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By Noemi Aime

ABSTRACT

The following research aims at identifying the relationship between personality traits, customer experience and satisfaction through text mining techniques on a dataset of more than six thousand online reviews. Specifically, it assesses personality traits based on linguistic cues through *Linguistic Inquiry and Word Count* dictionaries, finding a negative effect of neuroticism on star rating and word of mouth and an opposite effect of conscientiousness. Moreover, it investigates what aspects of the customer experience mostly emerge from reviews, differentiating among a total of 10 topics and assessing their relative effect on star rating and word of mouth. Ultimately, the study analyzes the moderating effect of personality in shaping the relationship between product or service attributes and the dependent variables, finding a consistent strengthening effect of neuroticism on negative attributes. Last but not least, a deep dive on the effect of user location reveals the importance of big cities for word of mouth spread.

1. INTRODUCTION

A great customer experience requires the right message or product
to the right person at the right time in the right place.
(Fanderl, Maechler & Perrey, 2014)

1.1. Phenomenon, Managerial Relevance, and Problem

Customer experience, in its holistic nature, does find in individual differences an important component of its whole. As a consequence of the growing 'customer-centric' managerial mindset, purchase journeys aim to be more and more based on individual customer profiles (Agarwal et al., 2020). Indeed, it is of fundamental importance for success to deliver 'the right message or product to the right person at the right time in the right place' (Fanderl, Maechler & Perrey, 2014) and to deliver upon expectations. To win competitors and deliver an extraordinary customer experience, personality traits become an essential part of analysis as they are increasingly seen as a non-cognitive skill that impacts individuals' economic decisions and consequent outcomes (Cobb-Clark & Schurer, 2012; Rentfrow & Gosling, 2003). These arguments are the foundations of the following research, whose focal point will be to assess from online reviews the direct link between personality traits and satisfaction – measured as star rating – and word of mouth – measured as likelihood to recommend – and to see the weight that different personalities assign to negative or positive attributes during post-purchase customer experience online. The relevance of this analysis is supported by the growing importance of the online setting as a consequence of the pandemic. Specifically, the e-commerce has become the preferred channel (Fedewa & Holder, 2022), leading to an increase in available textual data. Not only, it has also been proved that customers are influenced by other customers' reviews and word of mouth even more than they are by alternative marketing activities (Fedewa & Holder, 2022; Hu, Liu & Zhang, 2008; Zhu & Zhang, 2010). This, together with the advances in analytical tools and the applicability of the abundant language-based methods in the modern digital age (Boyd & Pennebaker, 2017), facilitates the shift to text mining techniques, capable of identifying important customer experience insights from online reviews.

Targeting consumers based on personality traits, rather than only on past behavior and explicit preferences, allows for a better message tailoring. Graves and Matz (2018) argue that 'the potential payoff of using personality science is to be able to better match how you engage individuals by personality profile, and to predict behaviors by personality traits'. Among other positive consequences, personality-based management and segmentation gives the possibility to tailor the entire customer journey based on customer's preferences, interests, and foremost on individuals' unique ways of reacting and responding to proposals (Rawat & Mann, 2016; Sarker et al., 2013; Storlie, 2021), thereby offering opportunities to better connect with customers (Graves & Matz, 2018), ultimately improving the overall customer experience in terms of costs, return on investment, revenues, trust, loyalty and possibly reducing failures (Agarwal et al., 2020). In case of need, this approach also offers the chance to personalize responses when the customers reach out for help or issues (Agarwal et al., 2020), providing benefits to overall complaint management.

Yet, there is little research on the automatic recognition of personality traits (Mairesse et al., 2007) and many companies do not have specific programs in place to measure personality from textual data (Agarwal et al., 2020; Fedewa et al. 2021) and still do not act in this direction – overlooking the relevance of personality assessment for customer experience management – for several motives, including the costs of doing so, both in terms of money, time, organizational effort, and in terms of ability (Agarwal et al., 2020; Markey, 2020). One aspect that needs consideration related to profiling based on personality traits is that the latter are not fixed over time, rather change, both in a systematic and unsystematic way, which could provide difficulties in tracking.

1.2. Current Research and Gaps

Previous research in this field strongly highlights the holistic nature of customer experience (Lemon & Verhoef, 2016), the role of emotions, and their moderating effect on satisfaction and loyalty (Kuuru et ell., 2020; Manthiou, et al., 2020). At the same time, many authors of the psychological area have deeply investigated consumer personality. Academic works highlight the connection between personality and consumer's tastes (Hu & Pu, 2010), involvement (Rawat & Mann, 2016), decision making processes (Rentfrow & Gosling, 2003), and brand preference (Lin, 2010; Mann & Rawat, 2016). Matzler, Bidmon & Grabner (2006) and Tsao & Chang (2010) have confirmed the influence of personality – specifically the Big Five personality traits – on consumers' evaluation of products. Also, previous studies identify an effect of personality on the likelihood to write online reviews (Manner & Lane, 2017; Marbach, Lages & Numan, 2016; Picazo-Vela et al., 2010; Swaminathan & Dokumaci, 2021; Tata, Prashar & Parsad, 2021).

However, in comparison, still limited research tries to investigate the specific link between personality traits – rather than emotions – and overall customer experience. Going deeper, an investigation of the effect of specific personality types on star rating and, even more, on the likelihood to recommend, relating such variables also to specific product attributes considered important in the post-purchase customer experience is lacking. Last but not least, most previous studies of personality have assessed individual differences through self-reported questionnaires (Boyd & Pennebaker, 2017), while the use of textual data and text mining techniques is still scarce in the field. Yet, research has highlighted the limitations of self-reported measures or, better said, the advantages of language analysis (Boyd et al., 2015; Fast & Funder, 2008; John & Robins, 1993; Kolar, Funder & Colvin, 1996; Mehl, Gosling & Pennebaker, 2006; Spain, Eaton & Funder, 2000) and the following paper will consider this aspect as an important milestone.

1.3. Theory and Framework

The basis of the following research can be found in the five-factor model of personality (also known as the Big Five model), which finds its foundation in the *Lexical Hypothesis* that argues that main individual differences are encoded in language use (Allport & Odbert, 1936). Nowadays, the Big Five theory is still at the core of many studies regarding personality. It identifies five main personality types – agreeableness, conscientiousness, extraversion, neuroticism, and openness to experience – and it represents a robust model for understanding personality traits and related differences in terms of purchase motivations, preferences, interests, attitudes, and differences in emotions (Costa & McCrae, 1980; Hu & Pu, 2010; Rawat & Mann, 2016; Rentfrow & Gosling, 2003; Rusting & Larsen, 1997; Tsao & Chang, 2010). Given the proved association between personality and language use (Berger et al., 2019; Boyd & Pennebaker, 2017; Mairesse et al., 2007; Qiu et al., 2012; Yarkoni, 2010), the following paper will exploit the use of the *Linguistic Inquiry and Word Count* framework (LIWC, 2022) to identify the five personality traits through an analytical approach. The selection of vocabularies and words that will be used for each personality type will be decided based on previous studies.

1.4. *Contributions*

The following analysis will first of all contribute to the psychological stream of research by giving further evidence to the link between personality and language use, expanding its proof of existence in the e-commerce setting and in the tobacco industry, by examining consumers' spontaneous writing in online reviews.

Compared to most of the previous studies on personality traits, whose aim was mainly to investigate its link with linguistic cues, this research will also contribute to the literature on the link between personality and post-purchase customer experience online, therein fulfilling the existing gap, by investigating the relationship between different categories of consumer's personalities and product or service attributes that shape post-purchase customer experience online. This will give important and new insights to managers regarding the link between personality and customer satisfaction, in the form of star rating and likelihood to recommend, contributing to the understanding of what companies should leverage on – in a personality-based segmentation setting – to improve online consumer engagement.

Worth pointing out is also the method that this research will exploit, which allows to overcome the limitations of self-reported questionnaires and represents an innovative technique in the field of personality and customer experience. Indeed, using the largely available textual data is the future of customer experience management (Diebner et al. 2021; Holmlund et al. 2020; McColl-Kennedy et al., 2018). Specifically, the use of text mining techniques and language-based measures adds important insights to the existing literature and managerial understanding, as it allows to assess the embedded constructs and aspects that underpin personality (Boyd & Pennebaker, 2017; Pennebaker & King, 1999). Language-based measures have, indeed, been proved to be more predictive of behavior and preferences than self-reported measures (Boyd & Pennebaker, 2017; Tausczik & Pennebaker, 2009). Also, LIWC's reliability and strength in assessing individual differences based on the use of language is of no doubt (Boyd & Pennebaker, 2017; Pennebaker & King, 1999; Tausczik & Pennebaker, 2009).

2. LITERATURE REVIEW

2.1. *Customer Experience and Online Reviews*

Starting from the broad argument of Abbott (1955) stating that 'what people really desire are not products but satisfying experiences', the notion of customer experience became more encompassing, central to marketing activities (Homburg, Jozić & Kuehnl, 2015; Lemon & Verhoef, 2016) and crucial for market competitiveness (Kranzbühler et al., 2017). Yet, the growing number of studies investigating the concept has led to confusion and fragmentation (Becker & Jaakkola, 2020). In 2016, Lemon and Verhoef identified the holistic nature of the construct that is nowadays widely accepted among researchers and marketers. They argued how customer experience is shaped by customer's cognitive, emotional, behavioral, sensorial, and social responses to a company's offer over time and across multiple touchpoints. Customer experience can, indeed, be managed and influenced through different touchpoints at different stages of the customer journey over time (Herhausen et al., 2019; Kuppelwieser & Klaus, 2021; Lemon & Verhoef, 2016; McKinsey, 2019). As a consequence, insights about how to improve overall customer experience and linked satisfaction should be inferred and measured pre, during and after purchase (Klaus, 2015).

A positive customer experience is argued to result in both short-term and long-term improvements in terms of sales and retention (Court et al., 2018), revenues and returns (Markey, 2020), satisfaction (Lindecrantz, Gi & Zerbi, 2020), and loyalty (Agarwal et al., 2020; Villarroel Ordenes, Diaz Solis & Herhausen, 2021). Among other measures, satisfaction score, NPS and EXQ Scale have been the most widely used measures of customer experience (De Haan & Menichelli, 2020; Diebner et al., 2021; Kuppelwieser & Klaus, 2021; Villarroel Ordenes, Diaz Solis & Herhausen, 2021). However, such measures have been proved to report several limitations in terms of response rate and ambiguity about performance drivers (Diebner et al., 2021), and also fail to reveal the more profound processes of individuals' preferences (Boyd & Pennebaker, 2017). This aspect, together with the explosion of text data generated by consumers has led to a shift from traditional customer feedback metrics to a deeper analysis of available unstructured data.

The advent of internet and technology has created an entirely new way of managing customer experience, affecting how consumers respond to stimuli and offerings (Holmlund et al. 2020; Kumar & Anjaly, 2017). Park, Cho & Rao (2012) highlight the strong contribution of post-purchase processes to overall experience and repurchase intentions and the importance of delivering upon expectations, arguing that consumers mostly complaint when the product does not meet expectations in terms of performance, size, color, or design. With a focus to post-purchase user-generated content (UGC), research has proved the relevance of deeply understanding online reviews, indicating digital behaviors as a reliable source of prediction for personality traits (Azucar, Marengo & Settanni, 2018). The trust and reliance of consumers on online reviews has and keeps increasing consistently (Hu, Liu & Zhang, 2008; Lee et al., 2019; Liu et al., 2021; Zhu & Zhang, 2010): 93% of them state that reviews impact their purchasing decisions, with 60% who read reviews on a weekly basis (Fullerton, 2017). The emergence and growth of social media, e-commerce, and other online platforms has increased the availability of textual data (Azucar, Marengo & Settanni, 2018; Holmlund et al., 2020; Mehl, Gosling & Pennebaker, 2006) but the intensity of customer-generated content online has also been growing has a consequence of the Covid-19 pandemic, which has led to a further explosion of the e-commerce business (Fedewa et al., 2021) and of online reviews. Using the largely available textual data has, thus, been argued to be the future of customer experience management (Diebner et al., 2021; Holmlund et al., 2020; McColl-Kennedy et al., 2019) as, nowadays, numerous people express their thoughts and beliefs by writing posts and reviews (Azucar, Marengo & Settanni, 2018), which reflect one's spontaneous self and actual personality and traits (Back et al., 2010; Seidman, 2013).

2.2. *Personality Traits and Language*

2.2.1. The Big Five Model of Personality

Personality traits are at the core of many psychological studies but have also found interest in economics and marketing research. The Big Five Model of personality traits is the most widely accepted and explored framework by researchers for measuring personality (McCrae & Costa, 1987; McCrae & John, 1992), due to its stability, validity, and generalizability (Gebauer et al., 2014; Kluemper et al., 2015; Simha & Parboteeah, 2019). Such theory identifies five main categories of personality, namely neuroticism, conscientiousness, agreeableness, openness to experience and extraversion.

In particular, McCrae & Costa (1987) define *neurotic* individuals (vs emotionally stable) as worrying, insecure, self-conscious, and temperamental and associate such personality trait with impulsive behaviors, including the tendency to overeat, smoke and drink excessively (Costa & McCrae, 1980). Teilegen (2019), instead, views neuroticism as the propensity to experience negative emotions. Other authors link to neuroticism mistrust and self-reference (Guilford, Zimmerman & Guildford, 1976), irrational beliefs (Vestre, 1984), anger (Mehl, Gosling & Pennebaker, 2006), and anxiety (Komarraju et al., 2011). Personalities associated with neuroticism thus tend to present hostile reactions, disruptive emotions, and irrational beliefs. However, even if with less strength, being sociable and talkative is also correlated with neuroticism (Komarraju et al., 2011).

Consciousness is associated with being independent, disciplined, organized, careful, efficient, and achievement- and goal-oriented (Mairesse et al., 2007; Mehl, Gosling & Pennebaker, 2006; Rawat & Mann, 2016) and seems to facilitate learning and performance (Komarraju et al., 2011). Grohol (2019) relates consciousness with an individual's ability to regulate impulse control to prioritize goal-directed behaviors. Conscious individuals are more prone to follow rules and norms (Giluk & Postlethwaite, 2015; Roberts et al., 2009), appear more diligent and hard-working and usually meet expectations (Kalshoven et al., 2011; Simha & Parboteeah, 2019). McFerran et al. (2010) link consciousness to the propensity to be honest and engage in socially advantageous behaviors.

The personality trait defined as *agreeableness* is related to being helpful, sympathetic, honest, and altruistic (Goldberg, 1990; Kalshoven et al. 2011; Komarraju et al., 2011; McCrae & Costa, 1987). Agreeable individuals tend to cooperate with others and avoid conflicts (Giluk & Postlethwaite 2015; Graziano & Tobin 2009; Graziano et al. 1996), forgive (Lim, 2020) and to be in accordance with the rules established by others (Rawat & Mann, 2016; Tsao & Chang, 2010).

Individuals whose personality falls within the openness to experience trait are argued to be curious about new experiences, new methods and ideas, as well as others' viewpoints and options (Mehl, Gosling & Pennebaker, 2006; Simha & Parboteeah, 2019; Rawat & Mann, 2016). They are imaginative, spontaneous, unconventional, creative, and tend to have a wide range of interests for which they express strong excitement (John & Srivastava, 1999; Mehl, Gosling & Pennebaker, 2006; Rawat & Mann, 2016).

Last but not least, the framework identifies *extraversion*. Extraverted individuals tend to be particularly talkative, sociable, fun-loving, assertive, and enthusiastic (Costa & McCrae, 1992; Goldberg, 1990; Komarraju et al., 2011; Mehl, Gosling & Pennebaker, 2006). They are likely to experience positive affect (Campbell, 1983; Smits & Boeck, 2006) and enjoy engaging in social situations and activities (Snyder, 1983). Rawat & Mann (2016) associated such personality traits with being advantageous, outgoing, and energetic.

2.2.2. Personality, Customer Experience and Language use

Research has proved the link between personality and customer experience. Personality may be predictive of many aspects of life and different traits reflect individuals' behavioral characteristics and emotions expression and shape responses to stimuli. Personality can, indeed, explain several differences in consumption behavior, purchase decisions and preferences. Academic works highlight the connection between personality and consumer's tastes (Hu & Pu, 2010), involvement (Rawat & Mann, 2016), decision making processes (Rentfrow & Gosling, 2003), and brand preference (Lin, 2010; Mann & Rawat, 2016). Personality characteristics are argued to have an effect on individuals' feelings, attitudes, and behavior (Boyd & Pennebaker, 2017; Mann & Rawat, 2016; Pennebaker & King, 1999; Singh, 1990). Matzler et. al (2006) and Tsao & Chang (2010) have confirmed the influence of personality – specifically the Big Five traits – on consumers' motivation and evaluation of products. Research also reveals the role of personality in shaping consumers' emotions and attachment in response of the experience with the brand or product (Orth, Limon & Rose, 2010; Rawat & Mann, 2016). Cobb-Clark & Schurer (2011) highlight how embedded individual differences influence consumers' decisions and consequent outcomes. Bosnjak, Galesic & Tuten (2007) represent personality as an antecedent of consumers' willingness to purchase online. Other authors argue how important it is for companies to shape their offerings and communication based on target customers' personalities and to categorize consumers on the base of specific personality traits (Rawat & Mann, 2016; Sarker et al., 2013; Storlie, 2021), which supports and further strengthen the expanding customer-centric mentality.

Overall, customer experience can be improved by focusing on the consequences that each product attribute may have on different customers due to their personalities (Nunes & Hu, 2012), as consumer personality is a fundamental determinant of product's experiencing (Mann & Rawat, 2016). Lin (2010) also argues that an alignment between consumer's and brand's personality improves customer experience and customer's attachment to the brand. In this perspective, research also proves that including personality assessment in customer experience management may increase return on investment, purchase probability, and even improve post-purchase processes such as satisfaction and loyalty (Singh, 1990; Tan, Der Foo & Kwek, 2004; Rawat & Mann, 2016; Tsao & Chang, 2010; Orth, Limon & Rose, 2010; Agarwal et al., 2020). Studies have also highlighted the impact of personality on complaint behavior (Berry et al., 2014; Gursoy, McCleary & Lepsito, 2007; Jones, McCleary & Lepisto, 2002), with a focus on online shopping (Huang & Chang, 2008). Thus, understanding the different consumers profiles may not only allow companies to prevent issues (Agarwal et al., 2020) but may also lead to improvements in the ability to manage and solve complaints (Berry et al., 2014), as individuals with different personalities differently face problems or the failing of delivering on expectations and also respond to complaint management in different ways, thus personalizing the response is of high value for businesses (Agarwal et al., 2020).

With such framework in mind, the idea that specific characteristics of individuals' personality and consequent preferences and behavioral outcomes are embedded in spontaneous language use has lately grown in importance (Berger et al., 2019; Boyd & Pennebaker, 2017; Hovy, Melumad & Inman, 2021; Humphreys & Wang, 2018; Packard, Moore & McFerran, 2018; Yarkoni, 2010). Most of past research has tried to identify differences in personality and their link with customer experience preferences through self-reported measures (Boyd & Pennebaker, 2017). Yet, surveys have several limitations in assessing personality: they only reveal individuals' explicit idea of who they are (Boyd & Pennebaker, 2017), they are sometimes hard to apply in particular contexts such as e-commerce because of their length and time requests and may be influenced by the desirability of the trait (Mairesse et al., 2007). Authors highlighted the urgence of linking individuals' personalities to spontaneous behaviors and interactions in natural environments so that the correlation between personality and language use was not influenced by demand characteristics (Bradac, 1999; Mehl, Gosling & Pennebaker, 2006; Yarkoni, 2010). The large availability of text data generated by consumers online together with the improvement of tools and strategies for analyzing language facilitate the emergence of this stream of research and give space to deep improvements in accuracy (Azucar, Marengo & Settanni, 2018; Hovy, Melumad & Inman, 2021; Humphreys & Wang, 2017; Tausczik & Pennebaker, 2009), leading scholars to investigate the relationship between digital footprints and psychological characteristics more deeply.

The roots of psychological text analysis go back to Freud's idea that a person's hidden intentions are revealed in apparent linguistic mistakes. From here, research has kept investigating this phenomenon. Pennebaker & King (1999), but also Boyd and Pennebaker (2017), argued that language use differs consistently among people and can be considered reliable and internally consistent. Other studies also find association between personality and word use (Boyd & Pennebaker, 2017; Hirsh & Peterson, 2009; Mehl, Gosling & Pennebaker, 2006; Pennebaker & King, 1999), and suggest that content generated online reflects the actual personality of individuals (Back et al., 2010; Seidman, 2013; Yarkoni, 2010) and that personality can be assessed by computers through linguistic cues (Mairesse et al., 2007). The way people express their feelings, thoughts, intentions, and preferences varies consistently and is expressed in its fundamental nature in individuals' language use (Boyd & Pennebaker, 2017; Hovy, Melumad & Inman, 2021), which reflects who we are and our social relationships (Tausczik & Pennebaker, 2009). Moreover, language-based measures allow to shed light on psychological features that underpin personality and on lower-level processes (Boyd & Pennebaker, 2017). 'Language use may be thought of as an arena in which the impact of the person is unavoidable' state Pennebaker & King in 1999. With this idea, they have developed a computer program – *Linguistic Inquiry and Word Count (LIWC)* – with two essential features, the processing component and the dictionaries, which has been proved to be a robust tool for measuring individual personalities (Boyd & Pennebaker, 2015; Boyd & Pennebaker, 2017; Mairesse et al., 2007; Pennebaker, Booth and Francis, 2007; Tausczik & Pennebaker, 2009). Essentially, the processing features opens text files and compares each word with the dictionary file (Tausczik & Pennebaker, 2009). Research has shown that some of the existing LIWC categories correspond with the big five personality traits, as shown in Table 1 (Mairesse et al., 2007; Mehl, Gosling & Pennebaker, 2006; Pennebaker & King, 1999; Qiu et al., 2012; Yarkoni, 2010). In particular, these studies have shown the prevalence of social and uttered words, as well as of words indicative of positive emotions, friendliness and cheerfulness and few first-person singular pronouns and few words per sentence for extravert individuals. People falling within the agreeable personality trait instead avoid the use of swear and emotionally negative words, but use some sexual words, whereas conscious people tend to terms of optimism, home, school, and occupation. Neuroticism was correlated with the use of negative emotion words. Openness to experience was instead link to a tendency to refrain from third-person pronouns and past tense verbs, while using longer words and words associated with intellectual or cultural experience.

Thus, unstructured data analysis – in the form of language use investigation – can reveal important differences in terms of consumers' personality, shedding light on the profound needs and preferences of each individual, allowing mangers to reach a more efficient targeting and long-lasting gains for the business.

Table 1: overview of correlation between LIWC categories and the Big Five personality traits

STUDY	NEUROTICISM	EXTRAVERSION	OPENESS TO EXPERIENCE	AGREEABLENESS	CONSCIENTIOUSNESS
Mairesse et al., 2007	affect; anger; anxiety; feeling; first person sing; negations; negative emotions; present tense verbs; pronouns; sadness; total first person; word count; words captured	first person plur; friends; other references to people; positive emotions; positive feelings; pronouns; sexuality; social processes; total first person; total third person	anger; apostrophe; articles; comma; exclusive; metaphysical issues; music; other references to people; parenthesis; positive feelings; punctuation; question; quote; religion; seeing; semi-colon; sexuality; swear words; total second person; type/token ratio; words longer than 6 letters; words per sentence	exclamatio; family; school; time; total first person; words captured	future tens verbs; home; occupation; optimism; prepositions; school; time; words captured; work and job

STUDY	NEUROTICISM	EXTRAVERSION	OPENESS TO EXPERIENCE	AGREEABLENESS	CONSCIENTIOUSNESS
Qiu et al., 2012	anger; body; negative emotions; personal pronouns; sadness; sexual; swear words; total pronouns	affective processes; perceptual processes; personal pronouns; positive emotions; present tense; social processes; swear words; third person plur	perceptual processes	positive emotions	cognitive processes; prepositions; quantifiers; work
Yarkoni, 2010	anger; causation; certainty; cognitive proocesses; discrepancy; first person sing; negations; swear words; tentative	communication; first person plural; hearing; humans; music; religion	inclusive	down; friends; positive feelings; sleep; social processes; time; total pronouns; up	-
Pennebaker & King, 1999	first person sing; negative emotions	social processes; positive emotions	words of more than 6 letters; articles; tentative;	-	-
Positive correlation; sig. 0.01					

Table 2: Literature Review Overview

STUDY	AREA of RESEARCH	GOAL	KEY FINDINGS
Lemon & Verhoef, 2016	Customer Experience	To develop a stronger understanding of customer experience and the customer journey in the era of increasingly complex customer behavior.	Customer experience is a holistic construct, entailing cognitive, emotional, behavioral, sensorial, and social aspects.
McCrae & Costa, 1987	Personality	To examine the correspondence between assessments of five major personality dimensions among peer ratings and between peer ratings and self-reports.	Results show cross-observer and cross-instrument validation for all five factors, posing the model as a reliable framework.
Holmlund et al., 2020	Customer Experience and Big Data	To develop a strategic framework for CXM based on CX insights resulting from BDA.	Results show the relevance of CX data and how to transform them into CX insights through analytics.
Diebner et al., 2021	Customer Experience and Big Data	Presenting the advantages of reducing the use of survey-based measures for customer experience, moving towards textual data.	They provide fact base to the shortcomings of surveys, showing how companies that have implemented data-driven CX management have had improvements.
Tausczik & Pennebaker, 2009	Customer Experience and Language Use	To review computerized text analysis methods and describe how Linguistic Inquiry and Word Count (LIWC) was created and validated.	LIWC is able to detect meaning in a wide variety of experimental settings, and also to show individual differences.
Agarwal et al., 2020	Customer Experience and Personality	Explaining the importance of tailoring customer experience to individual profiles.	Results show that personalized offering reduces costs, allows for issues prevention, and increases trust, revenues, and loyalty. It also allows for personalized complaint responses.
Berry et al., 2014; Huang & Chang, 2008	Customer Experience and Personality	To investigate the effect of personality types on consumer complaint.	Results show that personality characteristics have an influence on consumer complaints, also with reference to online shopping.
Rawat & Mann, 2016	Customer Experience and Personality	1) To identify the role of consumer personality and consumer involvement in evaluation of a product; 2) to find the emotions that product evaluation elicits due to the usage of the product; 3) to understand the level of satisfaction customer experience results into.	Results show that consumer personality plays an important role in evaluation of the product and elicitation of the emotions, which helps to predict the consumer's level of satisfaction.
Tsao & Chang, 2010	Customer Experience and Personality	To investigate the impacts of personality traits of e-shoppers on their purchase behavior.	Results show that the Big Five personality traits have an impact on online shoppers' purchase motivation, with differences based on hedonic or utilitarian products.
Orth, Limon & Rose, 2010	Customer Experience and Personality	To examine how store-evoked affect, human personality, and brand personality influence consumers' emotional attachments to brands.	Results show the effect of the Big Five personality traits on consumers' emotional attachment to a brand, with a mediating role of satisfaction, and ultimate effect on loyalty.

STUDY	AREA of RESEARCH	GOAL	KEY FINDINGS
Boyd & Pennebaker, 2017	Personality and Language Use	To explain the link between personality and language use, with a focus on big data.	Results show that language-based measures of personality can be useful for capturing/modeling lower-level personality processes that are more closely associated with important objective behavioral outcomes than traditional personality measures.
Mehl, Gosling & Pennebaker, 2006	Personality and Language Use	To examine the expression of personality in a natural habitat.	It identified a number of ways in which participants' personalities were manifested in their daily social interactions, locations, activities, moods, and language use – with an effect of gender.
Yarkoni, 2010	Personality and Language Use	To analyze the relationship between personality and language, using participants for whom extremely large and topically diverse writing samples were readily accessible – namely, bloggers.	Results show that personality correlates for virtually all LIWC categories, both for broad word categories and individual words, suggesting that personality plays a relatively pervasive role in shaping the language people use.
Pennebaker & King, 1999	Personality and Language Use	To investigate the degree to which language use is reliable across time and topic, possesses a reliable factor structure, and exhibits good construct and divergent validity in comparison with established personality measures.	It proved that linguistic style represents a meaningful way to explore personality. Language use is a reliable individual difference, across time and situations.
Mairesse et al., 2007	Personality and Language Use	To report experimental results for recognition of all Big Five personality traits, in both conversation and text, utilizing both self and observer ratings of personality.	Results show that personality can be automatically recognized by computers through language cues. Observed personality may be easier to model than self-reports.
Azucar et al., 2018	Personality and Language Use	To determine the predictive power of digital footprints collected from social media over Big 5 personality traits, investigating the impact of different types of digital footprints on prediction accuracy.	Results show the predictive power of digital footprints over personality traits and that accuracy improves when analyses include demographics and multiple types of digital footprints.

3. HYPOTHESIS

Having assessed the differences between the Big Five personality traits, IQOS case will be used for assessing relevant connections between such psychological characteristic and post-purchase customer experience processes. The following analysis will focus on neuroticism and conscientiousness. Many studies have examined the relationship between personality and smoking behavior and, despite the divergences among research, the majority of them find a correlation of smoking habits with neuroticism and extraversion and lower support for the relation between smoking and conscientiousness, openness to experience, and agreeableness. Among the five personality traits, the strongest evidence has been found for neuroticism (Cherry & Kiernan, 1976; Gilbert & Gilbert, 1995; Munafò, Zetteler & Clark, 2007; O'Gara et al., 2008; Terracciano & Costa, 2003; Waters, 1971). Such personality trait has been identified as a driver of initiation and cessation dynamics (Leventhal & Cleary, 1980). Indeed, smokers tend to score higher on neuroticism compared to non-smokers and are argued to smoke to reduce anxiety and tension (Berlin et al. 2003; Eysenck, 1980) because of their low ability of control and resistance to cravings (Terracciano & Costa, 2003).

Besides the relation with smoking, personality traits have also been more recently indicated as predictors of the likelihood, way, and motives of writing reviews and of spreading eWOM. In this sense, the embedded characteristics of neurotic individuals drive a tendency to be sensitive to negative events and to easily get frustrated and upset (Manner & Lane, 2017; Picazo-Vela et al., 2010, Tata, Prashar & Parsad, 2021), as well as to be willing to release those negative emotions (Marbach, Lages & Numan, 2016; Swaminathan & Dokumaci, 2021). Neurotic individuals will thus be more propense to the externalization of bad moods and irritability (Tata, Prashar & Parsad, 2021), negative aspects and punishment signals (Swaminathan & Dokumaci, 2021). Studies also argue that neurotic individuals find in the venting of negative feeling a motive for creating word of mouth and find a significant effect of neuroticism on negative eWOM (Manner & Lane, 2017, Swaminathan & Dokumaci, 2021). With respect to the other personality traits, results are often mixed, but most papers find agreeableness and conscientiousness to be significant predictors of the likelihood to provide reviews and spread eWOM, with a direction opposite to that found for neurotic individuals. Among research, slightly stronger evidence for conscientiousness has been found. Based on the support that the literature provides for the relationship between neuroticism and conscientiousness with smoking, and the directions of their effect on the likelihood to and modes of providing online reviews and spread word of mouth, it is hypothesized that:

H1a: neuroticism will have a negative effect on star rating and word of mouth
H1b: conscientiousness will have a positive effect on star rating and word of mouth

Moving on to deeper details on the relationship between personality, customer experience and satisfaction – in terms of star rating and word of mouth intentions – the following analysis tests the effect of specific post-purchase product attributes on such variables, in the smoking industry. Online customer experience is a complex environment, where consumers receive an extended number of stimuli that might affect their perception of the brand and product, and individuals may place different levels of priority to different attributes (Hu & Pu, 2010; Lin, 2010; Mann & Rawat, 2016), affecting satisfaction. Aspects such as functionality, cost, aesthetic, charging capacity, ease of use, quality, practicality, product availability and delivery, and others have long been argued to be important components of overall customer experience. Going more in details, despite the low availability of studies investigating consumers' perception of IQOS attributes specifically, Hair et al. (2018) reported the results of a focus group that described IQOS as a clean, chic, and pure product, revealing packaging, lack of ash and smoke and social acceptability as positive attributes of the product, together with the possibility to use it even in areas where combustible cigarettes are forbidden. On the other hand, consumers indicated price, taste and smell, charging capacity, maintenance, and cleaning as negative aspects of the experience with the product and as potential barriers for full satisfaction. Provided that the anonymous dataset used for aggregated analysis includes reviews from IQOS Italia, a cross-validation with insights provided by the company's panel of IQOS owners (Philip Morris International, 2022) resulted in the selection of some specific attributes. In particular, starting from the presented research, Italian consumers confirm the absence of ash and smoke and the smell to be positive attributes compared to traditional cigarettes. Moreover, convenience to use and look also appear to be viewed as liking factors. On the other hand, price, short battery life and cleaning processes are argued to be negative factors of IQOS products. Based on such analysis it is hypothesized that:

H2a: aesthetic, lack of smoke and smell vs cigarettes, and practicality will have a positive effect on star rating and word of mouth
H2b: price, charging capacity, and maintenance will have a negative effect on star rating and word of mouth

Furthermore, based on the specific characteristics of the two personality traits analyzed, neurotic individuals tend to get frustrated and to be more propense to the externalization of bad moods and irritability, whereas conscientious individuals are calmer and more able to regulate impulse control, engaging in socially advantageous behaviors. Thus, it is hypothesized that:

H3a: the positive effect of attributes on star rating will be weaker when moderated by neuroticism than when moderated by conscientiousness
H3b: the negative effect of attributes on star rating will be stronger when moderated by neuroticism than when moderated by conscientiousness
H4a: the positive effect of attributes on word of mouth will be weaker when moderated by neuroticism than when moderated by conscientiousness
H4b: the negative effect of attributes on word of mouth will be stronger when moderated by neuroticism than when moderated by conscientiousness

4. METHOD

4.1. Data Description

To investigate the effect of personality on post-purchase satisfaction and likelihood to recommend, data from Philip Morris International (Italia) has been used after internal approval. Specifically, the dataset included a total of 9662 reviews from April 2020 to May 2022 extracted from the company's IQOS e-commerce website, excluding sensible personal data that could not be shared externally. The sample included review texts and associated information on the date of submission, moderation status, user location, overall rating, and intention to recommend to a friend. In terms of date of submission, only data from 2021 to 2022 was ultimately selected. Moderation status reflects whether each review has been approved to be shared on the website, with reasons for rejection being set by the company as a consequence of strict legal regulations of the tobacco industry; for example, reviews that provide statements about health cannot be included. Therefore, the analysis excluded all reviews that were rejected in status to avoid the sharing of unlawful outcomes. Last but not least, review texts associated with empty fields in terms of 'recommend to a friend' were void of inclusion. Reviews were originally associated with specific userIDs, which however have been excluded for privacy purposes, and have been replaced by random and non-linked IDs. Consequentially to the aforementioned considerations, the final dataset included a total of 6027 reviews.

4.2. Measurement Development

Hypothesis 1a and 1b see personality traits – narrowed down to neuroticism and conscientiousness – as independent variables. LIWC is one of the most used language analysis programs in psychological studies and has with time developed a series of standard dictionaries for text mining. Thus, in the following analysis, LIWC-2022 dictionaries will be used as a base to link review text to personality through language use patterns. In particular, the research papers presented in Table 1 will be the starting point to select which dictionaries are relevant for inclusion. Whereas Yarkoni (2010) excluded non-semantic categories, Mairesse et al. (2007) and Qiu et al. (2012) included an assessment of non-semantic categories. The decision here will be to use both semantic and non-semantic LIWC categories found to have a 0.01 significant and positive relationship with neuroticism and conscientiousness. Among others, Word Count will be excluded and used as a control variable. Therefore, excluding categories that do not meet such standards, and those not anymore included in LIWC-22 versus previous versions, dictionaries presented in Table 3 – each containing a specific number of words – will be used on LIWC-22 to assess the personality of consumers writing the reviews. Each review text will thus be assigned to a value indicating the presence of words related to each dictionary. The average of the values resulting for each category will then be computed to assess how much each text can be argued to be a result of the writing of a neurotic or conscientious individual, with the personality trait that has the highest factor being the one mostly associated with the specific review.

Table 3: LIWC-22 categories used for analysis

NEUROTICISM	CONSCIENTIOUSNESS
emo_anger (anger); emo_anx (anxiety); emotion (feeling); I (first person sing); negate (negations); emo_neg (negative emotions); verb; focuspresent (present tense); pronoun; emo_sad (sadness); we (total first person); physical (body); ppron (personal pronouns); sexual; swear; cause (causation); certitude (certainty); cogproc (cognitive processes); discrep (discrepancy); tentat (tentative)	verb; focusfuture (future tense); home; work (occupation); tone_pos (optimism); prep (prepositions); time; cogproc (cognitive processes); quantity (quantifiers)

Moving to dependent variables, star rating is of no doubt one of the most important measures of overall customer experience satisfaction used in marketing and consumer research, in particular with the advent of the e-commerce (Fedewa et al., 2021), and has also been found to influence other measures such as purchase intention and brand attitude (Chevalier & Mayzlin, 2006; Filieri, 2015; Ramachandran, Sudhir & Unnithan, 2021; Srivastava & Kalro, 2019). Also, small improvements in star rating have been proved to drive explosive product growth (Fedewa et al., 2021). Yet, research also sustain the relevance of linking such measure to other aspects obtainable from reviews, in particular in an online setting (Liu et al., 2021), which will here be done. Star rating will be measured on a five-star scale, as self-reported by consumers during the online evaluation process, with five stars being a positive satisfaction with overall experience, three stars being the midpoint, and one or two stars being a negative satisfaction score. Word of mouth, on the other hand, finds extreme relevance nowadays both for companies and for customers. Indeed, being a behavioral outcome, it is a good concrete proxy of consumer satisfaction but is also highly trusted by other customers. Indeed, word of mouth is seen as a source of information that can influence potential acquisition and brand attitude (Bughin, Doogan & Vetvik, 2010; Chevalier & Mayzlin, 2006; Elwalda, Lü & Ali, 2016; Gruen, Osmonbekov & Czaplewski, 2006; Zhu & Zhang, 2010). The likelihood of spreading word of mouth, offline or online, will here be measured through a binary variable giving two options (*yes* or *no*) to the question "would you recommend the product to a friend?", using the answer expressed by reviewers on the company's website as measure.

A second part of the analysis (H2, H3, H4) will try to assess the effect of specific product attributes on star rating and word of mouth, adding a moderating effect of the two personality traits selected for analysis. Specifically, product attributes will be the result of an analysis of words that are included in each review text, consequently classified under a broader topic. Such attributes will thus be extracted from review texts through topic model techniques. Personality, star rating and word of mouth will again be measured as explained above.

4.3. Modelling

Investigating the aforementioned hypothesis requires a combination of deep learning and explanatory models. In particular, this analysis exploits prediction for the assessment of all independent variables and regression to assess their effect on dependent variables. Apart from the initial phase, where *Linguistic Inquiry and Word Count (LIWC)* will be used, the remaining analysis will rely on *Konstanz Information Miner (KNIME)* for model estimation. KNIME is a free and open-source data analytics platform which integrates machine learning and data mining components. Its intuitive visual workflows for data analytics have been released in 2006, and since then have acquired prestige among researchers, being used in different areas including pharmaceutics, customer data analysis, text mining and business intelligence.

Whereas most papers in the personality literature have assessed traits through self-reported questionnaires, it is argued that using deep learning techniques will allow to get more unbiased results, revealing the deep nature of language use, personality, and consumer preferences and thus the processes that guide individuals' satisfaction with online purchases. First of all, personality traits will be extracted directly from consumers' individual reviews through LIWC-22 system of semantic and non-semantic dictionaries, computing the percentage of words in a given review that fall within each specific category. The output tables of LIWC analysis will then be used as inputs on KNIME to model the personality trait – between neuroticism and conscientiousness – associated with each review text in the dataset. Missing values will be in this case represented as zeros. Data will then be normalized to allow for comparison among variables. Once this has been accomplished, H1a and H1b will ultimately be tested through explanatory models. In particular, the relationship between personality traits and star rating will be investigated through linear regression, whereas the relationship between personality and likelihood to recommend will see logistic regression as a model, due to the binarity of the dependent variable. Both regressions will consider Word Count as control variable.

Deep learning models on KNIME will also be used for topic modelling. First step in modelling will be to translate review strings into documents – bag of words – to allow the applicability of the Latent Dirichlet Allocation (LDA) model for topic extraction, one of the most widely used topic modelling methods (Anupriya & Karpagavalli, 2015; Ling, Jinyu & Chunling, 2017; Neishabouri & Desmarais, 2020; Zhao et al., 2015). Consequently, all sort of unnecessary words or textual misalignments will be removed through specific preprocessing nodes such as stop word filter, Kuhlen Stemmer, N Chars filter, Case Converter, Punctuation Erasure, Bag of Words Creator, etc., leaving only text that may be relevant for topic extraction. Also, few non-descriptive terms will be excluded from the model to improve the performance of LDA. Indeed, unsupervised LDA model will be used to extract the topics a document belongs to, giving back the probability that the document belongs to the topic. Given the lack of a priori knowledge of the number of relevant themes, perplexity will be used to select how many topics to extract. Perplexity has indeed been argued to be a good measure to evaluate how well a model describes a dataset (Ling, Jinyu & Chunling, 2017; Neishabouri & Desmarais, 2020; Zhao et al., 2015). Multiple linear regression and logistic regression will then been run on normalized variables to understand the effect of each topic on star rating and word of mouth respectively, coding maintenance as reference category in both analyses.

Moving forward to the assessment of moderation effects, a Joiner node will be used to aggregate in a unique table the outcome of personality analysis and topic modelling to then create interaction terms between each topic and the two personality traits through a Math Formula node. The analysis will then be concluded with multiple linear and logistic regressions assessing the relationship of the interaction terms with star rating and word of mouth, thus revealing the moderating effects of personality traits on the relationship between attributes and the two dependent variables.

5. RESULTS

5.1. Main results

H1a and H1b. Analysis with LIWC-22 revealed the consistent presence of both personalities among reviewers. Specifically, 2827 reviews found higher correlation with conscientiousness dictionaries, whereas 3200 had higher values for neuroticism. The multiple regression analysis among personality indexes and star rating, with a controlling effect of word count [Table 4] reported an adjusted R^2 of 0.595, meaning that conscientiousness and neuroticism explained about 6% of the variation in star rating. Overall, the β-values indicated a negative effect of neuroticism on star rating and a positive effect of conscientiousness, yet the latter being not significant at a 95%

confidence level (*p-value* < 0.05). Word count appeared to be a significant control variable in the relationship among personality and star rating. The same direction of effects and significance was found when looking at the relationship between personality and word of mouth, tested through logistic regression [Table 5]. The results thus confirmed H1a and found an effect of conscientiousness on both dependent variables as suggested by H1b, but void of significance.

Table 4: linear regression between personality traits and star rating

Variable	Coeff.	Std.Error	t-value	p-value
WC	-0.2337	0.0127	-18.3438	0.0
Neuroticism	-0.0427	0.0134	-3.1894	0.0014
Conscientiousness	0.0106	0.0132	0.8065	0.42
Intercept	0.0	0.0125	0.0	1
Adjusted Rsquared: 0.0595				

Table 5: logistic regression between personality traits and word of mouth

Variable	Coeff.	Std.Error	z-score	p-value
WC	-0.471	0.041	-11.457	0.0
Neuroticism	-0.405	0.079	-5.123	0.0
Conscientiousness	0.11	0.085	1.298	0.194
Constant	3.486	0.081	43.273	0.0

H2a and H2b. Topic modelling was hereby initiated through the computation of perplexity to assess the optimal number of themes to be extracted. Based on such measure, the dataset of this analysis appeared to be best explained by the extraction of 10 topics, which have been identified as ‘smoke and smell vs cigarettes’, ‘charging capacity’, ‘quality’, ‘purchase choice’, ‘practicality’, ‘product experience’, ‘device’, ‘aesthetic’, ‘online purchase experience’, and ‘maintenance’. As evident, price was not found to be a recurring topic in reviews. Words per topic and occurrences per topic can be found in Appendix A. Although the difficulties in the interpretation of some of them, all extracted topics were included for analysis to provide a further exploratory meaning to H2a and H2b. The model for multiple linear regression [Table 6, Appendix B] resulted in an adjusted R^2 of 0.2046, thus 20% of the variation in star rating was explained by the extracted topics, which appeared to be all significant at a 95% confidence level (*p-value* < 0.05). Since all topics have positive magnitude effects and thus greater than that of the reference category, maintenance was associated with the worse effect on star rating, followed by charging capacity and online experience. Smoke and smell, aesthetic, and practicality all had a more positive effect on star rating than maintenance, with the absence of smoke and the smell compared to traditional cigarettes being the one with the most positive effect. With the help of a linear correlation matrix [Appendix C] and testing topics relevant for hypothesis individually, charging capacity and maintenance were found to also have a negative effect on star rating, whereas smoke and smell, practicality, and aesthetic appeared to positively affect star rating.

Table 6: linear regression between selected topics and star rating				
Variable	**Coeff.**	**Std.Error**	**t-value**	**p-value**
Number of terms	0.0104	0.0127	0.8245	0.4097
Smoke & smell vs cigarettes	0.5705	0.0188	30.29	0.0
Charging capacity	0.3724	0.0165	22.5698	0.0
Practicality	0.5406	0.0176	30.6439	0.0
Aesthetic	0.5249	0.017	30.9405	0.0
Intercept	0.0	0.0115	0.0	1
Reference Category: Maintenance; Adjusted Rsquared: 0.2046				

Logistic regression revealed similar results [Table 7, Appendix D], with all topics being significant with respect to the reference category and maintenance being the attribute leading to the lowest likelihood to recommend the product. All other topics were found to have a more positive effect on word of mouth compared to maintenance, with smoke and smell, practicality, and aesthetic leading the way. Individual results proved the directions of the effect of charging capacity, maintenance, smoke and smell, aesthetic, and practicality as hypothesized but the relationship between charging capacity and word of mouth was void of significance.

Table 7: logistic regression between selected topics and word of mouth				
Variable	**Coeff.**	**Std.Error**	**z-score**	**p-value**
Number of terms	0.363	0.088	4.118	0.0
Smoke & smell vs cigarettes	1.212	0.111	10.911	0.0
Charging capacity	0.584	0.074	7.88	0.0
Practicality	1.365	0.122	11.211	0.0
Aesthetic	1.212	0.118	10.233	0.0
Constant	3.918	0.104	37.684	0.0
Reference Category: Maintenance, No				

H3a, H3b, H4a, and H4b. When looking at the moderating effect of personality in the relationship between product attributes and star rating or word of mouth, results appear mixed. Particularly, with respect to neurotic personalities, significance has been found only for the interaction between neuroticism and maintenance, purchase choice, device, and online experience (*p-value* < 0.05). All direct effect remained confirmed. Hypothesis H3a could not be tested because none of the attributes tested positive in H2 appeared significant in the moderation analysis. Going in detail on the moderating effect of neuroticism on star rating [Table 8, Appendix E], the model reported a good fit, with an adjusted R^2 of 23%. Worth mentioning is the interaction of neuroticism with maintenance, which saves the negative effect of the cleaning process. The model assessing the moderating role of conscientiousness [Table 9, Appendix F] instead reported a 21% model fit and, despite its non-significant direct effect on star rating, conscientiousness was found to be a significant moderator for maintenance and online experience. In this case, the negative effect of maintenance was stronger when moderated by neuroticism, thereby confirming H3b. Worth mentioning is also the change in effect direction (β-value) of online experience. Indeed, it appeared to have a negative effect on star rating when moderated by neuroticism and a positive effect when moderated by conscientiousness, which provides further evidence for the hypothesis.

Table 8: linear regression between selected topics, moderation terms (neuroticism) and star rating

Variable	Coeff.	Std.Error	t-value	p-value
Number of terms	0.0037	0.0126	0.2928	0.7697
Smoke & smell vs cigarettes	0.4905	0.0205	23.8920	0.0
Charging capacity	0.3053	0.0173	17.6066	0.0
Practicality	0.4709	0.0188	25.1110	0.0
Aesthetic	0.4549	0.018	25.2775	0.0
N*Smoke&Smell	0.0521	0.0381	1.3666	0.1718
N*ChargingCapacity	0.0166	0.0418	0.3971	0.6913
N*Practicality	0.0722	0.0493	1.4655	0.1428
N*Maintenance	-0.2826	0.026	-10.8671	0.0
N*Aesthetic	0.0299	0.0377	0.7952	0.4265
Intercept	0.0	0.0113	0.0	1
Reference Category: maintenance; Adjusted Rsquared: 0.2317				

Table 9: linear regression between selected topics, moderation terms (conscientiousness) and star rating

Variable	Coeff.	Std.Error	t-value	p-value
Number of terms	0.0096	0.0127	0.7534	0.4513
Smoke & smell vs cigarettes	0.5737	0.019	30.1384	0.0
Charging capacity	0.3754	0.0166	22.6750	0.0
Practicality	0.544	0.0177	30.7272	0.0
Aesthetic	0.5272	0.0174	30.3140	0.0
C*Smell&Smoke	0.0208	0.0399	0.5214	0.6021
C*ChargingCapacity	0.0199	0.0429	0.4632	0.6432
C*Practicality	0.0163	0.046	0.3542	0.7232
C*Maintenance	-0.0954	0.0289	-3.3071	0.0009
C*Aesthetic	-0.0063	0.0382	-0.1641	0.8697
Intercept	0.0	0.0115	0.0	1
Reference Category: maintenance; Adjusted Rsquared: 0.2059				

Moving to the moderating effect of personality on word of mouth [Table 10, Appendix G; Table 11, Appendix H], significance has been found for the interaction between neuroticism and maintenance, device, and online experience, whereas conscientiousness appears to be moderating only the effect of device on word of mouth. For this reason, as argued before, H4a and H4b cannot be tested. Yet, it can be seen that device had a more negative effect when moderated by neuroticism than when moderated by conscientiousness. Therefore, H4b can be partially confirmed.

Table 10: logistic regression between selected topics, moderation terms (neur.) and word of mouth

Variable	Coeff.	Std.Error	z-score	p-value
Number of terms	0.295	0.087	3.372	0.001
Smoke & smell vs cigarettes	1.026	0.119	8.61	0.0
Charging capacity	0.457	0.077	5.924	0.0
Practicality	1.225	0.126	9.743	0.0
Aesthetic	1.057	0.124	8.527	0.0
N*Smoke&Smell	0.642	0.336	1.911	0.056
N*ChargingCapacity	-0.11	0.228	-0.481	0.63
N*Practicality	0.094	0.465	0.202	0.84
N*Maintenance	-0.499	0.124	-4.017	0.0
N*Aesthetic	-0.635	0.364	-1.742	0.082
Constant	4.059	0.114	35.498	0.0
Reference Category: maintenance, No				

Table 11: logistic regression between selected topics, moderation terms (consc.) and word of mouth

Variable	Coeff.	Std.Error	z-score	p-value
Number of terms	0.353	0.088	4.003	0.0
Smoke & smell vs cigarettes	1.212	0.112	10.796	0.0
Charging capacity	0.592	0.074	7.950	0.0
Practicality	1.374	0.123	11.211	0.0
Aesthetic	1.212	0.12	10.116	0.0
C*Smoke&Smell	0.035	0.322	0.110	0.913
C*ChargingCapacity	0.041	0.232	0.177	0.86
C*Practicality	0.065	0.436	0.148	0.882
C*Maintenance	-0.201	0.109	-1.843	0.065
C*Aesthetic	-0.235	0.355	-0.662	0.508
Constant	3.948	0.106	37.247	0.0
Reference Category: maintenance, No				

5.2. Robustness Check

A further analysis has been performed to test whether results remained valid when controlling for user location differences. In particular, a split between big and small cities has been done, considering big cities only those with more than 250k inhabitants, as reported by ISTAT (ISTAT, 2020). All user location missing values were removed from the dataset, which therefore ultimately included a smaller number of reviews (3826 vs 6027). Also, cities that were associated with less than 10 reviews were excluded from the analysis. The direction of the effects of personality traits on the dependent variables (H1a and H1b) were proved coherent also when including the effect of user location, with reviews associated with users from big cities being associated with a more positive star rating. However, conscientiousness was also found to have a significant effect on star rating, differently from the main study which proved it non-significant. Same results were found regarding the effect on word of mouth.

Moving to topic modelling, user location appeared to have no effect on star rating, decreasing model fit to 19%, but a positive effect on word of mouth, which seems logical given the nature of big cities. Same can be argued when considering the moderation of personality traits. However, whereas in the analysis of direct effects, all variables remained significant, some interaction terms lost significance when including user location in the regression. Also, model fit was again lower than the models of the main study.

6. DISCUSSION

6.1. Contributions

The performed analysis contributes to the psychological stream of literature on the link between personality and language use, expanding its proof of existence in the e-commerce setting and in the tobacco industry, with an assessment of personalities in a spontaneous environment such as online reviews writing. Personality assessment might be an essential input for many sectors, one of them being the tobacco industry, given the strong evidence of the link between personality and smoking behaviors. Thus, this research provides an important kick off to a further investigation of personality traits in such field, with attention to text mining techniques rather than self-reported measures.

Not only, results also contribute to a further understanding of the link between consumer personality and post-purchase customer experience and satisfaction, depicting personality through linguistic cues as many major studies, but additionally revealing its relationship with product or service attributes and relative effect on ultimate customer satisfaction. Indeed, the presented research shows the effect of different product attributes on star rating and word of mouth, the latter being less common among research on online customer experience. Moreover, not many available analyses investigate the effect of personality in moderating the relationship between product attributes and satisfaction or likelihood to recommend through text mining techniques.

Worth mentioning is also the strong contribution that this paper provides through the method exploited. Specifically, most previous research has developed an assessment of personality through surveys or other self-reported measures, which present a series of limitations in depicting the true nature of one's personality and lack in behavior and preferences predictive power compared to language-based assessments. Not to be forgotten is that text mining is an innovative technique also in the field of customer experience. Finally, the combination of two software, LIWC and KNIME, represents a strength of the performed analysis, the former being previously mainly used for personality assessment with no convergence with customer experience and the latter being a new and not yet familiar data-analytic platform among researchers.

6.2. Managerial Implications

The presented research illustrates the importance of personality in shaping customer experience, and the relevance of language cues for its assessment. Indeed, it has been proved that different personalities shape post-purchase consumers' responses, affecting satisfaction and likelihood to recommend. Specifically, consumers with neurotic personalities tend to focus on negative aspects of their experience and provide more negative reviews and are less likely to promote the product. Performing such analysis can provide important insights to managers for a better targeting and product offering. Understanding that some personalities have a tendency to experience the negative more deeply and complaint about it may also suggest a better complaint management for such consumers. Also, consumers being resident of big cities rather than of small ones appear to have an effect on reviews being positive in terms of satisfaction and even more significantly on word of mouth, which could be a further targeting input for management.

Moreover, topic modelling revealed which attributes mostly emerge from IQOS consumers spontaneous writing and their direct effect on satisfaction and likelihood to recommend. This can provide important – and eventually new – insights about what managers should leverage on to further improve a product that is in its first years of expansion, which could be key for acquisition and retention.

Last but not least, the final study proves that personality traits somehow interact with different product attributes, ultimately having an impact on how consumers experience the product and on how they consequently act as ambassadors. In other words, different consumers appear to have a different response to the same attribute based on their personality type. It can be therefore valid for companies to categorize consumers following their psychological characteristics and implement a communication and strategy based on these inputs, thus prioritizing those attributes whose effect on star rating and likelihood to recommend is positively affected by such interaction, keeping in mind that consumers from big cities have stronger power in terms of word of mouth spread.

To sum up, this research provides important and new insights to managers regarding the link between personality and customer satisfaction, in the form of star rating and likelihood to recommend, contributing to the understanding of what companies should leverage on – in a personality-based segmentation setting – to improve consumer acquisition, engagement, and retention.

6.3. Limitations and Directions for Further Research

Considering the performed studies, noticeable is the massive potential for further analysis regarding the effect of personalities on customer experience.

First, it is undoubtfully worth including an assessment of all five personality traits, and an inclusion of such as moderating variables. This would also overcome the limitation of the presented analysis, which revealed a low model fit and a non-significant effect of conscientiousness in the proposed setting. Also, this study considered both non-semantic and semantic LIWC dictionaries for personality recognition. In this sense, including a comparison between results across the two categories or using different software or algorithms such as *Wordify* could provide new important insights and differences. In language-based assessment, it may be worth of attention that reviews have hereby been translated from Italian to English, with the probability of some details being lost. In this sense, further studies may avoid the translation process.

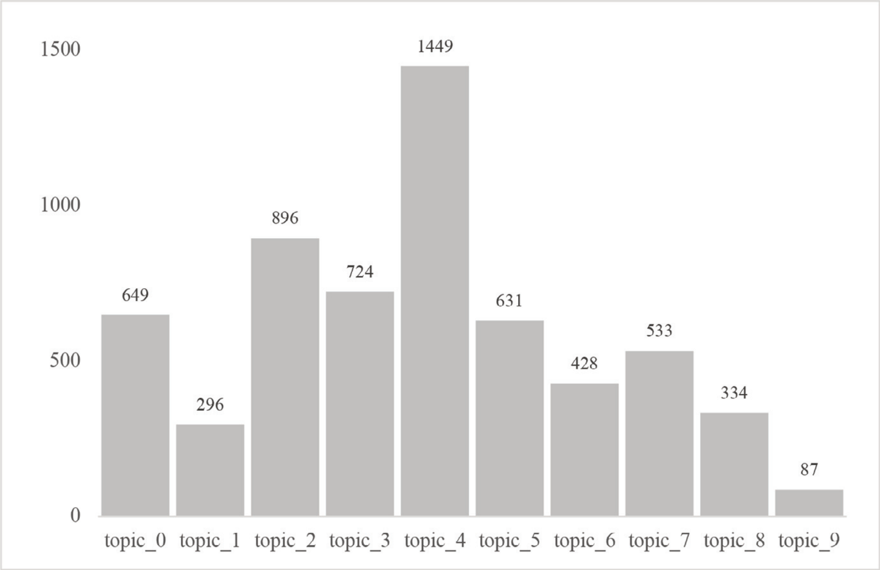
Second, future research could maintain a more exploratory view to deeply test how personalities differ in the importance they assign to various topics. Further analysis could separate each of the five personality traits and see whether differences in the topics extracted emerge, revealing important insights also in terms of the differential effects of such on star rating and word of mouth. This would provide deeper knowledge about the relevance of personality in shaping customer experience preferences. For a more specific analysis, it could also be of value to focus on online-related topics to understand how to improve the online purchase experience specifically.

Last, generalizability of results could be improved through the consideration of other industries or companies, provided that the peculiarity of the tobacco industry may have represented a limitation due to the presence of very specific attributes. Comparing results with direct or indirect competitors, or with other countries, may also be valuable. Not only, testing whether results would be confirmed considering other satisfaction measures, such as NPS, might be worth.

APPENDIX

A) Topic Analysis

Topic	**Topic name**	**10 identified words**
Topic_0	smoke & smell vs cigarettes	smoke, cigarettes, cigarette, smell, feel, bad, traditional, alternative, anymore, hand
Topic_1	charging capacity	convenient, charge, heet, model, battery, last, little, quick, charg, smoke
Topic_2	quality	product, excellent, quality, price, time, compare, assistance, improve, advise, functional
Topic_3	purchase choice	purchase, satisfy, time, happy, duo, top, use, short, previous, device
Topic_4	practicality	comfortable, practical, easy, design, elegant, light, functional, useful, carry, nice
Topic_5	product experience	recommend, buy, product, fantastic, high, experience, friend, smoker, gift, fine
Topic_6	device	bought, multi, device, duo, try, kit, plus, month, ago, found
Topic_7	aesthetic	beautiful, color, nice, love, aesthetical, elegant, gorgeous, white, gold, blue
Topic_8	online experience	perfect, fast, arrive, day, delivery, super, shipp, service, times, customer
Topic_9	maintenance	stick, clean, cleane, tobacco, complete, dry, previous, useles, ones, remain



B) Linear regression between all extracted topics and star rating

Variable	Coeff.	Std.Error	t-value	p-value
Number of terms	0.0104	0.0127	0.8245	0.4097
Smoke & smell vs cigarettes	0.5705	0.0188	30.29	0.0
Charging capacity	0.3724	0.0165	22.5698	0.0
Quality	0.4798	0.0165	29.0869	0.0
Purchase choice	0.4397	0.0159	27.7272	0.0
Practicality	0.5406	0.0176	30.6439	0.0
Product experience	0.4664	0.0159	29.4151	0.0
Device	0.3719	0.0161	23.1721	0.0
Aesthetic	0.5249	0.017	30.9405	0.0
Online experience	0.3999	0.0164	24.4483	0.0
Intercept	0.0	0.0115	0.0	1
Reference Category: Maintenance; Adjusted Rsquared: 0.2046				

C) Reference Category: Maintenance; Adjusted Rsquared: 0.2046

	Overall rating
Number of terms	-0.1402
Smoke & smell	0.0185
Charging capacity	-0.0641
Quality	0.0960
Purchase choice	0.0727
Practicality	0.0857
Product experience	0.1132
Device	-0.0308
Aesthetic	0.1029
Online experience	0.0024
Maintenance	-0.4335

D) Logistic regression between all extracted topics and word of mouth

Variable	Coeff.	Std.Error	z-score	p-value
Number of terms	0.363	0.088	4.118	0.0
Smoke & smell vs cigarettes	1.212	0.111	10.911	0.0
Charging capacity	0.584	0.074	7.880	0.0
Quality	1.151	0.112	10.282	0.0
Purchase choice	0.809	0.089	9.116	0.0
Practicality	1.365	0.122	11.211	0.0
Product experience	1.159	0.116	10.002	0.0
Device	0.592	0.076	7.797	0.0
Aesthetic	1.212	0.118	10.233	0.0
Online experience	0.681	0.081	8.461	0.0
Constant	3.918	0.104	37.684	0.0
Reference Category: Maintenance, No				

E) Linear regression between topics, moderation terms (neuroticism) and star rating

Variable	Coeff.	Std.Error	t-value	p-value
Number of terms	0.0037	0.0126	0.2928	0.7697
Smoke & smell vs cigarettes	0.4905	0.0205	23.892	0.0
Charging capacity	0.3053	0.0173	17.6066	0.0
Quality	0.4162	0.0174	23.9583	0.0
Purchase choice	0.3817	0.0164	23.2525	0.0
Practicality	0.4709	0.0188	25.111	0.0
Product experience	0.4083	0.0165	24.7016	0.0
Device	0.3148	0.0171	18.4493	0.0
Aesthetic	0.4549	0.018	25.2775	0.0
Online experience	0.2942	0.0176	16.6992	0.0
N*Smoke&Smell	0.0521	0.0381	1.3666	0.1718
N*ChargingCapacity	0.0166	0.0418	0.3971	0.6913
N*Quality	0.093	0.0486	1.9144	0.0556
N*PurchaseChoice	0.1084	0.0464	2.338	0.0194
N*Practicality	0.0722	0.0493	1.4655	0.1428
N*ProductExperience	0.0587	0.0457	1.285	0.1989
N*Device	0.0893	0.044	2.0276	0.0426
N*OnlineExperience	-0.33	0.0383	-8.6078	0.0
N*Maintenance	-0.2826	0.026	-10.8671	0.0
N*Aesthetic	0.0299	0.0377	0.7952	0.4265
Intercept	0.0	0.0113	0.0	1
Reference Category: maintenance; Adjusted Rsquared: 0.2317				

F) Linear regression between topics, moderation terms (consc.) and star rating

Variable	**Coeff.**	**Std.Error**	**z-score**	**p-value**
Number of terms	0.295	0.087	3.372	0.001
Smoke & smell vs cigarettes	1.026	0.119	8.610	0.0
Charging capacity	0.457	0.077	5.924	0.0
Quality	0.997	0.118	8.417	0.0
Purchase choice	0.694	0.092	7.502	0.0
Practicality	1.225	0.126	9.743	0.0
Product experience	1.069	0.123	8.662	0.0
Device	0.445	0.08	5.54	0.0
Aesthetic	1.057	0.124	8.527	0.0
Online experience	0.577	0.091	6.323	0.0
N*Smoke&Smell	0.642	0.336	1.911	0.056
N*ChargingCapacity	-0.11	0.228	-0.481	0.63
N*Quality	-0.443	0.404	-1.097	0.273
N*PurchaseChoice	0.584	0.34	1.717	0.086
N*Practicality	0.094	0.465	0.202	0.84
N*ProductExperience	0.162	0.437	0.37	0.711
N*Device	0.977	0.283	3.445	0.001
N*OnlineExperience	-1.063	0.257	-4.132	0.0
N*Maintenance	-0.499	0.124	-4.017	0.0
N*Aesthetic	-0.635	0.364	-1.742	0.082
Constant	4.059	0.114	35.498	0.0
Reference Category: maintenance, No				

G) Logistic regression between topics, moderation terms (neur.) and word of mouth

Variable	Coeff.	Std.Error	z-score	p-value
Number of terms	0.295	0.087	3.372	0.001
Smoke & smell vs cigarettes	1.026	0.119	8.610	0.0
Charging capacity	0.457	0.077	5.924	0.0
Quality	0.997	0.118	8.417	0.0
Purchase choice	0.694	0.092	7.502	0.0
Practicality	1.225	0.126	9.743	0.0
Product experience	1.069	0.123	8.662	0.0
Device	0.445	0.08	5.54	0.0
Aesthetic	1.057	0.124	8.527	0.0
Online experience	0.577	0.091	6.323	0.0
N*Smoke&Smell	0.642	0.336	1.911	0.056
N*ChargingCapacity	-0.11	0.228	-0.481	0.63
N*Quality	-0.443	0.404	-1.097	0.273
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N*Practicality	0.094	0.465	0.202	0.84
N*ProductExperience	0.162	0.437	0.37	0.711
N*Device	0.977	0.283	3.445	0.001
N*OnlineExperience	-1.063	0.257	-4.132	0.0
N*Maintenance	-0.499	0.124	-4.017	0.0
N*Aesthetic	-0.635	0.364	-1.742	0.082
Constant	4.059	0.114	35.498	0.0
Reference Category: maintenance, No				

H) Logistic regression between topics, moderation terms (consc.) and word of mouth

Variable	Coeff.	Std.Error	z-score	p-value
Number of terms	0.353	0.088	4.003	0.0
Smoke & smell vs cigarettes	1.212	0.112	10.796	0.0
Charging capacity	0.592	0.074	7.950	0.0
Quality	1.164	0.114	10.198	0.0
Purchase choice	0.822	0.089	9.204	0.0
Practicality	1.374	0.123	11.211	0.0
Product experience	1.172	0.117	9.995	0.0
Device	0.605	0.076	7.916	0.0
Aesthetic	1.212	0.12	10.116	0.0
Online experience	0.671	0.081	8.268	0.0
C*Smoke&Smell	0.035	0.322	0.110	0.913
C*ChargingCapacity	0.041	0.232	0.177	0.86
C*Quality	-0.064	0.409	-0.157	0.875
C*PurchaseChoice	0.009	0.337	0.028	0.978
C*Practicality	0.065	0.436	0.148	0.882
C*ProductExperience	-0.56	0.395	-1.416	0.157
C*Device	0.642	0.263	2.440	0.015
C*OnlineExperience	0.255	0.212	1.203	0.229
C*Maintenance	-0.201	0.109	-1.843	0.065
C*Aesthetic	-0.235	0.355	-0.662	0.508
Constant	3.948	0.106	37.247	0.0
Reference Category: maintenance, No				

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