral response (i.e. purchase), expressed over time, by some decision-making unit with respect to one or more alternative brands out of a set of such brands, and is a function of psychological (decision making, evaluative) processes" (Jacoby and Chestnut, 1978).*

This definition was the first to include both attitudinal and behavioral factors. To complete this statement, Moolla & Bisschoff (2012) performed empirical research in which they depicted all possible factors of BL and tested the strength of each relationship. The factors that were concluded to have to strongest relationship to BL were brand relevance, relationship proneness, brand affect, perceived value (price & quality; social and emotional), and commitment (Please refer to figure 2). Brand relevance is characterized by the contemporary consumers' demand for brands that hold meaning. Brand messages need to become more complex and orchestrated to carry more meaning to establish brand relevance. Relationship proneness is defined as the consumers personal engagement with the brand. It is the tendency of the consumer to engage in a relationship with the brand rather than acting on an inertia or convenience. Brand affect describes the emotional effect the usage of the product of the brand has on the average individual consumer. Perceived value is split in two sections, firstly price and quality and then social and emotional. Both sections address the ability of the brand to fulfill the needs or requirements of the consumer. Lastly, the commitment factor refers to the extent to which a consumer is dedicated to a particular brand and is inclined to make future purchases or continue using it. The level of commitment reflects the extent to which a brand's consumer base is shielded from competition (Moolla & Bisschoff, 2012). Similarly, in Knox & Walker's study (2001), it was indeed confirmed that brand commitment is an essential element in the creation of BL among consumers.

Figure 2: Brand loyalty relations



Source: Moola et. al. 2012

To summarize, regrettably, most studies measuring BL focus on the behavioral aspects by looking at the repeat purchases over time. Dawes et al., 2015; Dekimpe et al., 1997; Yim & Kannan, 1999; Casteran et al., 2019; Nagar, 2009 all use collected panel data to draw their conclusions. Yet, this measure does not encompass the entirety of BL as not every repeat purchase should be labeled as a commitment of the consumer towards to the brand (Liu-Thompkins, & Tam, 2013). Howard and Sheth (1969) suggested that households tend to establish a routine for purchasing a particular brand in frequently bought items, particularly for low-priced product categories. This results in those brands having a higher probability to be chosen again in the future compared to other brands, a behavior known as Brand Inertia (BI) or a habit. This behavior is either habitual or driven by situational factors such as the unavailability of other options or high switching costs and is associated with a low level of relative affection towards the brand. Indeed, consumers may switch to a competitor's brand if an alternative becomes available, indicating that this repeated behavior cannot be considered as long-term loyalty (Dick & Basu, 1994). Households may also seek variety and switch brands, causing the current brand to have a lower chance of being chosen in the future compared to other brands (Kahn et al., 1986). In such a situation, marketers can only benefit if consumers exhibit loyalty or commitment to consistently repurchasing a preferred brand, despite situational influences

and marketing efforts that may encourage switching behavior (Oliver, 1999). In summary, measuring BL is challenging and multifaceted and needs to be done using several different mechanisms.

1.2 Brand loyalty or costumer brand engagement

One of the main challenges when measuring BL, is separating BI from BL (Oliver, 1999). To do so, Fernandes & Moreira (2019) argue that more emphasis should be placed on the relational aspect of BL. Determinants of brand relationships are brand-trust, brand-love, brand-experience, but especially brand engagement (BE) (Goldsmith, 2012). A well-established and well-maintained brand conveys trust and dependability to the consumer which in turn leads to BL (Ibid). A direct and positive correlation between BE and BL has been proven, forming a reciprocal influence loop (Fernandes & Moreira, 2019; Hollebeek et al., 2014, Helme-Guizon, & Magnoni, 2019). Furthermore, when referring to the approved model of BL by Moolla & Bisschoff (2012) the factors which were identified to have the biggest impact on BL were commitment, perceived value, brand affect, relationship proneness and brand relevance. These five factors can be easily linked to Hollebeek's affection (AFF), cognitive (COG) and activation (ACT) determinants of brand engagement (Please refer to Appendix 1 for illustration).

1.3 Consumer brand engagement

The concept of Consumer Brand Engagement (CBE) is closely aligned with social exchange relationships, drawing heavily from the theoretical framework of the Social Exchange Theory (SET) (Hollebeek 2014); (Fernandes & Moreira, 2009). This theory states that when consumers receive positive actions from a brand, such as high-quality products, prompt issue resolutions, or personalized consumer attention, they reciprocate these favors by exhibiting positive word-of-mouth, demonstrating loyalty, or engaging in repeat purchases. In today's era of engagement and participation, consumers have transitioned from a passive approach of simply receiving brand messages, to an active role of actively engaging with brands. Engaged consumers are more likely to repurchase the same brand and act as advocates for those brands (Obilo et al., 2021). This is also known as the cost/ reward perspective, where consumers and brands provide a benefit to the other but expect something in return (Bove et al., 2009). SET acknowledges that consumer engagement with a brand represents a reciprocal response to positive experiences, thereby fostering a social connection with the brand. Whilst many definitions strive to clarify CBE, Goldsmith (2012) states that at its core it involves forging a personal

connection with the brand, as if the consumer harbors an emotional attachment to it. This emotional bond often stems from the brand's embodiment of a significant aspect of their self-identity or acting as a profound symbol to the consumer. The best understood definition of CBE is that of Hollebeek's which is:

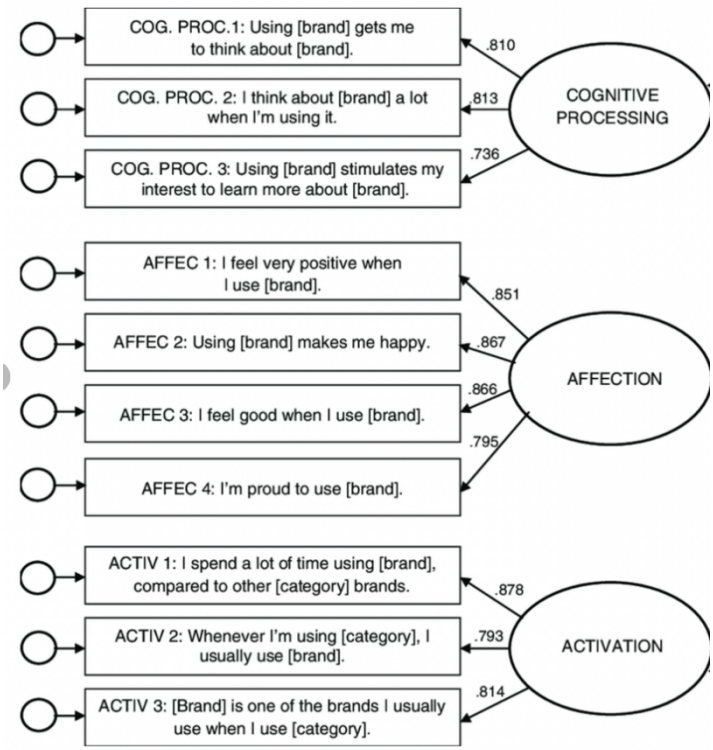
"*CBE is the level of consumers cognitive, emotional, and behavioral investment in specific brands and interactions. Three key CBE themes include 'immersion', 'passion', and 'activation'".* (Hollebeek, 2011).

1.3.1 Brand engagement measurements

Hollebeek et al.'s (2014) CBE scale, shown in figure 3, is widely acknowledged as the primary tool for measuring CBE (Razmus, 2021). Hollebeek's definition of CBE focuses on the cognitive processing, emotional, and behavioral interactions between consumers and a brand, specifically during or related to interactions (Hollebeek, 2011); (Hollebeek, 2014); (Islam & Rahman, 2016). It comprises three key dimensions: cognitive processing (CP), affective (AFF) emotional response, and behavioral activation (ACT). The CP dimension refers to the extent of a consumer's brand-related thoughts and elaboration during a specific brand interaction. The AFF dimension represents a consumer's level of positive emotional connection with the brand during the interaction, encompassing the emotional aspect of CBE. Lastly, the behavioral or ACT dimension refers to the level of energy or effort a consumer invests in a brand during the interaction, illustrating the behavioral dimension of CBE (Hollebeek, 2014).

Hollebeek's CBE measurement model offers a comprehensive framework for assessing BL by considering multiple dimensions of consumer engagement. By incorporating cognitive, emotional, and behavioral aspects, it provides a holistic perspective on BL and enhances the understanding of the underlying mechanisms that drive it. The measurement system employed by Hollebeek's model is precise and clear, unlike the measurement system used for BL itself.

Figure 3: CBE scale



Source: Hollebeek 2014

1.4 Brand switching behavior

Brand switching behavior (BSB), as defined by Ping (1993), refers to the act of ending a relationship with one brand to establish a new one, driven by overall satisfaction with the existing relationship and influenced by factors such as alternative attractiveness, investment in the relationship, and switching costs. This behavior directly relates to the level of BL or non-loyalty. When BL is low, BSB tends to be high, whereas high BL leads to less frequent BSB (Uncles & Dowling, 1998).

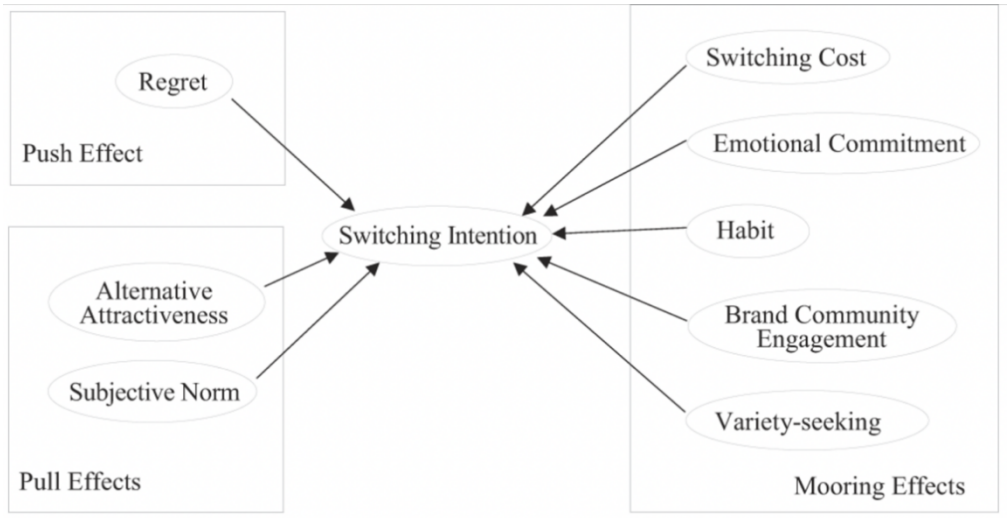
1.4.1 Measuring Brand Switch Behavior

The Push-Pull-Mooring (PPM) framework by Liao (2021) as illustrated in figure 4 can be used to assess BSB. The model originates from early migration frameworks, where it was used to understand underlying motivators of why people migrate (Ghasrodashti, 2017). When one leaves their country because of reasons associated with a negative feeling towards their home country, then it qualifies as a push factor. On the other hand, reasons associated with the country of migration offering something more attractive than one's current country would be considered a pull factor (Ghasrodashti, 2017). The push factor pushes people away from their own country,

and the pull factor pulls them out of their own country. In the 1990s, this framework was applied and tested in diverse marketing studies to measure its ability to predict BSB. The push factors were defined as negative aspects of the original brand pushing people away from the brand. The pull factors were defined as positive factors of competing brands pulling people away from the original brand. Lastly, a third pillar was adding being the mooring factors which promoted BSB based on personal, social or situational influences (Bansal, 2005); (Ghasrodashti, 2017). The different factors withing the PPM model have been explored and defined in research performed by Liao et. al. (2021) and were defined as one push (PUS) factors, two Pull (PUL) factors, and 6 Mooring (MOO) factors. The (1) PUS factor is defined as *Regret*: a negative emotion stemming from cognitive processes, regret is an emotion that arises when consumers realize or imagine that they could have been in a better situation if they had taken different actions (Zeelenberg, 1999); (Tzeng & Shiu, 2019). It can be a motivator to switch brands and has been shown to be result from low satisfaction with a current service provider. It has a negative impact on both repurchase and reuse intentions and can exacerbate a consumer's desire to choose alternative options. The (2) PUL factors are (2a) *Alternative attractiveness*: decisions of consumers to continue their relationship with their current brand is influenced by both their level of satisfaction with the brand and the appeal of alternative brands. Previous studies have shown that the perceived attractiveness of alternative brands can prompt consumers to switch brands (Bansal et al., 2005). (2b) *Subjective norms:* refers to an individual's perception of what is expected of them regarding a particular behavior. According to the planned behavior theory, subjective norms directly predict an individual's behavioral intention (Hung et al., 2003). As a major social factor, subjective norms have found to affect a user's willingness to switch to alternative brands. Social factors, such as aligning with the choices of significant others (e.g. friends), play a significant role in shaping users' product adoption and usage decisions. This social pressure is especially high when purchasing social products (Zhou & Lu, 2011). Finally, the (3) Mooring factors are (3a) *switching costs:* the incurred costs in terms of time, money, and effort (Chang et al., 2013). Before switching, consumers must weigh the benefits of purchasing a new brand against the costs of switching. Higher switching costs decrease the likelihood of consumers terminating their relationship with a brand, even if they are dissatisfied (Vasudevan et al., 2006); (Edward & Sahadev, 2011). (3b) *Habit:* unconscious form of inertia that is driven by repetition (Polites & Karahanna, 2012). It does not necessarily equate to the frequency of action but rather the behavioral responses that are performed automatically and unconsciously, requiring minimal cognitive effort and time. They are learned behaviors resulting from repeated actions and reduce the cost of making decisions (Sun et al., 2017). (3c)

Emotional commitment: refers to an individual's attachment to a particular relationship partner and results in the continuation of the relationship (Fullerton, 2009). Research demonstrates that emotional commitment aids users in preserving relationship with their current brands due to their emotional attachment and sense of belonging (Bateman et al., 2011). (3d) *Brand and community engagement:* occurs when a group of like-minded individuals share passions for a specific brand (Muniz & O'Guinn, 2011). Engaging in a brand community can deepen consumers' connections with the product, brand, company, and other consumers (De Vries & Carlson, 2014). Increased community engagement can reduce consumers' intentions to switch to alternative brands (Habibi et al., 2014). (3e) *Variety-seeking:* refers to the desire for a range of products and services, regardless of contentment with what is currently being used. The impact of this preference of consumer behavior has a detrimental effect on consumer BL and encourages consumers to explore alternative options even if they are satisfied with what they have (Huy Tuu & Olsen, 2013).

Figure 4 : PPM in BSB



Source : Liao et. al., 2021

1.5 Market segmentation

Market segmentation is a key tool for any company as it enables targeted marketing which enhances overall consumer understanding, helps meet their satisfaction and hence improve return on investments (Paley, 2000); (Martin, 2011); (Kotler, 2010). Companies cluster groups of people with similar traits to create consumer segments, enabling them to predict future behavior based on deeply explored traits. By thoroughly understanding different consumer segments, companies can transform this knowledge into personalized targeting campaigns which can provide them competitive advantage in the market (Weinstein, 2013). The table

below illustrates the widely accepted methods of consumer segmentation, being demographic, psychographic, and geographic and product attribute factors (Paley, 2000).

Table 1: Consumer segmentation

Demographic	Psychographic	Geographic	Product attributes
Age Sex Family/ life cycle Race ethnic/ group Education Income Occupation Family size Religion Home ownership	Personality Self-image Cultural influences	Region (urban/ suburban/ rural) Population density City size Climate	Usage rates Product benefits

Source: Own elaboration; Paley 2000

For BL, relevant demographic characteristics include age, gender, and educational level (Klopotan et al., 2014). The geographic characteristics that are worth exploring are the country in which the consumers live and whether this is a rural/ urban or sub urban area as these are factors prone to influence BL (Knox & Walker, 2001); (Dawes et al., 2015); (Dekimpe et al., 1997); (Yim & Kannan, 1999); (Casteran et al., 2019); (Nagar, 2009).

1.6 Ecommerce

E-commerce has witnessed a remarkable growth trajectory over the past few decades (Goldberg, 2022). The COVID-19 epidemic triggered an unprecedented surge in the FMCG category within e-commerce. In the Netherlands alone, e-commerce accounted for a significant 16% of FMCG sales between 2020 and 2021 and is expected to increase in the future as consumers take on an omnichannel shopping approach (Deloitte, 2022). The shift toward an omnichannel purchasing model necessitates that companies engage with consumers through multiple touchpoints, resulting in more intricate and adaptable customer journeys (Ibid). The abundance of touchpoints empowers customers, granting them greater control over the creation of their own unique customer journeys. Consequently, the process becomes customer-driven rather than solely business-driven (Herhausen et al. 2019). By understanding these evolving dynamics, businesses can capitalize on the advantages offered by market segmentation to thrive in the ever-changing e-commerce landscape. Market segmentation facilitates targeted marketing efforts, enabling companies to tailor their strategies, products, and services to meet the specific needs and preferences of distinct customer segments (Goldberg, 2022); (Kotler, 2010). This level of customization enhances customer understanding, leading to increased

satisfaction and loyalty. Moreover, market segmentation enables efficient allocation of resources, allowing companies to focus on the most promising segments (Martin, 2011).

In summary, BL refers to the positive emotional connection that customers develop with a particular brand, leading them to prefer and repurchase that brand over competitors. While traditional strategies have focused on nurturing BL, there is a growing concern about its recent decline. As a result, managers often resort to aggressive competitive tactics, inadvertently worsening the erosion of BL. Moreover, the FMCG industry is experiencing a shift towards e-commerce, requiring managers to make informed strategic marketing decisions. As consumer behavior online differs from offline, there is a need for new research to understand the factors influencing BL. This study aims to measure the customer factors that impact BL using the PPM BSB scale and the CBE scale.

2. Methodology

This chapter is dedicated to the method used to collect and analyze available information regarding the research problem of the dissertation. The methodology includes information concerning the data collection, explains the conceptual model, the hypotheses, the questionnaire design, and data treatment and finally the sampling method. Considering that this research will observe and analyze the interaction between different consumer characteristics and CBE and BSB, it qualifies as a correlation research design (Bhandari, 2022).

2.1 Research conceptual model

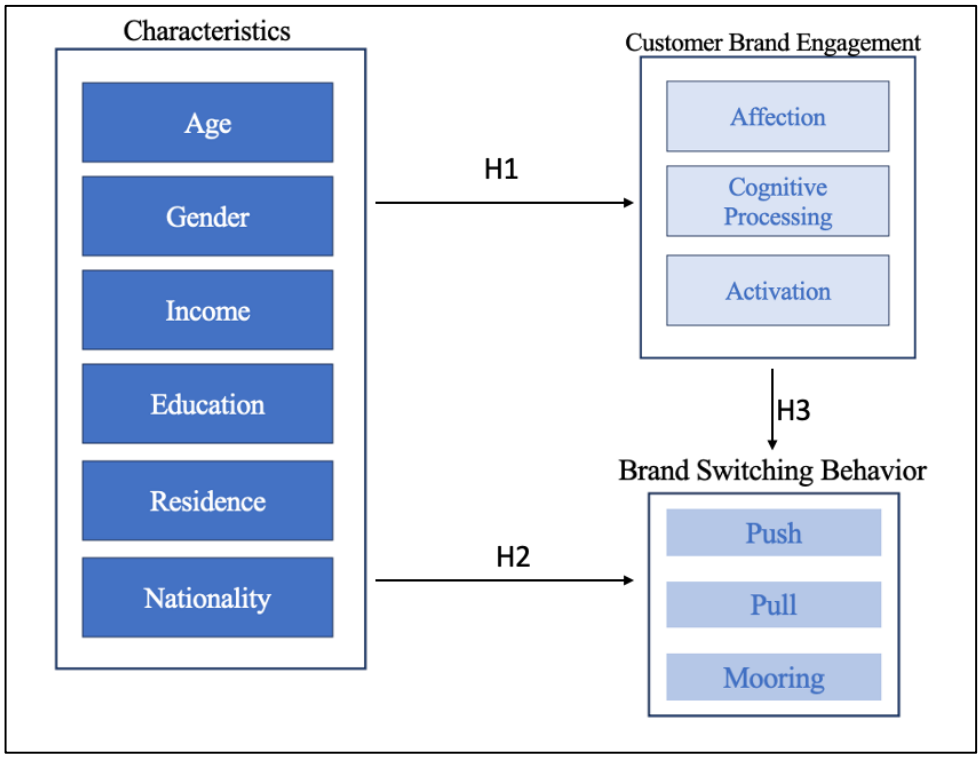
Over the past years, several studies (Knox & Walker, 2001); (DeKimpe et al., 1997); (Yim & Kannan, 1999); (Casteran et al., 2019); (Nagar, 2009) have researched eroding BL in the FMCG industry (Please refer to appendix 2 for overview of research paper results) with contradicting results. Research is often solely based on behavioral trends even when BL should be measured in a way that includes cognitive, behavioral, and affectionate factors (Liu-Thompkins & Tam, 2013). As Hollebeek's' CBE model and Liao's PPM BSB model include those factors and both are in a direct loop with BL, they will be used in this research to observe BL. By the time this research is published, to the awareness of the researcher, no other papers explaining the potential correlation between consumer characteristics and trends in BL have been published.

The aim of this research is to identify the factors that influence consumer BL in the online environment. Given the direct relationship between BL, BE, and BSB, the study will employ a combination of perceptible measures to assess the factors impacting BL. The conceptual framework is depicted in the figure below. Both the CBE model (Hollebeek, 2014) and the BSB model generate scores (Liao, 2021). Those scores will be used to understand the extent to which the different characteristics impact BL. This research aims to answer to the following research question: investigating the factors of brand loyalty in eCommerce through brand engagement and brand switching behavior.

Firstly, the relation between the selected consumer characteristics and the factors of CBE will be tested. Then, the relation between the selected consumer characteristics and their impacts on the factors of the BSB will be tested. If a relation is found between a consumer characteristic and BE or BSB, then the internal factors will be tested to understand roots of the relation. Finally, the relation between BSB and BL will be tested. It is expected that when BL

is high, BSB is low. A more detailed version of the conceptual model can be found in appendix 3.

Figure 5: Conceptual framework with hypotheses



Source: Own elaboration

2.2 Scale analysis

The variables employed in the study (BE and BSB) were derived from the previously published CBE model and BSB model. For the CBE model, the set questionnaire was kept the same as it could be applied directly and clearly to the target audience. However, for the BSB model, some modifications were necessary. As aforementioned, the BSB model refers to different PUS, PUL and MOO factors that entice consumers to switch their brands. Within those factors lay underlying topics, these are (1) Push, (1.a) regret, (2) Pull, (2.a) alternative attractiveness, (2.b) subjective norm, (3) mooring, (3.a) switching costs, (3.b) emotional commitment, (3.c) habit, (3.d) brand community engagement, (3.e) variety seeking. Scenarios relevant to the research theme were sketched to question each of these underlying factors. In the analysis they were then computed into a score to assess each one properly.

2.3 Hypotheses

The hypotheses, as illustrated in the conceptual framework, were tested categorically. In the conceptual model, all CBE assumptions were categorized as H1 and all BSB assumptions were categorized as H2. The different respondent characteristics filtered these two different categories. A positivistic approach was applied when formulating the hypotheses.

The hypotheses 1 include the assumptions about CBE:

H1a. There is a significant correlation between age and CBE.

H1b. There is a significant correlation between gender and CBE.

H1c. There is a significant correlation between income level and CBE.

H1d. There is a significant correlation between educational level and CBE.

H1e. There is a significant correlation between the type of residence and CBE.

H1f. There is a significant correlation between nationalities and CBE.

The hypotheses 2 are the assumptions concerning BSB:

H2a. There is a significant correlation between age and BSB.

H2b. There is a significant correlation between gender and BSB.

H2c. There is a significant correlation between income level and BSB.

H2d. There is a significant correlation between educational level and BSB.

H2e. There is a significant correlation between the type of residence and BSB.

H2f. There is a significant correlation between nationalities and BSB.

As aforementioned, the relation between BSB and CBE will be tested as well to see the distinguish between attitudinal (BSB) scores and a more balanced score (CBE). This will also serve to individualize BL in terms of engagement and distinguish whether this translates in buyer behavior.

H3. There is a correlation between the CBE score and the BSB score.

2.4 Questionnaire

2.4.1 Method construction and Data collection

Data for the research study was collected using an online structured questionnaire, with prearranged standardized questions. The survey started with a brief introduction to the research topic, thereby informing the participants of the objectives and area of research of the study. Using a pre-structured questionnaire allowed respondents to choose from a predefined set of response options (Ka Lok Cheung, 2014).

The online survey was constructed using Qualtrics Experience Management (QM), a research management platform which streamlines survey creation. The platform provides survey improvement tips and alerts the researcher in case of suspicious answers (i.e. robotized answers) thereby increasing the reliability and quality of the research (Qualtrics, 2023). Furthermore, by using this online platform to create the survey, its distribution was quicker and more cost efficient than it would've been when sharing it in an offline setting. The scale used was the Likert scale which ranged from 1-7 using Hollebeek's CBE model's example (Hollebeek, 2014). By utilizing a predetermined scale, both conformity with the theoretical model and consistent data was achieved. The respondents were constrained to choose from predetermined alternatives, which helped minimize result variability and facilitated easier coding, analysis, and interpretation of the data (Ka Lok Cheung, 2014).

Due to its extensive global acceptance and comprehension, the survey was formulated in the English language. Before making the survey available to the public online, a group of 10 individuals were chosen to review and provide feedback on the question structure, clarity, and practicality, as well as the elements under analysis. This led to small adjustments in the wording and a few typos but no adjustments in the general constructs nor big comprehension misconceptions. After implementing this feedback, the questionnaire was then distributed via the internet and spread using multiple online platforms such as Facebook, LinkedIn, Instagram, WhatsApp and SurveyCircle. Consequently, the research sample was obtained through a non-probability convenience sampling method, as individuals who had access to the survey link were able to participate. This initial sampling approach was then supplemented by network sampling, where sampling begins with some people from the researchers' network and is then sent to others as referrals (Nikolopoulou, 2022).

The questionnaire was designed based on the theoretical models discussed previously in the literature review. It started off with a brief introduction to the topic, explaining the purpose and goal of the study as well as a disclosure of privacy and data protection. The questionnaire itself consisted of 5 sections with in total 39 different questions. The first section derived from Hollebeek's CBE model aimed at evaluating CE with a brand of their preference within the FMCG sector. Subsequently, in the second and third section, participants' general online and offline consumer behavior was assessed through a series of questions. In the fourth section, to examine BSB, several scenarios were presented using the PPM model and questions were asked accordingly. Finally, as this research aims to determine the influence of consumer demographics on BL, the last section was dedicated towards asking the respondents their personal information. Where all previous sectors could be answered using a 1–7-point Likert

scale, the demographics section was presented as a multiple-choice section. The questionnaire was available from June 1st till July 6th, 2023, and a total of 378 responses were collected, of which 230 responses were viable.

2.4.2 Universe and Sample

The target population for this study encompassed individuals who had previously made online purchases. As a result, a non-probability sampling method, specifically network sampling, was employed. Initially, the participants were randomly selected, but the research was subsequently shared through referrals from the primary participants. Consequently, the individuals who participated in the study were chosen at random (Nikolopoulou, 2022). To ensure an adequate sample size, a minimum threshold of 200 participants was set, and the collected sample of 378 surpassed this requirement. However, only 230 out of the 378 surveys were deemed valid and considered for analysis.

2.5 Quantitative study

2.5.1 Data treatment

Whilst the survey was live, the progress of responses could be tracked using Qualtrics XM. This allowed for the observation that the number of participants who had started the survey was significantly higher than the number of participants who had fully completed it. Once the desired sample size was reached, the data was exported from Qualtrics XM and transferred to an Excel file. Out of the 378 collected responses, only 230 were considered complete with all required information, while the remaining responses were excluded. Subsequently, the data was imported into IBM Statistical Package for the Social Sciences (SPSS) 29 software to facilitate the computation of the desired tests. By using SPSS, the research performed several relevant analyses such as the descriptive analysis, ANOVA test, Spearman, Pearson Correlations as well as a multiple and single regression analysis. As the data exported into SPSS was coded when exported into the software, the first step was to cleanse and simplify the data. This was done by deleting information that was no longer required (e.g. duration of the survey, date of participation and IP address, etc.) in order to declutter the overview. Then the variables were renamed into relatively more comprehensive names. Then, the correct type of variable was identified for each item that was to be evaluated. Gender, nationality and geographical residence were inserted as nominal variables. Age, annual income, and level of education were entered as ordinal variables and all the other variables were identified as scale variables as the 7-Point Likert scale was used.

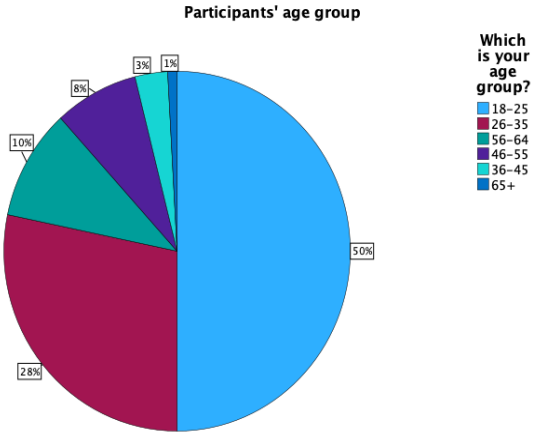
2.5.2 Respondent profile

The following section presents an overview of the respondent profiles. This research aims to identify which consumer characteristics impact CBE and BSB and therefore, the analysis started with an identification of how many participants responded to each of the segmented groups. Some categories within psycho-, socio-, or demographic segments needed to be excluded for a more reliable assessment of their relation to CBE and BSB as there was too little representation of those groups.

The respondents' age was gathered using a multiple-choice question that grouped participants into five age categories. Figure 6 illustrates the distribution of respondents within each age group. The largest segment, comprising 50% of the participants, fell within the 18 to 25 age range, thus constituting most of the population. Approximately 28% of respondents fell between the ages of 26 and 35. Around 10% of respondents were in the age range of 56 to 64. Additionally, approximately 8% of participants belonged to the 46 to 55 age group. The

remaining two categories, 36 to 45 and those above 65 years old, were relatively underrepresented in this study, accounting for only a combined 4% of the total respondents.

Figure 6: Pie chart for age

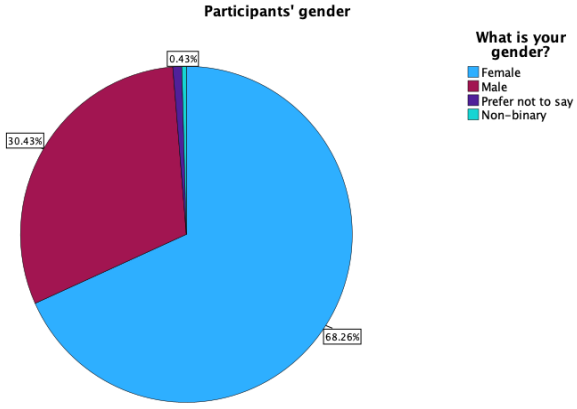


Source: Own elaboration

The available data for the age groups of 36 to 45 and 65 plus was insufficient to draw meaningful conclusions. As a result, the analysis will focus on the age groups of 18-25, 26-35, 56-64, and 46-55, where more substantial data exists. By narrowing down the analysis to these specific age ranges, a more reliable assessment of the relationship between demographics and BL can be conducted.

To determine the gender distribution among the respondents, they were provided with the options male, female, prefer not to say, or non-binary. The results revealed that approximately 70% of the participants identified as female, accounting for 157 respondents. On the other hand, around 30% identified as male, totaling 70 respondents. However, the combined percentage of non-binary respondents and those who preferred not to disclose their gender was less than one percent.

Figure 7: Pie Chart for gender

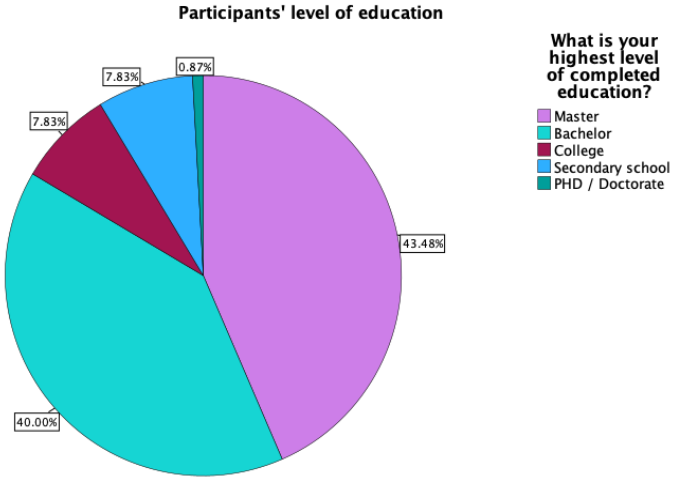


Source: Own elaboration

Due to the limited representation of these groups, it is not feasible to draw conclusive findings regarding their influence on the study. Therefore, the analysis will primarily focus on the gender comparison between male and female participants.

The demographic factor of educational level was divided into five distinct categories: secondary school, college, bachelor's degree, master's degree, and PhD/doctorate. Among these categories, the largest proportion of respondents, a comprising 43%, held a master's degree. Additionally, 40% of participants had completed a bachelor's degree, while 8% had achieved a college degree or completed secondary school. Notably, less than 1% of respondents held a PhD or doctorate degree. Considering the research's objective of examining the relationship between demographic factors and BL, it is necessary to exclude the group of doctorate degree holders from the analysis due to its small representation in the sample. The size of this subgroup is insufficient to draw meaningful conclusions, thus it will not be included in the research. Therefore, when drawing causal links between the level of education and BL, the only types of degree taken into consideration will be secondary school, college, bachelors', and masters.

Figure 8: Pie chart for educational level

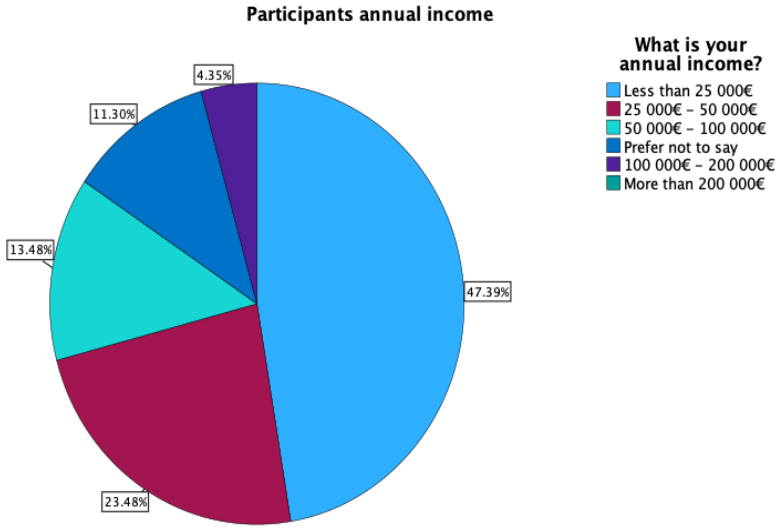


Source: Own elaboration

Similar to the previously mentioned demographic factors, income was categorized into several levels. The first category represented respondents earning less than 25K per year, followed by the range of 25K to 50K, 50K to 100K, 100K to 200K, and finally, those earning more than 200K. The largest segment, comprising 47% of respondents, fell into the category of earning less than 25K annually, which aligns with the majority of respondents being in the 18-24 age range. The subsequent category, with 23% of respondents, represented those earning between 25K and 50K, followed by the 13% earning between 50K and 100K. Additionally,

11% of respondents chose not to disclose their income, and less than 5% reported earning between 100K and 200K. No responses were recorded from individuals earning over 200K annually. Considering the research objective of examining demographic factors that potentially influence BL, only the three smallest income sections will be included in the analysis. Therefore, only income categories up to 100K per year will be considered for drawing conclusions related to the study.

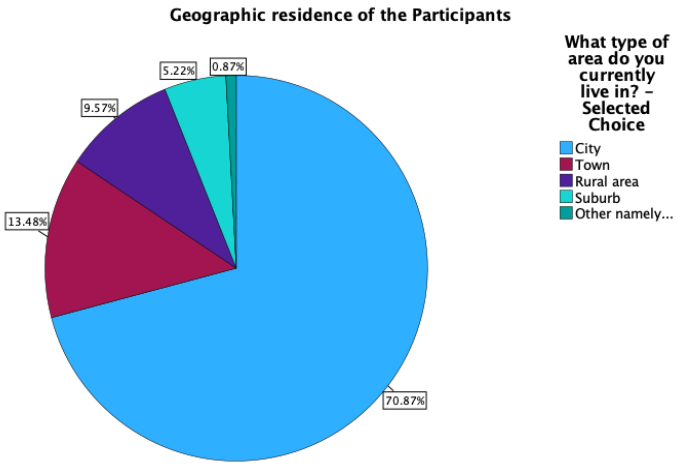
Figure 9: Pie chart for income level



Source: Own elaboration

The geographic area where respondents reside was categorized into several options: City, Town, Suburb, Rural area, and Other. The distribution among these categories is as follows: City accounted for the majority with 71% of respondents, followed by Towns with 13%, Rural areas with 10%, Suburbs with 5%, and a small percentage of 0.8% falling into the Other category. Given the research objective of examining the potential impact of demographic factors on BL, the "Other" category will be excluded from the analysis due to its small representation. Its reliability could also be doubted as the respondents who answered “other” did not supplement what they meant. Therefore, the analysis will primarily focus on respondents living in Cities, Towns, Suburbs, and Rural areas.

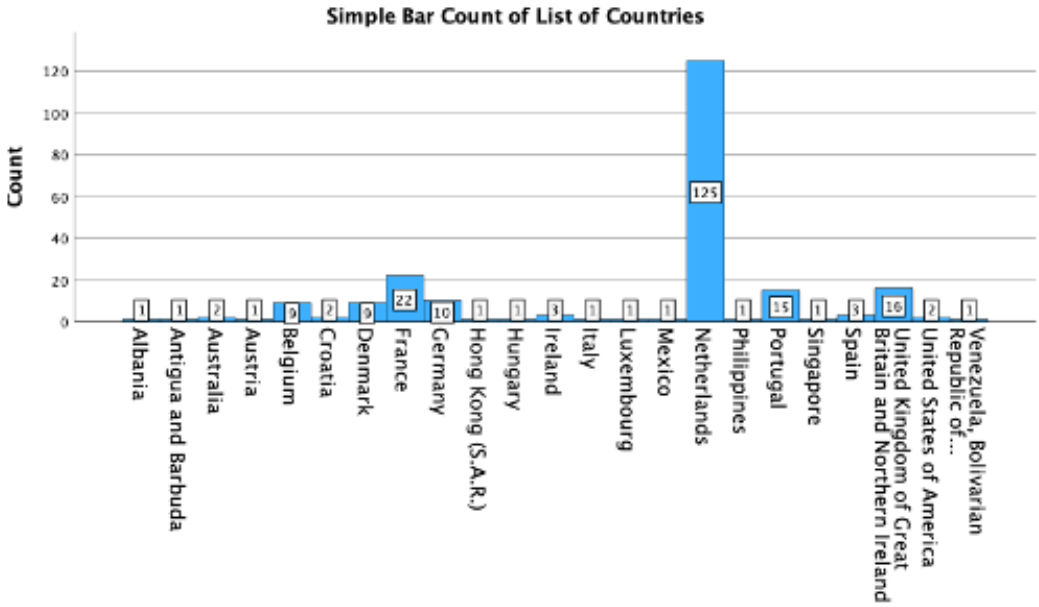
Figure 10: Pie chart for residence



Source: Own elaboration

To collect information about the nationality of participants, a drop-down menu with a list of countries was provided. The survey received responses from participants representing 24 different nationalities. The most prominent clusters were selected, being individuals born in the Netherlands (125), France (22), United Kingdom (16), Portugal (15), Germany (10), Belgium (9), and Denmark (9). Therefore, for the purposes of analysis, it is appropriate to consider these major nationality groups to draw meaningful conclusions. Whilst doing future analysis, the dispersion of answers within each nationality will be critically assessed to determine whether valid conclusions can be drawn upon them.

Figure 11: Bar chart for nationalities



Source: Own elaboration

3. Results

4.1 Descriptive and exploratory statistics

In this section, an analysis of the acquired survey results is provided, calculated using SPSS Statistics 29. The mean score for the CBE score and the BSB was calculated through an SPSS calculation computing new average variables for the scales. To make the necessary analyses, new variables with the average scale of the CBE scale and the BSB scale were calculated as well as the median scores of the scales. It is worth noting that the maximum score achievable on both the CBE scale and the BSB scale is 7.

4.1.1 Consumer Brand Engagement

Consumer brand engagement was measured using 10 different items, in accordance with the Hollebeek CBE model. The different items can be categorized in CP, AFF and ACT. The values for these three categories were calculated by computing a mean of all those items belonging to each category. The results can be seen in table 2. This reveals that the highest score within the model is achieved for the ACT ($\bar{x}$ = 5.28) with a standard deviation (SD) of 1.186 which also happens to be the highest among the three computed variables. It is closely followed by the AFF score ($\bar{x}$ = 5.25) which in turn has a SD of 1.129. This means that that AFF and ACT item scores highest in the CBE score but that there is greater variability in answers in the ACT item than the AFF item. The CP item scores the lowest which, when taking a closer look, is justified again when looking at the individual means of the item which all three score relatively low. Lastly, the computed average CBE score is set at $\bar{x}$ =5.02 which is slightly positive as it qualifies at “somewhat agree” on the Likert scale.

Table 2: Descriptive statistics CBE

	Minimum	Maximum	Mean	Std. deviation
Using [brand] gets me to think about [brand]	1	7	4,78	1,535
I think a lot about [brand] when I'm using it	1	7	4,2	1,554
Using [brand] stimulates my interests about [brand]	1	7	4,29	1,59
CP	1	7	4,42	1,358
I feel positive when I use [brand]	1	7	5,41	1,222
Using [brand] makes me happy	1	7	5,23	1,309
I feel good when I use [brand]	1	7	5,35	1,237
I'm proud to use [brand]	1	7	5	1,437
AFF	1	7	5,25	1,129
I spend a lot of time using [brand] compared to other category brands	1	7	4,98	1,48
Whenever I'm using [category] I usually use [brand]	1	7	5,36	1,356
[Brand] is one of the brands I usually use when I use [category]	1	7	5,5	1,253
ACT	1	7	5,28	1,187
CBE_avg	1	7	5,02	0,977

Source: own elaboration; data obtained using SPSS

4.1.2 Brand Switching behavior

BSB was measured using the PPM model where 8 items were categorized in either PUS, PUL or MOO categories. Again, the values for these three categories were calculated by computing a mean of all those items belonging to each category. As can be seen, the category ranking the lowest is the MOO category which has an $\bar{x}$=3.99 and a SD of 1.000. When going more into depth it can be observed that especially the habit item (BSB_MO_HA) scores very low with $\bar{x}$= 2.64 with a SD of 1.431. On the other hand, the PUL category scores an $\bar{x}$=4.97 with a SD of 1.171 which is very similar to the PUS category which scores a $\bar{x}$=4.93 with a SD of 1.436.

Table 3: Descriptive statistics for BSB

	Minimum	Maximum	Mean	Std. deviation
BSB_PUS_RE	1	7	4,93	1,436
PUS	1	7	4,93	1,436
BSB_PUL_AA	1	7	5,38	1,695
BSB_PUL_SN	1	7	4,57	1,659
PULL	1	7	4,97	1,171
BSB_MO_SC	1	7	4,46	1,826
BSB_MO_EC	1	7	3,75	1,898
BSB_MO_HA	1	7	2,64	1,431
BSB_MO_BCE	1	7	5,2	1,639
BSB_MO_VS	1	7	3,9	1,717
MOO	1	7	3,99	1
BSB_AVG	1	7	4,4	0,841

Source: own elaboration; data obtained using SPSS

It should be considered that the higher one scores on this model, the more likely they are to switch brands. The average BSB score is $\bar{x}$=4.40 meaning that overall, respondents are indifferent (neither likely nor unlikely) to switch to a different brand. It can also be observed that the MOO factors, notably the Habit, emotional commitment and variety seeking item, make it less likely for consumer to switch brands as they score lower on average than the other categories.

4.1.3 Exploratory analyses – simple linear regression

This part of the analysis will aim to accept or refute the hypotheses 1 and 2. This will be done by firstly observing the means of each of the data groups observed, followed by ANOVA or independent t-tests to explore whether statistical relations can be found. If this is the case, then the data is fitted with the single linear regression model to determine how much of the variance obtained in CBE or the BSB model is determined by that specific group. The assumptions for the linear regressions will be briefly mentioned and their proof will be available in the appendix 4. The results of all these tests will be discussed to then accept or reject the hypotheses and find which groups are predictors of the independent variables (IV).

AGE

H1a. There is a significant correlation between age and CBE.

Table 4 illustrates the varying average scores on the CBE scale achieved by different age groups as well as the ANOVA test results. To ensure statistical reliability, the age groups 36-45 and 65+ were excluded from the analysis due to their limited number of respondents. The average score for the 18-25 age group is 5.2, while for the 26-35 age group it is 5.17. Conversely, participants in the 46-55 age group scored an average of 4.38, while those in the 56-64 age group scored 4.25. The SD however indicates that the results for age group 26-35 and 56-64 is slightly less consistent than for that of the other two age groups. The results of the ANOVA test indicated a significant difference among the four age groups regarding the level of CBE ($p > .001$) with an F-value of 6.377. Consequently, the hypothesis was accepted, signifying that there is indeed a difference between the age groups in terms of brand engagement.

Table 4: mean CBE per age score and ANOVA test

Age group	Mean	N	St. Deviation
18-25	5,197	115	0,819
26-36	5,171	65	1,086
46-55	4,383	18	0,862
56-64	4,248	23	1,019
ANOVA		**F**	**Sig.**
Between groups		6,377	<,001

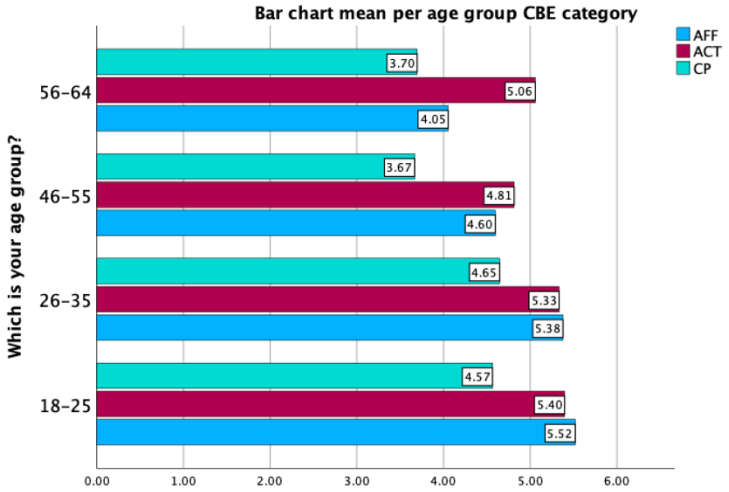
Source: own elaboration; data obtained from SPSS

Further analysis using post-hoc tests revealed specific patterns. Firstly, there was no significant relationship in CBE score between respondents in the age groups of 18-25 and 26-35. Similarly, no significant difference was found in CBE score between the age groups of 46-55 and 56-64. However, a significant difference was observed between the age group of 18-25 and 46-55, and this difference was even more pronounced when comparing the younger group to those in the 56-64 age group. Additionally, the age group of 26-35 scored significantly higher than the age group of 46-55 and exhibited similarly higher scores compared to the age group of 56-64. Therefore, the results indicated that age has an impact on the BE of the consumers. Indeed, younger groups (18-25 and 26-35) generally showed higher levels of BE compared to the older groups (46-55 and 56-64).

The table below displays the score achieved by each age group for the different categories composing CBE. The chart shows that the consistent lowest score among all groups is scored for CP. The eldest age group is the only group with a big difference between the ACT and AFF score, where the ACT score is much higher than the affection score. When performing

an ANOVA test, one sees that there is a significant difference between age group responses in CP (p=0.01) and in AFF (P= <0.01) but not in ACT. The post-hoc test (please refer to appendix 5) shows that in the CP category, the two youngest generations are unanimous and so are the two older generations. However, when comparing them to one another, there is a significant difference between the two youngest and the two eldest generations where the younger generations score higher in terms of CP. In the AFF category, the same applies where the two youngest and the two eldest categories are unanimous but the youngest score significantly higher on the AFF than the eldest.

Figure 12: Bar chart age group per CBE category



Source: Own elaboration; data obtained from SPSS

Then, a simple regression analysis was performed using dummy codes to verify whether the age groups were indeed predictors of the CBE score (please refer to appendix 4 for the checked assumptions). In Table 5, the age group of those below <25 is used as the constant. The model summary indicated that 12,2% of the variance in the CBE score is explained by the difference age groups (Please refer to appendix 6).

Table 5: Coefficients table Age and CBE

Coefficients

	Unstand. B	Coef. Std. Error	Stand. Beta	t	Sig.	Collinearity Tolerance	Statistics VIF
(Constant)	5,197	,087		59,954	<,001		
26-36	-,026	,144	-,012	-,179	,858	,905	1,105
46-55	-,813	,236	-,226	-3,452	<,001	,941	1,062
56-64	-,949	,212	-,295	-4,468	<,001	,930	1,075

Source: Own elaboration; data obtained from SPSS

The following regression formula was applied, where β_0 was the constant.

Consumer Brand Engagement = $\beta_0 + \beta_1 x$ **Age**

Following the model, the following predictions could be assumed.

<25: CBE = 5,197 + (5,197 x 0) = 5,197

26-36: CBE = 5,197 + (-,026 x 1) = 4,937

46 – 55: CBE = 5,197 + (,813 x 1) = 6,01

56 – 64: CBE = 5,197 + (,949 x 1) = 6,146

To summarize, hypothesis H1a is accepted, there is a difference between age groups with regards to their CBE scores. Younger groups (18-25 and 26-35) generally showed higher levels of BE compared to older groups (46-55 and 56-64). The post-hoc test showed significant differences in CBE scores between the youngest and oldest age groups, as well as between the 26-35 age group and the 46-55 and 56-64 age groups. Furthermore, the three categories of CBE (AFF, ACT, CP) showed differences between age groups. The youngest and oldest groups exhibited unanimity in certain categories, with the younger groups scoring higher in CP and AFF. The regression analysis indicated that age groups were predictors of the CBE score, explaining around 12.2% of the variance in brand engagement. Overall, the results suggest that age plays a significant role in influencing consumers' brand engagement, with younger age groups generally showing higher levels of engagement compared to older age groups.

H2a. There is a significant correlation between age and BSB.

In the BSB scale, the higher the model, the higher the likeliness to switch brand and thus the lower the BL. Table 6 presents the average scores on the BSB scale for different age groups. Across all age groups, there is a consistent pattern with average scores ranging between 4 and 4.5. The ANOVA test revealed a p score of .375 which > 0.05 and therefore it can be concluded that there is no significant difference between the different age groups and the BSB of the participants. Considering no significant relationship was found in the ANOVA test, no regression analysis was performed.

Table 6: mean CBE per age score and ANOVA test

Age group	Mean	N	St. Deviation
18-25	4,48	115	0,8528
26-36	4,556	65	0,789
46-55	4,432	18	1,932
56-64	4,058	23	0,8625
ANOVA		**F**	**Sig.**
Between groups		1,0759	0,375

Source: own elaboration; data from SPSS

GENDER

H2a. There is a significant correlation between gender and CBE.

Table 7 illustrates the varying average scores on the CBE scale achieved by different genders. To ensure statistical reliability, only males and females were considered considering the low respondents rate of the remaining categories. As can be seen in figure 12, both males and females scored an average of 5 on the CBE score. An independent sample t-test confirms that there is no significant difference between the CBE score between genders, as p=.447. The hypothesis can therefore be rejected, there is no difference between CBE and genders.

Table 7: Mean CBE by gender and independent sample t-test

Gender	Mean	N	St. Deviation
Male	5,02	157	1,039
Female	5,001	70	0,849
T-test		**F**	**Sig.**
Between groups		2.820	.095

Source: own elaboration; data from SPSS

H2b. There is a significant correlation between gender and BSB.

Table 8 displays the average scores on the BSB scale for different genders. To ensure statistical reliability. Both males and females obtained an average score of around 4 on the BSB scale. Based on the results of an independent t-test (p = 0,095 > 0.05), there is no significant difference between genders regarding the BSB score.

Table 8: Mean BSB by Gender and independent sample t-test

Gender	Mean	N	St. Deviation
Male	4,483	157	0,835
Female	4,229	70	0,831
T-test		**F**	**Sig.**
Between groups		2,820	,095

Source: own elaboration; data from SPSS

INCOME

H1c. There is a significant correlation between income and CBE.

The income groups considered in the analysis are the three groups that either earn less than 25K per year, between 25K and 50K and those that earn between 50K and 100K. Table 9 shows some variability in the CBE mean score of the respondents where the score varies between 4.7 and 5.2. The ANOVA reveals that indeed, there is a significant difference between the three different groups (p=.009 which is <0.05).

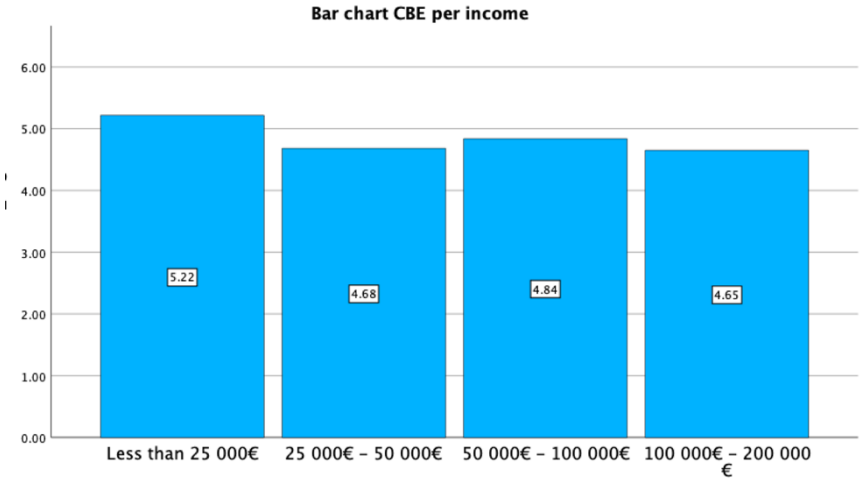
Table 9: Mean CBE and ANOVA by income group

	Mean	N	St. Deviation
Less than 25K€	5,209	109	0,894
25K€ - 50K€	4,678	54	1,12
50K€ - 100K€	4,877	31	1,071
100K€ - 200K€	4,71	10	0,638
ANOVA		**F**	**Sig**
Between groups		3,47	.009

Source: Own elaboration; data from SPSS

According to the post hoc analysis (Please refer to appendix 7), the only observed significant difference is between the group with an income below 25K and the group with an income between 25K and 50K. Specifically, the group earning between 25K-50K obtains significantly lower scores on the CBE scale compared to the group earning less than 25K. However, there is no significant difference between the group with the highest income and the group with the lowest income when it comes to the CBE scale. The bar chart in figure 13 is a demonstration of the post-hoc which makes obvious that the CBE score between the lowest income group and the medium income group are close to one another, as is the income group between 25K-50K to the 100K and 200K.

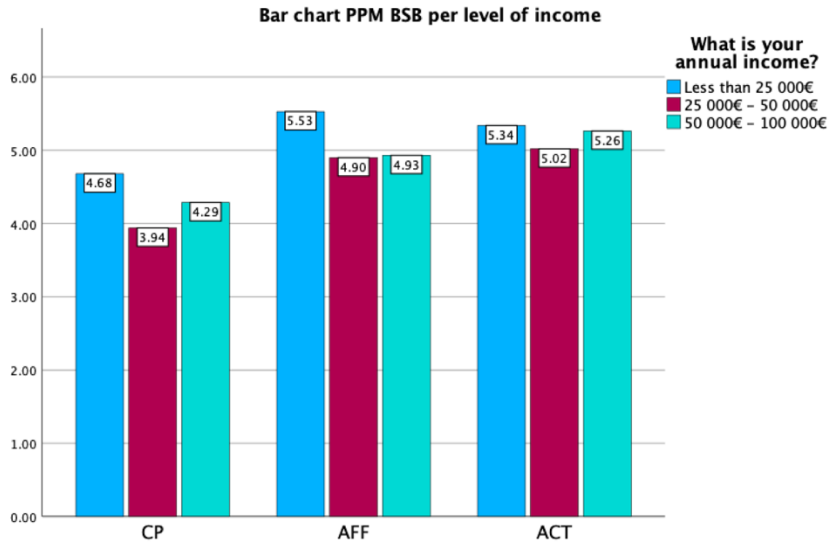
Figure 13: Bar chart CBE per income group



Source: Own elaboration; data from SPSS

The figure 14 demonstrates that the AFF and ACT factors have the greatest influence on increasing the CBE score for all income groups. Moreover, the ANOVA test reveals that the only significant difference in the underlying PPM factors exists between the income group earning less than $25K annually and the income group earning between $25K and $50K annually, particularly in the AFF and CP items. Other PPM factors do not show statistically significant differences among income groups based on the ANOVA test results.

Figure 14: Bar chart CBE category per income group



Source: Own elaboration; data from SPSS

A simple regression analysis was then performed using dummy codes to verify whether the income groups were indeed predictors of the CBE score (Please refer to appendix 4.2 for the checked assumptions). In table 10, the age group of those earning below <25K€ annually is used as the constant. The model summary indicated that 6% of the variance in the CBE score is explained by the difference income groups (Please refer to appendix 8 for proof).

Table 10: Coefficients table income group and CBE

Coefficients

	Unstand. B	Coef. Std. Error	Stand. Beta	t	Sig.	Collinearity Tolerance	Statistics VIF
(Constant)	5,214	0,083		62,758	<,001		
25K€ - 50K€	-0,532	0,159	-0,227	-3,339	<,001	0,941	1,062
50K€ - 100K€	-0,376	0,197	-0,129	-1,910	0,057	0,946	1,057
100K€ - 200K€	-0,564	0,350	-0,107	-1,612	0,108	0,979	1,021

Source: Own elaboration; data obtained from SPSS

The following regression formula was applied, where β_0 was the constant.

Consumer Brand Engagement = $\beta_0 + \beta_1 x$ **Income level**

Following the model, the following predictions could be assumed.

<25K€: CBE = 5,214 + (5,214 x 0) = 5,214

25K€-50K€: CBE = 5,214 + (-,0532 x 1) = 4,682

50K€ – 100K€: CBE = 5,214 + (-,376 x 1) = 4,838

150K€– 200K€: CBE = 5,214 + (-,564 x 1) = 4,65

In summary, income groups show differences in CBE scores, with the group earning between 25K and 50K exhibiting significantly lower scores compared to the group earning less than 25K. However, no significant difference exists between the highest income group and the

lowest income group in terms of CBE. The PPM factors that most influence CBE scores are AFF and ACT for all income groups. The regression analysis shows that income groups have a minimal impact on predicting the CBE score.

H2c. There is a significant correlation between income and BSB.

The BSB score for the relevant income groups varies between 4.3 and 4.5 and seems relatively homogenic with the naked eye. The ANOVA test confirms there is no significant difference between the groups with regards to the BSB scale.

Table 11: Mean BSB and ANOVA by income group

Income			
	Mean	**N**	**St. Deviation**
Less than 25K€	4,477	109	0,814
25K€ - 50K€	4,467	54	0,825
50K€ - 100K€	4,294	31	0,708
100K€ - 200K€	3,700	10,000	1,218
ANOVA		**F**	**Sig**
Between groups		2,222	0,068

Source: Own elaboration; data obtained from SPSS

EDUCATION

H1d. There is a significant correlation between the level of education and CBE.

The average CBE score achieved by the different age groups is depicted in table 12 and shows an average of 4.9 to 5.1. The ANOVA test reveals p=.964 meaning there is no significant difference between the groups here.

Table 12: Mean CBE and ANOVA educational group

Education			
	Mean	**N**	**St. Deviation**
Secondary school	4,506	18	0,827
Collefe	4,198	18	0,66
Bachelor	4,448	92	0,814
Master	4,383	100	0,907
ANOVA		**F**	**Sig**
Between Groups		0,412	0,800

Source: Own elaboration; data obtained from SPSS

H2d. There is a significant correlation between the level of education and BSB.

Table 13 displays the different BSB scores achieved by the different educational levels. As can be seen all groups score about 5 on the scale. The ANOVA test reveals p=.800, thereby confirming that there is no difference between the groups with regards to their BSB score.

Table 13: Mean BSB and ANOVA educational group

Education			
	Mean	**N**	**St. Deviation**
Secondary school	4,906	18	1,079
College	5,067	18	0,79
Bachelor	5,004	92	0,986
Master	5,047	100	1,838
ANOVA		**F**	**Sig**
Between Groups		0,148	0,964

Source: Own elaboration; data obtained from SPSS

TYPE OF RESIDENCE

H1e. There is a significant correlation between the type of residence and CBE.

The CBE score per type of residence is depicted in table 12 and as can be seen, there seems to be a very slight difference between the groups. The ANOVA test confirms this difference as p=.016. The Post-hoc test illustrates that this difference lies between the participants living in cities and those living in rural areas (Please refer to appendix 9). Indeed, participants living in cities score slightly higher on the CBE scale than those living in suburbs.

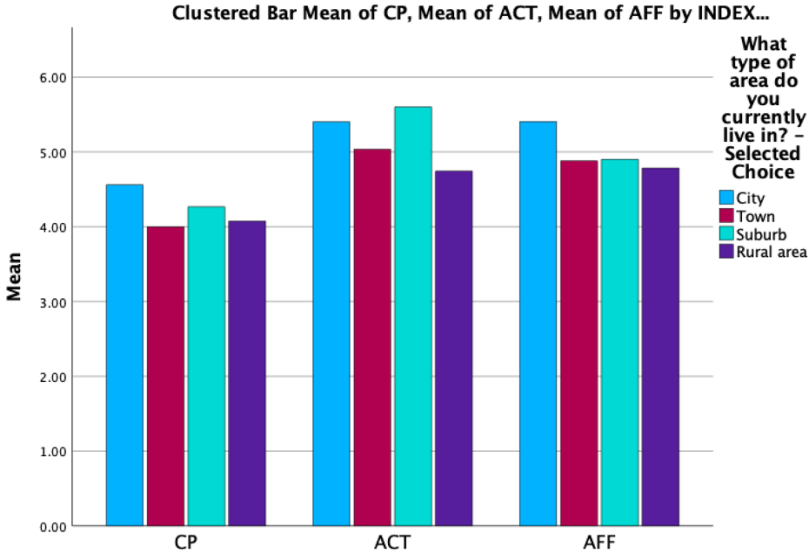
Table 14: Mean CBE and ANOVA type of residence

	Mean	N	St. Deviation
City	5,149	163	0,921
Town	4,69	31	1,079
Suburb	4,9	12	0,707
Rural area	4,559	22	1,188
ANOVA		**F**	**Sig.**
Between groups		3,108	0,016

Source: Own elaboration; data obtained from SPSS

To dive deeper in the differences between types of residence with regards to the CBE score, the underlying roots were separated. The ANOVA test revealed that there is a significant difference between the groups with regards to their score in AFF and ACT but not concerning CP.

Figure 15: Bar chart CBE category per residence group



Source: Own elaboration; data obtained from SPSS

A simple regression analysis was then performed using dummy codes to verify whether the type of residence were indeed predictors of the CBE score (Please refer to appendix 4.3 for the checked assumptions). In Table 15, the group that lives in cities is used as the constant. The model summary indicated that 4,1% of the variance in the CBE score is explained by the different types of residences (Please refer to appendix 10 for proof).

Table 15: Coefficients table residence group and CBE

Coefficients

	Unstand. B	Coef. Std. Error	Stand. Beta	t	Sig.	Collinearity Tolerance	Statistics VIF
(Constant)	5,160	0,077		67,292	<.001		
Town	-0,498	0,195	-0,171	-2,549	0,011	0,947	1,027
Suburb	-0,240	0,315	-0,051	-0,761	0,448	0,986	1,015
Rural area	-0,601	0,220	-0,183	-2,731	0,007	0,976	1,025

Source: Own elaboration; data obtained from SPSS

The following regression formula was applied, where β_0 was the constant.

Consumer Brand Engagement = $\beta_0 + \beta_1 x$ **type of residence**

Following the model, the following predictions could be assumed.

Cities: CBE = 5,160+ (5,160x 0) = 5,160

Town: CBE = 5,160+ (-,498 x 1) = 4,662

Suburb: CBE = 5,160+ (-,240 x 1) = 4,92

Rural area: CBE = 5,160 + (-,601 x 1) = 4,559

In summary, the type of residence has a significant but relatively minor impact on the CBE score. Participants living in cities tend to have slightly higher CBE scores compared to those in suburbs and rural areas. The regression analysis confirms that the type of residence is a predictor of the CBE score, but it explains a relatively small portion of the variance in the scores.

H1e. There is a significant correlation between the type of residence and BSB

The BSB score per type of residence can be seen in figure 20. The ANOVA test came back at p=2.30 and therefore it can be deducted that there is no significant difference between the score achieved on the BSB scale with regards to the different types of residence of the participants.

Table 16: Mean BSB and ANOVA type of residence

Type of residence

	Mean	N	St. Deviation
City	4,444	163	0,808
Town	4,219	31	0,846
Suburb	4,207	12	0,987
Rural area	4,389	22	0,972
ANOVA		**F**	**Sig.**
Between groups		0,994	0,23

Source: Own elaboration; data obtained from SPSS

NATIONALITY

H1f. There is a significant correlation between the nationalities and CBE.

As aforementioned, this section focuses on Belgium, Denmark, France, Germany, the Netherlands, Portugal, and the United Kingdom, as these countries had the highest number of respondents. The average CBE scores obtained by participants from all nationalities were

approximately 4. According to the ANOVA test results, with a p-value of .129, there is no significant variation in CBE scores based on the nationality of the participants.

Table 17: Mean CBE and ANOVA – Nationality

Countries	Mean	N	St.Deviation
Belgium	4,333	9	0,892
Denmark	4,161	9	0,397
France	4,641	22	0,783
Germany	4,656	10	1,136
Netherlands	4,388	125	0,84
Portugal	4,37	15	0,672
United Kingdom	4,074	16	0,1335
ANOVA		**F**	**Sig.**
Between groups		0,608	0,921

Source: Own elaboration; data obtained from SPSS

H2f. There is a significant correlation between the nationalities and BSB.

The results for the BSB score were similar to that of the CBE score. The means score totaled around 4 for all nationalities as can be seen in table 18. The ANOVA test proves that again, with a p value of .921, there no significant difference between the score achieved with regards to the nationality of the respondents.

Table 18: Mean BSB and ANOVA – Nationality

Countries	Mean	N	St.Deviation
Belgium	5,533	9	0,848
Denmark	5,167	9	0,876
France	4,946	22	0,99
Germany	4,82	10	1,577
Netherlands	4,958	125	0,946
Portugal	5,513	15	0,821
United Kingdom	4,781	16	0,933
ANOVA		**F**	**Sig.**
Between groups		1,368	0,129

Source: Own elaboration; data obtained from SPSS

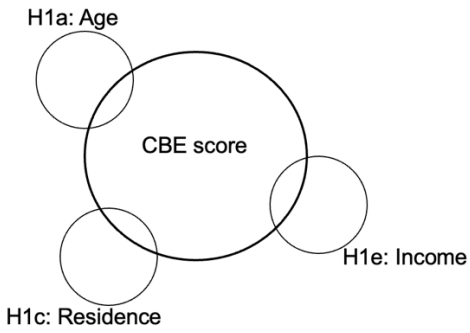
4.5 Multiple regression analysis

Hypotheses H1a, H1c and H1e were supported, indicating that there were significant relationships between those factors and CBE. To dive deeper into these relationships, simple regression analyses were conducted in the previous section. What follows is the multiple regression analyses, where the respondents' characteristics (IVs) were examined in relation to the dependent variable (DV), the CBE score for Hypotheses H1. For H1, a multiple regression analysis was applied as it includes more than two IVs in the model (age, income, and type of residence).

The research conceptual analysis included multiple analyses which were tested under the same assumptions. These assumptions remained the same because the factors in the model were the same. Through the previous part of the analysis, it was found that for H1, three analyses deemed relevant and meaningful making them fit for a multiple regression analysis. The confidence level for all the intervals is 95.000. To assure the suitability of the multiple regression analysis, the following underlying assumptions must first be assessed (Fein et al., 2023):

1. Linearity of the Model
2. Mean of the residuals
3. Linear independence (no multicollinearity)
4. Exogeneity of the IVs
5. Constancy of the residual variances across predicted values (homoscedasticity)
6. Normally distributed error component

Figure 16: Illustration of multiple regression analysis



Source: Own elaboration

Linearity of the Model

By construction, the theoretical model assumes linearity meaning the assumption holders. The multiple regression model is as follows:

$$\textbf{Consumer Brand Engagement} = \beta_0 + \beta_1 \text{ x } \textbf{Age\_18-25} + \beta_2 \text{ x } \textbf{Age\_26-35} + \beta 3 \text{ x } \textbf{Age\_46-55} + \beta 4 \text{ x } \textbf{Age\_55-64} + \beta 5 \text{ x } \textbf{Inc\_<25K} + \beta 6 \text{ x } \textbf{Inc\_25K-50K} + \beta 7 \text{ x } \textbf{Inc\_50K-100K} + \beta 8 \text{ x } \textbf{Inc\_100K-200K} + \beta 9 \text{ x } \textbf{Res\_City} + \beta 10 \text{ x } \textbf{Res\_Town} + \beta 11 \text{ x } \textbf{Res\_Suburb} + \beta 12 \text{ x } \textbf{Res\_RuralArea} + \varepsilon$$

Random sample

Considering the goal of the study is to have general results suiting an entire population, it is of importance that the sample is selected in a random matter. The study has been shared on online platforms thereby collecting responses from random respondents. It therefore fulfills this assumption.

Linearity of the variables

When creating dummies to perform the multiple regression test, one could fall into the dummy variable trap. This is when several dummy variables are highly correlated (multicollinear), and it would mean that one variable could be predicted from others and therefore wrongly influence the coefficient variables in the regression models (Karabiber, 2023). To ensure this assumption holds a collinearity diagnostics test with the dummy variables was performed.

Table 19: Multi-collinearity statistics

	Tolerance	VIF
Income=25 000€ - 50 000€	.763	1.311
Income=50 000€ - 100 000€	.691	1.448
Income=100 000€ - 200 000€	.799	1.252
Income=Prefer not to say	.866	1.155
Demographics_=26-35	.769	1.300
Demographics_=46-55	.554	1.805
Demographics_=56-64	.619	1.617
Residence_area=Town	.870	1.149
Residence_area=Suburb	.825	1.212
Residence_area=Rural area	.709	1.411
Residence_area=Other namely...	.898	1.114

a. Dependent Variable: CBE_avg

Source: SPSS own elaboration

If the VIF values is smaller 0.01 or bigger than 10 then it indicates a linearity between the variables that would disrupt the coefficient variables in the regression model. As can be seen, the assumption that the variables are linearly independent holds.

Exogeneity of the IVs

The assumption of exogeneity of the IVs aims to ensure that the IVs are not influenced by or related to the things one cannot measure or control (such as errors or unknown factors). It ensures that the variables are truly independent and not affected by hidden factors that would bias the results. As the table below illustrates, all the variables show a Pearson correlation of .000 with the residual meaning they are not related with the residuals. Therefore, the assumption holds.

Table 20: Pearson relation between IVs and the residuals

Correlations

	Inc <25K€	Inc 25K€ - 50K€	Inc 50K€ - 100K€	Inc 100K€ - 200K€	18-25	26-35	46-55	56-64	City	Town	Suburb	Rural area	Residual
Inc <25K€	1	-.529**	-.380**	-.189**	.413**	-.134*	-.225**	-.274**	.187**	-.031	-.126	-.174**	.000
Inc 25K€ - 50K€	-.529**	1	-.210**	-.105	-.217**	.221**	-.003	.028	-.023	.046	-.066	.037	.000
Inc 50K€ - 100K€	-.380**	-.210**	1	-.075	-.298**	.073	.178**	.219**	-.115	-.072	.173**	.139*	.000
Inc 100K€ - 200K€	-.189**	-.105	-.075	1	-.202**	-.019	.208**	.172*	-.149*	.140*	.074	.016	.000
18-25	.413**	-.217**	-.298**	-.202**	1	-.672**	-.310**	-.355**	.308**	-.137*	-.183**	-.165*	.000
26-35	-.134*	.221**	.073	-.019	-.672**	1	-.192**	-.220**	.116	.014	-.045	-.148*	.000
46-55	-.225**	-.003	.178**	.208**	-.310**	-.192**	1	-.101	-.403**	.080	.094	.398**	.000
56-64	-.274**	.028	.219**	.172*	-.355**	-.220**	-.101	1	-.315**	.131	.282**	.134*	.000
City	.187**	-.023	-.115	-.149*	.308**	.116	-.403**	-.315**	1	-.622**	-.349**	-.532**	.000
Town	-.031	.046	-.072	.140*	-.137*	.014	.080	.131	-.622**	1	-.085	-.129	.000
Suburb	-.126	-.066	.173**	.074	-.183**	-.045	.094	.282**	-.349**	-.085	1	-.072	.000
Rural Area	-.174**	.037	.139*	.016	-.165*	-.148*	.398**	.134*	-.532**	-.129	-.072	1	.000
Residual	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	1

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

*. Correlation is significant at the 0.05 level (2-tailed).

Source: SPSS own elaboration

Constancy of the Residual Variance across predicted values

Homoscedasticity among the residuals means that the variability in error is the same among all the IVs (the predictors). To assess this, a scatter plot with the standardized residual and the standardized predicted value was created as shown in the table in appendix 11. For equality of variances to exist, the points in the scatter plot must be evenly distributed among the horizontal axes. In the scatterplot, one can see a slight inclination towards the positive side of the axis and therefore, the assumption does not hold.

Normally distributed error component

Normal distribution is one of the multiple regression assumptions and can be tested using the histogram displayed in appendix 12. The residuals should closely align the normal curve and the mean value should approach 0 and the SD should be nearing 1, which is the case. The P-Plot displayed in appendix 13 compares the observed cumulative probabilities of the data to the cumulative probabilities expected from the theoretical distribution. The data should be closely aligned to the diagonal, which they are. Therefore, the assumption of normality of distribution holds once again.

Correlation of the Residual terms

For a reliable multiple regression analysis, the residuals must be independent to ensure that they are not autocorrelated. This would mean that a variable is correlated with itself at different times. The Durbin-Watson statistic was used to ensure their independence and it was found at a value of 2.317. This is close to 2, indicating no correlated residuals (See appendix 4.3). Therefore, this assumption is satisfied.

Evaluation of the model

Once ensuring the assumptions of the multiple regression model were met, the suitability of the model could finally be tested. This meant determining how well the model can predict the observed values. As displayed in the table below, the multiple correlations coefficient is .416, meaning there is a mild correlation between the predicted values and the actual values. The adjusted R^2 for the overall model was .130 (R^2 = .173), which, according to Cohen is a between moderately and substantially fit (1998).

Table 21: Model summary of the DV CBE

	R	R Square	Adjusted R Square
1	.416[a]	.173	.130

Source: Own elaboration; data obtained through SPSS

One of the assumptions of the six requirements is not fulfilled, meaning that the multiple regression model merely provides a characterization of the sample. The model can therefore not be used for inference and should not generalize the population.

Multiple Regression – Age, Income, Residence as IV, CBE as DV

As per the conceptual model, the strength of influence of each consumer characteristics on consumer BE needed to be measured. The ANOVA tests revealed that the only consumer characteristics which had an influence on CBE were age, income and residence. A multiple regression analysis was performed to evaluate the role of these variables where age, income and residence were the IVs and CBE was the DV. From the regression coefficients, it is now possible to calculate the adjusted regression equation (please refer to table 22).

Consumer Brand Engagement = 5.248 + 0.394*(Inc=25K € - 50K €) - 0.033*(Inc=50K € - 100K €) + 0.080*(Inc=100K € - 200K €) + 0.196*(Inc=Prefer not to say) + 0.089*(Dem=26-35) - 0.785*(Dem=46-55) - 0.908*(Dem=56-64) - 0.235*(Res=Town) + 0.270*(Res =Suburb) - 0.093*(Res =Rural area) + 0.736*(Res=Other namely...)

The CBE model was measured with the predictor's income group, age, and type of residence. Considering these were categorical variables, dummy codes were created which were included in the model. All the dummy codes were included in the model considering they still have an overlapping theoretical significance on the prediction, however, not all dummies had a significant influence on the CBE score. In the model, when all the IVs are set to their reference categories or are zero, the predicted value of CBE starts with a baseline of 5.248. This means that when a consumer falls into the reference category for each categorical variable (e.g., the lowest income group, the youngest age group, and residing in the reference area), their predicted level of CBE is 5.248. The coefficients for the other categories (income, age, and residence) modify this baseline. Positive coefficients (e.g., 0.394 for income between 25,000€ and 50,000€) indicate an increase in the predicted CBE level compared to the baseline, while negative coefficients (e.g., -0.785 for age between 46 and 55) indicate a decrease in the predicted CBE level compared to the baseline. Overall, this regression equation helps predict the consumer CBE based on their income, age, and type of residence. This therefore supports the following hypotheses:

H1a: There is a significant correlation between age and CBE.

H1c: There is a significant correlation between income level and CBE.

In these findings, the type of residence does not significantly influence the CBE scale as the p values are consistently <.05. As the ANOVA test showed previously, there is a significant difference between the type of residence and the CBE score, however the regression analysis

shows that this difference is not a predictor. Therefore, H1e: There is a significant correlation between the type of residence and CBE is denied as there is a significant difference but no correlation between the type of residence and the CBE score.

Table 22: coefficients of the Multiple Regressions, BC as DV

Coefficients[a]

Model

	Unstandardized B	Std. Error	Sig.
(Constant)	5.248	.100	<.001
Income=25 000€ - 50 000€	-.394	.169	.021
Income=50 000€ - 100 000€	-.033	.220	.880
Income=100 000€ - 200 000€	.080	.370	.829
Income=Prefer not to say	.196	.206	.343
Demographics_=26-35	.089	.155	.564
Demographics_=46-55	-.785	.304	.010
Demographics_=56-64	-.908	.257	<.001
Residence_area=Town	-.235	.196	.232
Residence_area=Suburb	.270	.328	.410
Residence_area=Rural area	-.093	.245	.706
Residence_area=Other namely...	.736	.972	.450

a. Dependent Variable: CBE_avg

Source: Own elaboration; data obtained through SPSS

4.1.4 Hypotheses 3

H3: There is a correlation between CBE scale and the BSB scale

The relationship between the two measurement scales CBE and BSB was tested by first computing the medians of all the variables. This was necessary as when variables are categorical, they should be interpreted using a non-parametric spearman test rather than a parametric Pearson's test (Kent State University, 2017). As can be seen in Table 23, the significant level is at 0.01 and $\bar{x}$=.004 which is bigger than the significant level. Therefore, it can be concluded that there is no significant relation between the BSB score and the CBE score. This conclusion was already to be expected considering the conflicting results of the hypotheses 1 and 2, where very few of the respondents had the same answer in BSB as in CBE.

Table 23: Spearman Correlation BSB & CBE

Correlations

			CBE_med	BSB_Med
Spearman's rho	CBE_med	Correlation Coefficient	1.000	.187**
		Sig. (2-tailed)	.	.004
		N	230	230
	BSB_Med	Correlation Coefficient	.187**	1.000
		Sig. (2-tailed)	.004	.
		N	230	230

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

Source: Own elaboration; data obtained from SPSS

4.1.5 Reliability

The reliability of the CBE model and the BSB model were tested using Cronbach's alpha which measures the internal consistency between items in the scale. The Cronbach's alpha ranges between 0 and 1, where the closer the value to one, the higher the reliability of the reliability. As illustrated in table 1, CBE scale with its 10 items passed the reliability test with α=.880 which qualifies as excellent. For the BSB model, there were 8 different items and therefore achieving the normally accepted reliability score above .70 is less likely but rather, the reliability score should be above .50. As shown in table 2, the reliability score for the BSB was found to be α=.637 which is a good level of reliability.

Table 24: Reliability overview

Construct	**Sub construct**	**Item**	**Cronbach's Alpha**	
Customer Brand Engagement	Cognitive	CP1	.840	.880
		CP2		
		CP3		
	Affective	AFF1	.889	
		AFF2		
		AFF3		
		AFF4		
	Activation	ACT1	.837	
		ACT2		
		ACT3		
Brand Switching Behavior			.637	

Source: Own elaboration; data obtained through SPSS

4.1.6 List of hypotheses and validation

To summarize the outcomes of the research, an overview of the validated and non-validated hypotheses was made and displayed in table 25.

Table 25: Validation of the hypothesis

	Validated?
H1a. There is a significant correlation between age and CBE.	Yes
H1b. There is a significant correlation between gender and CBE.	No
H1c. There is a significant correlation between income level and CBE.	Yes
H1d. There is a significant correlation between educational level and CBE.	No
H1e. There is a significant correlation between the type of residence and CBE.	Yes
H1f. There is a significant correlation between nationalities and CBE.	No
H2a. There is a significant correlation between age and BSB.	No
H2b. There is a significant correlation between gender and BSB.	No
H2c. There is a significant correlation between income level and BSB.	No
H2d. There is a significant correlation between educational level and BSB.	No
H2e. There is a significant correlation between the type of residence and BSB.	No
H2f. There is a significant correlation between nationalities and BSB.	No
H3. There is a correlation between the CBE score and the BSB score.	No

Source: Own elaboration

As can be seen, the only hypothesis that were validated were related to the CBE score. The BSB PPM score which was tested in the hypotheses 2 and 3 remained unaffected.

4. Conclusions and implications

4.1 Theoretical contribution

The nature of this study was to examine whether consumer characteristics had an impact on brand loyalty in the Fast-Moving-Consumer-Goods industry in an online environment. As the world increasingly shifts towards an omnichannel shopping environment, research lags in terms of its knowledge and awareness of online brand loyalty. Although there are many studies focusing on eroding brand loyalty, none take into consideration that consumer behavior is greatly impacted by a switch to omnichannel shopping. Current studies draw conclusions based on the offline situations which may not necessarily fit this new way of shopping. Misunderstanding brand loyalty could lead to managers taking misinformed decisions that in turn would further deplete brand loyalty. Previous research indicates that there are numerous conflicting ways of measuring brand loyalty, where most studies follow an empirical research approach in which a data panel is studied to observe repeat purchase behavior among consumers. Other researchers indicate that brand loyalty should not be measured through repeat purchases as this only indicates inertia or habitual behavioral which should not be confused with brand loyalty. They argue that instead, it should be measured in terms of cognitive, affectionate, and behavioral measures. Therefore, alternatives ways of measuring brand loyalty through other consumer behavior measure models which included these three dimensions but had a more measurable scale were explored. Consumer brand engagement was found to have a direct positive influence on brand loyalty, where brand loyalty cannot occur without brand engagement. Hollebeek's' consumer brand engagement model (2014) includes cognitive processing, affectionate and activation factors within its scale. This thereby covers all three aspects of brand loyalty and on top of this, another research paper indicated that brand loyalty and brand engagement encourage each other in a positive loop, where if one increases, so does the other (Fernandes & Moreira, 2019); (Hollebeek et al., 2014); (Helme-Guizon, & Magnoni, 2019). Although all three aspects of brand loyalty are already covered, another model was added to further evaluate the behavioral aspect of brand loyalty, as this has previously been most documented. The model added was the Push-Pull-Moore model of brand switching behavior by Liao (2021). This model aims to identify underlying push, pull, or mooring factors that motivate people to migrate to a different brand. The conclusion was hence taken to examine the impact of consumer characteristics on brand loyalty through the combined efforts of the consumer brand engagement scale and the brand switching behavior scale. The independent variable consisted of the characteristics examined which included age, gender, educational

level, income, type of residence and nationality. In turn, dependent variables were both the consumer brand engagement scale and the brand switching behavior scale. Lastly, the relationship between the consumer brand engagement scale and the brand switching behavior scale was tested to verify the hypotheses that their correlation would lead to a clear composure of brand loyalty. The online shared questionnaire yielded a total of 230 valid responses, with a wide variety of consumer characteristics.

Hollebeek's' consumer brand engagement is measured through ten different items, known as cognitive processing, affectionate and activation categories. In general, respondents indicated to somewhat agree with the statements questioning them about brand loyalty. A deeper look reveals that this positive inclination towards brand engagement is led by the affectionate and activation parts of the score, whereas the cognitive processing category relatively lags the overall score. One could therefore assume that the respondents do not actively think about a brand when using it and are not necessarily interested in learning more about it but do feel some sort of affection towards the brand and do use the same brand repeatedly. The positive answers in the activation category in relation to the lagging conscious processing could suggest a brand inertia or habit response, where individuals act out of ease without any intention towards a brand. In Howard & Sheths' research about brand loyalty, they indicate that it should not be confused with brand inertia or habit, as this encompasses no affectionate of cognitive processing (1969). Yet, this current study found active activation triggers as well as active affectionate triggers.

The PPM model for BSB contains 9 items which were subdivided in categories Push, Pull and Mooring. For the overall three categories, respondents indicated to be neither likely nor unlikely to switch to different brands when presented different scenarios. Where people are least likely to switch within the habit, emotional commitment and variety seeking items within the mooring factors. Respondents were less likely to switch to a different brand when acting out of a place of habit or when they felt an emotional commitment to a brand. They also indicated that they do not necessarily seek variety in the fast-moving-consumer-goods industry which essentially suggests that if brands succeed in creating an emotional bond with the consumer, then this may lead them to repurchase the brand eventually creating a habit. Alternative attraction is the strongest reason for which consumers decide to switch brands, meaning that brands must try to remain attractive to the consumer thought, for instance, effective targeting.

The consumer characteristics which had an impact on consumer brand engagement were age, income level and the type of residence. Starting with age, the younger age groups (18-25

and 26-35) were significantly more engaged than the older age groups (46-55 and 56-65). When looking specifically at where this difference comes from the cognitive processing aspect scores lowest among the three categories throughout all age groups. The activation and affection scores pull the score up but does so more significantly for the youngest two groups than for the eldest groups. The eldest groups show less affection towards a brand than the youngest groups, but their activation level is only slightly significantly lower than that of the youngest groups. Surprisingly, there were no significant differences between the two youngest or two eldest age groups with regards to their brand switching behavior.

Income also has a significant influence on consumer brand engagement; the respondents with an annual income below 25K were most brand engaged. Surprisingly, those earning between 25K and 50K annually are less brand engaged than both the lower income group and the higher income groups. The affection and activation factors play a significant role in increasing the consumer brand engagement score among all income groups.

The type of area of residence of the respondents had an impact on the consumer brand engagement score of the respondents. The difference in the score lies notably between the respondents who live in cities and those living in rural areas, where city residents are significantly more engaged than suburb residents.

The consumer characteristics that influenced consumer brand engagement were therefore age, income level and the type of residence. However, when looking in depth it was found that for all three characteristics, the difference in variance between the different groups is only very partially explained by these groups. This means that although these are predictors, there are more factors in play that cause perhaps a bigger change in the consumer brand engagement score.

There were no significant differences between the consumer characteristics nor the consumer brand engagement score with regards to the brand switching behavior score. This, considering the general results that all consumers score relatively high on the scale, means that regardless of the characteristics of the consumers and the engagement the consumer has with a brand, they are still neither likely nor unlikely to switch brands. Consumer brand engagement and brand switching behavior in this study were unrelated, meaning that regardless of how brand engaged a consumer is, it does not make them more or less likely to switch brands. This conflicts previous research (Sharma et. al., 2016; Ali et. al., 2020) as well as this research's initial research model which assumes that brand loyalty and brand switching behavior are directly related, where decreased brand switching behavior is a sign of increased brand loyalty. With the results of the brand switching behavior scale yielding an average score of "neither

likely nor unlikely", one could therefore carefully suggest that brand loyalty is indeed fragile. Consumers are seemingly unwilling to outspokenly "commit" to a brand even when they engage with that brand.

To conclude, this research contributes to a deeper understanding of brand loyalty in the fast-moving-consumer-goods industry's online context. It found that age, income level and type of residence has a direct impact on consumer brand engagement which therefore should be used by managers in segmentation strategies for creating and structuring marketing campaigns. It was found that consumer brand engagement is mostly driven by affectionate and activation components thereby highlighting the importance of emotional bonds and engagement in fostering brand loyalty and the need for further exploration of consumer behavior in the evolving omnichannel shopping landscape.

4.2 Managerial contribution

As the market is becoming more competitive, managers need to be able to distinguish themselves from other brands to achieve or maintain brand loyalty. This can be done through specifically targeted marketing campaigns. This research found that age, income, and the type of residence has an influence on consumer brand engagement. Considering that consumer brand engagement has a direct link to brand loyalty and that brand loyalty leads to a higher return on investment and better competitive advantage, managers should use this knowledge to better structure their marketing campaigns. For example, they could focus on improving their targeted marketing strategies to specifically segment audiences by income, type of residence and age. They can design specific marketing efforts for each different segment to then build emotional connections with each of these groups. Overall, better marketing segmentation could yield higher returns on investments through higher consumer retention, consumer brand engagement and more effective market penetration.

4.3 Limitations

In the context of this study, like many other research endeavors, it was evident that limitations existed due to factors such as research design, methodology, and time constraints. The primary limitation of this research was its sample size. Despite the collection of 230 responses, certain subcategories within the data set exhibited scarcity, prompting questions about the adequacy of the dataset to discern the point of saturation within these groups. Saturation, defined by Godwill in 2015, occurs when additional data ceases to offer new insights. To attain reliable results, a 95% confidence level was deemed necessary, indicating that respondents' results had a 95%

probability of predictability, as per Israel's recommendations in 1992. Given the sample size of 230 respondents in a population exceeding one million, it was reasonable to anticipate larger margins of error.

Additionally, the research was carried out via the online platform QM Qualtrics, which allowed participants to access it outside of the reach of the researcher. Consequently, the contextual settings of the respondents were beyond the researcher's control, potentially leading to results diverging from real-world scenarios due to uncontrolled external factors. Online research inherently lacks the ability to ensure the authenticity of respondents' answers. The Qualtrics platform however does fool proof this limitation to some extent as it identifies duplicate responses, monitors response time, and detects multiple responses from the same IP address.

The final limitation of the study concerns its scope which is focused on all the categories within the fast-moving-consumer-goods industry. It is possible that brand loyalty varies significantly across different categories within this industry. By not concentrating on one specific product category, we are potentially obscuring any meaningful trends. Suggestions for future research includes replicating the study with a concentrated focus on a single product category within the industry to yield more specific and insightful results.

4.4 Future research

As a continuation of this study, future research could focus on the found relations as well repeating the same study whilst addressing the limitations. This study found no significant relation between brand switching behavior and customer brand engagement which is a new and concerning finding. More research is necessary to assess the translation of brand engagement with actual customer buying behavior. The assumption that customer brand engagement and brand switching behavior leads to brand loyalty is debatable considering the relation between brand switching behavior and customer brand engagement is disproven in the study. Therefore, future research should explore a new scale which would measure the relation between the three concepts, combining the different theoretical models.

Furthermore, future studies could focus on one singular product category within the fast-moving-consumer-goods-industry to identify trends within the industry. This could be done instead of focusing on the entire industry and prevent the obscuration of potential trends.

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Appendices

Appendix 1: Illustration CBE to BL

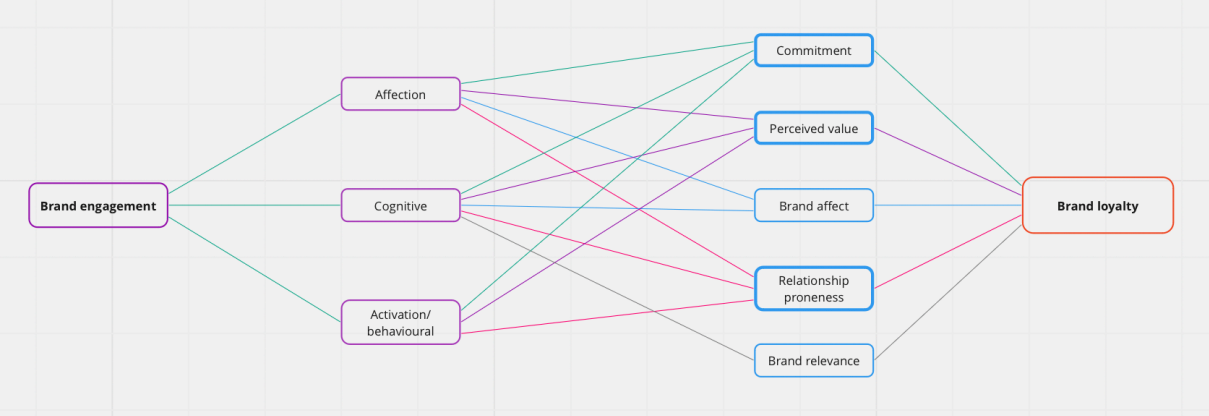


Figure 1: Linking brand engagement with brand loyalty. Source: own elaboration

Appendix 2: Previous research overview

Prior research on measuring brand loyalty lacks a unanimous methodology. The table below showcases key studies in this area, detailing their measurement approaches and findings.

Writers	Research question	Research method	Conclusions
Knox & Walker 2001	Managing and measuring brand loyalty	Purchase frequency	"Loyals", Habituals" "Variety seekers", "Switchers"
Dekimpe et al.,1997	Decline and variability in brand loyalty	Purchase frequency	Little support for trend of declining brand loyalty
Yim et al.,1999	Decline in behavioral brand loyalty	Purchase frequency	"hard core loyal" or "switchers/ reinforcing loyal"
Casteran et al., 2019	Decline in brand loyalty	Purchase frequency	Increase in brand loyalty & brand loyalty is category specific
Nagar, 2009	Effect of brand sales on brand loyalty	Purchase frequency	

Appendix 3: Detailed conceptual model

In the next figure, a more detailed version of the conceptual model can be perceived. Here, the individual most relevant traits of BL as identified by Moolla (2012) are illustrated and included in the framework.

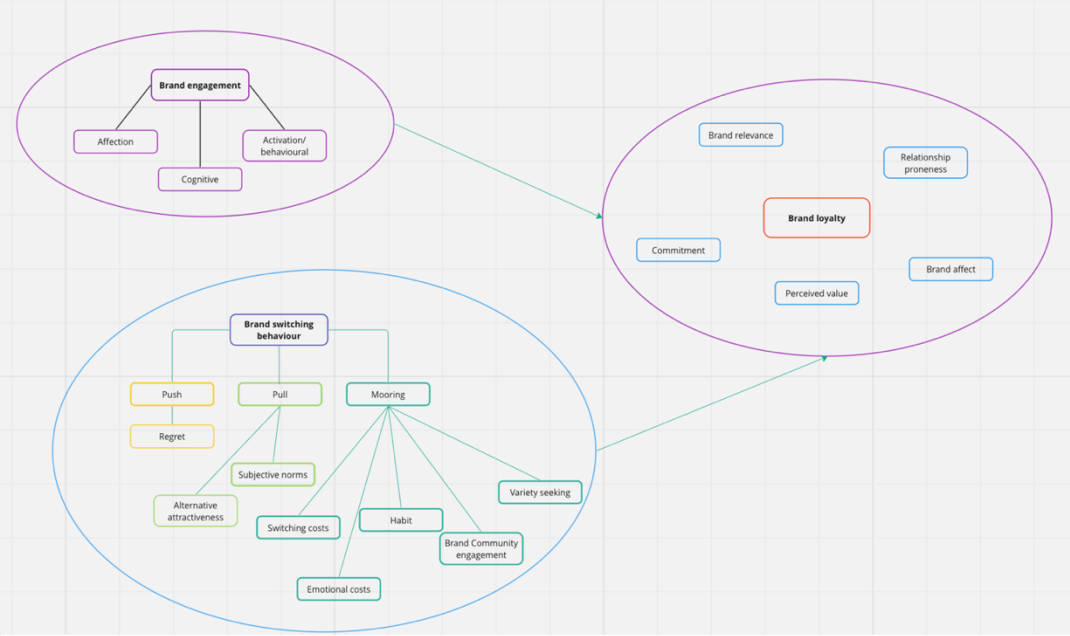


Figure 2: Conceptual framework – own elaboration

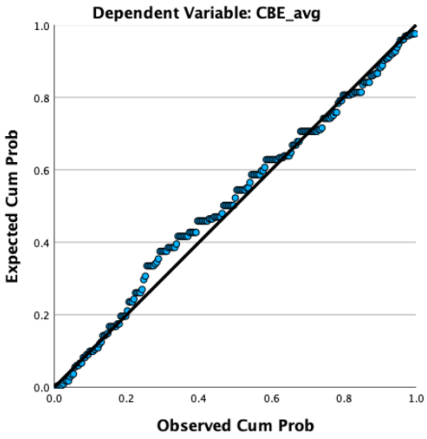
Appendix 4: Assumptions simple linear regression

Appendix 4.1: Age

Age assumptions for linear regression

1. Normal distribution

P-Plot of regressions Standardized residual CBE – Age

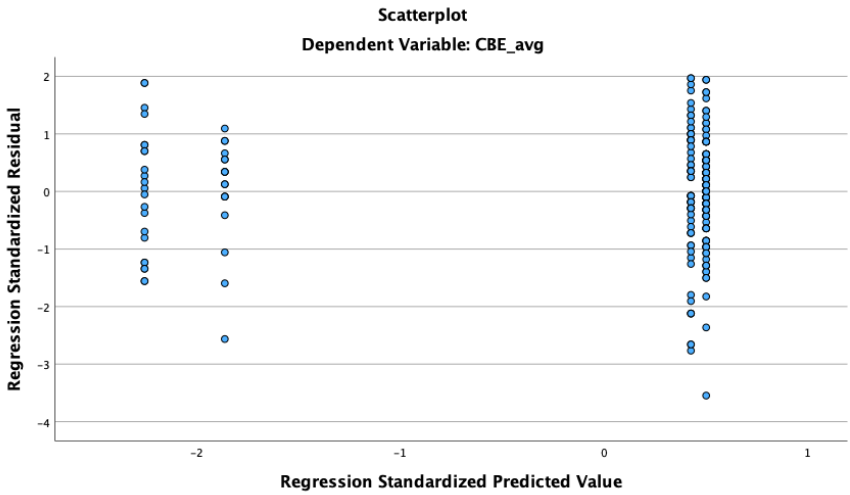


Source: Own elaboration of SPSS data

2. Homoscedasticity

Considering both the IV and DV are ordinal, testing the homoscedasticity through a regular scatter plot was insignificant as the data did not show random distribution. Heteroscedasticity assumes that the residuals for the regressions model have the same variability or spread along the regression line, which is not the case as can be seen in the figure below. This assumption not being met means the coefficients will be less accurate but it does not increase the bias in the coefficients (Mysiak, 2020)

Residuals for the regression model



Source: SPSS data; own elaboration

3. Multicollinearity

The multicollinearity was checked using the VIF values. These values do not exceed 10 in any of the table, indicating that the assumption is indeed met.

Coefficients regression model age x CBE

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients			Collinearity Statistics	
		B	Std. Error	Beta	t	Sig.	Tolerance	VIF
1	(Constant)	5.197	.087		59.954	<.001		
	Demographics_=26-35	-.026	.144	-.012	-.179	.858	.905	1.105
	Demographics_=46-55	-.813	.236	-.226	-3.452	<.001	.941	1.062
	Demographics_=56-64	-.949	.212	-.295	-4.468	<.001	.930	1.075

a. Dependent Variable: CBE_avg

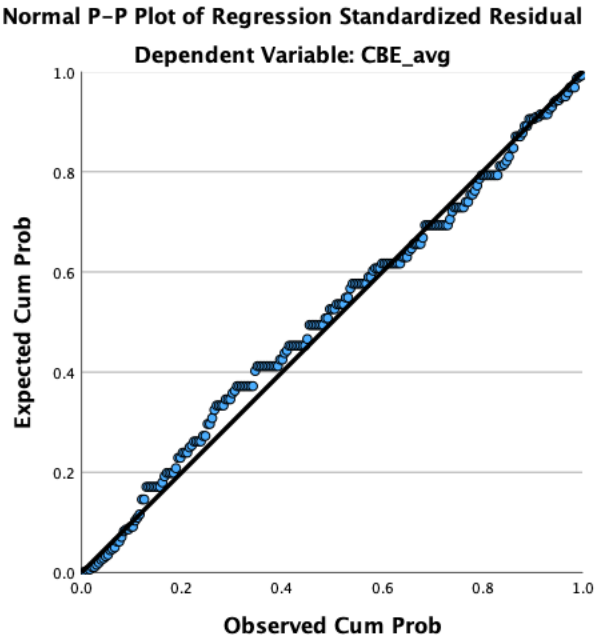
Source: Data from SPSS; own elaboration.

Customer Brand Engagement = $\beta_0 + \beta_{1X}$ **Age**

Appendix 4.2: Income

1. Normal distribution

P-Plot of regressions Standardized residual CBE - income

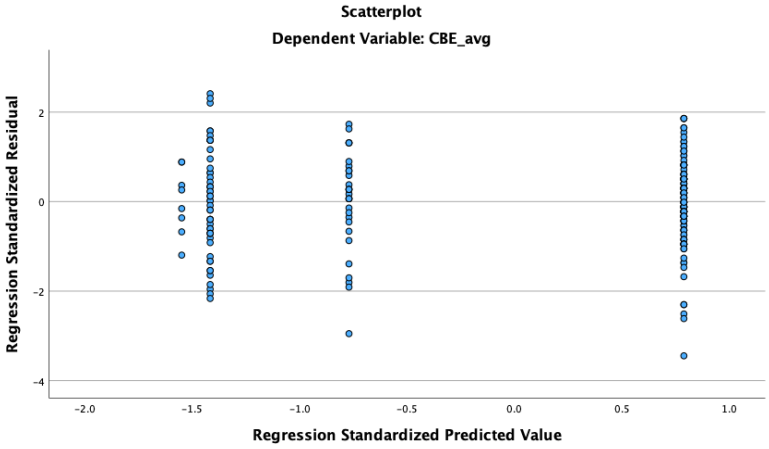


Source: Own elaboration; data obtained from SPSS

2. Homoscedasticity

Please refer to the same text about homoscedasticity for the CBE and age.

Residuals for the regression model



Source: SPSS data; own elaboration

3. Multicollinearity

The multicollinearity was checked using the VIF values. These values do not exceed 10 in any of the table, indicating that the assumption is indeed met.

Coefficients[a]

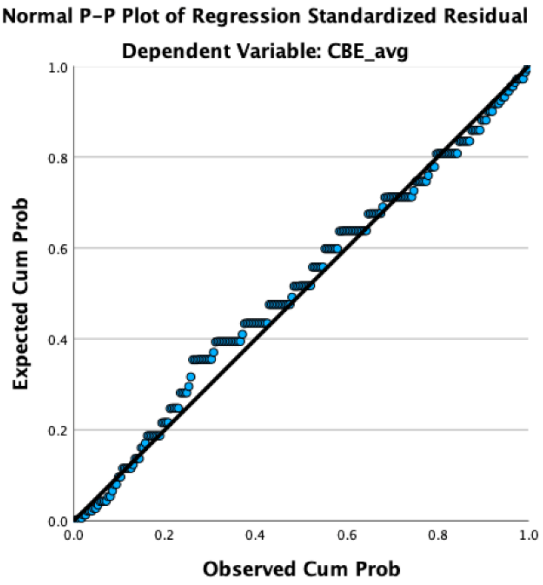
Model		Unstandardized Coefficients		Standardized Coefficients			Collinearity Statistics	
		B	Std. Error	Beta	t	Sig.	Tolerance	VIF
1	(Constant)	5.214	.083		62.758	<.001		
	Income=25 000€ - 50 000€	-.532	.159	-.227	-3.339	<.001	.941	1.062
	Income=50 000€ - 100 000€	-.376	.197	-.129	-1.910	.057	.946	1.057
	Income=100 000€ - 200 000€	-.564	.350	-.107	-1.612	.108	.979	1.021

a. Dependent Variable: CBE_avg

Appendix 4.3: Residence

1. Normal distribution

P-Plot of regressions Standardized residual CBE – type of residence

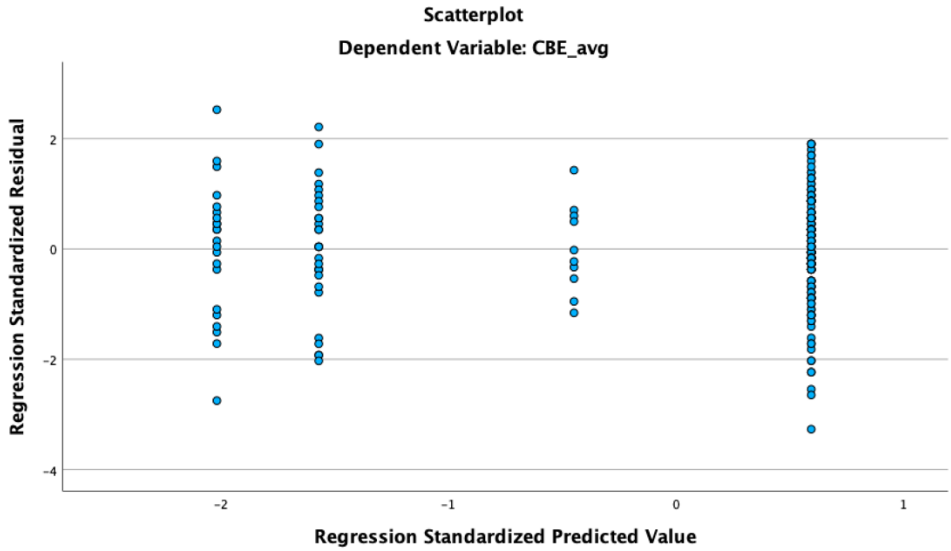


Source: own elaboration; data from SPSS

2. Homoscedasticity

Please refer to the same text about homoscedasticity for the CBE and age.

Homoscedasticity – type of residence CBE



Source: own elaboration; data from SPSS

3. Multicollinearity

The multicollinearity was checked using the VIF values. These values do not exceed 10 in any of the table, indicating that the assumption is indeed met.

Multicollinearity type of residence CBE

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients			Collinearity Statistics	
		B	Std. Error	Beta	t	Sig.	Tolerance	VIF
1	(Constant)	5.160	.077		67.292	<.001		
	Residence_area=Town	-.498	.195	-.171	-2.549	.011	.974	1.027
	Residence_area=Suburb	-.240	.315	-.051	-.761	.448	.986	1.015
	Residence_area=Rural area	-.601	.220	-.183	-2.731	.007	.976	1.025

a. Dependent Variable: CBE_avg

Source: own elaboration; data from SPSS

Appendix 5: Post-hoc Age

Multiple Comparisons

Dependent Variable: CBE_avg
Tukey HSD

(I) Which is your age group?	(J) Which is your age group?	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
18-25	26-35	.02575	.14339	1.000	-.3864	.4379
	36-45	.51081	.35971	.715	-.5232	1.5448
	46-55	.81319*	.23422	.008	.1399	1.4865
	56-64	.94870*	.21106	<.001	.3420	1.5554
	65+	-.25348	.65903	.999	-2.1479	1.6409
26-35	18-25	-.02575	.14339	1.000	-.4379	.3864
	36-45	.48505	.36757	.774	-.5715	1.5416
	46-55	.78744*	.24611	.019	.0800	1.4949
	56-64	.92294*	.22418	<.001	.2785	1.5674
	65+	-.27923	.66335	.998	-2.1861	1.6276
36-45	18-25	-.51081	.35971	.715	-1.5448	.5232
	26-35	-.48505	.36757	.774	-1.5416	.5715
	46-55	.30238	.41159	.977	-.8807	1.4855
	56-64	.43789	.39886	.882	-.7087	1.5844
	65+	-.76429	.74085	.907	-2.8939	1.3653
46-55	18-25	-.81319*	.23422	.008	-1.4865	-.1399
	26-35	-.78744*	.24611	.019	-1.4949	-.0800
	36-45	-.30238	.41159	.977	-1.4855	.8807
	56-64	.13551	.29078	.997	-.7004	.9714
	65+	-1.06667	.68871	.633	-3.0464	.9131
56-64	18-25	-.94870*	.21106	<.001	-1.5554	-.3420
	26-35	-.92294*	.22418	<.001	-1.5674	-.2785
	36-45	-.43789	.39886	.882	-1.5844	.7087
	46-55	-.13551	.29078	.997	-.9714	.7004
	65+	-1.20217	.68119	.491	-3.1603	.7559
65+	18-25	.25348	.65903	.999	-1.6409	2.1479
	26-35	.27923	.66335	.998	-1.6276	2.1861
	36-45	.76429	.74085	.907	-1.3653	2.8939
	46-55	1.06667	.68871	.633	-.9131	3.0464
	56-64	1.20217	.68119	.491	-.7559	3.1603

*. The mean difference is significant at the 0.05 level.

Appendix 6: Model summary age

Table: Model summary Age regression CBE

Model summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	0,349	0,122	0,11	0,92948

Source: own elaboration; data from SPSS

Appendix 7: Post-hoc ANOVA income groups

Multiple Comparisons

Dependent Variable: CBE_avg
Tukey HSD

(I) What is your annual income?	(J) What is your annual income?	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
Less than 25 000€	25 000€ - 50 000€	.53140*	.15914	.009	.0937	.9690
	50 000€ - 100 000€	.33175	.19466	.433	-.2036	.8671
	100 000€ - 200 000€	.49917	.31599	.512	-.3698	1.3681
	Prefer not to say	.00533	.20872	1.000	-.5687	.5793
25 000€ - 50 000€	Less than 25 000€	-.53140*	.15914	.009	-.9690	-.0937
	50 000€ - 100 000€	-.19964	.21550	.886	-.7923	.3930
	100 000€ - 200 000€	-.03222	.32923	1.000	-.9376	.8732
	Prefer not to say	-.52607	.22828	.147	-1.1538	.1017
50 000€ - 100 000€	Less than 25 000€	-.33175	.19466	.433	-.8671	.2036
	25 000€ - 50 000€	.19964	.21550	.886	-.3930	.7923

Table 1: : Post-hoc analysis Income

Appendix 8: Model summary income groups

Table: Model summary Income regression CBE

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.245[a]	.060	.047	.96177

a. Predictors: (Constant), Income=100 000€ - 200 000€, Income=50 000€ - 100 000€, Income=25 000€ - 50 000€

b. Dependent Variable: CBE_avg

Source: own elaboration; data from SPSS

Appendix 9: Post-hoc residence

Multiple Comparisons

Dependent Variable: CBE_avg
Tukey HSD

(I) What type of area do you currently live in? - Selected Choice	(J) What type of area do you currently live in? - Selected Choice	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
City	Town	.45876	.18818	.109	-.0587	.9763
	Suburb	.24908	.28726	.909	-.5409	1.0391
	Rural area	.58999	.21814	.056	-.0099	1.1899
	Other namely...	.04908	.68325	1.000	-1.8299	1.9280
Town	City	-.45876	.18818	.109	-.9763	.0587
	Suburb	-.20968	.32652	.968	-1.1076	.6883
	Rural area	.13123	.26773	.988	-.6050	.8675
	Other namely...	-.40968	.70066	.977	-2.3365	1.5172
Suburb	City	-.24908	.28726	.909	-1.0391	.5409
	Town	.20968	.32652	.968	-.6883	1.1076
	Rural area	.34091	.34465	.860	-.6069	1.2887
	Other namely...	-.20000	.73351	.999	-2.2172	1.8172
Rural area	City	-.58999	.21814	.056	-1.1899	.0099
	Town	-.13123	.26773	.988	-.8675	.6050
	Suburb	-.34091	.34465	.860	-1.2887	.6069
	Other namely...	-.54091	.70929	.941	-2.4915	1.4097
Other namely...	City	-.04908	.68325	1.000	-1.9280	1.8299
	Town	.40968	.70066	.977	-1.5172	2.3365
	Suburb	.20000	.73351	.999	-1.8172	2.2172
	Rural area	.54091	.70929	.941	-1.4097	2.4915

Appendix 10: Model summary income group

Model summary CBE type of residence

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.233[a]	.054	.041	.96686

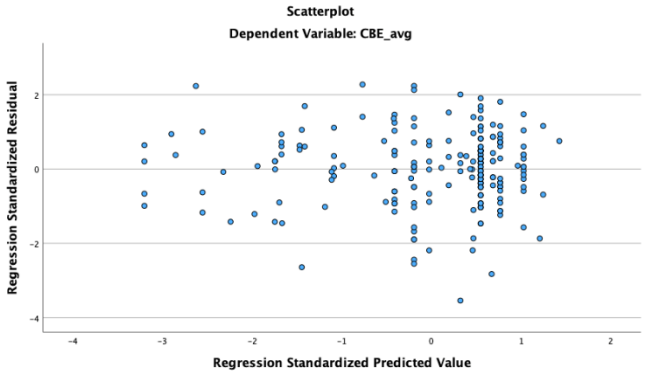
a. Predictors: (Constant), Residence_area=Rural area, Residence_area=Suburb, Residence_area=Town

b. Dependent Variable: CBE_avg

Source: own elaboration; data from SPSS

Appendix 11: Scatterplot homoscedasticity CBE

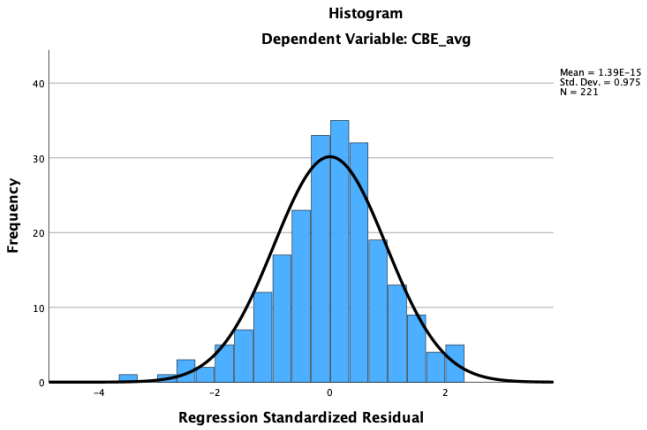
Figure 17: Scatterplot homoscedasticity



Source: Own elaboration; data obtained through SPSS

Appendix 12: histogram of distribution of residuals CBE

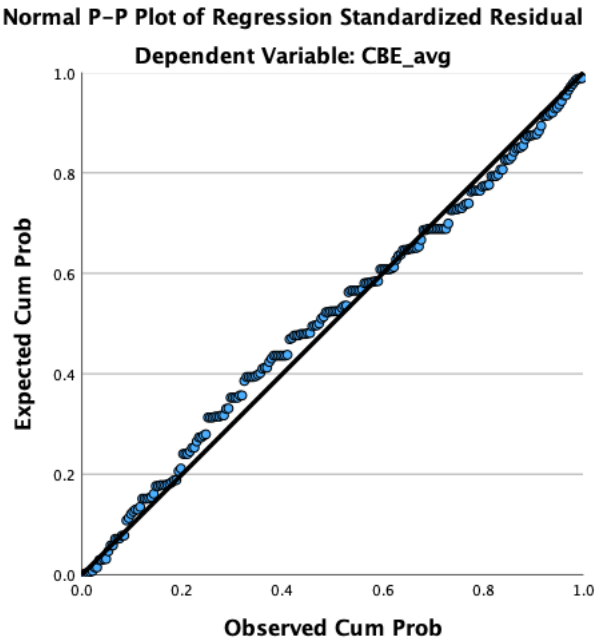
Figure 18: Histogram of distribution of residuals



Source: own elaboration, data obtained through SPSS

Appendix 13: P-plot

Figure 19: P-Plot of distribution of residuals



Source: own elaboration, data obtained through SPSS

Appendix 14: Reliability

Table Cronbach's Alpha CBE

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.880	.883	10

Source: Own elaboration; data from SPSS

Table: Cronbach's Alpha BSB

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.637	.634	9

Source: Own elaboration; data from SPSS