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"When RE-cycled becomes RE-viewed"

The effect of green co-branding, perceived product value, perceived greenwashing on eWOM

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Knowledge and understanding
are life's faithful companions
who will never prove untrue to you.
For knowledge is your crown,
and understanding your staff;
and when they are with you,
you can possess no greater treasures.
(Khalil Gibran)

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Abstract

With consumers' increasing awareness of environmental problems, many firms are striving to improve their environmental positions by presenting their efforts to the public. This phenomenon has doubled since the spread of the Internet. So, firms are applying green marketing strategies to gain competitive advantages. This occurs particularly in the fashion industry because of the significant influence daily fashion production and consumption practices have on the environment, society, and economy. The linear economy "take-make-use-throwaway" system has highly significant adverse effects such as environmental destruction, economic loss, and threats to human society. To avoid this process there has been a growing demand for changing to a circular economy in the fashion business though the difficulty to make it accepted. Indeed, lots of products made of recycled materials are still perceived as lower in quality. Additionally, not all green marketing claims accurately reflect firms' environmental conduct and can be viewed as "greenwashing". Greenwashing may not only affect a company's profitability but more importantly, result in ethical and brand image harm.

The growing digitalization of the economy has opened new opportunities. The fashion industry is more characterized by the use of digital platforms and digital marketing strategies. Thus, eWOM is becoming one of the main tools to gain strong competitive advantages. There is a lack of research in understanding what strategies might be used to allow the spreading of products made using circular economy systems. Therefore, this research examines how the use of a green co-branding strategy between a fashion company and an environmentally concerned organization can increase perceived recycled product value and reduce the perceived greenwashing effect thus leading to both product and brand positive eWOM. Additionally, gender and culture will be considered as moderators. Two studies will be conducted: a survey study as well as a text mining analysis. For the purpose, in the first part of the work a parallel mediation analysis will be performed as well as a moderation analysis. Whereas, in the second part, text mining techniques will be applied to a case: "Adidas X Parley for the Oceans".

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Part one

Quantitative research aims to establish general laws of behavior and phenomenon across different contexts by testing a theory and ultimately support or reject it. It is possible to collect objective data about the object of study through quantitative research. The collection of numerical values allows to measure the occurrence of a phenomenon; therefore, a quantitative analysis offers an overview of the actual market conditions. This type of approach characterizes the first part of the present paperwork. Specifically, the development and analysis of the research model are going to be presented by giving a general panorama of past-to-present literature as well as explaining in detail the methodology used to carry on the study.

Introduction

"The power for change lies in the hands of the consumer – given we all have a choice – and the power to shape this new consumer mindset lies in the hands of the creative industries […] to develop alternative business models and ecologically sensible products to give us earthlings an alternative choice, an everyday option to change something" (Parley for the Oceans, s.d.).

The XXI century is an age of deep transformations that encompass the intertwined environmental and digital metamorphosis. With climate changes, recurring of natural disasters, over-population, wear and tear of natural resources, the spread of the Internet and social medias, and the increased importance of big data, companies, and consumers are modifying both the supply and the demand characteristics.

For long, producers and consumers have adopted a "linear economy" model (take, make, use, throw away) that implies the extraction of a large number of non-renewable resources. After product commercialization, linear economy goods are used a few times by shoppers and then thrown away generating a lot of waste. But, in the last decades, firms and consumers are trying to change towards new, more conscious systems. In other words, they are drifting from linear economy to a model that considers the finite nature of resources and thus endorses a restorative economic system (make, use, reuse, reuse again and again) which is designed for marketing use and reuse of resources to close the loop of material flows and thereby eliminate waste (Ki, Chong, & Ha-Brookshire, 2020).

In this landscape, the United Nations have set seventeen sustainable development goals (SDGs) defined to provide a shared blueprint for peace and prosperity for people and the planet now and into the future (United Nations, 2020).

New business models have emerged providing an increasing relevance of circular economy in the worldwide spotlight. Circular economy is a cyclic scheme that, by a "system thinking" approach, aims at eliminating waste by turning worn-out goods into resources for new ones (Ferasso, Beliaeva, Kraus, Clauss, & Ribeiro-Soriano, 2020). So linear models getting into offscourings should be replaced by new ones incorporating durability, re-use, repair, refurbishment, and recycling (Chamberlin & Boks, 2018). This strategy might be applied in business areas that generate high percentages of natural defilement like the fashion industry that, according to the UN News, is the world's second polluter after the oil sector. That is why many fashion companies are striving to improve their environmental positions by making changes and presenting their efforts to the public. However, the success of the circular economy and related sustainable practices depends on consumers' behavior and perceptions. The main goal of outlining a product should be both matching the requirements of a circular economy as well as people's needs, desires, and patterns of behavior (Wastling, Charnley, & Moreno, 2018).

Consumers have become the lever of change and companies have to identify the fundamental principles to better exploit this lever.

A tool that businesses boast to make the best use of the above-cited lever is "green marketing" which refers to all the marketing activities that aim at stimulating and sustaining environmentally friendly attitudes and behaviors (Jain & Kaur, 2004). It can be one of the most effective weapons to reinforce the corporate image in response to the needs of society.

Eco-advantages derive from green branding whose main target is to highlight the importance of protecting the environment in the context of mass consumption (Moravcikova, Krizanova, Kliestikova, & Rypakova, 2017). In fact, it allows firms to establish a strong brand image so that consumers show a certain degree of trust in the company and the quality of products (Lin, Lobo, & Leckie, 2017).

Nevertheless, fashion companies might face two major problems when presenting green and circular economy efforts to their public. The first one is related to the *attitude-intention gap theory* as well as to the company's ability to motivate consumers to choose products positioned at their ethical attributes over products positioned on self-benefit attributes (e.g., performance) (Peloza, White, & Shang, 2013). Many people process pro-environmental thinking and information even if they do not necessarily engage in pro-environmental behavior (Groubor & Milovanov, 2017). Indeed, even if the demand for circular economy products is increasing, consumers are still reluctant to shop for them mainly because circular economy outcomes are still perceived as lower in quality, thus leading to inconsistency between demand and purchase intention (Ki, Chong, & Ha-Brookshire, 2020).

The second problem is linked to the recognized difficulty of fashion firms to ensure company transparency and truly sustainable performance because of the involvement of various members intertwined in the fashion supply chain and demand side of the value chain leading to a high level of fragmentation (Ki, Chong, & Ha-Brookshire, 2020). So, the main trouble in today's green marketing landscape is the lack of consumers' confidence in companies' communication of environmental information (Martìnez, et al., 2020).

Scholars have tried to fix those teasers formulating theoretical solutions as well as general strategies to greening the marketing mix and making circular economy acceptable, feasible and effective. Ki, Chong, & Ha-Brookshire (2020) identify seven strategies to address the issues: (1) design initiatives (embracing circular fashion principles from the beginning of the product lifecycle); (2) product value initiatives (increase the value of circular fashion offerings); (3) collaborative initiatives (internal stakeholder could align their values with other stakeholders in the fashion supply chain, to share a common goal for the successful creation of circular fashion); (4) operational initiatives (improvement of operational efficiency, by collecting consumers data to analyze whether their current circular fashion programs are effective); (5) technological initiative (all fashion stakeholders are involved in making technological innovations to enhance efficiency); (6) social initiative (increase social awareness toward circular fashion); (7) governmental initiative (external stakeholder are involved to announce strategic regulations).

Other studies suggest adapting all the three dimensions of a business model (value proposition, creation, and capture) to the closed-loop economy system (Ferasso, Beliaeva, Kraus, Clauss, & Ribeiro-Soriano, 2020). In particular, they analyze strategic collaboration with supply chain partners, the transition from ownership to sharing/leasing (De Angelis, Howard, & Miemczyk, 2018), reverse logistics (Lechner & Reimann, 2019), and waste management systems (Horvat, Mallinguh, & Fogarassy, 2018). Further works focus on designing efficiency strategies to encourage consumers to use "less" (Daae & Boks, 2015).

Companies have to reassure consumers about their products and advertising with a clear and faithful promise that they are following ethical principles since they have to deal with the possible consumers' distrust due to the practice of greenwashing (Chen, Lin, & Chang, 2014). Greenwashing, a way of misleading consumers about a company's environmental performance, is one of the main reasons why people are skeptical towards green, recycled, or eco-friendly products. It leads customers to experiment confusion, rising questions of trust and confidence in the company and its products, and may result in the loss of buyers' enthusiasm to engage in eco-friendly behavior. In this respect, creating appropriate green brand strategies is required in order to reduce the gap and accelerate for large-scale adoption of sustainable behavior of all members of the society (Groubor & Milovanov, 2017). Many consumers place larger spotlights on the actions of brands and seek out brands that demonstrate purpose-driven marketing and authentic messaging. Marketers who respond to responsibility-focused consumer expectations, leveraging environmentally conscious products, and displaying sincerity can create connections with buyers encouraging immediate sales and long-term loyalty (Martìnez, et al., 2020). For the purpose, a company should develop a circular economy system, deliver concrete actions and create a sense of product uniqueness (Ki, Park, & Ha-Brookshire, 2020).

However, even if scholars have concentrated on those issues, current understanding of how managers can best begin greening their firms' marketing efforts is far from comprehensive. There is the necessity to discern the way to successfully communicate circular offers to users and to identify facilitating conditions that may influence the successful implementation of circular strategies (Ferasso, Beliaeva, Kraus, Clauss, & Ribeiro-Soriano, 2020).

Taking into consideration the above literature about all the possible approaches to make firms circular economy efforts to be accepted and adopted, it has been found that many firms rely on strategic partnerships (Wassmer, Paquin, & Sharma, 2014). One of the first and most famous collaborations has been fostered by "Foron" and "Greenpeace" to develop the first "greenfreeze" refrigerators in 1992. Another important example is "Wal-Mart". The world-famous retailer signed twenty partnerships with suppliers, universities, and NGOs only in 2014. A recent partnership in the fashion industry was signed in 2020 between Puma and a waste management and recycling company called "First Mile" to launch a new athletic footwear and clothing line made almost entirely from sustainable materials. So, firms rely on co-branding strategies to enhance consumers' perception of product value (Chernev & Blair, 2015) as well as to reduce the perceived consumer risk related to innovation, new technology, and environmental communication (Crane, 1998). Translated in the circular economy and eco-friendly field, partnership as a green marketing strategy is a powerful tool to allow changes and the spread of more environmentally safe behaviors.

Despite the growing significance of alliances to business practices, there is a lack of research concerning the clarification of the role of green strategic collaborations as an integral part of Corporate Social Responsibility

(CRS) efforts. Indeed, the phenomenon and economic potential of green partnerships or inter-firm strategies still remain vague, not fully explored (Sadovnikova & Pujari, 2017), and not focused on co-operative approaches to green marketing (Crane, 1998).

Giving the relevance of the topic in the marketplace, and in response to the call for more research into the outcomes of corporate green strategies, the present study aims at filling the gap by understanding how green co-branding strategies can influence perceived product value, perceived risk, or greenwashing and link it to another important social transformation, that is the worldwide spread of digital technologies and the birth of the big data phenomenon.

With the sprawl of social media platforms, blogs, and e-commerce websites, consumers' decision-making process and firms' strategies have deeply changed. People are even more affected by the opinions formed by thought leaders and other buyers shared through the Internet. According to a study carried on by Holst (2021), the total amount of data created, captured, copied, and consumed in the world is forecast to increase rapidly, reaching 59 zettabytes in 2020 and a forecast of 149 zettabytes in 2024. Internet has become a way to create awareness, spread ideas and beliefs, increase engagement and allow firms to extract information about what customers think and believe about offerings.

In the sustainability field, it is worth noting that the Internet and digitalization may nourish circular economy and sustainable practices in the way that it enables the dissemination and sharing of huge volumes of information about this phenomenon. The Internet, working virally, can amplify and broaden certain practices dissemination (Chalamon, Guiot, & Chouk, 2012) allowing individuals from all over the world to talk and trade with one another.

The activity of talking and exchanging information about a product or a brand is also known as Word-of-Mouth (WOM) or, in the digital sector, electronic Word-of-Mouth (eWOM). It can play a crucial role in enhancing brand image, increasing awareness, allowing the adoption of products, and reducing the uncertainty of consumers' decision-making process. Its relevance is increasing and, recently, scholars have focused on various aspects of the issue such as a better understanding of its drivers and antecedents (King, Racherla, & Bush, 2014), how it can impact consumers' behavior (Berger, 2014), its key characteristics and consequences (King, Racherla, & Bush, 2014). But a few studies discuss WOM/eWOM about environmental issues. In particular, there is no research addressing how a firm adoption of a collaborative green strategy can lead to positive eWOM both for the brand and for the product. Additionally, studies indicate that there is a list of covariates considered as antecedents of WOM that have not been tested yet. This record includes satisfaction, loyalty, quality, commitment, trust, and perceived value all of which have established a strong link between brand-related experiences and WOM, but no research focuses deeply on them.

So, the current work tries to extend this area of research with new knowledge considering eWOM from the perspective of green co-branding strategy, perceived recycled product value, and greenwashing.

It is worth noting that in the context of circular economy, environmental practices, and digitalization two more main variables play a key role: culture and gender. According to recent works, culture and gender are crucial determinants of environmental performances (Larson & Kinsey, 2019) thus the current discursion needs to take into consideration such values.

As a result, the following research questions will be addressed: How does green co-branding lead to positive eWOM through perceived product value and perceived greenwash? Can culture influence the relationship between the use of green co-branding and perceived product value? Can gender influence the relationship between the use of green co-branding and perceived product value?

This study incorporates the concepts of perceived recycled product value and greenwash effect into an integrated framework to discuss the influence of green co-branding strategy on eWOM related both to the brand and to the product. It proposes an arrangement to find a solution to enhance the adoption of circular economy through the spread of eWOM from three factors: co-branding strategy, perceived recycled product value, and greenwash effect. Not only it takes into account other two determinants that can prejudice the adoption of a closed-loop business model (culture and gender), but it also discusses the positive relationship between co-branding strategy and eWOM. Besides, it explores the mediation effects of perceived recycled product value and greenwashing on the positive relationship between co-branding and eWOM.

This specific study concentrates on products made of recycled/refurbished materials because they have a higher purchase intention than either new green products or green processes attributed to the fact that using existing products and recycling is more environmentally friendly than using raw materials, green or to produce a new product (Borin, Lindsey-Mullikin, & Krishnan, 2013).

To have a deeper understanding of the topic and a projection in today's world, some data mining techniques will be applied to a real case: the "Adidas X Parley" partnership. Sentiment Analysis and Topic Modeling are useful tools to extract consumers' opinions about a product or brand allowing companies to monitor eWOM among buyers, brand reputation, and performance.

As to the structure, the present work develops through three chapters. Chapter I is focused on the research study. It contains four sections: "Literature Review" which is divided into five subsections (green co-branding, perceived product value, greenwash effect, gender, culture, and eWOM); "Hypothesis Development and Conceptual Framework" in which the role of each variable is analyzed; "Research Methodology" containing data collection, sample explanation, measurements, and data analysis; "Final Results and Discussion".

Chapter II is dedicated to the "Adidas X Parley" case with a general introduction in the first section, a description of the Adidas and Parley for the Ocean alliance has been provided in the second section; the explanation of what Sentiment Analysis and Topic Model are has been reported in the third and fourth sections. In section five methodology has been described involving web source characteristics, data collection, data cleaning, text corpus characteristics, and data analysis. Results have been reported in the last section.

Chapter III embodies "Managerial Implications and Suggestions", "Limitation and Future Research", "Conclusions".

Chapter I: Literature Review

1.1. Green co-branding

"Alone we can do so little; together we can do so much" (Helen Keller)

As fashion marketers try to reach a certain degree of sustainability in their supply chain mechanisms, product packaging, and production initiatives, they have to face consumers' misgiving towards firm eco-friendly behavior and products. As a result, the need to find some possible ways to make fashion sustainable products accepted and adopted emerges.

Research has shown that negative responses restraining from uncertainty about the benefits of ethical attributes can be mitigated through the use of guarantees (Peloza, White, & Shang, 2013). One way to reassure consumers about the fair of a firm ethical, sustainable, and eco-friendly performance is through the use of co-branding strategies as means of pledge.

Co-branding, also called partnership or alliance, includes all circumstances in which two or more brand names are presented jointly to consumers. It has been defined as the combination of two brands to create a single, unique product to get access to new markets while increasing existing consumers' awareness and engagement (Leuthesser, Kohli, & Suri, 2003). Co-branding is formed by multiple brands that are physically integrated into a product or that simply are featured in joint promotions (Rao, Qu, & Ruekert, 1999). According to Leuthesser, Kohli, & Suri (2003), there are several advantages for businesses that decide to join a partnership such as the ability of products to acquire essential attributes of both parent brands; the positive spillover effect that a co-branded product can have on parent brands and the enlargement of the customer base reaching new segments. The authors conclude that attitude towards the co-brand strategy may lead to a beneficial post-effect on attitudes concerning the parent brands. So, if the partnership is well perceived, also the product will be perceived positively.

Since brand names function as signals[1] of quality, linking two brand names may have win-win outcomes, in particular, it enhances consumers' product quality perceptions when product quality is not readily observable (Rao, Qu, & Ruekert, 1999). Entering in a partnership with another brand can assist in credibly signaling high quality to the marketplace. Additionally, Rao, Qu, & Ruekert (1999) found that if there is any inconsistency between brand claim and effective quality, consumers may punish the brand by not undertaking in repurchase behavior or engaging in negative word-of-mouth. From consumers' perspective, knowing that they have the power to impose sanctions on the co-branding initiatives and on the companies joining the alliance might be a useful apprehension that might get the quality of the claim credible to customers' eyes (Rao, Qu, & Ruekert, 1999).

More extensive research has shown that consumers' product perceptions are altered when businesses engage in operations of social goodwill (e.g., partnerships with NGOs or social cause promotions). Indeed, such

[1] A signal is defined as "any action taken by the seller to deliver truthful information about product quality" (Rao, Qu, & Ruekert, 1999)

operations are strong enough to influence customers' evaluations leading to evaluate companies as performing better (Chernev & Blair, 2015).

Chernev & Blair (2015) also focused on the effect of companies' prosocial behavior and found out that ethical businesses' practice may give rise to an overreaching perception that might influence the perception of unknown attributes, thus leading to the *Halo Effect* which has an impact on the interpretation of puzzling information. The *Halo Effect* has been defined as "the tendency of overall evaluations of a person/object to influence evaluations of the specific properties of that person/object in a way that is consistent with the overall evaluation" (Nisbett & DeCamp Wilson, 1977). The same effect derives the consumers' idea of a partnership as more socially responsible causing positive attitudes and an increase in product value perception (Chernev & Blair, 2015). This is consistent with research that demonstrates that consumer attitudes towards a brand relate closely with attitudes towards brand alliances (Huertas-Garcìa, Lengler, & Consolaciòn-Segura, 2017) and they achieve superior results working together rather than operating by themselves.

Other scholars discovered different effects produced by socially responsible actions and in particular by partnerships. McCracken (1989) proposed the so-called *Meanings Transfer Model* suggesting that meaning associated with an object can be transferred to another object (such as a brand). It also explains linkages among consumer attributions producing shared and positive associations as the result of the correlation between two different objects. Schwarz (1997), instead, based its assumptions on the *Valence Affective Hypothesis*, which distinguishes arousal that generates positive and negative feelings. If a campaign announces that a brand is supporting a social cause, the message generates positive feelings in consumers that are attracted by the opportunity to contribute to society improvement providing them with a feeling of self-satisfaction and generating emotional wellbeing.

What just stated might be very useful in the context of green products and the circular economy. Indeed, closed-loop outcomes are typically credence goods for which eco-quality often cannot be fully asserted even after a purchase. So other factors such as firm green reputation play an increasingly important role (Sadovnikova & Pujari, 2017) and such a reputation might be leveraged by using green co-branding strategies as a new strategic approach to green marketing.

A green marketing partnership is a voluntary, formal collaboration or agreement among organizations focusing on the green value chain activities, penetration of green markets, promotion of green product and services, customer acquisition, and retention (Sadovnikova & Pujari, 2017). It tries to find common solutions to the collaborators' environmental problems, as well as the sharing or co-developing "green" products and technologies to pursue a set of strategic green goals or address critical business needs that are at the core to help to respond to green market demands, optimize costs and improve operational efficiencies (Sadovnikova & Pujari, 2017).

In such a context, partnerships with environmental activist groups, research institutions, and NGOs might furnish firms with environmental knowledge as well as carrying out firms' environmental strategies and generate economic gains. Collaborations may provide the organization with environmental skills and competence, access to environmental technologies, greater influence over its environmental inputs/outputs, presence in green markets, and other benefits unavailable to the organization alone (Crane, 1998). They stimulate image transfer from ecological and environmental purposes of a cause to a brand, increase public awareness of a cause and brand, willingness to buy products, and improve the brand image (Huertas-Garcìa, Lengler, & Consolaciòn-Segura, 2017).

Considering the studies linked to the above-cited *Halo Effect*, it is possible to add that the effect deriving from a company's socially responsible activity such as green co-branding can influence both the overall company image and the perceived performance of company products, such that the products are perceived to have superior performance and value (Chernev & Blair, 2015). All in all, the announcement of a green marketing partnership has an immediate positive and significant effect on products perceived value and firm reputation (Sadovnikova & Pujari, 2017) allowing firms stakeholders to engage in positive interactions (e.g., word-of-mouth).

It is worth to underline that the green consumption landscape is very complicated, fragmented, and uncertain. Many companies apply unethical activities, such as greenwashing, to attract consumers to buy their products. This might at least lead consumers and other stakeholders to adopt a vigilant attitude when they receive information about companies' CSR, eco-friendly and sustainable undertakings (Martìnez, et al., 2020). Taking social actions to improve the environment is insufficient; a target audience needs to be aware of such actions, through effective messages and credible ventures. Additionally, researchers have found that the more ambiguous the product experience is, the greater the likelihood that a CSR will positively influence this experience, strengthening consumers' preferences and increasing the likelihood of buying the product. So, using green co-branding strategies may allow consumers to transfer intangible associations between the brand and NGOs, environmental activist groups, research institutions, etc. steering to the achievement of greater market value, enhancement of brand image, creation of higher purchase intention, and positive brand reputation (Huertas-Garcìa, Lengler, & Consolaciòn-Segura, 2017).

A co-branding strategy is more effective when interfacing with those consumers who are mistrusted and confused by green claims, especially when a firm collaborates with NGOs. This is because consumers are more confident in the NGOs' environmental claims rather than in the company's ones (National Consumer Council, 1996). On the whole, by partnering with green market leaders, firms elevate their environmental profile and provide stronger signals of green value (Sadovnikova & Pujari, 2017).

Concluding, it is possible to state that green co-branding strategies may not be a sovereign remedy to green marketing problems but at least may have the potential to elicit commitment, attachment, and positive communication about the brand performance in a way that the company alone may not.

1.2. Perceived Product Value

"Always deliver more in perceived value than you take in cash value" (Jeff Blackman)

Consumers are value-driven (Sweeney & Soutar, 2001). They are aware, involved, and sensitive to social issues. They look for transparency, compliance, and inclusion. Customers want to know what a brand stands for and what it is doing to make a difference.

It turns out that perceived value is considered as a critical motivator for consumers and an essential factor determining business-to-consumer (B2C) success, loyalty, and higher profits (Fang, Wen, George, & Prybutok, 2016). As a result, one of the most important challenges for marketers is to find the best strategy in order to deliver superior and unique value to consumers.

People's perceived value (PV) is a multidimensional concept that encompasses different aspects of a product or a firm. Generally speaking, it is defined as a "consumer's overall assessment of the utility of a product or service based on perceptions of what is received and what is given" (Zeithaml, 1988). This definition underlines the relationship, thus comparison, between what a buyer gets from the purchase and what it is given to him/her. In other words, the value is conceptualized as a customer's perceived net trade-off received from all benefits and sacrifices delivered by a product, service, or supplier and its use (Snoj, Pisnik Korda, & Mumel, 2004).

Perceived value has been widely discussed in literature at a generic level. Scholars have highlighted the fact that it can be easily confused with satisfaction defined as the action of meeting customers' needs (Alexandrov, Lilly, & Babakus, 2013). The two concepts are distinct and refer to different stages of the consumer's funnel. Satisfaction is a post-purchase and post-use evaluation depending on the experience of having used the product or service. It has also been conceptualized as a unidimensional construct due to the assumption that it varies along a hedonic continuum from unfavorable to favorable (Sweeney & Soutar, 2001). On the contrary, perceived value is considered as a multidimensional construct which might occur during all the purchase process, including the pre-purchase stage. As a consequence, value perception can be generated without the product or service being bought or used (Sweeney & Soutar, 2001).

A relationship between perceived value and satisfaction exists when firms satisfy people-based needs, they are delivering value which puts them in a stronger position in the long term (Sweeney & Soutar, 2001). Additionally, higher levels of perceived value led to higher levels in customers' satisfaction, loyalty and retention, thus to a greater success of an organization (Snoj, Pisnik Korda, & Mumel, 2004).

Consumers' PV is the core construct and foundation in all relational exchange activities, and it is a critical factor influencing repeat buying action (in particular in the online shopping context) (Fang, Wen, George, & Prybutok, 2016). Therefore, it is crucial to identify the factors affecting consumers' perception of the product value.

Some scholars regarded consumer choice as a function of multiple "consumption value" dimensions which contributes differently according to the specific alternative situations (Sweeney & Soutar, 2001; Snoj, Pisnik Korda, & Mumel, 2004; Fang, Wen, George, & Prybutok, 2016; Arunrangswed, 2021).

From this stream of research, a five-dimension structure of PV emerges. The dimensions have been defined as follow:

Emotional value. It is the utility derived from the feelings or affective states that a product generates.

Social value. Also defined as enhancement of social self-concept, it is the utility derived from the product's ability to enhance social self-concept.

Functional value related to price or value for money. It is the utility derived from the product due to the reduction of its perceived short-term and longer-term costs.

Functional value related to performance and quality. It is the utility derived from the perceived quality and expected performance of the product

Functional value has been considered to be the key aspect influencing consumers' choice. According to Chen, Lin, & Chang (2014), high levels of perceived quality could increase product sales, decrease the costs of retaining customers, enhance marketing performance and build up a positive word-of-mouth (WOM) effect. However, it is clear that different value dimensions may be important depending on the decision level (e.g., buy/not buy or buy brand A/brand B), as well as on the type of product or service being considered (Sweeney & Soutar, 2001). When assessing products, consumers not only focus on the functional aspect, value for money, and versatility but also on the enjoyment or pleasure derived from the product itself (emotional value) and on the social consequences of what the product communicates to others (social value) (Sweeney & Soutar, 2001).

Another conceptualization of perceived value has been given by Arunrangswed (2021) who have distinguished between epistemic, hedonic (about positive emotions, aesthetics, and pleasure), and utilitarian value (actual experience after using the product). They state that the organization should not only focus on the quality of the product but also on the aesthetic of packaging, the design, and ethical aspects that might motivate customers to buy it. Hence, customers might highly perceive product value before the actual usage (Arunrangswed, 2021).

This is especially true when dealing with green items. Since being green sometimes implies difficulties in estimating the real green value of the product prior to and after the purchase, a new notion emerges perceived green value. This concept can be explained as a trade-off between consumers' costs and benefits when dealing with environmental desires, sustainable expectations, and green needs (Szabo & Webster, 2020). If costs exceed benefits consumers will perceive a green product as less worth in quality so there is the need to find a way to reassure people about green product quality and value (Wang, Krishna, & McFerran, 2017).

As previously stated, quality is an important component of PV but not the only one. In the green field, emotional and social values may play a major role. Wang, Krishna, & McFerran (2017) found out that when the firm signals commitment to the environment, consumers tend to respond positively with favorable attitudes towards the company as well as towards the products. The authors add that consumers will engage in green behavior when they perceive a firm to be greener and that these perceptions will be influenced by cues of the firm's environmental efforts.

Since the image of the company perceived by consumers can significantly influence their behaviors (Chen, Huang, Wang, & Chen, 2020), increasing firm adherence to environmentally sustainable actions (e.g., the adoption of circular economy) might result in boosting the company's image, thus creating favorable consumers' behaviors (e.g., the spread of positive WOM).

All in all, perceived product value plays a key role in the adoption of green products, indeed as Arunrangswed (2021) states, PV could strongly predict purchase and repurchase intention for green products. As a result, enhancing perceived green value should become one of the main goals for those firms that want to adopt closed-loop business models.

1.3. Greenwash Effect

"Persuasion is an act of communication, falling between manipulating and convincing" (Andreas Spahn)

Green markets are proliferating, and people are paying more and more attention to consume products or services that have a positive impact on the environment. Thus, companies are striving to include green initiatives into their Corporate Social Responsibility (CSR) actions.

Firms have applied green marketing strategies to communicate green efforts, help raise awareness, motivate existing consumers and appeal to new ones. With the spread of mass media, the internet, and social medias, consumers can acquire a lot of information about every aspect of companies' endeavors, hence, also their sustainable conduct or misconduct.

Indeed, not all green marketing claims accurately reflect firms' environmental bearing. While some companies have genuinely engaged in eco-friendly initiatives, others exaggerate their efforts or simply claim to be environmentally responsible while they are not. The result of those actions represents one of the main problems with today's green marketing: the lack of consumers' confidence in companies' communication of environmental information, a phenomenon known as *the Greenwash Effect*.

Even though the term "greenwashing" has emerged in the 1980s, only in recent years it has gained wide recognition in the academic field leading to a stronger concern about the issue.

Greenwash derives from the word "environmental white-wash", a negative term that implies corporate deception. It is defined as a form of advertising whose main aim is to mislead or cheat consumers about environmental practices of a company (firm-level greenwashing) or the environmental benefits of a product/service (product-level greenwashing) (Martìnez, et al., 2020; Szabo & Webster, 2020; Chen, Huang, Wang, & Chen, 2020; Zhang, Li, Cao, & Huang, 2018). So, greenwash can be identified as the intersection of two firm behaviors: poor environmental conduct and positive communication about environmental performance (Delmas & Burbano, 2011).

Researchers have pointed out diverse antecedents, signs, and consequences of the greenwash effect. For what concerns antecedents, Delmas & Burbano (2011) spotted and classified different drivers of greenwashing that, joined with limited or imperfect information about firm environmental performance and uncertainty about regulatory punishment, contribute to such practice. They classified triggers into three main groups: external (pressures from both non-market actors such as regulators and NGOs, and market actors like consumers, investors, and competitors), organizational (firm incentive structure and ethical climate, effectiveness of intra-firm communication, and organizational inertia) and individual (narrow decision framing, hyperbolic intertemporal discounting and optimistic bias).

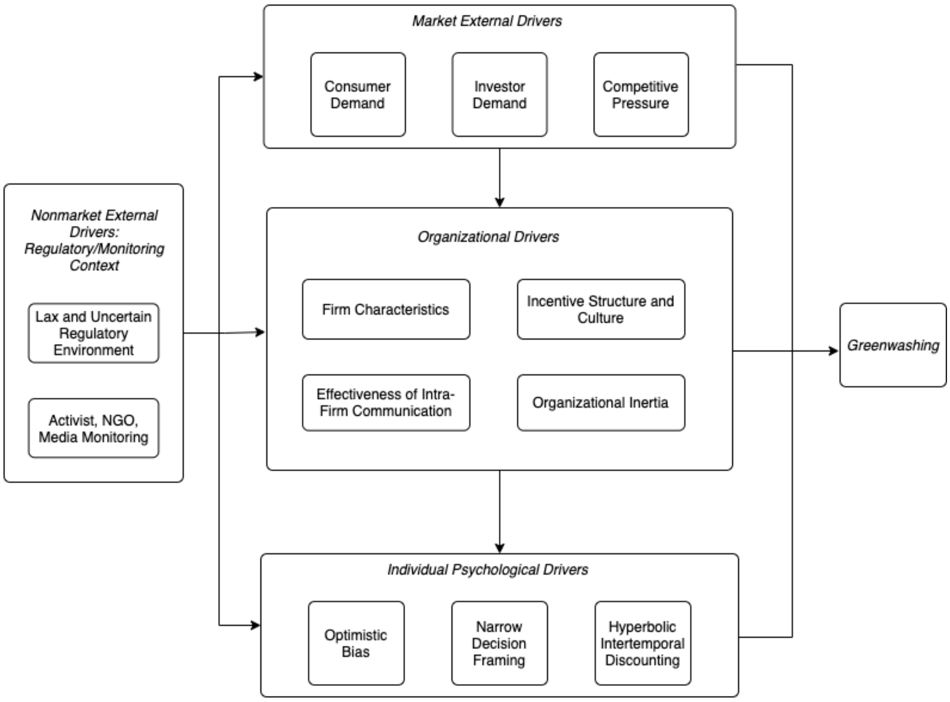

Figure 1: Drivers of Greenwashing *(Delmas & Burbano, 2011)*

Other research has identified brand image enhancement and word-of-mouth (WOM) as important drivers of a firm greenwash activity. This is due to the fact that companies want to improve them in order to gain a competitive advantage (Chen, Lin, & Chang, 2014).

Terra Choice[2] stated that it is possible to recognize green deceptive behaviors thank to the so-called "seven sins" being summarized as follow: (1) sin of the hidden tradeoff, (2) sin of fibbing, (3) sin of no proof, (4) sin of vagueness, (5) sin of irrelevance, (6) sin of lesser of two evils, (7) sin of worshiping false labels. When consumers perceive one of the above symptoms, they feel confused leading to negative consumers' evaluations and consequences for the firm (Delmas & Burbano, 2011).

The repercussions of engaging in greenwash are several and related to different aspects of an organization or product. According to Martìnez, et al. (2020) the perception of greenwashing has a negative relationship with loyalty and satisfaction. These findings have been proved using a mixed-method (survey and fuzzy logic), allowing researchers to state that when consumers perceive the product to be advertised through greenwashing, they will have a negative attitude in the purchase intention phase, thus a lower level of satisfaction. So, people tend not to buy or use up a good when they discover the practice of greenwashing, reducing their degree of

[2] Society acquired by the UL Group. Underwriters Laboratories Inc. is an independent safety certification organization. Founded in 1894, it is headquartered in Northbrook. Underwriters Laboratories develops standards and tests for products, materials, components, and tools with a focus on safety.

ease towards the product. Chen, Lin, & Chang (2014) found out that this point has another important implication: the relation with WOM which is influenced by greenwash through an indirect effect of satisfaction.

Another aspect that is affected by greenwash is "product quality". When consumers discern misleading practices in businesses' green marketing, they will perceive a commodity as lower in quality thus resulting in negative attitudes such as the sprawl of negative WOM (Chen, Lin, & Chang, 2014), lower credibility towards the advertised product, and the company (Szabo & Webster, 2020). This leads buyers to experiment states of confusion, thus judging the asset acquisition process as risky. Since firms engage in greenwash, this derives that advertisements come out to be misleading. That is why people get confused and perceive buying green products as risky in their decision-making process (Martìnez, et al., 2020). Higher perceptions of greenwashing will result in greater inherent and psychological perceived risk so ending in experiencing anxiety arising from the expectation or anticipated post-behavioral reactions to possible negative environmental consequences associated with purchase behaviors (Szabo & Webster, 2020).

Consumers are becoming aware of green cheating practices, consequently, they are intended not to purchase green products leading to the imperilment of the entire green market and the weakening of green marketing power (Chen, Lin, & Chang, 2014).

As greenwash would lead to consumers' suspicion and skepticism towards green claims, there is the need to find solutions to enhance consumers' attitudes such as positive WOM towards green products. Companies should decrease their greenwash behaviors and enable buyers to obtain enough information revealing more signals about their products. If more firms exaggerate the green functionality of their goods, their customers will not believe them anymore (Chen, Lin, & Chang, 2014). Thus, greenwash of companies would harm consumers' attitudes towards their activities of green marketing.

All in all, in order to come to be a useful marketing stream and pervade the market in a flourishing way, businesses ought to reduce greenwash.

1.4. Culture

"Culture is a way of coping with the world by defining it in detail" (Malcom Bradbury)

Culture is a complex concept related to multiple aspects of life. It serves as a source of theory that shapes individual perception, influences psychological processes, determines the identity of a human group, affects how people perceive and manage information that comes from the surrounding environment. All in all, it structures how people attend, think, and react.

Culture has been heavily studied in different fields. As a result, several definitions of such a heterogeneous phenomenon have been postulated during the past decades without leading to a universal and unanimous definition.

From an anthropological point of view, culture consists of "patterns, explicit and implicit, of and for behavior acquired and transmitted by symbols, constituting the distinctive achievements of human groups, including their embodiments in artifacts; the essential core of culture consists of traditional (i.e. historically derived and selected) ideas and especially their attached values; culture systems may, on the one hand, be considered as products of action, and on the other as conditioning elements of further action" (Kroeber & Kluckhohn, 1952). Kroeber & Parsons (1958) focused on a cross-disciplinary definition of culture, describing it as "transmitted and created content and patterns of values, ideas, and other symbolic-meaningful systems as factors in the shaping of human behavior and the artifacts produced through behavior". A more recent interpretation of culture has been made by Minkov & Hofstede (2011) depicting it as a "multiple packages" containing different variables.

Culture is not unique: the world is characterized by different people with different values and rationalities. No one can determine which costumes are the most plausible, only comparison among them can show that different ideas exist and that they might be possible alternatives.

The influence that culture has on people (so on consumers) is essential from a marketing perspective. Its "unpackaging" is a far-reaching task that marketers and researchers have to carry on.

Cultural differences have an impact on the adoption and diffusion of products (Yalcinkaya, 2008). Since cultural values and norms are strong drivers determining people's attitudes, behaviors, patterns of communication, and processing of information in the diverse parts of the world, a better understanding of their influence on the adoption of products may enable firms to set their marketing strategies (Yalcinkaya, 2008).

Many scholars have tried to rank cultures basing themselves on several codes of behavior, but one of the most applied classifications is the Hofstede's one. The popularity of the Hofstede model is not due to the fact that it is the absolutely right one, but to its coherence, predictive capability, validity, reliability, stability, and usefulness that has been confirmed over time and in various settings (Minkov & Hofstede, 2011).

In his book *"*Culture's Consequences: Comparing Values, Behaviors, Institutions, and Organizations Across Nations" (1991; 2001), Hofstede defines national culture as "the collective programming of the mind which distinguishes the members of one human group from another". In other words, a system of collectively held values. In this work, the author identifies five dimensions on which countries can be arranged, considering the implicit assumption that societies with higher ratings on a value give more emphasis to that value. The five dimensions pinpointed by Hofstede are the following:

Power distance. It is defined as the extent to which a society accepts that power in institutions is distributed unequally among individuals.

Individualism-collectivism. It refers to the relationship between the individual and the group. Better said, the extent to which people are expected to stand up for themselves as a member of the group or organization.

Masculinity-femininity. They represent the social implications of being born as a boy or a girl. They refer to the sex role pattern in society. As an example, masculine cultural values tend towards competition, ambition, career advancement, and self-achievement.

Uncertainty avoidance. It depicts the extent to which a society feels threatened by ambiguous situations and tries to avoid them by providing particular rules, regulations, and religions.

Long-term/short-term orientation. It is related to the idea of a society rejecting any historical attitude (short-term orientation) in favor of a pragmatic and future-oriented society (long-term orientation).

Hofstede states that a country can be positioned along the above-mentioned five dimensions to provide an overall summary of a country's cultural type. For example, he cataloged Australia, Great Britain, and the USA as smaller in power distance, more individualistic, more feminine, weaker in uncertainty avoidance, and more short-term oriented. On the other hand, Argentina, Japan, Mexico, and Portugal are supposed to be larger in power distance, more collectivist, more masculine, stronger in uncertainty avoidance, and more long-term oriented.

Since the five cultural dimensions have been also associated with the innovativeness aspect of consumers and with the adoption of new products and consumption concepts (Yalcinkaya, 2008), they could be a powerful tool to understand how different societies perceive products.

The cultural value worth to be mentioned in this study is "individualism-collectivism" mainly because its specific role has not been widely tested in the environmental setting (Yalcinkaya, 2008).

According to Gudykunst, et al. (1996) cultural "individualism-collectivism" has both a direct and indirect influence on people's behavior, values, and self-construal when being socialized into the culture. The authors identify some main values characterizing both groups. Indeed, individualistic cultures rely on independent self-construal, achievement, direct request (the most effective strategy for accomplishing their goals), and clarity in conversations. Whereas, collectivistic cultures lean on harmony, solidarity, interdependent self-construal, and avoid hurting others.

Other streams of research light upon manifold aspects. Taking into account individualistic cultures as an example, they show a preference for uniqueness over conformity (Kastanakis & Voyer, 2014), tend to focus predominantly on objects due to a more analytical cognitive style referring to information processing, engage in self-enhancement, and on attributes that emphasize positive aspects of their lives (Kastanakis & Voyer, 2014), increase the relative importance of internal attributes (personally held attitudes and preferences) and self-expression in driving individuals' actions (Eom, Kim, Sherman, & Ishii, 2016).

Table 1 summarizes the main contrasting aspects retrieved from the literature of the two categories.

In the context of circular economy and sustainable business models, their spread across nations requires an understanding of how culture determines which psychological factors drive human action.

Research suggests that cross-cultural differences should be taken into account in promoting pro-environmental attitudes, behaviors, and business models around the world. Indeed, people feel and behave differently about the environment due to different cultural backgrounds (Maeder, Uzzell, & Gatersleben, 2006). The specific history, values, and beliefs of a country may determine whether engagement in environmentally friendly behaviors will be promoted by individuals or not.

Although it is important to consider the cultural background as a variable for sustainability research, there is a lack of works concerning the topic (Larson & Kinsey, 2019).

According to Eom, Kim, Sherman, & Ishii (2016) as national-level individualism increases, the association between environmental concern and environmental behavioral intentions becomes stronger. Authors' findings suggest that individuals living in countries showing individualistic values are more concerned about the environment and more likely to take action. Whereas, in collectivistic countries, only normative regulations may lead people to embark on eco-friendly practices.

On the whole, self-standards are heavily influenced by social norms having their roots in cultural socialization. Societies deem certain actions to be desirable; as a consequence, people adopt these behaviors as standards for their behaviors (Peloza, White, & Shang, 2013). Thus, national culture is a significant determinant of individual environmental preferences.

Table 1: Culturally conditioned perceptual & cognitive orientation(s): individualistic/independent vs. collectivist/interdependent *(Kastanakis & Voyer, 2014)*

		Individualistic/independent orientation	**Collectivistic/interdependent orientation**
Perception	Self-perception	Autonomous, detached, differentiated	Inseparable, connected, non-differentiated
	Perception of others	Group exists to serve individual needs	Individuals exists to serve group needs
	Perception of emotions	Individual-orientation, de-contextualized, non-relational	Group-orientation, contextual, rational
	Perception of the environment and aesthetics preferences	Analytical, focal	Holistic, contextual
	Sensory perception	Differences across sensory channels	Differences across sensory channels
Cognition	Perspective-taking	Low perspective-taking ability, egocentric errors, insider	High perspective-taking ability, less egocentric errors, outsider's perspective
	Attribution & causal judgements	Tendency for dispositional attributions	Tendency for situational, contextual attributions
	Self-esteem	High need for self enhancement	Low need for self-enhancement
	Information processing	Field-independent, focal, analytical,	Field-dependent, contextual, holistic
	categorization	Ruled-based, categorical	Rational
	memory	Self-related memories	Other-oriented relational memories
	Processing of persuasion messages and decision-making	Central orientation (content of the message), uncomfortable with contradictory information	Peripheral orientation (how is the message delivered), comfortable with contradictory information.

1.5. Gender

"People share a common nature but are trained in gender roles" (Lillie Devereux Blake)

Consumers often buy products for their symbolic benefits. As a result, the different value that male and female assign to product connotative rewards (e.g., women show higher levels of brand sensitivity and consciousness) plays a key role. This is true in particular in the context of sustainability and circular economy related to the fashion industry.

Meyers-Levy & Loken (2015) identify five propositions that depict and differentiate the two groups: (a) males are more self-oriented and females are more other-oriented, (b) females are more cautious and avoidance focused while males are more risk-taking and assertive, (c) females are more responsive than males to negative stimuli, (d) males are more selective in their intake and processing data, whereas females are more comprehensive, (e) females are more sensitive to environmental cues and differentiating factors, whereas males' responses are more consistent across context. Consequently, the two authors conclude that males emphasize instrumentality and independence, whereas females give prominence to inclusiveness and interdependence. Following this line of thoughts, *self-construal research* indicates that males typically adopt an independent self-view meaning that the self is separate from others. It is an autonomous and unique entity that is individualistic in its pursuit. On the contrary, women embrace an interdependent view allowing them to be connected with others and the environment. Interdependence implies also higher levels of *moral sensitivity*, where *moral sensitivity* is defined as a morality-based construct that measures awareness of how one's action affects others, including an understanding of the cause-consequence chain of events and the use of empathy and perspective-taking skills (Meyers-Levy & Loken, 2015). The higher level of moral sensitivity brings women to have a stronger "world view"[3] than men thus making them more interested and engaged in environmentally-conscious actions (Zelezny, Chua, & Aldrich, 2000).

For what concerns product usage and consumption, men tend to be more outcome-focused placing a higher value on product efficiency (Fang, Wen, George, & Prybutok, 2016). On the contrary, women rely on products social elements in order to disclose self-identity patterns. They tend to use a great amount of mental resources to evaluate products experiencing high levels of product involvement[4] that have a positive influence on perceived product value (Prebensen, Woo, Chen, & Uysal, 2013).

Another important stream of research in analyzing gender differences concerns *socio-cultural theories.* It points out that gender roles affect attitude in a consistent way. Societal expectations influence behavior through social rewards and punishment for adapting or not to them creating gender differences. Gender roles generate pressure to conform and become internalized as "gender identities" that represent the framework through which people elaborate information about themselves and the environment in which they live (Brough, Wilkie, Ma, & Gal, 2016).

What just mentioned has even more relevance if reckon with one of the most significant results related to the gender gap in sustainable consumption. Brough, Wilkie, Ma, & Gal (2016) highlight the existence of a psychological tie between sustainability and femininity. They assume that men tend to resist green behaviors because of different drivers. First, they avoid buying sustainable products viewing them through the lens of

[3] Calculated considering caring moral views over justice concerns.

[4] *Involvement*: "individual's perceived importance of the decision to the individual in terms of basic goals, values, and self-concept" (Fang, Wen, George, & Prybutok, 2016).

stereotype (green consumers are for the most part women). Secondly, men want to be sure their masculine identity to be safeguard paying a lot of attention not to harm their individuality. Consuming green products could threaten their "macho values" leading to gender-inconsistency transgression thus to severe social punishments. So, males are more influenced by impression management and self-perception when deciding to buy eco-friendly goods. All in all, due to the green-feminine stereotype, gender-identity maintenance can influence men's likelihood of adopting green behaviors.

1.6. Internet word-of-mouth (eWOM)

"People influence people. Nothing influences people more than recommendation from trusted friends. A trusted referral influences people more than the best message. A trusted referral is the Holy Grail of advertising" (Mark Zuckemberg).

Humans are social entities. They like to be surrounded by others, to interact, chat and share opinions.
They talk about personal experiences, the last movie released in theatres, important political issues, sports rumors, etc.
The activity of sharing information between people is called Word-of-Mouth (WOM) or Interpersonal Communication. It is defined as "any kind of informal communication directed to other consumers about the ownership, usage or characteristics of particular goods and services or their sellers" (Westbrook, 1987).
In order to express achievement, seek confirmation, and fulfill therapeutic feeling, people rely on social communication which depends on self-need and it is influenced by emotions (Berger, 2014).
Until the last decades, WOM was characterized by one-to-one relationships, oral, synchronous, causal, and private communication. It was non-persistent over time, homogeneous and non-anonymous (King, Racherla, & Bush, 2014).
Up to now, face-to-face conversation was the only means for exchanging information, but things have been rapidly evolving and modifying leading to new conceptualizations of WOM and the circulation of new notions.
With the development of new technologies (e.g., computers or smartphones), the growing presence of social networks (e.g., Facebook, Instagram, WhatsApp, YouTube, Twitter), the importance of blogs (e.g., The Blond Salad), forums, and review platforms, user's ability to interconnect, share and exchange opinions is even easier and more immediate. Some statistics suggest that on the Twitter platform users send half a billion tweets every day (Mention, 2018). This equates to 5,787 tweets per second. For what concerns WhatsApp there are 2 billion people around the world who use the app to stay in touch with friends, family, and co-workers. Given that, on average at least 100 billion messages are sent every day on WhatsApp. This means that each person sends about 50 messages within twenty-four hours (Will Cathcart[5]). Half of all internet users say that they post online product or brand reviews at least once a month (GWI, 2019).

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[5] Chief Executive Officer, WhatsApp Inc.

All the new ways of sharing information have been classified by scholars as "electronic" WOM (eWOM). Henning-Thurau, Gwinner, Walsh, & Gremler (2004) defined it as "any positive or negative statement made by potential, actual, or former customers about a product or company, which is made available to a multitude of people and its institutions via the Internet". Even though traditional WOM is still dominant, eWOM is statistically growing in volume (Mention, 2018) with the ability to reach a vast public all over the world, allow people with the same interests to connect and increase consumer engagement both with companies and with other consumers (King, Racherla, & Bush, 2014).
From a marketing perspective, eWOM relevance is pervasive. First of all, consumers do not perceive the manipulative intent of the communication since it involves an exchange of information among peers. So, eWOM has a higher persuasive power compared to traditional advertising. Notwithstanding, it exists the danger of fake reviews defined as any positive, neutral, or negative reviews that are not made by an actual consumer. They can be created by competitors to harm company reputation or even by the company itself to increase its image. In both cases when consumers perceive a piece of information as fake or misleading, they will respond negatively decreasing their trust in the firm's image.
Besides, eWOM has a strong and effective targeting power, it is directed to an interested audience or better said, to people who want to acquire specific information. It has a relevant role in buyers' decision-making process because they take into account messages decreasing uncertainty (Chen, Lin, & Chang, 2014). As a result, eWOM power is spreading and firms cannot leave it apart anymore.
Even in the field of circular economy and sustainability eWOM can play a major role because it can affect choice, diffusion, and sales. This is true in particular when products are related to social or moral values as people tend to pay a lot of attention to social issues, conveying codes of conduct and moral rules when sharing information. Indeed, up to 70% of daily discussions are dominated by social topics (Alexandrov, Lilly, & Babakus, 2013).
An important stream of research views social information as a way to deliver moral stories about life and society. In line with this belief, it applies Social Learning Theory to the field of WOM (Alexandrov, Lilly, & Babakus, 2013). Social Learning Theory has been fostered by Albert Bandura. The author highlighted how learning did not only imply direct contact with objects but also took place through indirect experiences such as the observation of other people. Bandura has used the term *modeling* (imitation) to identify a learning process that is activated when the behavior of an observing individual change according to the behavior of a sample acting individual. The identification between model and modeled is considered as a fundamental characteristic of observational learning. The higher it is, the more learning will have an effect on the behavior of the model.
Therefore, eWOM can be a key tool for conveying moral stories, norms about society and reducing the uncertainty of consumers' decision-making process leading to the adoption of more effective consumption models.

Other works identify the most common antecedents of WOM/eWOM activity distinguishing between satisfaction, loyalty, quality, commitment, trust, and perceived value, thus creating a strong link between brand-related experiences and eWOM. As a result, when engaging in sharing information about products or brands environmental performances, also defined “green WOM”, people may express uniqueness, self-enhance their image in the eyes of others, share knowledge about a product or a firm performance.
In summary, in a more and more complicated marketing environment, consumers play a role of an effective information channel to contribute eWOM (Zhang, Li, Cao, & Huang, 2018). But the major challenge is to understand which strategy is necessary to lead to an increase in eWOM leveraging some of its critical antecedents and drivers.

In the next section, the research framework of this work and hypothesis development will be explained.

Chapter II: Hypothesis development and conceptual framework

The research model advanced and tested in the current work is presented in **Figure 2.**

The conceptual framework has been developed from the literature related to fashion circular economy and green marketing described above and taking into consideration the gaps in such field. As a matter of fact, there is the need to find a successful strategy to let closed loops business models being accepted in the fashion world and so to enhance the perceived value of circular economy outcomes. Moreover, firms should try to find a way to decrease the recent phenomenon of the Greenwash Effect making consumers less suspicious.

Many scholars have tried to procure different solutions, but a road that has not been fully traveled is the one of green co-branding.

So, this work aims to fill this gap by suggesting a direct relationship between the use of green co-branding as a green marketing strategy and both product and brand eWOM. A parallel mediation is also described considering perceived product quality and greenwash effect as mediators between green co-branding strategy and eWOM. Additionally, culture and gender will be considered two moderators of the model.

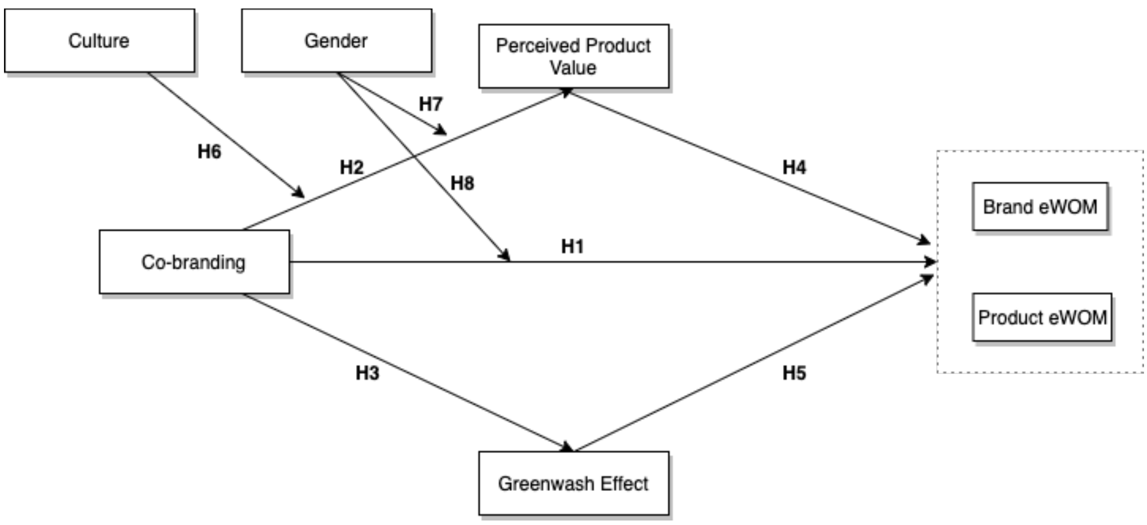

Figure 2*:* Research Model

In the next sections the route to hypothesis development is going to be presented.

2.1. The role of co-branding

Corporate Social Responsibility (CSR) is usually considered as a way of improving companies' reputation and making consumers experiment helpful feelings. People tend to judge socially responsible firms as warmer, more compassionate, more ethical, and less blameworthy (Chernev & Blair, 2015).

For what concerns fashion industry companies, engaging in circular economy models might be a way for increasing their CSR. However, as much research demonstrates, even if consumers demand CSR changes, they are still skeptical about adopting them (Ki, Chong, & Ha-Brookshire, 2020; Ferasso, Beliaeva, Kraus, Clauss, & Ribeiro-Soriano, 2020; Ki, Park, & Ha-Brookshire, 2020). So the need to make closed-loop models being accepted and embraced emerges. This work focuses on co-branding as a possible solution to address this necessity.

Green co-branding implies collaboration with external parties about organizational exchanges, communication, and relationship which might bring potential benefits to the environment and the businesses involved (Crane, 1998). By partnering with green market leaders, NGOs, and other organizations, firms elevate their environmental profile and provide stronger signals of green value to stakeholders (Sadovnikova & Pujari, 2017).

Perrini, Castaldo, Misani, & Tencati (2009) suggest that consumers build up a positive attitude (that is trust) in a company when it improves its regulations to meet CSR actions. According to later studies, the above findings might be applied to green partnerships resulting in a higher level of consumers' trust for firms engaging in such a practice (Huertas-Garcìa, Lengler, & Consolaciòn-Segura, 2017; Sadovnikova & Pujari, 2017). Consumers' will develop positive perspectives towards efforts (e.g. engaging in green co-branding) and the products of a circular fashion company if they perceive that the company aims to create a circular economy. Besides, they will judge them as unique, socially relevant, and trustful (Ki, Chong, & Ha-Brookshire, 2020).

Uniqueness and social enhancement are two main components of impression management that lead to an increase of WOM/eWOM when combined with trust (Berger, 2014; King, Racherla, & Bush, 2014).

All in all, green partnerships can be instrumental in carrying out environmental strategies of firms and generate performance gains and reputational gains (Sadovnikova & Pujari, 2017).

It is possible to state that using a green co-branding strategy will lead to a more positive eWOM regarding both the brand and the product. Thus, a green co-branding strategy might directly influence eWOM. Hence:

> **H1:** The use of co-branding as green marketing strategy will have a positive influence on a) product eWOM, b) brand eWOM.

Consumers' perceived value is one of the main constructs and foundations characterizing all relational exchange activities (e.g., buyer/seller) and it is a crucial element influencing consumers' action both in the offline and in the online landscape (Fang, Wen, George, & Prybutok, 2016).

Chernev & Blair (2015) found that CSR impact can influence the way consumers evaluate products. More specifically, they found that products of companies engaged in acting to the benefit of society are considered to perform better, thus having a higher value. Vahdati, Mousavi, & Tajik (2015) showed that the more consumers see that a company is taking the moral responsibility for performing in a sustainable way, the higher the consumers' propensity to value the company and its sustainable offerings positively. In line with this stream of research co-branding studies assess that products labeled as being the result of an alliance score higher in

perceived value (Leuthesser, Kohli, & Suri, 2003; Huertas-Garcìa, Lengler, & Consolaciòn-Segura, 2017; Wang, Krishna, & McFerran, 2017).
After all, using a green co-branding strategy will lead to a higher perceived recycled product value. Thus, a green co-branding strategy positively influences perceived recycled product value. Hence:

H2: The use of co-branding as green marketing strategy will have a positive influence on perceived recycled product value.

Co-branding strategies might be a powerful tool to diminish risk related to circular fashion products. Alliances stimulate image transfer from eco-friendly, sustainable purposes of a cause, NGOs principles, etc. to the brand. Thus, promoting a co-branding strategy results to be extremely important to increase the awareness of the cause as well as of the brand (Huertas-Garcìa, Lengler, & Consolaciòn-Segura, 2017).
Risk is considered an essential component of greenwash which is supposed to be a barrier to the adoption of circular fashion products (Ki, Chong, & Ha-Brookshire, 2020; Ferasso, Beliaeva, Kraus, Clauss, & Ribeiro-Soriano, 2020) leading consumers to be suspicious and skeptic towards firms' green outcomes.
If a company removes greenwash by delivering a trustful, reliable, and more transparent advertising campaign, it will enhance its brand image, consumers' loyalty, and purchase behavior (Chen, Huang, Wang, & Chen, 2020).
Joining those findings with the ones related to co-branding it is possible to state that using a green co-branding strategy will lead to a lower perceived Greenwash Effect. Thus, green co-branding strategy negatively influences perceived greenwashing. Hence:

H3: The use of co-branding as green marketing strategy will have a negative influence on perceived greenwash effect.

2.2. The role of perceived product value

Perceived product value (PPV) is one of the most important factors that give rise to marketing outcomes (Arunrangswed, 2021). Indeed, consumers' positive PPV translates into their favorable behavioral intention and attitudes (Ki, Park, & Ha-Brookshire, 2020). The same effect has been identified in the context of fashion circular economy and sustainability.
Ki, Park, & Ha-Brookshire (2020) posit that the more positively consumers value circular fashion offerings, the more likely to engage in positive attitudes (e.g., the spread of information) towards the company and the products they will be. As the perceived value increases, the less important the role of functional aspects in buyers' decision-making processes and more important the emotional and social ones (Medeiros, Duarte Ribeiro, & Nogueira Cortimiglia, 2016). In line with these findings, Chen, Lin & Chang, (2013) demonstrate that the higher the degree of functional, emotional, and social components, the more positive WOM is.

As a result, it is possible to state that a higher level of the perceived recycled product value will lead to more positive eWOM regarding the brand and the product. Perceived recycled product value may potentially mediate the relation between a green co-branding strategy and positive eWOM. Hence:

H4: A higher perceived recycled product value will have a positive effect on a) product eWOM, b) brand eWOM.

2.3. The role of Greenwash Effect

As the literature suggests, green purchases are strongly related to consumers' perceived risk (Essoussi & Linton, 2010; Martìnez, et al., 2020). One of the most recent phenomena linked to risk perception over green products is Greenwash Effect.

Martìnez, et al. (2020) suggest that perceived greenwash has several negative effects on a firm's overall performance. Indeed, it tends to confuse consumers leading to low buying attitudes, satisfaction, and negative behaviors.

Szabo & Webster (2020) demonstrate that perceived greenwash can deeply affect an organization in a negative way such that greenwash may lead to consumers' lower levels of happiness expression and little website interaction. According to other studies, greenwash is negatively related to both image and loyalty leading to uncooperative green behaviors (Chen, Huang, Wang, & Chen, 2020).

Additionally, if a firm misleads or cheats its consumers about its environmental conduct, buyers will spread negative WOM to warn friends and relatives about the poor performance of the product (Zhang, Li, Cao, & Huang, 2018).

The need to diminish greenwash comes forth. In fact, as Ki, Park, & Ha-Brookshire (2020) state, the less consumers perceive the gap between what a company says and what it does, the more they perceive the company to be authentic, shaping positive consumer attitudes toward the company's communication message and offerings. The authors also say that when consumers experiment a gap between the mission of a fashion company and its performances, that same gap will negatively influence buyers' attitudes (e.g., delivering positive information to other consumers) toward the companies' offerings.

Chen, Lin & Chang, (2013) state that if firms plan to improve their consumers' WOM for their green products, they will have to decrease greenwash perception and enhance green perceived quality and satisfaction.

As a result, it is possible to assert that a lower level of greenwash effect will lead to more positive eWOM regarding the brand and the product. Greenwash may potentially mediate the relation between a green co-branding strategy and positive eWOM. Hence:

H5: A lower perceived Greenwash Effect will have a positive effect on a) product eWOM, b) brand eWOM.

2.4. The moderating role of culture

The socialization process helps individuals to become aware of values and ways of conduct (Gudykunst, et al., 1996).

Hofstede (2001) classified cultures according to five dimensions. However, the most relevant one to this study is "individualism-collectivism".

Cultures differ in what drives environmentally friendly actions. They highlight that individualism influences the extent to which people's environmental concern predicts pro-environmental behaviors because individualistic cultures score high results in expressing internal values and ideas (Eom, Kim, Sherman, & Ishii, 2016).

A more recent study has discovered that environmental attitudes in countries with distinctive power distance and indulgent cultures tend to differ from the attitudes in other countries, so individualism is linked to pro-environmental values. Citizens of more individualistic countries tend to have stronger links between intentions and green behaviors, between attitudes and green behaviors (Larson & Kinsey, 2019).

As a result, one of the goals of this research is to test the role of individualism as a moderating variable that explains the effectiveness of co-branding strategy in enhancing perceived recycled product value.

So, it is possible to state that a green co-branding strategy will be more effective and leading to a higher perceived product value for individualistic cultures rather than for collectivistic ones. Culture may potentially moderate the relation between a green co-branding strategy and the perceived value of a product made of recycled materials. Hence:

> **H6:** The positive effect of the use of co-branding as green marketing strategy on perceived recycled product value is more likely to occur for individualistic cultures rather than for collectivistic ones.

2.5. The moderating role of gender

According to the literature, gender might play an important role in determining purchases. Females and males show different needs and decision-making processes when shopping (Fang, Wen, George, & Prybutok, 2016). This is even more evident when dealing with green products, in particular in the fashion industry (Gazzola, Pavione, Pezzetti, & Grechi, 2020).

Women and men may react to the same stimuli inconsistently resulting in differences in the perceived product value (Fang, Wen, George, & Prybutok, 2016). Females are more other-oriented, comprehensive in selecting data, sensitive to detailed information, more easily persuaded when ads generate sympathy, and favor equity-based allocations that benefit others and the self (Meyers-Levy & Loken, 2015; Fang, Wen, George, & Prybutok, 2016). Males are more self-oriented and pragmatic and they tend to avoid green purchases mainly because of the green-feminine stereotype (Brough, Wilkie, Ma, & Gal, 2016).

As a result, it is possible to state that a green co-branding strategy will be more effective and leading to a higher perceived product value and positive eWOM for women rather than for men. Gender may potentially moderate the relation between a green co-branding strategy and the perceived value of a product made of recycled materials. Hence:

H7: The positive effect of the use of co-branding as green marketing strategy on perceived recycled product value is more likely to occur for females rather than for males.

H8: The positive effect of the use of co-branding as green marketing strategy on brand and product eWOM is more likely to occur for females rather than for males.

Chapter III: Methodology

The hypothesis has been investigated using a randomized between-subject experimental study distinguishing between green co-branding strategy and green strategy without co-branding.

Sports shoes have been chosen as subject products to carry on the analysis.

Greenpeace has been selected as the firm's co-branding partner because it is one of the worldwide known NGOs for environmental safety.

The section to come will be about the several stages of development required to fulfill the analysis.

3.1. Data collection and sample

This work is based on a questionnaire survey method to test the hypotheses and research framework. Data have been collected using an online questionnaire edited in Qualtrics.

It is worth to underline that a pre-test has been developed before proceeding with the questionnaire administration in order to check the effectiveness of the two stimuli. It has been delivered to a random sample of thirty-six people of different ages. They were exposed to the two stimuli and then they had to answer to some questions. The first one was related to product recyclability perception and the second one was linked to the presence or absence of a partnership between sponsored brand and an environmentally concerned NGO (Greenpeace). The results of the pre-test have shown that respondents exposed to the advertisements were able to discern if the poster sponsored a co-branding strategy or not. Then a two-sample *t* test was run to verify if there is a shift in product recyclability characteristics between the group exposed to the advertisement showing a partnership and the group exposed to the advertisement without the presence of the Greenpeace logo. The confidence interval does not contain 0, which is in accordance with the *p-value* (*p-value* = 0.003283) indicating a significant difference at the 5% level.

Table 2: Two sample t-test for the pre-test output

	Welch Two sample t-test
data:	Recyclability by man
t = -3.1666,	df = 33.443, p-value = 0.003283
alternative	hypothesis: true difference in means is not equal to 0
95 percent	Confidence interval:
-1.4596972	-0.3180806
sample	estimates:
mean in group 0	mean in group 1
5.277778	6.166667

So, the manipulation stimuli have resulted into being an effective tool to address the model and have been used in the main survey.

In the main survey participants were randomly assigned to one of the two conditions: co-branding vs no co-branding. They were advised to read and watch the advertisement carefully and then answer the questions. The system was set up not to allow them to skip responses.

The questionnaire started with questions about perceived product value considering four dimensions: quality, price, the emotional value of the product, and social one. The section about perceived greenwash and eWOM followed.

An attention-check question was also asked to test the level of respondents' commitment. The survey ended with demographics information such as gender, age, and nationality.

A probability sampling technique such as the random sample technique was used to select respondents. The questionnaire was distributed through the WhatsApp platform to people from different countries.

Of the original 360 participants, 20 were excluded from the study: 10 of them did not finish to answer the questionnaire questions, 6 because of nonserious answering behavior, 4 participants took too long to answer the questions. As a result, 340 questionnaires were used for the analysis.

Participants were randomly assigned to one of the two conditions, specifically 178 (52%) were assigned to the No Partnership condition and 162 (48%) were assigned to the Partnership condition.

In total 166 (49%) females and 174 (51%) males participated in the study.

The average age of the participants was 34 (range = 19 -70). The graph below shows the age distribution for the entire survey dataset.

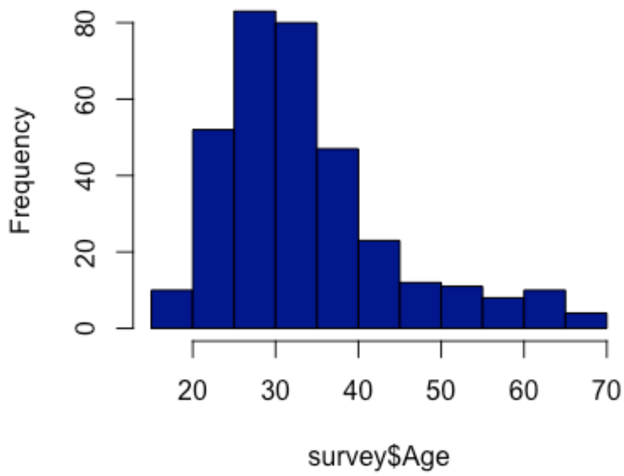

Figure 3: Age distribution among respondents

Participants'' nationality was inspected finding that respondents pertain to twenty-eight different nationalities: Albanian (0.3%), Algerian (0.3%), Colombian (0.3%), Greek (0.3%), Hungarian (0.3%), Latvian (0.3%), Malaysian (0.3%), Mexican (0.3%), Persian (0.3%), Polish (0.3%), Romanian (0.3%), Turkish (0.6%), Venezuelan (0.6%), Saudi (0.6%), Jamaican (0.6%), Portuguese (0.9%), Korean (0.9%), Australian (1.2%), French (1.2%), Spanish (2.3%), Canadian (5%), Brazilian (10%), Italian (14%), English (14%), seventy-two Indian (21%), American (24%).

The following graph gives a visual representation of the different nationalities in the survey dataset.

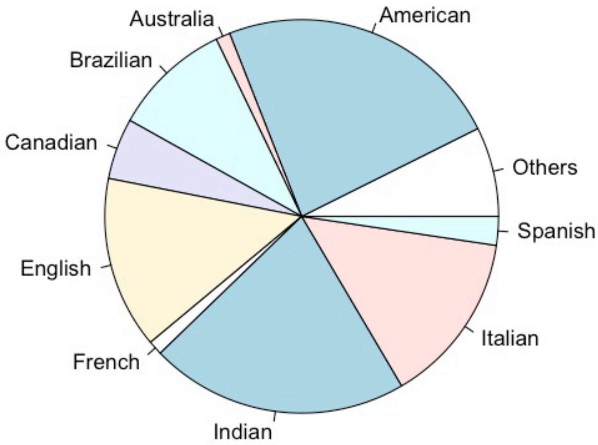

Figure 4: Nationality pie chart

Respondents were considered part of collectivistic or individualistic culture basing the classification on the *Hofstede Index*. So, people coming from United States, Australia, United Kingdom, Canada, Netherlands, Hungary, New Zealand, Italy, France, Belgium, Ireland, Switzerland, Germany, South Africa, Luxemburg, Czech Republic, Austria, Israel, Slovakia, Poland, Lithuania, Latvia, Estonia were considered as belonging to individualistic culture (Hofstede, 2001). All the other ones were taken as collectivistic cultures.

3.2. Measurement

To avoid the influence of prior knowledge, experiences, or preferences, a fictitious product (*Infinity Shoes*) was used and introduced to participants as a new product developed by a fictitious company.

Respondents were randomly exposed to two manipulations. The first one explained the launch of a new shoe line made of recycled plastic. The second one contained the same content of the first one underlining also the fact that the new line was made in partnership with *Greenpeace*.

The three dependent variables were measured using validated scales retrieved from previous literature.

This work evaluates the questionnaire items by means of a “seven-point Likert scale from 1 to 7” rating from “strongly disagree” to “strongly agree”. The measurement of the construct is described as follows:

Perceived product value. Due to the different shades that perceived value embeds, a multi-item scale from Sweeney & Soutar (2001) considering quality, emotional, price, and social value was applied. Quality was measured considering five items: (1) The product has consistent quality; (2) The product is well made; (3) The product has an acceptable standard of quality; (4) The product would perform consistently; (5) The product would perform well.

Emotional value was measured considering five items: (1) The product is one that I would enjoy; (2) The product would make me want to use it; (3) The product would make me feel good; (4) The product would give me pleasure; (5) I would like this product.

Price was measured considering three items: (1) The value I would receive from this product would be worth the time, effort, and money I would invest; (2) The product would offer value for money; (3) The product would be economical.
Social value was measured considering four items: (1) The product would help me to feel acceptable; (2) The product would improve the way I am perceived; (3) The product would make a good impression on other people; (4) The product would give its owner social approval.

Perceived Greenwash. The present work refers to Chen, Huang, Wang, & Chen (2020) to measure greenwash perception. The scale takes into account five items: (1) The brand misleads with words in its environmental features; (2) This brand deceives me by means of visuals or graphics in its environmental features; (3) The brand deceives me by means of green claim that are unclear; (4) The brand exaggerates or overstates its green functionality; (5) The brand hides important information, making green claim sound better than it is.

Product eWOM. The present work refers to Chen, Lin & Chang (2014) to measure product eWOM including four items: (1) Highly recommend this product to others because of its environmental image; (2) Say positive things about this product because of its environmental functionality; (3) Encourage others to purchase this product because it is environmentally friendly; (4) Introduce this product to other because of its environmental performance.

Brand eWOM. For what concerns the measurement of brand eWOM Alexandrov, Lilly, & Babakus (2013) scale was considered. It contains six items answering the question "How likely would you be doing any of the following?": (1) Say positive things about this brand; (2) Recommend this brand to others; (3) Recommend this brand to someone else who seeks my advice.

3.3. Results

3.3.1. Reliability and validity

Factor analysis was carried on to test the reliability of the questionnaire.
Factor analysis is a technique that is used to reduce a large number of variables into fewer numbers of factors. This technique extracts maximum common variance from all variables and puts them into a common score. Factor analysis is part of a general linear model (GLM) and it includes several assumptions: there is a linear relationship, there is no multicollinearity and there is a true correlation between variables and factors. Several methods are available, but the most common one is the *Principal Component Analysis* (Statistics Solutions, s.d.).
Principal component analysis[6] was performed to decide the ideal number of factors.

[6] PCA starts extracting the maximum variance and puts them into the first factor. After that, it removes that variance explained by the first factors and then starts extracting maximum variance for the second factor. This process goes to the last factor.

Three factors resulted into a higher than one eigenvalue and a cumulative percentage higher than 60%. Factors were rotated using the "*varimax*" method. The pattern matrix of **Table 2** offers a clearer picture of the relevance of each variable in the factor.

Factor one is mostly defined by the questions related to "Perceived Value". Factor two is mostly defined by the questions related to "greenwash". Factor three is defined by those values related to eWOM.

It is possible to state that the scales are valid (construct validity is correct) and they are separated (i.e. distinct measure, different concepts) as well, so discriminant validity is fine.

Even if the validity of the scale is correct, it is possible to notice a problem with the item: "Highly recommend this product to others because of its environmental image". Indeed, its value corresponds to 0.30.

From the Cronbach's Alpha analysis, it came out that the "α" value results as it follows: as to Perceived Value, $\alpha = 0.96$; as to greenwash, $\alpha = 0.94$; as to positive Brand eWOM, $\alpha = 0.95$. For what concerns product positive eWOM, the value of the Cronbach's Alpha was $\alpha = 0.74$. But removing the item "Highly recommend this product to others because of its environmental image" it increased to $\alpha = 0.94$. So, the problematic item was delated to allow more correct and trustful analysis.

Table 3: Factor Analysis of the Dependent Variables

	Factors		
	1	2	3
Scale Items			
The product has consistent quality	0.69		
The product is well made	0.71		
The product has an acceptable standard of quality	0.69		
The product would perform consistently	0.72		
The product would perform well	0.74		
The product is one that I would enjoy	0.79		
The product would make me want to use it	0.82		
The product would make me feel good	0.82		
The product would give me pleasure	0.84		
I would like this product	0.86		
The value I would receive from this product would be worth the time, effort and money I would invest	0.62		
The product would offer value for money	0.64		
The product would be economical	0.63		
The product would improve the way I am perceived	0.73		
The product would make a good impression on other people	0.72		
The product would give its owner social approval	0.59		
The brand misleads with words in its environmental features			0.91
This brand deceives me by means of visuals or graphics in its environmental features			0.92
The brand deceives me by means of green claim that are unclear			0.87
The brand exaggerates or overstates its green functionality			0.81
The brand hides important information, making green claim sound better than it is			0.79
Highly recommend this product to others because of its environmental image		0.30	
Say positive things about this product because of its environmental functionality		0.81	
Encourage others to purchase this product because it is environmentally friendly		0.79	
Introduce this product to other because of its environmental performance		0.81	
Say positive things about this brand		0.79	
Recommend this brand to others		0.82	
Recommend this brand to someone elese who seeks my advice		0.78	

3.3.2. Intercorrelation and variables relative importance

In this paragraph correlation, regression, diagnostics analysis, and multicollinearity check are going to be explained. To introduce the concept some notions have been given.

A correlation coefficient is a symmetric, scale-invariant measure of association between two variables. It ranges from minus one to plus one, where the extremes indicate perfect correlation and zero means no correlation. The sign is negative when large values of a variable are associated with small values of another one; instead, it is positive if both values tend to be large or small simultaneously (Dalgaard, 2008).

Multiple Regression analysis is a kind of model that searches aspects, namely among a set of potential descriptive variables to look for a subset that describes the response sufficiently well.

Regression diagnostics are used to evaluate the model assumptions and investigate whether or not there are observations with large influence on the analysis (Dalgaard, 2008).

Multicollinearity is a state of very high intercorrelations or inter-associations among the independent variables. It is therefore a type of disturbance in the data, and if present the statistical inferences made about the data may not be reliable (Statistics Solutions, s.d.).

In order to inspect and have a visual representation of how the different variables allocate across the dataset, two different pairwise correlation plots were generated. Indeed, the plots are considered as an effective way of obtaining an overview of multidimensional issues (Dalgaard, 2008).

In **Figure 6** each individual plot shows the relationship between the variable in the horizontal versus the vertical of the grid. For example, co-branding vs perceived product value (continuous vs discrete variable) or greenwash vs brand eWOM (two discrete variables). The diagonal is showing a histogram of each variable distribution. Indeed, it is possible to point out that both brand and product eWOM are left-skewed as well as perceived product value.

The numeric values of the correlations among variables are provided as well. As it appears, greenwash and culture are negatively correlated both with brand eWOM and product eWOM. While all the other variables are characterized by a positive correlation with the dependent variables.

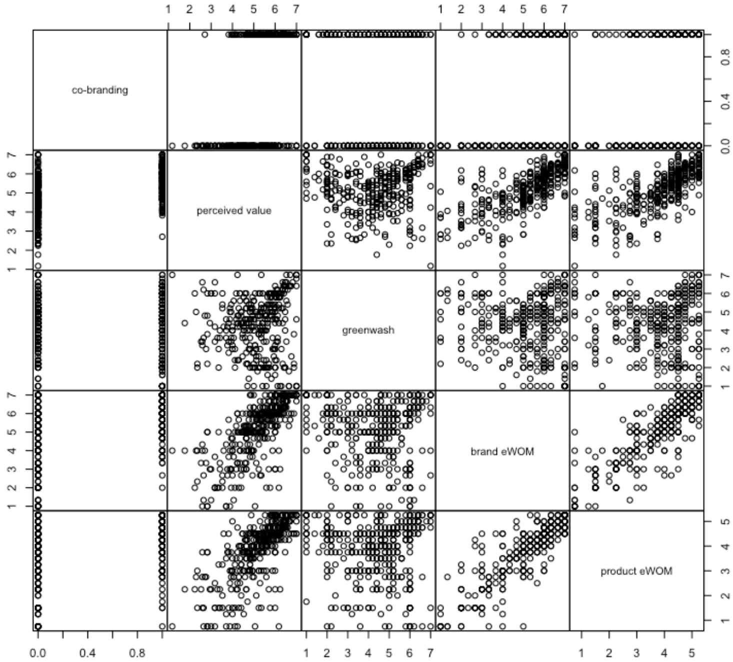

Figure 5: Pairwise plots for survey data

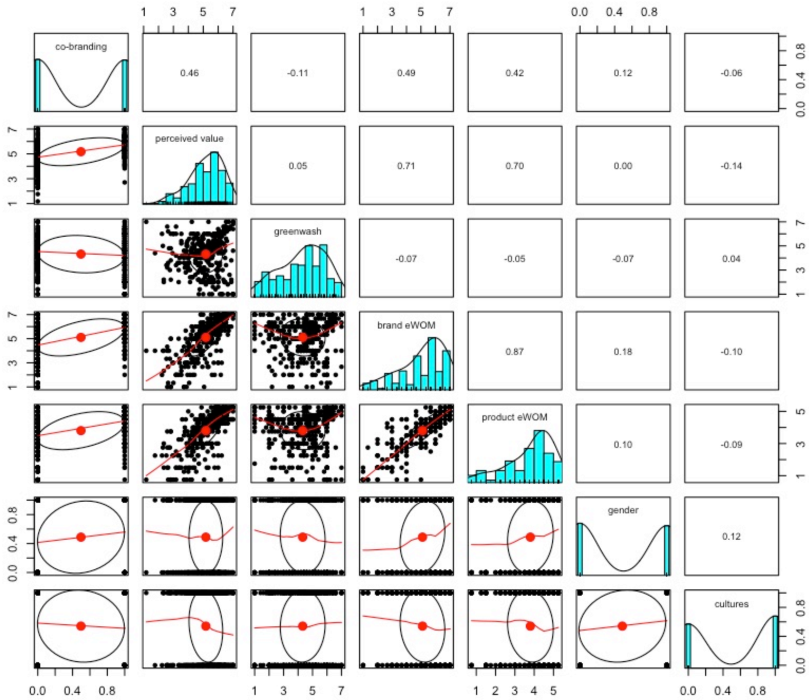

Figure 6: Scatterplot matrix of survey data

Product eWOM

Multiple regression analysis was used to test which variable among co-branding, perceived product value, greenwash, culture and sex has more influence on product eWOM. The results of the regression indicate that all the independent variables explained 50.8% of the model $(Adj\ R^2 = 0.51,\ F(5, 334) = 71.08, p < 0.001)$. It was found that perceived product value significantly influences product eWOM $(\beta = 0.69, p < 0.001)$, co-branding slightly significantly influences product eWOM $(\beta = 0.23, p < 0.05)$, and sex slightly significantly influences product eWOM $(\beta = 0.20, p < 0.05)$.

The table below reports all the values obtained by running the regression analysis for product eWOM.

Table 4: Summary regression table of product eWOM

Coefficients					
	Estimate	Standard Error	t value	Pr (> |t|)	
(Intercept)	0.210835	0.259918	0.811	0.4179	
co_branding	0.227431	0.103798	2.191	0.0291	*
PV	0.694839	0.045848	15.155	<2e-16	***
GW	-0.050966	0.029565	-1.724	0.0857	.
culture	0.008383	0.092229	0.091	0.9276	
sex	0.201103	0.091960	2.187	0.0294	*
Residual standard error	0.8318 on 334 DF				
Multiple R-squared	0.5155		Adjusted R-squared	0.5083	
F-statistics	71.08 on 5 and	334 DF	p-value	< 2.2e-16	

Figure 7 visually represents the importance of each variable for the model using four different methods. As it is possible to notice, comparing all the four methods the most important variable that influences positive product eWOM is perceived product value.

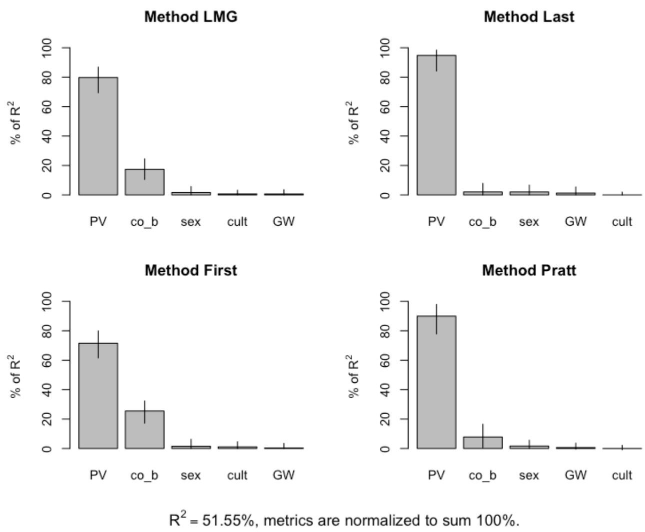

Figure 7: Relative importance for product eWOM with 95% bootstrap confidence intervals

The following step was the regression diagnostics. The top right panel of **Figure 8** shows the Q-Q normal distribution plot of standardized residuals. Whereas the top left panel shows residuals versus fitted values. The third plot is the square root of the absolute value of the standardized residuals. It shows a reduction in the skewness of the distribution making it easier to detect dispersion. Finally, the *Cook's Distance*[7] was calculated. The overall graph illustrates that observation no. 94 represents an extreme in several aspects.

[7] Measure of the influence of each observation on the regression coefficients.

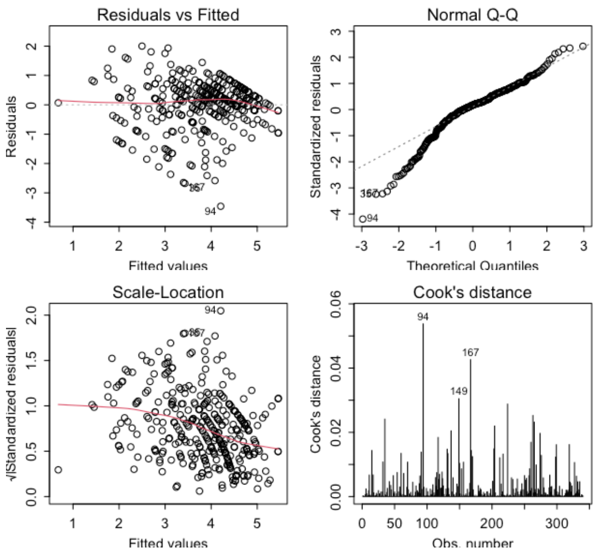

Figure 8: Regression Diagnostics for product eWOM

Considering the above findings, regression was run removing the extreme observation (no. 94) resulting into no significant changes in the overall result.

Brand eWOM

Multiple regression analysis was used to test which variable among co-branding, perceived product value, greenwash, culture, and sex has more influence on brand eWOM. The results of the regression indicate that all the independent variables explained 57.2% of the model $(Adj\ R^2 = 0.57,\ F(5, 334) = 89.46, p < 0.001)$. It turned out that perceived product value significantly influences brand eWOM $(\beta = 0.87,\ p < 0.001)$, co-branding significantly influences brand eWOM $(\beta = 0.52,\ p < 0.001)$, sex significantly influences brand eWOM $(\beta = 0.20,\ p < 0.001)$, greenwash slightly significantly influences brand eWOM negatively $(\beta = 0.08,\ p < 0.05)$.

The table below reports all the values obtained by running the regression analysis for brand eWOM.

Table 5: Summary regression table for brand eWOM

Coefficients					
	Estimate	Standard Error	t value	Pr (> |t|)	
(Intercept)	0.47852	0.31760	1.507	0.1328	
co_branding	0.52077	0.12683	4.106	5.07e-05	***
PV	0.87055	0.05602	15.539	<2e-16	***
GW	-0.07717	0.03613	-2.136	0.0334	*
culture	-0.06177	0.11270	-0.548	0.5840	
sex	0.47341	0.11237	4.213	3.24e-05	***
Residual standard error	1.016 on 334 DF				
Multiple R-squared	0.5725		Adjusted R-squared	0.5661	
F-statistics	89.46 on 5 and	334 DF	p-value	< 2.2e-16	

Figure 9 visually represents the importance of each variable for the model using four different methods. As it is possible to notice, comparing all the four methods the most important variable that influences positive eWOM is perceived product value. However, the relative importance of perceived product value over the other variables increases when using the *last method.* According to this method, gender becomes the second variable that has an influence on brand eWOM, while in all the other methods it is co-branding.

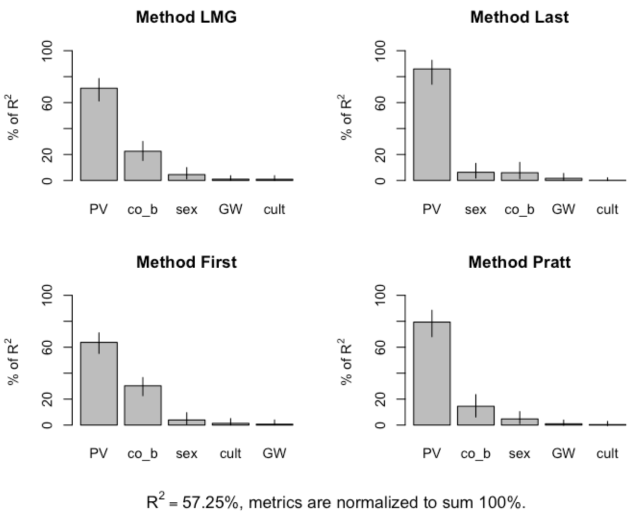

Figure 9: Relative importance for brand eWOM with 95% bootstrap confidence intervals

The next step was regression diagnostics. The top right panel of **Figure 10** shows the Q-Q normal distribution plot of standardized residuals. In this case, it is possible to notice that observation no. 294 has an extreme *x*-vale mainly due to overfitting. This result is also proved by the top left panel showing residuals versus fitted values. The third plot is the square root of the absolute value of the standardized residuals. It shows a reduction in the skewness of the distribution making it easier to detect dispersion. Finally, the *Cook's Distance* was calculated. The graph shows observation no. 249 as a conspicuous *Cook's Distance*. Observations no. 94 and 35 exhibit large residuals but not quite a conspicuous *Cook's Distance*.

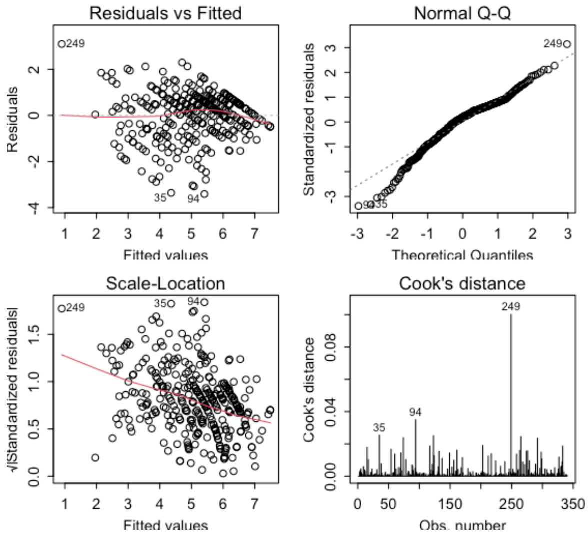

Figure 10: Regression Diagnostics for brand eWOM

Considering the above findings, regression was run removing the extreme observations (no. 249, 94, and 35) finding no significant changes in the overall result.

In order to check regression assumptions, a multicollinearity check was carried on. Since none of the VIF values are larger than ten, it is possible to state that there is no collinearity problem. **Table B** in the *Appendix* reports the VIF values for each variable.

3.3.3. Testing hypothesis

Mediation Analysis

To investigate if perceived product value and greenwash could mediate the relationship between co-branding strategy and product and brand eWOM, a parallel mediation analysis was carried out using the *Hayes Process Macro Model 4* as a method of analysis.

For what concerns the influence of the variables on product eWOM, results suggest that co-branding positively influences product eWOM ($\beta = 0.11,\ p < 0.05$). So, ***H1*** is supported.

Research highlights that the use of co-branding strategies allow the product to score higher in perceived value (Leuthesser, Kohli, & Suri, 2003; Huertas-Garcìa, Lengler, & Consolaciòn-Segura, 2017; Wang, Krishna, & McFerran, 2017). From these findings, ***H2*** was formulated and tested. The output of the model shows that co-branding significantly positively influences perceived product value ($\beta = 0.46,\ p < 0.001$). Thus, also this hypothesis is confirmed.

From the model emerges that co-branding significantly influences the perceived greenwash effect with a negative score coefficient ($\beta = -0.11,\ p < 0.05$), thus supporting ***H3***. Perceived product value positively significantly influences product eWOM ($\beta = 0.65,\ p < 0.001$) finding support to ***H4***.

Finally, ***H5*** was tested as well finding that greenwash slightly significantly influences product eWOM with a negative score coefficient ($\beta = -0.07,\ p = 0.05$).

For what concerns the influence of the variables on brand eWOM, results suggest that co-branding significantly influences product eWOM ($\beta = 0.19,\ p < 0.001$) in a stonger way compared to product eWOM. So, ***H1*** is supported. It is worth to notice that ***H2*** and ***H3*** report the same results both for the brand and for the product eWOM. Thus, as previously explained, both hypotheses are supported.

Perceived product value positively significantly influences brand eWOM ($\beta = 0.62,\ p < 0.001$) finding support to ***H4***.

Finally, greenwash significantly influences brand eWOM with a negative score coefficient ($\beta = -0.08,\ p < 0.05$) with an effect that is stronger for brand eWOM than for product.

The overall results of the models are fully reported in **Tables: C and D** in the *Appendix*.

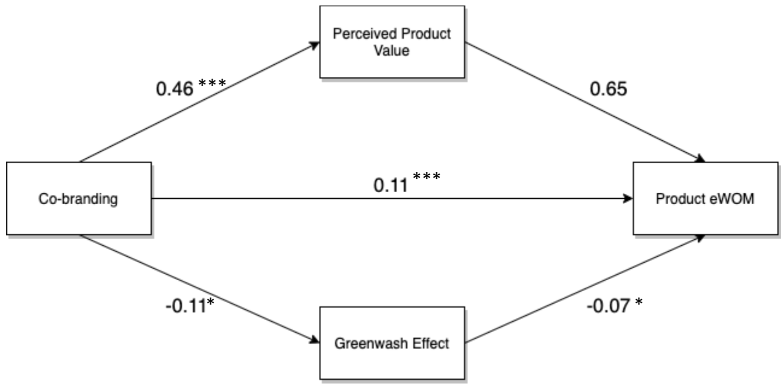

Figure 11: Research model results for product eWOM

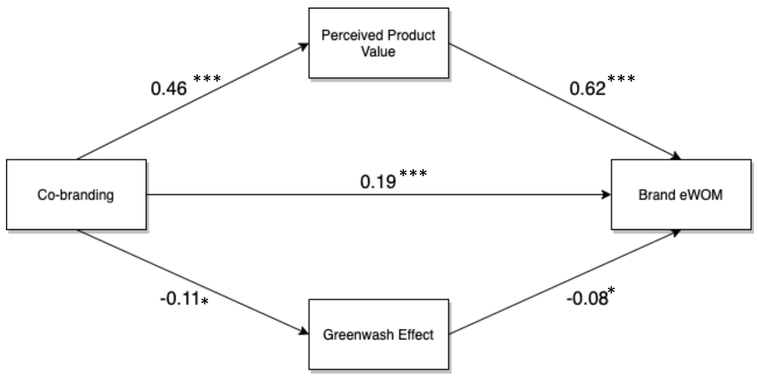

Figure 12: Research model results for brand eWOM

Moderation Analysis

In the present study culture and gender were considered as moderators. Specifically, gender was viewed as a moderator of the relationship between co-branding and product/brand eWOM as well as a moderator between co-branding and perceived product value. On the other hand, culture was thought as a moderator of the relationship between co-branding and perceived product value. This means that both gender and culture might alter the strength of the above-cited relationships.

To test the influence of culture on the relationship between co-branding and perceived product value, the *Moderated Mediation Process Macro Model 7* was used.

Results show that culture has a significant effect on perceived product value with a negative score coefficient ($\beta = -0.37,\ p < 0.05$). Importantly, the "co-branding strategy × culture" interaction is not significant ($p.value > 0.05$).

The model outcome suggests that there is not a significant moderation effect. Thus, the findings do not support ***H6***.

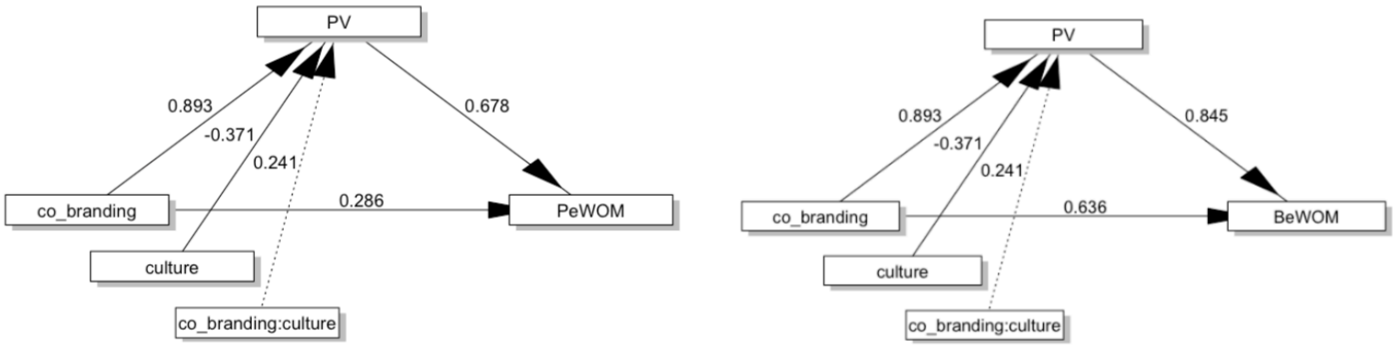

Figure 13: Results of moderation analysis considering culture as a moderator

When testing the influence of gender on the relationship between co-branding and perceived product value and on the relationship between co-branding and product/brand eWOM, the *Moderated Mediation Process Macro Model 8* was used.

Analyzing the effect of gender on perceived product value, the absence of a statistically significant effect of gender on perceived product value ($p.vale = 0.118$) comes out. The interaction effect "co-branding strategy × gender" on perceived product value is not statistically significant ($p.value = 0.618$). Thus, it is possible to state that ***H7*** is not supported.

For what concerns the moderating effect of gender between co-branding and product/brand eWOM, results indicate the presence of a statistically significant effect of gender on product eWOM with a positive score coefficient ($\beta = 0.33,\ p < 0.001$) and a statistically significant effect on brand eWOM with a positive score coefficient ($\beta = 0.63,\ p < 0.001$). The interaction effect "co-branding strategy × gender" on product eWOM is marginally significant ($p.value = 0.058$) as well as the interaction effect "co-branding strategy × gender" on brand eWOM ($p.value = 0.05$). So, it is possible to state that ***H8*** is partially supported.

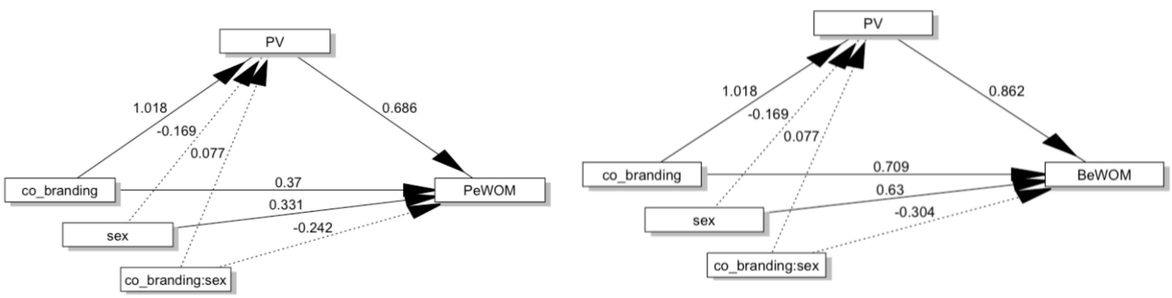

Figure 14: Results of moderation analysis considering gender as a moderator

3.4. Discussion

In this study, it has been assessed the effect of co-branding strategy on the perceived value of a product made of recycled materials, on greenwash effect, and product/brand eWOM. Additionally, gender and culture have been considered as potential moderators.

The analysis demonstrates that the use of a co-branding strategy may increase the possibility that consumers might spread positive word-of-mouth about the product and the brand among relatives as well as on the Internet. This is an essential finding because of the increasing importance and effectiveness of the world wide web (www) for companies to create awareness and interest for recycled products as well as to gain competitive advantages.

The model tested highlights that co-branding strategy between a fashion company and an NGO increases the way a recycled product is valued, and it enables the spread of positive eWOM.

For what concerns the greenwash effect, it has been found that co-branding reduces the perception of the greenwash effect and, at the same time, the lower level of greenwash discernment allows the spread of positive eWOM. However, the strength of the influence of greenwash as a mediator of the model is not as impactful as the one of the perceived product value. All in all, those results are in line with the overall literature about the topics.

According to the model tested and unlike what literature maintains, culture does not influence the relationship between co-branding strategy and perceived recycled product value. So, this result allows to state that being part of a collectivistic or individualistic culture does not influence the way a recycled product is perceived and valued.

Gender has been considered as a moderator variable between co-branding strategy and perceived product value and between co-branding and eWOM. The outcome of the model suggests that gender does not have a relevant influence on perceived product value while it has a slight influence on brand eWOM, meaning that being a male or a female influences the likelihood of spreading positive eWOM about a brand that engages in a co-branding strategy.

Part two

Exploratory or causal studies allow the examination of the cause-effect relationships. On the other hand, qualitative studies facilitate qualified descriptions of the market functions such as consumer perception, behaviors, and ways of approaching a specific market (Medeiros, Duarte Ribeiro, & Nogueira Cortimiglia, 2016). This characterizes the second phase of the present work which aims at verifying the results of the first part by gathering in-depth insights into the problem or generate new ideas. In light of these considerations, a mixed approach was employed by analyzing a specific real-life case: “Adidas X Parley for the Oceans”.

Introduction

> "To succeed, we need to find ways to synchronize the economic system of humankind with the ecosystem of nature" (Parley for the Oceans, s.d.).

Sustainable fashion, ethical, fashion, slow fashion, minimalism, greenwashing, circular fashion, recycling, upcycling, transparency, traceability, organic, second-hand, biodegradable, carbon offsetting, microplastic, fair trade, etc. are all terms that have recently entered the fashion industry to respond to the increase of consumers' demand for sustainable goods.

During the second half of the XX century, an important phenomenon has appeared, the so-called *Fast Fashion* defined as "low-cost clothing collections that mimic current luxury fashion trends" (Joy, Sherry, Venkatesh, Wang, & Chan, 2012). It originates from the Industrial Revolution. The use of assembly line enabled people to produce more in less time giving a blank cheque to dressing shops to open up. During the 1960s and 1970s, things changed and clothing became a form of personal expression. Finally, in the late 1990s and at the beginning of the 2000s, low-cost fashion appeared. Online shopping emerged, and fast-fashion retailers like H&M and Zara grabbed the market allowing everyone to shop for on-trend clothes (Rauturier, 2020). Such businesses have aggressively cut costs and streamlined their supply chains causing an extremely fast fall in clothing price; shorter lead times for production have also allowed clothing makers to introduce new lines more frequently; as an example, Zara offers twenty-four new collections each year, whereas H&M offers from twelve to sixteen new lines of clothing per year refreshing them weekly (Remy, Speelman, & Swartz, 2016).

Fast Fashion is characterized by several aspects such as its ability to embrace all the styles that match the latest trends; short turnaround time between when a trend item is advertised by a celebrity and when it is on the shelves; offshore manufacturing since labor is cheaper; limited quantity of a particular line (shoppers know that if they do not buy something, they will probably miss their chance); cheap, low-quality materials causing clothes to degrade after just a few wears and get thrown away (Joy, Sherry, Venkatesh, Wang, & Chan, 2012).

Although the success and economic gains that this model can derive to companies, it has brought fashion manufacturing to be the second polluter across different industries. According to the Ellen Mac Arthur Foundation, the textile sector, with its annual 1.2 billion tons of CO_2 emissions, exceeds the sum of emissions due to air or maritime transport. The Intergovernmental Panel on Climate Change (IPCC) has calculated that the fashion industry produces 10% of global carbon dioxide emissions every year using around 1.5 trillion liters of water annually and releasing 1.4 quadrillion microplastics in the sea. So, without any improvements, environmental pollution will grow proportionally as more clothes are produced.

To find a solution, both firms and consumers are trying to change heading towards business models marked by "inner loops" and enduring product value.

Wastling, Charnley, & Moreno (2018) identify two strategies for designing products and business models for a circular economy. The first one is the slowing of resource loops that implies increasing the use of products through extending product lifetime and through sharing schemes. The second one is closing resource loops to ensure that materials can be recycled in a closed-loop fashion at the end of use. Mani & Cova (2014), instead, take into account the notion of product value. They suggest that value creation can be ascertain into economic value (a substitution for a purchase and sometimes a resale); hedonic value (a practice that creates enjoyment); and social value (enhanced networking, strengthened identity). The possibility of creating value using different procedures may change the way people look at worn-out objects (Mani & Cova, 2014).

People's behavior is in the limelight because of the three main phases of consumers' engagement with products: acquiring the product, using, and end of use (Wastling, Charnley, & Moreno, "Design for Circular Behaviour: Considering Users in a Circular Economy", 2018). The customers and their behavior become an integral part of the business process increasing the need of making them perceive refurbished products as alternatives to traditional new ones by generating more benefits and less risk regarding both the product and firm's green performance (Mugge, 2018).

According to their green appearing and integrated green aspects, brands can be categorized into three groups based on the consideration of: "greenness" as a core value, "greenness" as integrated into core values, and "greenness" as a guarantee of value (Groubor & Milovanov, 2017).

Taking into account such classification, some apparel companies have formed coalitions to tackle environmental and social challenges together helping to accelerate change and to mitigate the risks of working on these challenges alone (Remy, Speelman, & Swartz, 2016) In this respect, it is worth to mention the so-called *Zero Discharge of Hazardous Chemicals* coalition and the *Better Cotton Initiative.* The former was signed by twenty-two brands to improve and expand the use of sustainable chemistry in the textile and footwear supply chain. The latter involves more than fifty retailers, brands, and a considerable amount of suppliers in setting standards for environmental, social, and economic responsibility in cotton production.

Some businesses have begun addressing sustainability goals alone. For example, Patagonia collects used clothing in its stores and offers repair services so garments last longer. Other brands have decided to use the strategy of partnership and co-branding to ensure environmental practices and reduce pollution. Co-branding allows both to develop new markets and to achieve greater market penetration through different strategies such as: *reaching out* (tap new markets by choosing a partner that adds significantly to the co-brand's core bundle of benefits, while bringing in a new customer base); *reaching up* (achieve greater market penetration by choosing a partner that contributes positive brand image and associations that elevate the co-brand's image and value); *reaching beyond* (choosing a co-branding partner that brings both strong image and access to new customers) (Leuthesser, Kohli, & Suri, 2003).

Successful co-branding occurs when both brands add value to a partnership (Leuthesser, Kohli, & Suri, 2003). For example, H&M and Levi's have partnered with I:CO to collect clothing and footwear for reusing and recycling. Puma and "First Mile" (waste management and recycling company) have launched a new athletic footwear and clothing line made almost entirely from sustainable materials. Adidas and Parley for the Oceans have joined an alliance to produce items made of recycled plastic retrieved from the oceans.

Previous examples show that fashion firms are adopting different marketing strategies but also different production methods to greener their business. One of particular interest is recycling. It is an ancient practice that has regained popularity nowadays due to economic crisis, environmental problems, and the need to reduce waste. Considering the circular economy landscape, recycling can be interpreted in "*cradle-to-cradle"* terms (Mani & Cova, 2014). It consists in a no-wasting design process that aims at recycling in order not to reduce quantities but resource depletion. The main target of the process is to enhance responsible consumption achieved through extensive use of the product itself and the avoidance of new purchases (Mani & Cova, 2014). Moreover, the growing use of the Internet has pushed this phenomenon even further ahead. Forums, blogs, social networks, and information sites are full of discussions and communicative exchanges relating to the topic (Mani & Cova, 2014).

Brands are increasing their efforts to monitor and enhance the spread of positive information (eWOM) about their green practices and products among those new channels resulting in an increase of consumers' awareness and brand image (Lin, Lobo, & Leckie, 2017).

To address the need for further understanding of how companies implement sustainability into their business models and which strategy they adopt to make their products accepted and positively considered by consumers (Groubor & Milovanov, 2017), the second part of the present study embraces a case study analysis: the "Adidas X Parley" case.

The analysis departs from what has been described in Chapter I, which is the influence of co-branding in generating positive eWOM. In this section opinions from Internet users have been extracted using Data Scraping, Sentiment Analysis, and Topic Modeling to fully understand the issue.

Data transformation into knowledge (described as an IT process in which data scientists analyze, review and convert data from one format to another to extract evidence from consumers) has become an essential aspect for marketers and analysts. It has been applied as a research method for two main reasons. First of all, it is a suitable way to investigate contemporary phenomena in a real-life context. The second reason relies on the presence (indirect through surveys or direct when performing interviews) of the researcher who might induce a consumer to respond favorably to sensitive questions. Whereas on the Internet, users might feel free to express their opinions not perceiving the authority of the experimenter. Internet sets users' narratives free by knowing that they were being read provoking a number of reactions (Mani & Cova, 2014).

Chapter IV: “Adidas X Parley for the Oceans”

Plastic is an innovative ,and versatile material, but it has devastating consequences. It is economical, durable and can be processed in hundreds of different ways. These characteristics make it extremely interesting for both producers and consumers, but it is also one of the worst causes of pollution on our planet.

Much of the plastic we throw away ends up in the oceans, it enters the food chain, kills marine fauna, destroys the environment and it is one of the main reasons for climate change. There is no place on the planet or in the oceans that does not suffer from the problems due to plastic. It is practically indestructible.

Eight million tons of such material end up in the oceans each year causing damage on an industrial scale. The waste reaches beaches, thousands of kilometers away from human settlements. Plastic has been found in the organisms of nearly 700 different species, including whales, fish, and seabirds (Ocean Crusaders, s.d.). The damage to marine fauna and flora is appalling. But despite all this being known, its production has not stopped yet, rather it is continuing to increase. After having realized the importance of such a problem, some companies are striving to look for concrete solutions. In this regard, since 2015, Adidas has decided to use recycled plastics in the production of Adidas items. This was the beginning of a long-term initiative project by Adidas to eliminate new plastic from its supply chain. To address the issue, the sportswear brand has chosen to create a partnership with “Parley for the Oceans” making a new entire line of sportswear products by turning plastic into raw material.

Adidas AG is a German sportswear multinational corporation, which designs and manufactures footwear, apparel, and accessories. The Adidas group consists of the Reebok sportswear company, part of the German football club Bayern München, and Runtastic, an Austrian fitness technology company.

Considering some financial performance data, the company’s net sales have experimented a drastic growth from year the 2000 till 2019 (Statista, 2020) shifting from €4,672 million to €21,505 million. The net income has drifted from €483 million in 2006 to €1,997 million in 2019 (Statista, 2020). Finally, considering global brand value, it has experienced a considerable increase reaching $16,481 in 2020. According to The Fashion United Top 100 Index[8], Adidas Original is listed at the ninth position with a market capitalization of $45.33 billion. Whereas in the list of the most valuable brands it is positioned at the tenth place. For what concerns the digital, and social media presence, the Facebook Index list positions it at the fourth place while the Twitter Index list places it at the ninth position.

Parley For The Oceans is an organization created to unite people, organizations, and brands in search of solutions to save the oceans. A collaborative network and a new type of environmental organization, Parley brings together creatives, innovators, and leaders to raise awareness of the beauty and fragility of the oceans, allowing them to work together on projects that contribute to their preservation (Parley for the Oceans, s.d.). It addresses threats towards the oceans trying to protect this still unexplored universe. In fact, 6.4 million tons of plastic (the equivalent of 3,200 kilometers of a truck loaded with garbage) are yearly dumped into the

[8] International fashion benchmark index that gathers the 100 largest listed companies worldwide within the apparel and fashion industry

oceans. Out of the 5.25 million pieces of plastic debris, 269,000-ton float on the surface, and four billion plastic microfibers per square kilometer litter the deep sea (Ocean Crusaders, s.d.). Additionally, the year 2048 seems to be the overall accepted deadline for the collapse of all commercial fisheries. By 2050, 90% of the world's coral reefs will be gone. So, Parley has been created to accelerate a process of change that is already in progress: the environmental cause.

The organization works running multiple projects with different stakeholders such as artists (Julio Le Parc, Katarina Grosse); brands ("Adidas"), and other organizations ("Oceans 2 Oceans"). They justify the strategy stating that "artists, musicians, actors, filmmakers, fashion designers, journalists, architects, product inventors, and scientists have the tools to mold the reality we live in and to develop alternative business models and ecologically sensible products to give us earthlings an alternative choice, an everyday option to change something" (Parley for the Oceans, s.d.).

With this view in mind, Adidas is a partner in the Parley A.I.R Strategy, a three-step strategy to change the way people address the threat of plastic pollution globally. Each letter of the acronym A.I.R. represents a key action: Avoid, Intercept and Redesign. Better said avoiding, recycling and reusing plastic. "Avoid" invites people to limit the use of plastic as much as possible and look for alternatives. "Intercept" means preventing plastics from ending up in the oceans by recycling and finding other solutions for this plastic waste. "Redesign" inspires individuals to find a new way to use materials, methods ,and products that contribute to the problem and, on a personal level, to change their perspective on the problem of pollution, thereby changing lifestyle.

In practice, plastic waste from remote islands and beaches and coastal communities, such as the Maldives, is collected and packaged by Parley. Plastic is cleaned and all foreign objects are removed manually, after which it is shipped to the production plants where it is broken down through a process of crushing, washing, and dehydrating the material (Parley for the Oceans, s.d.).

These plastic flakes are heated, analyzed, cleaned, and dried before being extruded, cooled, and ground into resin granules. These granules are then fused, to create a fiber that will become Ocean Plastic®, a high-performance polyester yarn that maintains all the qualities of virgin plastic. The yarn is used to create a wide range of shoes, T-shirts, tight and more, made with materials made up of at least 75% recycled plastic waste.

Whereas the Adidas-Parley shoes are made from recycled plastic collected by Parley, the outsole is crafted from recycled and re-ground rubber. Additionally, Adidas has worked with Parley to create mass-produced performance football products (e.g. "Adidas x Parley Real Madrid", "FC Bayern Munich" and "Manchester United FC collaboration").

After unveiling a shoe prototype at the United Nations in 2015, the partnership between Adidas and Parley For The Oceans resulted in the production of 15 million products. Adidas group applies the Parley A.I.R. in their businesses around the world. They are also raising awareness and encouraging employees, athletes ,and communities to participate in the fight against plastic. To date, they have created an annual Run For The Oceans event that involves more than 3 million runners to promote respect for the environment, raising more

than $ 2 million used to clean up beaches and educate new generations on the issue of plastic and the state of the oceans.
Adidas wants to be at the forefront in the fight against plastic pollution and the brand is committed to replacing 100% virgin plastic with recycled polyester by 2024. The long-term goal is to completely eliminate plastic from manufacturing processes, to save the oceans and the planet.
According to this collaboration, Adidas and Parley for the Oceans want to raise awareness of their products as well as ocean conservation bringing together different objectives such as financial goals, the decreasing of plastic pollution in the oceans and finally consumers' acceptance of products made of recycled materials. Better said, the spread of circular economy.

Chapter V: Data and Text Mining

"The goal is to turn data into information, and information into insights" (Carly Fiorina)

The XXI century is characterized by the spread of the Web phenomenon which has caused an acceleration in the textual revolution and a wider availability of information. Speaking about textual revolution, text and data mining are worth to be mentioned.

Data Mining (DM) is a subsystem used to identify the same patterns in large datasets and its focus is to unveil unknown and useful knowledge for decision making.

Data Mining can be applied to text mining in the information extraction phase. Text mining, or text data mining, is the process of transforming an unstructured text into a structured format to identify meaningful patterns and new insights (IBM Cloud Education, 2020). It is an interdisciplinary field that benefits from the contribution of several correlated topics like information retrieval, data mining, machine learning, probability, statistics, and computational linguistics. It allows the extraction of meaningful information and hidden relationships within big data thanks to the use of advanced analytical techniques, such as Naïve Bayes, Support Vector Machines (SVM), and other deep learning algorithms.

Text Data is relevant to point out some information such as (1) aspects about a specific natural language, its usage, its patterns; (2) knowledge derived from the observed world; (3) knowledge about an observer, that is inferring properties of a person; (4) predictive analytics to infer real-world variables.

Texts stored in databases can have different organizational structures. The first one is the so-called *structured data* that is data standardized into a tabular format with rows and columns. The second organization is named *unstructured data* which means that data do not have a predefined format since they are retrieved from sources like social media or product reviews. In other words, it neither has a predefined data model nor a pre-defined organization. Owing to their peculiar structure (text-heavy data), unstructured data are characterized by a certain degree of difficulty in understanding regular patterns through traditional programs because of their ambiguities and irregularities. The third organization is the so-called *semi-structured data* which means that data are a blend between structured and unstructured data formats. While they have some organizations they do not have enough structure to meet the requirements of a relational database.

Text mining tools and natural language processing (NLP) techniques allow the transformation of unstructured documents into a structured format to enable analysis.

Text mining allows sorting texts based on the similarity of their word usage. In order to better get what text mining is it is helpful to reflect on the differences between *manifest* and *latent information*. Indeed, the first type of information depicts details that are linked to individual terms (e.g. temperature measurement), while the second type refers to information that is not explicitly contained in text (e.g. categorization of text based on specific topics).

In order to apply text mining techniques to texts retrieved from the Internet, the data scraping activity is worth to be performed. However, before dealing with data scraping, it is necessary to be acquainted with data dissemination techniques, types of webpages, and data analysis techniques.

5.1. Data dissemination techniques

Content on the web is not disseminated in the same way. There are five main technologies that allow such broadcasting: Extensible Markup Language (XML), Hypertext Markup Language (HTML), AJAX, Hypertext Transfer Protocol (HTTP) ,and JavaScript Object Notation (JSON).

The HTML is a way for presenting content on the Web. This "language" has not changed over the years and this characteristic has made it one of the most important for working with and on the web. An HTML is a plain text with a fundamental feature: a marked-up structure. It allows determining each part of a document, for example, the one that displays headlines and the ones containing links. *Element selector* (developed by the majority of browsers) is used to pinpoint the part of the code that corresponds to specific elements of the browser window. The connection between a selected element on a webpage and the corresponding part of the HTML document is highlighted by the browser. The document has a tree structure meaning that elements need to be strictly nested within each other in a well-formed HTML file. The main way to extract information from HTML is by parsing the content of the marked-up page. Two steps are involved in web scraping: web content inspection and the import of HTML files into R. Parsing occurs at both steps (Munzert, Rubba, Meißner, & Nyhuis, 2015).

The XML is a markup language as the HTML, but its main purpose is to store data. Better said, it is data wrapped in user-defined tags. According to Harold and Mean (2004) "XML has become the syntax of choice for newly designed document formats across almost all computer applications. It is used on Linux, Windows, Macintosh, and many other computer platforms. Mainframes on Wall Street trade stocks with one another by exchanging XML documents. Children playing games on their home PCs save their documents in XML. Sports fans receive real-time game scores on their cell phones in XML. XML is simply the most robust, reliable and flexible document syntax ever invented". Like the HTML, it has a hierarchical structure for data storage.

The JSON is an alternative to the XML and its main aim is to provide data for web developers, specifically, it is the source that delineates the containers of plain text data.

The AJAX technology is formed by several techniques. It allows websites to asynchronously ask for data in the background of the browser and, at the same time, appraise its visualization dynamically.

The HTTP has been invented by Tim Berners-Lee and Roy Fielding in 1980 and it is a sort of *lingua franca* that enables a software to communicate with servers (computers that respond to requests from the network) and web services. Every website opened, every image or video viewed in a browser is delivered by HTTP (Munzert, Rubba, Meißner, & Nyhuis, 2015).

5.2. Static vs Dynamic Websites

How does the Internet supply websites?

The answer relies on the Internet communication which involves a server and a web browser whose connection is based on several rules called Hypertext Transfer Protocol (HTTP). Whenever the web browser sends an

HTTP request to the server, the server replies with an HTTP answer containing the requested webpage in HTML format.

There are two different types of websites: static and dynamic.

Analyzing a static website, it comes out that it is a very simple webpage based on HTML, JavaScript, CSS languages, it uses simple text editors like Notepad, it is steady (meaning that pages do not change unless someone does it manually) and shows no different content to users. Additionally, this type of websites is characterized by a fixed number of pages with a specific layout. This way, when a request for a webpage reaches the server, it sends the client a feedback without performing no further actions.

If the pages of a website need to look different, it is worth to duplicate the HTML code on each of the pages that should be different making the required changes. Although the website might display no different format, the static websites may also be characterized by multimedia elements and videos (Geeks for Geeks, 2020).

On the other side, a dynamic website uses both an HTML language and other advanced languages (CGI, AJAX, ASP, ASP.NET), programming tools and databases. Besides, it reveals different content and lets users to interact, it takes longer to load, and it is useful when the information is changed frequently. To create a dynamic webpage, it is worth to use a combination of server-side scripting (that is a code executed by the server before the content is sent to the users browser) and client-side scripting (that refers to code that is executed by the browser, usually with JavaScript) (WP Amelia, 2019).

All in all, static websites can be defined as informational and are easier to be created while dynamic websites need more work and are more functional allowing users to react to the information on the page. Obviously, that implies using more than just one HTML code.

5.3. Bag-of-Words Approach

The Bag-of-Words model is a representation used in natural language processing (NLP) and information retrieval (IR). In this model, a text (e.g. sentences or documents) is represented as the bag (multiset) of its words. It is called a “bag” of words because any information about the order or structure of words in the document is discarded thus, the model is only concerned with whether known words occur in the text (Dass, 2018). The Bag-of-Words model is commonly used in methods of document classification where the frequency or occurrence of each word is used as a feature for training a classifier.

All in all, a Bag-of-Words model is a way of extracting features from the text for use in modeling.

It involves different concepts and processes.

5.3.1. Data Processing

With a general view in mind, data processing is considered as the manipulation of data by a computer. It includes the conversion of raw data to machine-readable form, the flow of data through the CPU and memory to output devices, and formatting or transformation of output (Britannica, s.d.). In research instead, data processing is a series of actions or steps performed on data to verify, organize, transform, integrate, and extract data in an appropriate output form for subsequent use. Methods of processing must be rigorously documented to ensure the utility and integrity of the data (Tartu Ülikool, s.d.).

In this study, the process has involved two main steps: data import and clean-up activity. The first step implies using data produced by another application in a specific software. The second one is the process of correcting misspelled words, replacing emoji and deleting signs that can cause errors during the analysis phase.

5.3.2. N-grams Analysis

Many text analyses are based on the relationships between words, whether examining which words tend to follow others immediately or that tend to co-occur within the same documents that can be carried on performing n-grams Analysis. An n-gram is a contiguous sequence of n items (phonemes, syllables, letters or words) from a given sample of text or corpus. The idea of n-grams was born from a question posed by Claude Shannon who stated: “Given a sequence of letters, what is the likelihood of the next letter?”. The mathematician considered a training data from which he derived a probability distribution for the following letter when a history of size n: $a = 0.4,\ b = 0.00001,\ c = 0, \ldots$ has been provided and the probabilities of all possible "next-letters" sum to one. The n-gram model is based on the *Markov Model*[9] and predicts a pattern x_{i-1} based on $x_{i-(n-1)}, \ldots, x_{i-1}$ that, in probability terms, is $P(x_i \mid x_{i-(n-1)}, \ldots, x_{i-1})$. When used for natural language processing (NLP), independence assumptions are made so that each word depends only on the last $n - 1$ words. It is worth to notice that in a simple n-gram model, the probability of a word, (conditioned on some number of previous words) can be described as following a categorical distribution[10].

When dealing with Bag-of-Words analysis, the N-grams investigation can: it can help in deciding which n-gram can be chunked together to form single entities, it can help to correct spelling errors and it allows to build words networks to understand how they relate to one each other.

5.3.3. Corpus Creation

Corpus or plural corpora is a collection of linguistic data (e.g. written, spoken, signed, or multimodal). The main purpose of a corpus is to verify a hypothesis about language such as the understanding of how the usage of a particular sound, word, or syntactic construction varies. Corpus linguistics is also identified as any collection of data which have been retrieved and organized with a particular end in view. In the field of Computer Sciences, a corpus is a large body of machine-readable texts. All in all, text corpus is a large and unstructured set of texts used to do statistical analysis, checking occurrences or validating linguistic rules within a specific language territory (Crystal, 1992).

5.3.4. Document-Term-Matrix (DTM) or Term-Document-Matrix (TDM)

A Document-Term-Matrix is a mathematical matrix that describes the frequency of terms occurring in a collection of documents. Rows correspond to documents and columns correspond to terms. Whereas values contain the number of appearances of a specific term in that document. Each matrix row is a vector of term counts that represent the content of the document corresponding to that row. If considering the two sentences

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[9] *Markov Model* is a stochastic model used to model pseudo-randomly changing systems in probability theory. It assumes that future states depend only on the current state, not on the events that occurred before it. This assumption enables reasoning and computation with the model that would otherwise be intractable. For this reason, in the fields of predictive modelling and probabilistic forecasting, it is desirable for a given model to exhibit the Markov property.

[10] *Categorical Distribution* is a discrete probability distribution that describes the possible results of a random variable that can take on one of K possible categories, with the probability of each category separately specified.

"These shoes are awesome" and "Awesome sneakers", the document-term matrix will result as displayed in **Table 6** that shows which documents contain which terms and how many times they appear.

Table 6: Example of a Documet-Term-Matrix

	these	shoes	are	awesome	sneakers
Review 1	1	1	1	1	.
Review 2	.	.	.	1	1

A Term-Document-Matrix is the inverse of the DTM. Better said it is a way to arrange text in a matrix that contains individual terms as rows and texts as columns (Munzert, Rubba, Meißner, & Nyhuis, 2015). The cells encompass how often a term appears in a specific text. Considering the previous example and table, TDM can be represented as follow:

Table 7: Example of Term-Document-Matrix

	Review 1	Review 2
these	1	.
shoes	1	.
are	1	.
awesome	1	1
sneakers	.	1

5.3.5. Analysis

The analysis involves different measurements such as word frequency detection, syntagmatic relations and cluster analysis.

Word frequency. It is also known as Term Frequency (TF), which means how often a term occurs in a document and it can be inspected across all the text or grouped by a specific variable (e.g. book title, different sources) (Silge & Robinson, 2017). As documents can have different lengths, it is possible that a term would appear more frequently in longer documents than in shorter ones. This leads to a distortion effect that can be reduced using normalization. The term frequency weight function (tf-idf) is used to measure the importance of a term with respect to a document or collection of documents. The function increases proportionally to the number of times the term is contained in the document but increases inversely with the frequency of the term in the collection. The idea behind this behavior is to give more importance to the terms that appear in the document, but which in general are infrequent. The mathematical formula results to be:

$$(\mathrm{tf}-\mathrm{idf})_{ij} = \mathrm{tf}_{ij} \times \mathrm{idf}_i$$

The first factor is given by the following formula:

$$\mathrm{tf}_{ij} = \frac{n_{ij}}{|d_{ij}|}$$

where n_{ij} is the number of occurrences of the term i in the document j, while the denominator is simply the size, expressed in number of terms, of the document j.

The second factor results as:

$$\text{idf}_i = log_{10} \frac{|D|}{|\{d: i \in d\}|}$$

where $|D|$ is the number of documents in the collection, while the denominator is the number of documents containing the term i.

Word association. It aims at analyzing all those words that are associated and expressing such association with a percentage level. There are two different types of associations: *paradigmatic* (it computes context similarity) and *syntagmatic* (it compares words co-occurrence with their individual occurrence). In a paradigmatic relation, two terms can be substituted one for each other. For example, the elements "cat" and "dog" are said to have paradigmatic relation because they belong to the same semantic class, or syntactic class so they can be interchanged. In general, in a paradigmatic relation words can be replaced one by the other without affecting the understanding of the whole, which means that the result would still be a valid sentence. On the other hand, considering a syntagmatic relation, the two words can be combined with each other. Therefore, the elements "car" and "drive" can be combined in a sentence since they are semantically related although they cannot be replaced one by the other because the sentence would become meaningless (Correia, Teodoro, & Lobo, 2018).

Cluster analysis. It is the task of grouping a set of objects so that objects in the same group are more similar to each other than those in other groups (IPL, s.d.). There are different methods to perform cluster analysis. One of the most commonly used is *hierarchical clustering* which involves the construction of a hierarchy of treelike structure using agglomerative or divisive procedures. The agglomerative method is a bottom-up approach in which each observation starts in a cluster of its own and then continuously joins clusters together until there is only one cluster consisting of all the observations. The divisive clustering method is the opposite of the agglomerative one. It is a top-down approach in which all the points in the dataset belong to one cluster and split is performed recursively as one moves down the hierarchy.

5.4. Sentiment Analysis

Since the spread of the World Wide Web (www), social medias, forums, blogs and review websites the amount of text has exponentially increased. So, the information that can be pulled out from these sources plays a key role in understanding product or brand reputation as well as discovering new consumers' needs. It is in this landscape that *Sentiment Analysis* has burst.

Sentiment Analysis also called "opinion mining", is the task of finding the opinions of authors about specific entities (Feldman, 2013). This system (used for text analysis) combines natural language processing (NLP) and machine learning techniques to assign weighted sentiment scores to the entities, topics and categories within a sentence. It allows to systematically identify, extract, and study people's affective states, subjective information, understand customers' experiences or values. In other words, it is an approach to NLP that identifies the emotional tone behind a body of text (DATALAB, s.d.).

To better understand how sentiment analysis works it is worth to define some key terms. First of all, *sentiment* is depicted as the behavior of a person made of views, feelings and opinions. The sentiment is directed toward an entity or an *object* (Liu, 2010) that is the target thing mentioned in the text made of *components* and *attributes*. For example, let's consider the following review:

> "I really loved Bleecker Street Pizza. Prices were normal. Staff was kind. Foods were delicious. I ordered three slices of Italian pizza and taste was alike what I ate in Rome. I'll definitely visit again soon!" (Tripadvisor, s.d.)

In this case, Bleecker Street Pizza is the object having "price", "staff" and "foods" as components.
Sentiments might be positive, negative, neutral or can have fine-grained classification due to the use of amplifiers (e.g. very much, extremely, absolutely, etc.).
Sentences can be classified into subjective and objective. The first one contains explicit opinions, beliefs and views about topics or entities. Considering the previous example, the sentence "I really loved Bleecker Street Pizza" can be considered as subjective because it expresses the view and feelings of the writer. The sentiment is perceived as extremely positive due to the use of the amplifier "really". On the contrary, objective sentences contain factual or descriptive information. For example, "I ordered three slices of Italian pizza" is a phrase that only tells the reader that the consumer has eaten three slices of pizza without mentioning any feelings.
It is possible to extract sentiments at three different levels shifting from generality to specificity. They are described as follow:

Document-level sentiment analysis. It is the more general way of performing the analysis. Indeed, sentiment scores are calculated considering the entire document. The basic assumption is that the document embeds beliefs and views about only one general object. There are two approaches to address this analysis: *supervised* and *unsupervised*. The supervised technique presupposes a finite number of classes to categorize documents (the simplest case is positive VS negative). Unsupervised technique arranges documents basing itself on a threshold. If the average of the semantic orientation (SO) of specific phrases within the document is above or below this ideal value, the document is classified as positive or negative.
The main disadvantage of this type of analysis is that it does not consider multiple opinions about entities giving only a general picture of what the writer feels.

Sentence-level sentiment analysis. It is a fine-grained analysis compared to the one at the document level. Its main assumption is that there is a single entity assertion in each sentence. So, the review will be split into phrases each one of them containing a single opinion thus giving a single score. The final score will be calculated on the average of each sentence. It is worth to notice that only subjective constructions will be analyzed because the algorithm detects only statements that embed opinions and feelings. **Figure 15** represents an example of Sentiment Analysis at the sentence level.

Josh _9: *+.186*

great shoe for casual / runner / gym i'm a male but loved this colorway. i'm usually a men us7.5 but ordered a women us9 and the fit is perfect. i'm a longstanding ultraboost wearer having worn the ultraboost 1's and 3's previously. i strayed to a nike epic react between these shoes but regretted it immediately. highly recommend this shoe - fits tts, breathable / durable and feels comfortable on foot.

Kevvvn _10: *+.140*

those are one heck of comfortable running shoes feels light on feet, snug fit, very so. pliable too (you can lift your toes and shoes "bend" with them). i had nike air running shoes and those were - good.. but the air eventually leaked and shoes became unbalanced. tried ultraboost and wow. very so, stable and could wear all day. looks great too. i run 3-5 miles daily and these feels great!

Babs364 _11: *-.085*

don't buy i bought these shoes 3 months ago and have been wearing them everyday for walking and light walking! i am 5'4" and weigh 134. the balls of my feet have been hurting lately and i discovered that both of my shoes are split and cracking on the underside of the so in that area! these are too expensive not to last longer!

Figure 15: Sentiment split in each review

Aspect-level sentiment analysis. It is the most specific analysis, and it is also called feature-based or entity-based sentiment analysis. It is defined as "the research problem that focuses on the recognition of all sentiment expressions within a given document and the aspects to which they refer" (Kirange & Deshmukh, 2015). The process of this technique implies identifying aspects in a sentence (considering the above example, prices, staff and foods are all aspects); categorizing the features as positive or negative and finally valuing every computed aspect.

Sentiment analysis can be applied to different areas: from product and services reviews to the financial market. However, its aim is to realize what people think and feel in order to direct actions towards those ideas and views.

5.5. Topic Model

Topic modeling is a machine learning technique and statistical model capable of scanning a set of documents, detecting word and phrase patterns within them. It is mainly applied to *unstructured data* and is able to discover abstract "topics" that occur in a collection of documents using a probabilistic distribution based on term co-occurrence. It automatically clusters word groups and similar expressions that best characterize a set of records and that appear frequently. In other words, topic modeling is a list of topics with a likelihood score obtained from the Bag-of-Words representing a specific set of texts.

Topic Models are "unsupervised methods of automatic organizing, understanding, searching and summarizing text documents" (Blei, 2012). The word *unsupervised* refers to the fact that they do not require a predefined list of tags or training data previously classified by humans. Better said, they infer rather than assume the content of the topics under study (Blei, 2012). On the other hand, topic classification models (that allow the topic taxonomy) are classified as *supervised* machine learning techniques. Indeed, the textual data is labeled beforehand so that the topic classifier can make classifications based on patterns learned from labeled data. In other words, topics are defined beforehand, usually by hand-coding a cluster of documents into pre-established categories (Roberts, et al., 2014). This information allows to quickly deduce what each set of texts is talking about.

The key features related to this technique are: each document is a mixture of topics (in the same documents different topics can appear); each topic is a mixture of terms (different terms contribute to the creation of topics); terms have weights associated with topics and can be shared across topics.

It works taking into consideration the Document-Term Matrix (DTM) or the Term-Document Matrix (TDM). In topic modeling, the full Term-Document Matrix (TDM) or Document-Term Matrix (DTM) is broken down into two major components: the topic distribution over terms (representing the importance of terms in each topic) and the document distribution over topics (it enables to understand the importance of topics in the documents).

One of the main advantages of this technique is *feature reduction*. In the NLP each word present in the corpus is considered as a feature. Thus, decreasing the number of features helps to focus on the right content instead of wasting time going through all the text in the data.

There are different appliable methods for topic modeling. Vayansky & Kumar, 2020 distinguish between Latent Dirichlet Allocation (LDA); Correlated Topic Model (CTM); Pachinko Allocation Model (PAM); Dynamic Topic Models; Continuous-time Topic Models; Self-aggregating Topic Models; Non-negative Matrix Factorization (NMF); Non-negative Double Singular Value Decomposition (NNDSVD); Hierarchical Dirichlet Processes (HDP).

The present study has been based on the Structural Topic Modeling (STM) rather than on the Latent Dirichlet Allocation (even if widely used). In fact, the LDA method for Topic Modeling results being less accurate since it does not take into account the document-level covariates or metadata. In *mixed-membership* models (e.g. LDA) documents (indexed by *d*) are produced through several steps. The first step includes a distribution over topics (θ_d) carried on from an overall prior distribution. Then, a topic is extracted for each one of the words in the document (indexed by *n*) from a multinomial distribution which relies on its distribution over topics ($z_{d,n} \sim Mult(\theta_d)$). According to the selected topic, the observed word $w_{d,n}$ is obtained from a distribution over the vocabulary ($w_{d,n} \sim Mult(\beta_{z_{d,n}})$) in which $\beta_{k,v}$ represents the probability of extracting the *v*-th word in the vocabulary for topic *k*. The model just described, is accomplished by considering a Dirichlet distribution[11] prior for the topic proportions such that $\theta_d \sim Dirichlet(\alpha)$ (Roberts, et al., 2014).

The main drawback of such topic models is that distributions may have different local modes thus different initializations leading to several solutions.

A method to overcome this problem is the use of STM, which is a probabilistic extension of LDA. This implies that STM uses text-related metadata to upgrade the assignment of words to hidden topics in a corpus and, at the same time, it strengthens the document level covariates thus innovating the LDA model.

The effect of innovation is a new model characterized by a mixture of topics in each text. Metadata can influence the topic allocation while taking into account either the frequency at which a topic is debated (topic prevalence) or the words employed to speak/write about a topic (topic coherence).

In the STM, each document is the result of a combination of *K* topics and there can be a correlation among topic proportions (θ). Besides, some covariates *X* can influence the preponderance of topics through a standard regression model with covariates ($\theta \sim LogisticNormal(X_\gamma, \Sigma)$. Each word ($w$) in the text gets a topic (z)

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[11] The *Dirichlet distribution* is a multivariate generalization of the beta distribution, hence its alternative name of the multivariate beta distribution (MBD).

from the text-specific distribution. The topic impacts over the choice of a word from a multinomial distribution over words parameterized by β that is obtained by deviation from the baseline word frequencies (m) in log space ($\beta_k \propto \exp(m + k_k)$). Furthermore, this distribution includes a second set of covariates U (Roberts, et al., 2014).

To sum it up, three critical differences rise up when comparing the STM model and the LDA model. The first distinction is connected with topic correlation. Secondly, each document has its own prior distribution over topics, defined by covariate X rather than sharing a global mean. Finally, word use within a topic can change according to covariate U (Roberts, et al., 2014).

Figure 16 represents the phase to conduct the STM process.

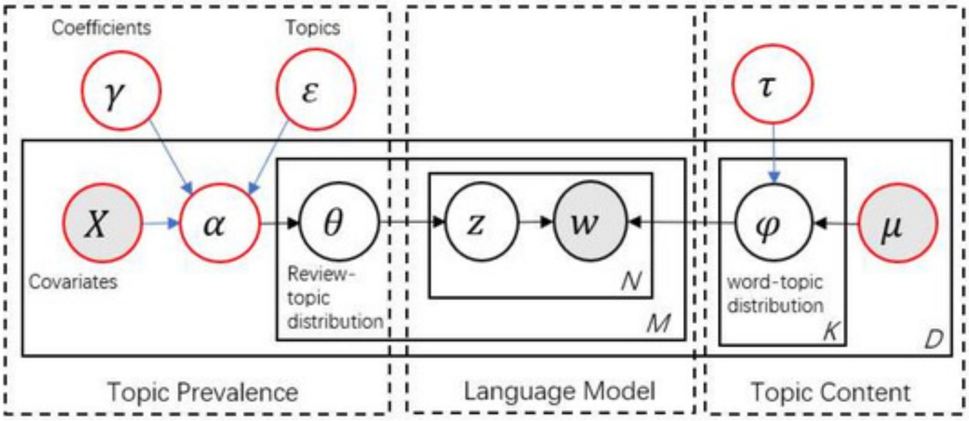

Figure 16: Plate diagram of Structural Topic Model (STM) *(He, Han, Zhou, & Qu, 2020)*

The STM provides fast, transparent, replicable analyses that require few ex-ante assumptions about the texts. Even if it is a computer-assisted method, the researcher is still essential in understanding the texts.

In choosing the ideal number of topics or assessing the goodness of fit, two measures can be used: semantic cohesion and exclusivity (Roberts, et al., 2014). A topic is cohesive when high-probability terms for a topic occur together in documents. A topic is exclusive if the top words of the topic are not likely to also be top words in other topics (Hill, s.d.).

To sum it up, The Structural Topic Model (STM) allows researchers to flexibly estimate a topic model (including document-level metadata) accomplished through a fast variational approximation.

Chapter VI: Methodology

In order to acquire useful information about the research model analyzed in the first part of this work, data mining has been applied. The event study allows to extract user sentiment about Adidas products as well as Adidas as an organization. Additionally, it enables to understand what are the main topics discussed by Adidas' audience.

All in all, the use of Text Mining techniques help to determine the overall evaluation of a brand that adopts a circular economy model and that engages in green co-branding.

The process for conducting the overall Text Mining Analysis is described in **Figure 17**.

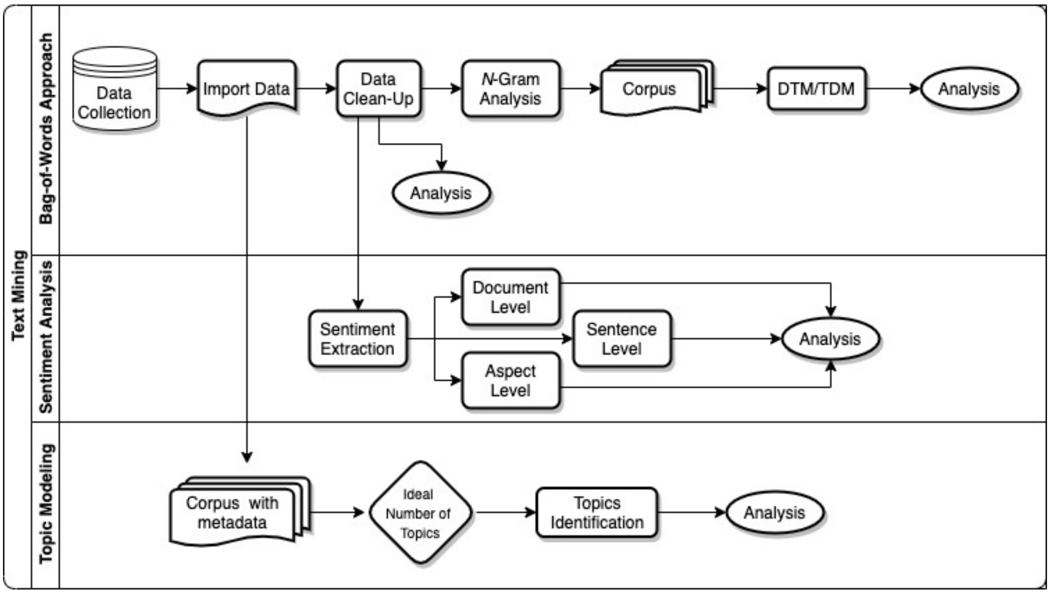

Figure 17: Text Mining flowchart

The present work relies on different libraries to conduct Bag-of-Word approach, Sentiment Analysis and Topic Modeling. In particular, seven main libraries have been used to conduct BoW, specifically `textclean`, `textshape`, `textdata`, `RWeka`, `NbClust`, `cluster` and `tm`.

For what concerns Sentiment Analysis, the library `syuzhet` and `bing` have been loaded to carry on the analysis at the document level. Besides, the `nrc` lexicon included in the same library has been used in order to extract sentiment scores. For analysis at the sentence and the aspect level, library `SentimentR` has been launched.

With respect to Topic Modeling, the STM method, which is more flexible in topic estimation, has been executed in this study by applying the `stm` library.

The next sections describe the overall analysis process and its results in detail.

6.1. Web Sources Characteristics

Three different review websites have been chosen to address the research. Indeed, review websites allow consumers to share information, opinions and feelings they have experienced while engaging with a product or brand. In particular, the data reported in this essay have been withdrawn from the Amazon, Google Reviews, Influenster and Adidas webpages. The main characteristics of the four sources have been analyzed and reported as it follows.

Influenster.com. Influenster.com is a review platform launched in 2010. It allows brands to work with Influenster through VoxBox or VirtualVox campaigns through which brands can offer complementary products or digital rewards to Influenster users who meet brand and product-specific criteria. So, users might join Influenster campaigns depending on "Impact Score"[12] and demographic information. There are different types of campaigns that usually involve delivering a product sample to users to be discussed on Influenter webpage or on social medias. Additionally, users have to complete a survey after the product trial. This allows each subscriber to unlock "Expert" and "Lifestyle" badges that are a part of a gamification system to reward specific types of users with invitations to specific Influenster campaigns matching their demographic. The webpage contains over eleven million reviews, a hundred thousand brands and 1.7 million product pages. Each brand or product page is divided into six sections: product/brand description, overall product/brand ratings (calculated as an average of all given ratings), highlights (best reviews), review section, Q&A (question and answers asked/written by users) and photos and video section.

When looking for a review, the page provides information about the writer, product/brand ratings (from one to five stars), information about where the reviewer is from, date and time in which the review has been written, the number of reviews delivered by the author, users badges, review text and likes.

Amazon.com Amazon is the world's largest online retailer and a prominent cloud services provider founded in 1994. It allows users to submit reviews for a huge variety of products ranging from books to kitchen appliances. Reviewers must rate the product on a rating scale from one to five stars. Amazon provides a badging option for reviewers which indicates the real name of the reviewer (based on confirmation of a credit card account) or which indicates that the reviewer is one of the top reviewers by popularity. Customers may comment or vote other consumers' reviews, indicating whether they found them helpful. If a review reaches a certain amount of helpfulness, it appears on the front page of the product.

The webpage is characterized as dynamic and gives information about members (they can use both their real name or a pseudonym), review text, popularity and helpfulness, average product ratings and reviewer's nationality. It has also a Q&A section for consumers to interact.

Adidas.com. Adidas-group.com is the brand e-commerce where consumers can buy Adidas products. Although Adidas has a general website, each country has its own, but all of them have the same features. Each product webpage is divided into different sections ("gallery", "highlights", "reviews", "description", "details", "story", "how to style", "complete the look"). The review section gives information about each review rating (from one to five stars), if the product size is too small or too big or if it is too narrow or too wide. The review

[12] Impact points are largely calculated based on the number of followers or friends a user has on any given social network such as Facebook, Twitter, Instagram, YouTube, Tumblr, Foursquare, Google+.

section embeds ratings, text, the title of the review, author (people can use both their real name or a pseudonym), date, helpfulness and if it is a verified purchase.
All the other sections of the page are used to advertise the products and its complements, to give some descriptive information and finally to choose the right size and color of it.

GoogleShopping.com. It is a service delivered by the Google platform in 2002 and allows users to search for products and compare prices between different online retailers. Each product page is characterized by pictures, details area (information about colors, materials, size), a section about buying option and price comparison, overall product ratings and reviews area. The review section publishes information about each review rating (from one to five), review date, author and text, source of the review (from which websites it is extracted).

6.2. Data collection

Carrying on the analysis implies collecting data from consumers by applying Web Scraping activity. Web scraping or web harvesting is used for extracting data from websites by copying gathered data into a local database for later analysis. This software may access the World Wide Web directly using the Hypertext Transfer Protocol.
To perform web scraping, Data Miner has been launched. Since the aim was to scrape a list of elements contained in the page, the option "list page" has been chosen. Rows have been selected by the selector tool. Columns have been created giving them a name, picking the "extract" option and taking the elements that each column contained. The "Next" button has been selected to scroll pages. Finally, the recipe has been saved and data scraped.
The output of the activity carried out with Data Miner has been several Excel Files containing different tables. The first one has been the result of the scraping activity from *Influenster* webpage resulting in 7,731 rows and four different columns named as Author, Date, Place and text. The second, instead, is the result of three different tables from three webpages: *Amazon*, *Adidas Official* and *Google Reviews*. Amazon file contains 278 rows; Adidas Official contains 331 rows and Google Reviews contains 465 rows. All the three tables are made of five columns named as: author, date, title, text and ratings.

6.3. Data cleaning

Data cleaning is the process of preparing data for analysis by removing or modifying incomplete, irrelevant, duplicated, or improperly formatted data.
It is not simply about erasing information, but rather finding a way to maximize a data set accuracy without necessarily deleting information. It includes actions such as fixing spelling and syntax errors, standardizing data sets and correcting mistakes like empty fields, missing codes and identifying duplicated data points.
These actions must be performed because incorrect data may lead to false conclusions.

6.3.1. Brand eWOM Dataset

In the *Brand_eWOM_Dataset* Excel File different mistakes have been found. These mistakes have been corrected using different libraries. `Stringr` library has been mostly used because of its three main domains of application: character manipulation (to manipulate individual characters within the strings in the character vectors); whitespace manipulation; pattern matching functions.

The activity has involved different steps and combination of codes. The functions used to perform the cleaning activity are summarized in **Table 8.**

Table 8: Libraries and functions for data cleaning for brand dataset

Library	Function	Description
	`duplicated`	determines which elements of a vector/data frame are duplicates by returning a logical vector indicating which elements are duplicates
`stringr`	`str_replace_all`	It replaces matched patterns in a string.
`stringr`	`str_split_fixed`	It splits up a string into pieces.
`texcat`	`texcat`	It determines the language of a string by comparing it to a model for each language basing itself on a list of *n*-grams.
`qdap`	`which_misspelled`	It allows to detect misspelled words for further corrections.
`countrycode`	`countrycode`	Creates a new variable with the name of the country to which each city belongs.
`dplyr`	`na_if`	hat replaces any values that are equal to "y" with NA.
`qdap`	`which_misspelled`	It allows to detect misspelled words for further corrections.

To prepare data for further analysis the ID column has been created and the reviews column called "text" has been set to lower case using the function `tolower`. Variables of column "date" have been turned into date variables and misspelled words have been replaced with correct ones.

It is worth to notice that when performing the country-of-origin extraction a new database has been created. This new dataframe results of 2,729 rows (because of the deletion of those rows containing NA values) and four columns named as: doc_id, country and text.

6.3.2. Product eWOM Dataset

Different mistakes that have been corrected using two different libraries (`stringi` and `stringr`) have been found in the *Shoes_Dataset* Excel File. Even in this case `Stringr` has been mostly used because of its domains of application. The activity has involved different steps and combination of codes. The functions used to perform the cleaning activity is summarized in **Table 9.**

Table 9: Libraries and functions for data cleaning for product dataset

Library	Function	Description
	`duplicated`	
`stringr`	`str_replace_all`	It replaces matched patterns in a string.
`stringr`	`str_split_fixed`	It splits up a string into pieces.
`texcat`	`texcat`	It determines the language of a string by comparing it to a model for each language basing itself on a list of *n*-grams.
`qdap`	`which_misspelled`	It allows to detect misspelled words for further corrections.

To prepare data for further analysis the ID column has been created and the reviews column called "text" has been set to lower case using the function `tolower`. Variables of column "date" have been turned into date variables and misspelled words have been replaced with correct ones.

6.4. Text Corpus Characteristics

A text corpus is a large and unstructured set of texts used for statistical analysis and checking occurrences. The current work is based on two different datasets: *Brand_eWOM_Dataset* for analyzeing what people think about Adidas as a brand and *Shoes_Dataset* for analyzing consumers' product evaluation.

6.4.1. Brand eWOM Datatset

The brand dataset contains 7,731 reviews from *Influenster* webpage that after the cleaning activity has dropped to 7,096 observations. Each review provides text, author name, author city of origin and review date.

The number of authors corresponds to the number of observations (7,096). In the column author, there are no missing values, but writers have used their first name and the first letter of their surname to identify themselves. During the cleaning activity, the nationality of each author has been detected using the function `countrycode` applied to the city each author lives in. The result of the analysis has been a column containing the name of the countries matching all those cities that the function has been able to detect. When performing the identification of the country of origin, a new database has been created. Rows containing NA values in the "country" column have been deleted. The resulting database contains 2,729 observations. The nationalities of the writers have been summarized in **Table A** in Appendix**.**

As to length, all the reviews are characterized by a quite short text. Having created a column containing numeric variables regarding the number of characters for each review, the **Table 10** summarizes character length results:

Table 10: Text length for brand dataset

Dataset	Characters mean	Maximum Characters	Minimum Characters
Brand eWOM Dataset	172.5	1985.0	12.0

For what concerns dates, comments started in 2012 a year after the launch of *Influenster* and ended in 2021 when the scraping activity has been performed. Date column consists of variables that *RStudio* can recognize as dates. The following table shows the reviews frequency and relative frequency per year.

Table 11: Years summary

2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
171	159	814	575	335	1639	886	382	2064	71
2.4%	2.2%	11.5%	8.1%	4.7%	23.1%	12.5%	5.4%	29.1%	1%

6.4.2. Product eWOM Dataset.

The product dataset contains 1,085 reviews from three different webpages, specifically *Amazon* (278 reviews), *Google Reviews* (465 reviews) and *Adidas Official* (331 reviews) that have dropped to 928 observations after the cleaning activity. Each review provides text, ratings, author name, review date.

Comments started in 2017 when the "Ultraboost Parley shoes" have effectively reached the market and has ended in 2021 when the scraping activity has been performed. The number of authors corresponds to the number of observations (918). In the column "author" there are no missing values, but some writers have used a pseudonym or just the word "Anonymous" to identify themselves. During the cleaning activity the gender of each author has been detected using the function `gender` with "`ass`"[13] as a method for gender detection. The result of the analysis has been a column containing the following characters: "M" for males; "F" for females and "A" for "anonymous". The column with review title has been joined with the text column because it could contain useful information.

As to reviews length, some of them are characterized by an extensive text. Others are made up by a few short sentences. Having created a column containing numeric variables regarding the number of characters for each review, the **Table 12** summarize character length results:

Table 12: Text length for product dataset

Dataset	Characters mean	Maximum Characters	Minimum Characters
Product eWOM Dataset	195.4	10.0	4,787

For what concerns ratings the overall product rating mean is $\mu = 4.47$, a value that is very near to the maximum that is five stars. Additionally, the average rating for each webpage has been analyzed as well as for gender. The results are summarized in the following table:

Table 13: Ratings mean

Webpage	Ratings mean (μ)	Gender	Ratings mean (μ)
Adidas Official	4.55	Males	4.47
Amazon	4.35	Females	4.49
Google	4.49	Anonymous	4.45

6.5. Data Analysis

Data Analysis involves actions and methods performed on data that help to describe facts, detect patterns, develop explanations and test hypotheses. This includes data quality assurance, statistical data analysis, modeling, and interpretation of results (Tartu Ülikool, s.d.).

In the following section, the analysis carried on for the two datasets will be described.

[13] It looks up names based on the U.S. Social Security Administration baby name. It uses the period between 1932 and 2012 as reference.

6.5.1. Brand eWOM

Bag of Words

The first step in the Bag-of-Words approach is the identification and replacement of *n*-grams such as "Ultra Boost", "Stan Smith", "customer service", "flip flops", etc. This operation has been carried on by joining words that otherwise the algorithm might interpret separately leading to mistrustful results.

Tables and graphs have been generated to better inspect *n*-grams. The table scan has revealed that a lot of n-grams were due to the combination of articles, verb and subject, article and noun, etc. An example of the main findings is shown in **Figure 18** and **Figure 19**.

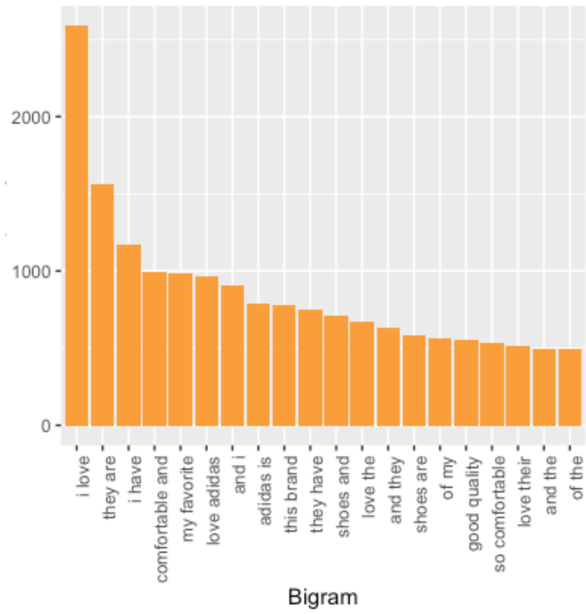

Figure 18: Most common bigrams

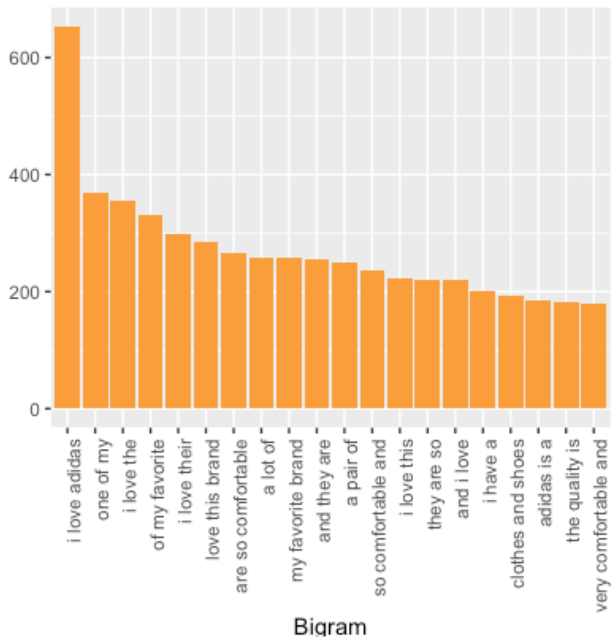

Figure 19: Most common trigrams

A Network Analysis has been performed as part of *n*-grams analysis in order to visualize the simultaneous relationship among words. Two network graphs, defined as a combination of connected nodes, have been constructed from a tidy object containing three main variables: *from* (the node an edge is coming from); *to* (the node an edge is going towards); *weight* (a numeric value associated with each edge).

Figure 20 represents common bigrams in *Brand_eWOM_Dataset*, showing the ones that occurred more than seven times. For example, "adidas", "shoes", "love" and "comfortable" form common centers of nodes. The first two are usually followed by adjectives, whereas the last two are followed by nous. It is also possible to notice pairs along the outside that forms composed words such as "gold rose", "single day", etc. The lines junking together the different words describe the number of times two words appear together. As it is possible to notice the word that most frequently appear together are "love" and "adidas".

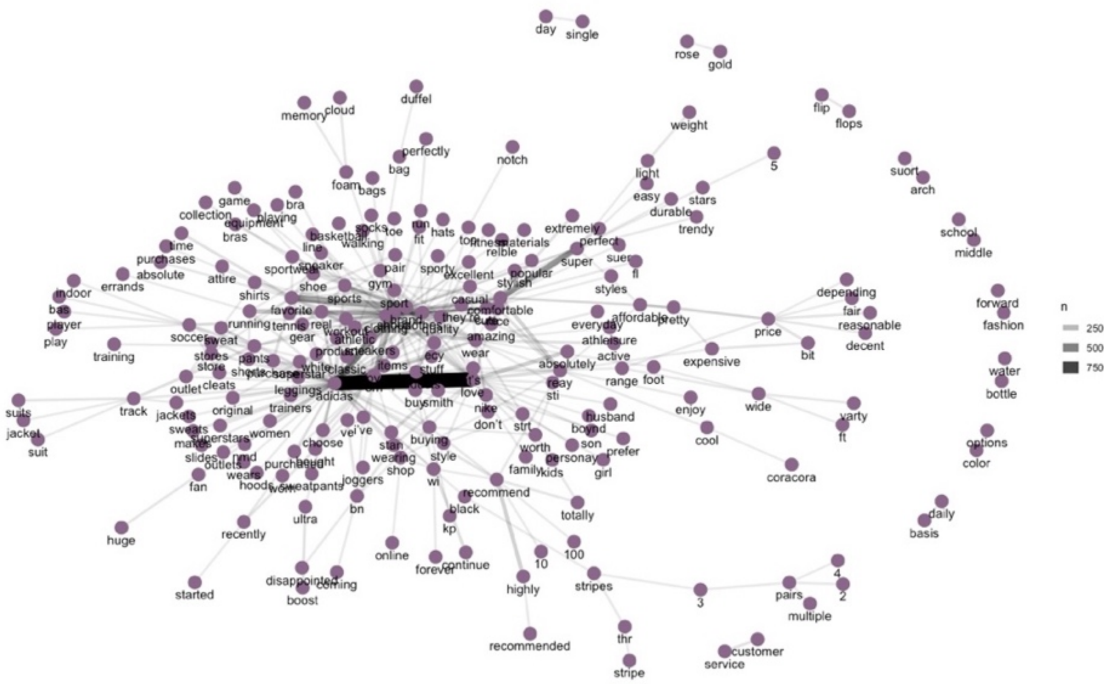

Figure 20: Common bigrams in Brand_eWOM_Dataset showing those that occurred more than seven times

Figure 21 has been created in order to understand the direction of the previous explained relationships. For the sake of clarity, common bigrams of the *Brand_eWOM_Dataset* that occur more than twenty times have been plotted as a network graph. In this case it is possible to notice that the word "love" is directed towards "adidas", meaning that people love the brand. For what concerns pair and triplets, it comes out that adjectives such as "reasonable ", "affordable" and "decent" are all related to "price".

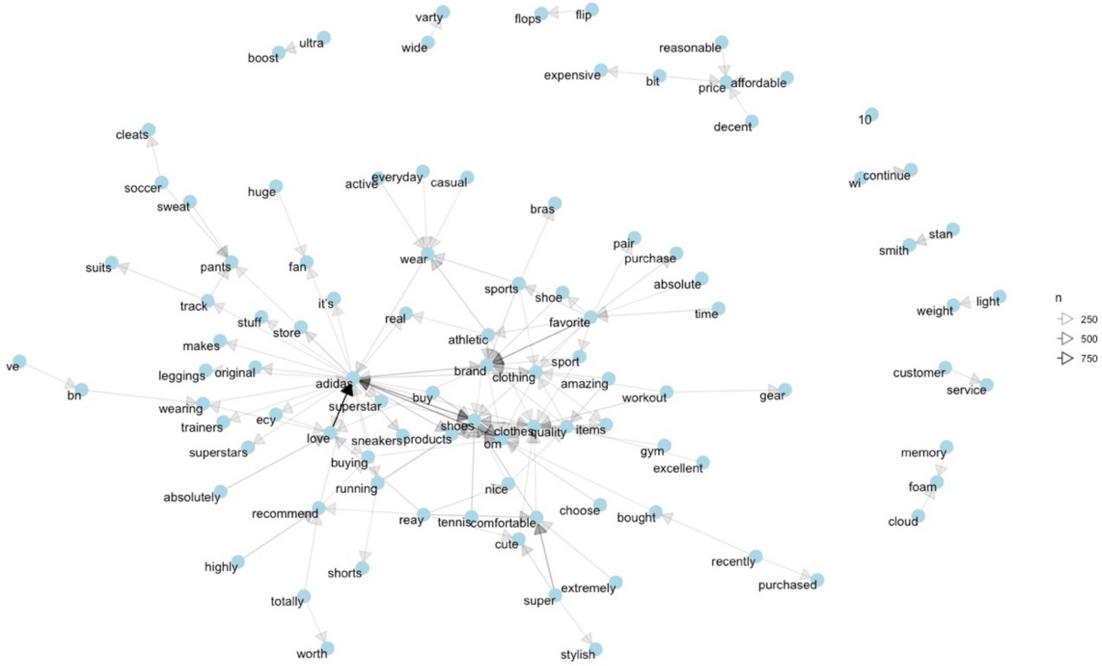

Figure 21: Common bigrams in Brand_eWOM_Datset with some polishing

The two graphs below help understanding which words people tend to use together and how they use them when speaking about “Adidas” finding that the two main central nodes are described by the words “Adidas” and “love” which also have the strongest relationship.

To get text mining and Bag-of-Words approach, both the Document-Term-Matrix (DTM) and the Term-Document-Matrix (TDM) have been generated. The creation of DTM has led to the possibility of inspecting word frequency represented in **Figure 22.**

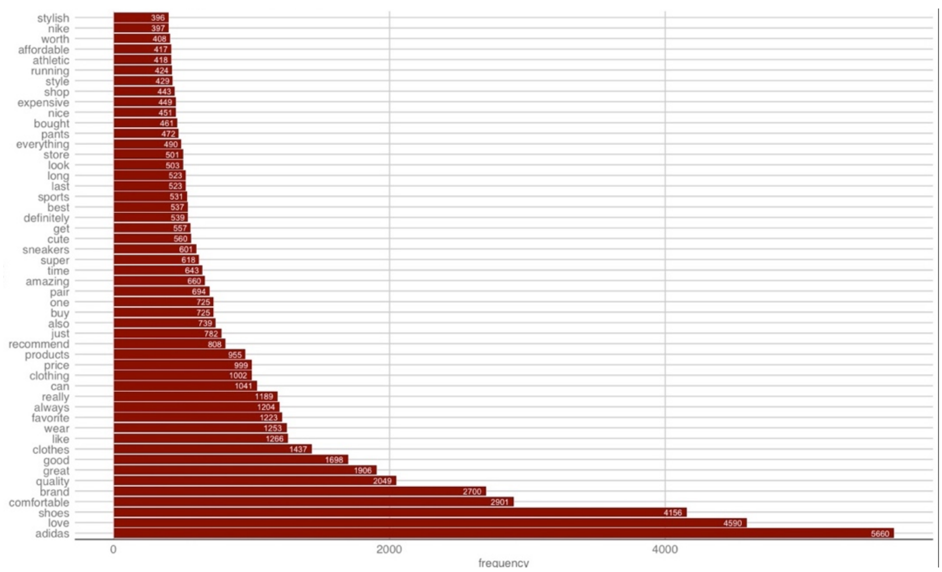

Figure 22: Words frequency

The above graph demonstrates that consumers focus a lot on the emotions that they feel when wearing and buying Adidas products (e.g. “love” f = 4,590), on the comfortability of Adidas (e.g. “comfortable” f = 2,901), on prices (e.g. “price” f = 999) and their propensity to endorse the product (e.g. “recommend” f = 808).

Besides, it is possible to detect that people tend to have a positive view of the brand leading to the spread of positive eWOM.

The association between terms has been analyzed as well. In particular, the one connected with the word "environment". The correlation has been set to 0.10 and a dot plot has been drawn to better illustrate the associations as **Figure 23** shows. The words connected with "environment" are several and mainly positive. The eco-friendly aspect of the Adidas product emerges from the association analysis as well as the aim of the brand that is helping to reduce plastic pollution. Indeed, when dealing with the environmental aspects of the brand, reviewers tend to notice and speak about the fact that the brand supports a great cause like the reduction of plastic in the oceans. For example, they use the words "helping" (association of 0.70) and "saved" (association of 0.50).

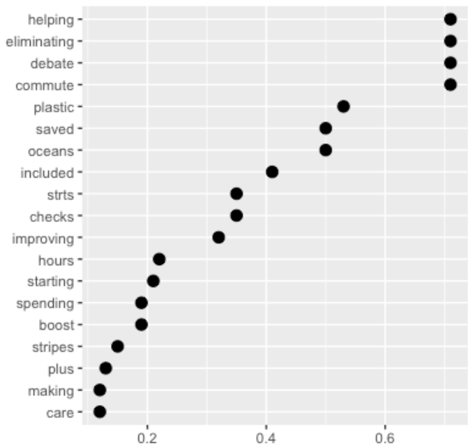

Figure 23: Word association with "environment"

A wordcloud has been generated (using the function `wordcloud`) to go deeper in frequency analysis. Indeed, it helps to quickly perceive the most prominent terms and to determine their relative prominence. Bigger terms mean greater weight.

In this specific case the word "love" is the biggest one and is the only word in violet meaning that it is the most prominent term in the entire dataset. There are other words highlighted such as "brand", "great" and "quality". Additionally, other words such as "recommend" and "favorite" are bigger than the others meaning that people want to spread positive eWOM about Adidas. The results suggest that positive terms have a greater weight than negative ones in the *Brand_eWOM_Dataset*.

Figure 24: Brand_eWOM_Dataset wordcloud

Cluster analysis has been performed clustering the Term-Document-Matrix (TDM) with the purpose of discovering relative significant words.

The *elbow method* has been applied for determining the ideal number of clusters. It consists in plotting the variation as a function of the number of clusters and picking the elbow of the curve to identify the ideal value. According to the computation, the ideal number is four.

Two different methods have been used: the method `cosine` to calculate the matrix distance, while the method `ward.D` to develop a hierarchical clustering.

Table 14: Most frequent terms for each cluster in brand dataset

Cluster	Size	Top words
1	4,988	wear, pair, shoes, comfortable, great
2	716	good, really, quality, price, expensive
3	750	love, adidas, everything, absolutely, cute
4	642	brand, favorite, one, best, recommend

The top ten words defining each cluster have been inspected Using the library `textmineR`. The results underline a huge discrepancy in clusters size composition. Specifically, the first cluster represents the 70.3% of the TDM whereas the fourth one represents only the 9%.

It is worth to notice that the words for cluster one, three and four are similar and positive. On the contrary cluster two contains words related to price describing the brand as expensive.

Wordclouds for the hugest clusters have been drawn and reported in **Figure 25** and **Figure 26**.

Figure 25: Wordcloud of cluster 1

Figure 26: Wordcloud of cluster 3

Sentiment Analysis at document level

The first analysis carried on to inspect reviews sentiment is at the document level.

Sentiment score has been extracted using the function `get_sentiment` and the `bing` lexicon has been used as an analysis method. A function has been created in order to detect positive, negative or neutral polarity. Then the polarity proportions across the dataset have been computed using the `str_detect` function. Results show that the 92% of the documents contain positive sentiment, 2.3% contain negative sentiment and the 5.6% are neutral.

Then, the sentiment score has been calculated using also the `nrc` lexicon as method of analysis. Emotion distribution has been plotted as shown in **Figure 27**. It comes out that the highest value is represented by the "positive" emotion, whereas the negative one is much lower. Two other important emotion emerging from the data are "trust" and "joy" that suggest positive feelings within people.

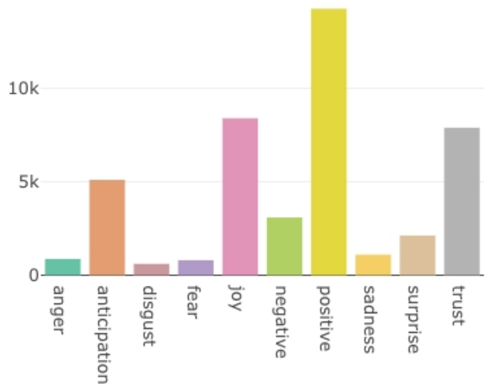

Figure 27: Brand_eWOM_Dataset emotion distribution

Considering the extremely positive review scores, the relationship between positive sentiment and culture has been examined. Indeed, individualistic cultures tend to perceive higher value for eco-friendly brands and products thus exhibiting higher positive sentiment scores as previous cited literature states.
In order to carry on the analysis, a simple linear regression model applying `lm` function has been used.
The *p-value* for the dummy variable *culture* is not significant ($p.value = 0.69$), suggesting that there is not a statistical evidence of a difference in average positive sentiment between collectivistic and individualistic culture.

Sentiment Analysis at sentence level

To carry on sentiment analysis at the sentence level, the library `sentimentR` has been used and a new data frame has been created and chunked with the initial one. This library computes not only the average sentiment (μ) but also the standard deviation (σ). If σ is high, it means that μ is the sum of sentiment scores at the extremes (extremely positive or negative). Whereas if σ is low, it means that the μ is the sum of very close sentiment scores.

Table 15: First five observations of `sentimentR` output

doc_id	Standard deviation ($\boldsymbol{\sigma}$)	Mean ($\boldsymbol{\mu}$)
1	0.25884813	0.49874138
2	0.19306749	-0.38582422
3	0.19756187	-0.21025875
4	0.21654639	-0.13234037
5	0.24086175	0.42031498

For example, σ of review one is 0.26 meaning that μ with value 0.50 has been computed considering extremely positive or negative scores.
Sentiment Score distribution has been plotted as it is shown in **Figure 28**. The graph shows an extremely polarized sentiment score whose distribution is positive skewed shifting towards one. This means that users'

sentiment is extremely positive on average. In particular the below Figure illustrates that a lot of users are slightly positive and fewer strongly positive.

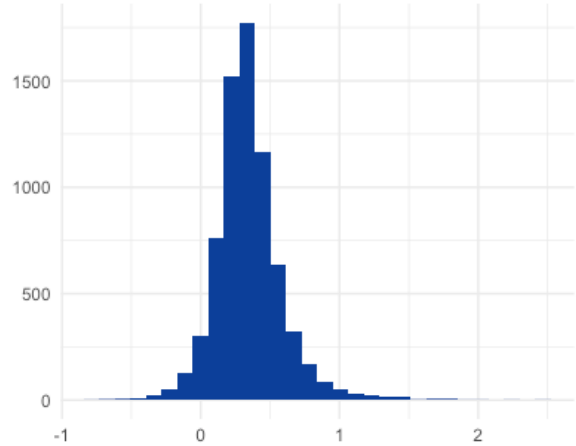

Figure 28: Brand_eWOM_Dataset sentiment score distribution

Sentiment mean across years has been inspected as well as the sentiment trend over time. As it is possible to notice the sentiment keeps on its positive value. It is not stable for the whole years of observation, but it increases over time. Specifically, it exhibits a huge increase between 2013 and 2014 and the sentiment continues to grow with another important peak between 2015 and 2016, the years in which the collaboration with Parley for the Oceans began.

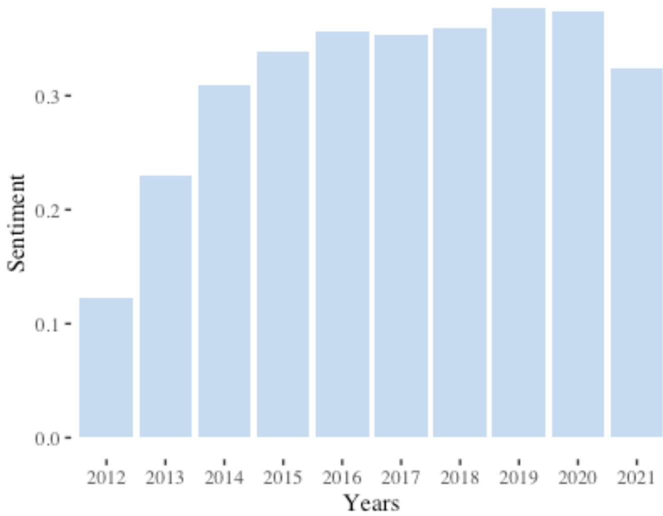

Figure 29: Sentiment Mean evolution across years

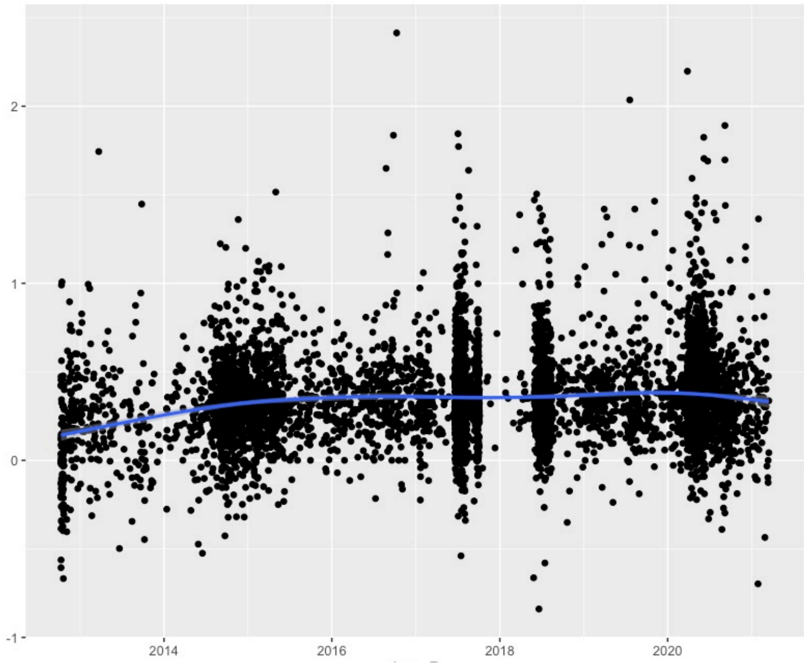

Figure 30: Sentiment trend across years

Considering the importance of perceived value for consumers, the relationship between positive sentiment and words related to PV has been examined. Terms such as "price", "quality", "love", "happiness" have been detected to represent the main construct of PV. Indeed, as previously cited literature states, PV is composed of several attributes that can play a strategic role in how consumers perceive brand products.

A simple linear regression model has been used to develop the analysis. So, the function `lm` has been run to inspect the values.

The *p-value* for the dummy variable *PV* is significant ($\beta = 0.16,\ p < 0.001$), suggesting that there is statistical evidence of the effect of PV on sentiment.

Table 16: Simple linear regression between PV and sentiment output

Coefficients					
	Estimate	Standard Error	t value	Pr (> |t|)	
(Intercept)	0.238239	0.004925	48.37	<2e-16	***
PVTRUE	0.158421	0.005942	26.66	<2e-16	***
Residual standard error	0.2321 on 7094 DF				
Multiple R-squared	0.09106		Adjusted R-squared	0.09093	
F-statistics	710.7 on 1 and	7094 DF	p-value	< 2.2e-16	

Sentiment Analysis at aspect level

Another brick in the research is to analyze sentiment by aspects. Aspects have been identified using the `stringr` library and the function `str_detect`. Columns containing boolean variables have been added to the data frame containing sentiment splitted by sentences. Boxplots have been generated to inspect differences among aspects.

All the plots show a positive tendency. There are some outliers defined by the "moustaches" of the graphs. The medians and mean of "quality" ($M_{quality} = 0.46$; $\mu_{quality} = 0.50$) and "price" ($M_{price} = 0.38$; $\mu_{price} = 0.40$) differ a little bit. Considering also the outliers, the range goes from a value higher than 2.0 to a -0.8. For what concerns the symmetry or asymmetry of the distribution, "price" exhibits a symmetric distribution (the median is in the center of the box). The boxplots of "quality" shows a positive skewed distribution because the upper quartile is farther from the median than the lower quartile.

The medians and means of "brand" ($M_{brand} = 0.34$; $\mu_{brand} = 0.36$) and "product" ($M_{product} = 0.36$; $\mu_{product} = 0.40$) are very close one to each other. Considering also the outliers, the range goes from a value higher than 2.0 to a -0.9. For what concerns the symmetry or asymmetry of the distribution, "Brand" exhibits a symmetric distribution (the median is in the center of the box). "Product" shows a positive skewed distribution because the upper quartile is farther from the median than the lower quartile

All in all, it is possible to notice that people concentrate a lot on the quality of Adidas products.

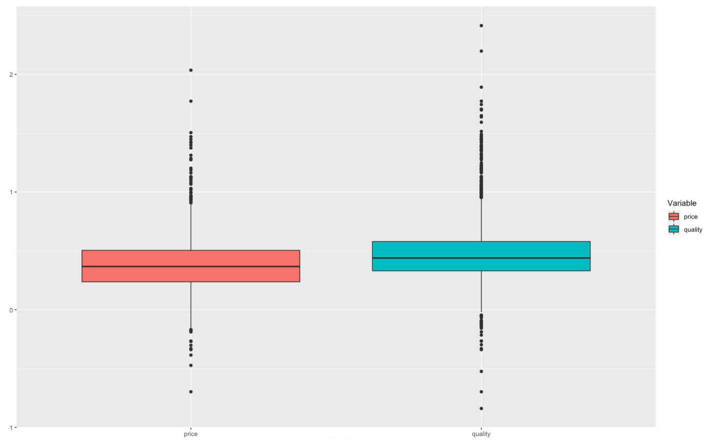

Figure 31: Sentiment comparison between quality and price

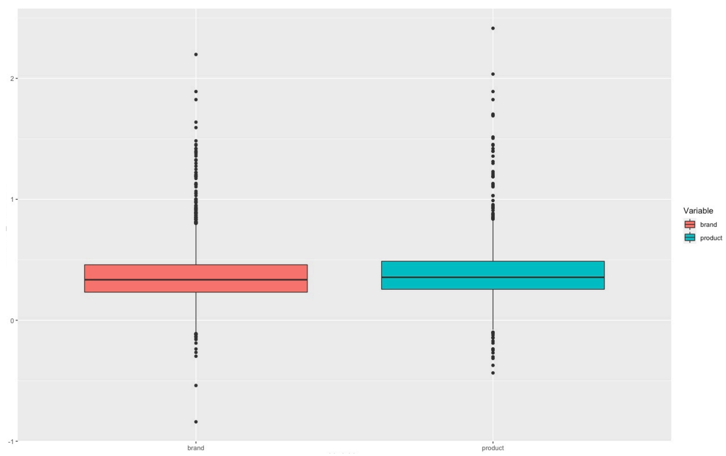

Figure 32: Sentiment comparison between brand and product

Topic Modeling

A further step in the analysis is the launch of the library `stm` and the dataset adjustment to carry on topic modeling. Then a new corpus has been created using `textProcessor` function.

Empty documents have been dropped and some words removed (2,785 words out of 5,628 terms; 2,785 out of 103,393 tokens due to frequency). Finally, the corpus contained 7,096 documents, 2,843 terms and 100,608 tokens.

The second step has been the identification of the ideal number of topics through the function `searchK` and setting the search range between two and twenty. Results are shown in **Figure 33**

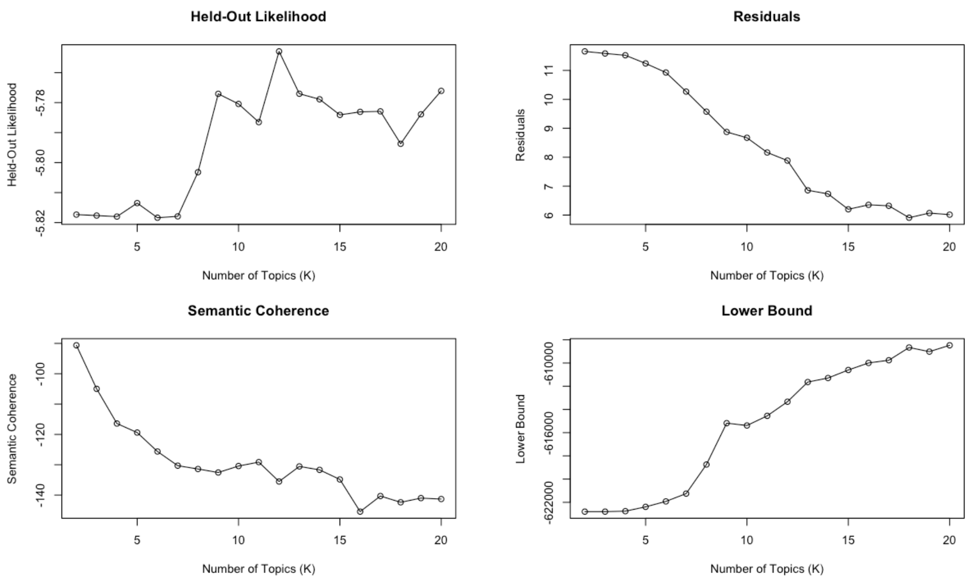

Figure 33: Diagnostic values for numbers of topics

Moreover, years and the sentiment orientation (resulting from the output of the `bing` dictionary) variables have been considered as metadata to be included during the search.

The choice of the ideal topic number has been based on two values: exclusiveness (how specific a topic is) and coherence (what a topic is about). The *k* that maximizes both values has been identified to be five. Indeed, this number is the nearest to the upper-right corner of the graph where the maximization of the two variables occurs.

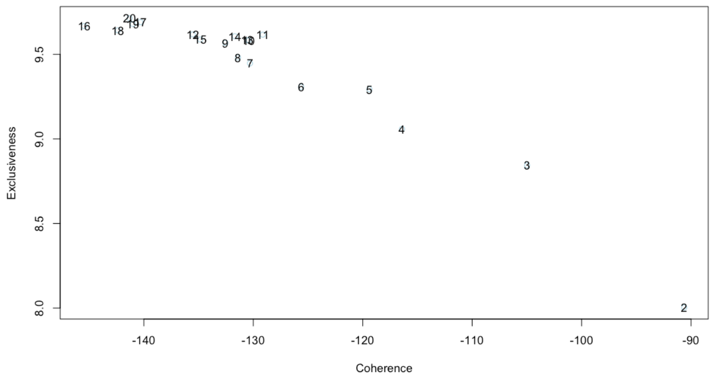

Figure 34: Ideal numbers of topics identification

To inspect the topic content, topic proportion has been calculated. Topic five has a likelihood higher than 30% and topic three has a likelihood score higher than 20%. This means that more than 50% of the corpus will be described by topic five and three. The other topics are all less relevant in the discussion with values that range between 10% and 20%. This is quite a good topic model because there is a huge gap between topic three and topic four, reinforcing the fact that topics five and three are very significant for the text corpus.

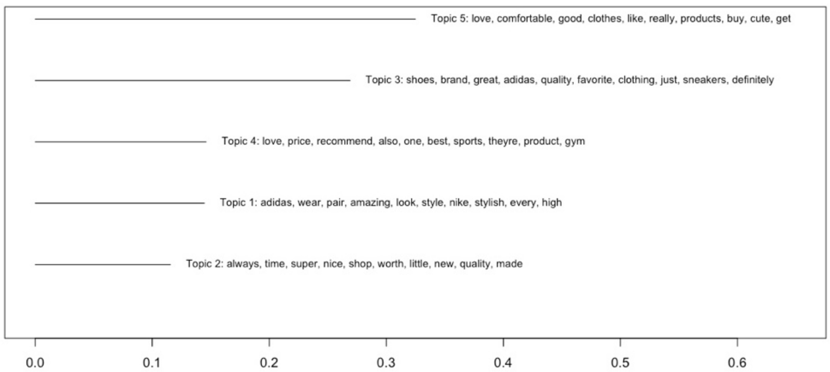

Figure 35: Expected topic proportion

Two wordclouds have been generated to better understand what the most relevant topics are about.

Figure 36: Wordcloud of topic three

Figure 37: Wordcloud of topic five

The wordcloud related to topic three shows that shoppers concentrate more on the brand and on the shoes as product. Specifically, they suggest that Adidas is their favorite brand and that they love their shoes. They pay a lot of attention on price. Indeed, they classify the brand as “affordable”. Additionally, reviewers consider the products as very good ones (e.g. “stylish”, “long-lasting”). For that reason, they would recommend them to other users.

On the other hand, the wordcloud related to topic five emphasizes that people focus more on “clothes” in general and on the “quality” of products. They also suggest that the value of those products is influenced by the environmental cause that the brand joins. They define clothes and Adidas as “good”, “cute” and “nice”.

Function `lableTopics` has been used to detect the most relevant keywords for each topic. The following list summaries what has been found using the *highest probability* method:

- **Topic one**: is about the consideration that writers have about the brand defining it as a great brand with very good products that they like a lot.
- **Topic two:** is about the quality of Adidas sneakers and clothes after the trial and wear of such items. Reviewers define them as cute and suggest that they will buy them again.
- **Topic three:** is about people’s feelings about Adidas. They state that they love the brand defining it as their favorite. They suggest that they have several pairs of shoes and different clothes and that they will recommend the brand.
- **Topic four:** is about what buyers think about Adidas. They define it as an amazing and super quality brand as well as the best one on the market.
- **Topic five:** is about clothing. Indeed, buyers define it as comfortable for sports activities and for that reason they recommend the brand. But, on the other side, they consider it a little bit expensive.

To help to extract more insights, reviews have also been inspected using `findThoughts` function. **Figure 38** shows an example related to topic three.

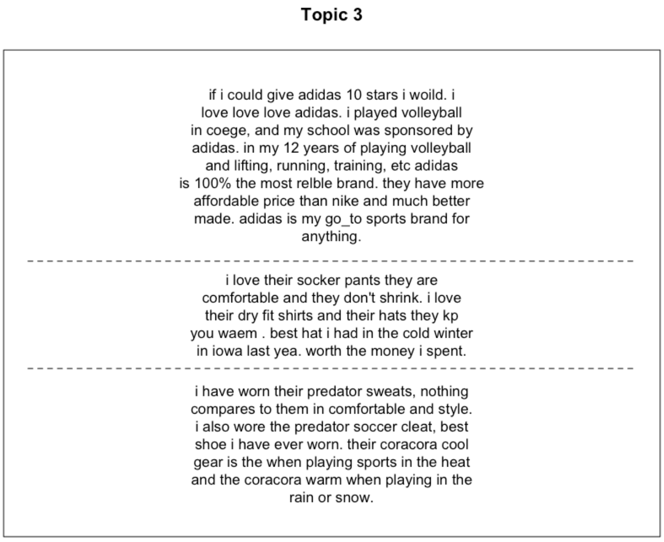

Figure 38: Reviews about topic three

Reviews from topic three underline the fact that buyers consider Adidas as an extremely successful brand thanks to its history and the materials they use for creating its products. From the review a strong positive feeling (reinforced by the brand actions and performances) towards the brand emerges.

The use of comparison clouds that highlight the most important words allowing to fully understand what topics are about has allowed the extraction of the previous results.

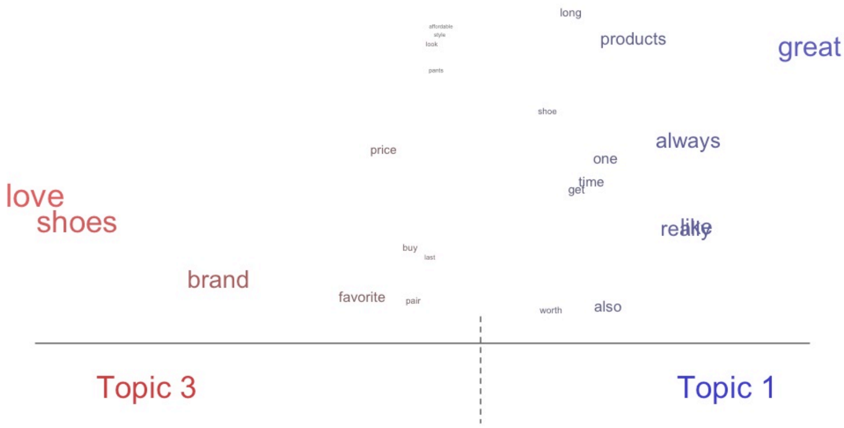

Figure 39: Comparison wordcloud

Correlation between topics and metadata has been analyzed as well. It enables to understand how topics are influenced by the presence or absence of covariates. In this particular case, years and sentiment polarity have been considered as influence factors.

The function `estimateEffect` has been used to carry on the computation.

For what concerns "year", it has been found that the entire period of ten years of observation is significant for topic three with a positive score coefficient ($p.value < 0.001$). This means that in the corpus of reviews topic three has been discussed across all the observation time span. Topic one is significantly negatively correlated with all the years except 2013 which shows no correlation at all ($p.value = 0.11$). Topic five is significantly negatively correlated ($p.value < 0.001$) with all the years except 2016 ($p.value = 0.96$) that shows no significant correlation like year 2013 for topic one. Topic two is significantly negatively correlated with years 2013 ($\beta = -0.04,\ p < 0.001$), 2014 ($\beta = -0.02,\ p < 0.01$), 2015 ($\beta = -0.02,\ p < 0.01$) and significantly positively correlated with 2012 ($\beta = 0.19,\ p < 0.001$) and 2020 ($\beta = 0.02,\ p < 0.05$) meaning that in those two years topic two is discussed. Finally, topic four is significantly positively correlated with all the years except 2014 ($p.value = 0.16$), 2015 ($p.value = 0.16$), 2016 ($p.value = 0.96$) which show no correlation.

Figure 40 summarizes what previously discussed.

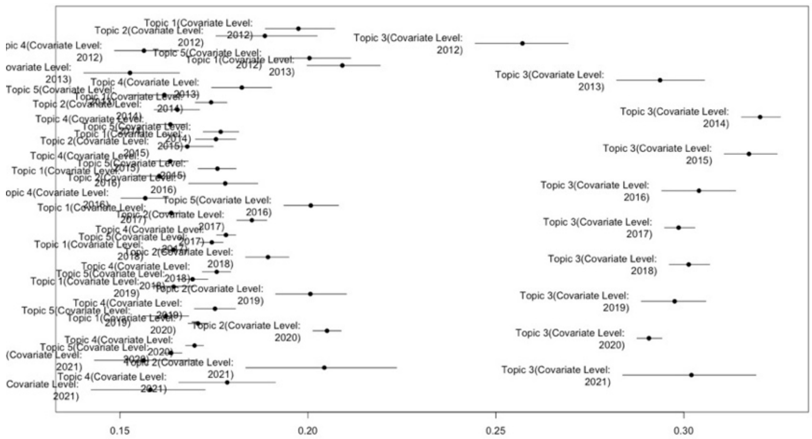

Figure 40: Topic correlation with covariate "year"

Considering the results of correlation analysis, and in particular the positive correlation among years and topic three, this specific relationship has been further studied. It has been found that topic three is heavily discussed in years 2014, 2015 and 2021.

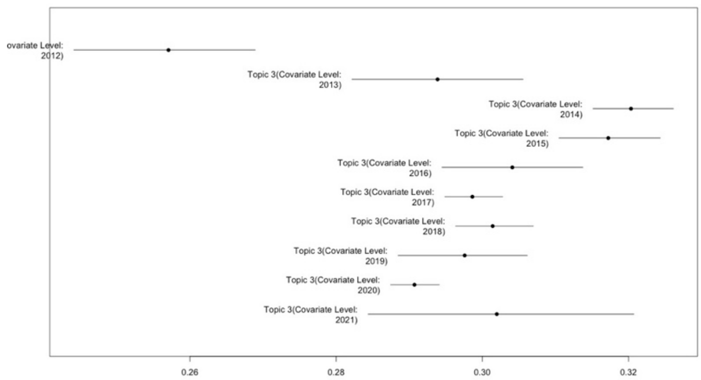

Figure 41: Correlation between topic three and covariate "years"

Regarding the correlation with sentiment polarity, results show that topic two is negatively correlated with positive reviews meaning that positive reviewers do not speak about topic two. But they tend to speak about topic three (*p.value* = 1.87e-05) and topic five (*p.value* = 0.00123).

The below graph gives a visual representation of the correlations between sentiment polarity and topics.

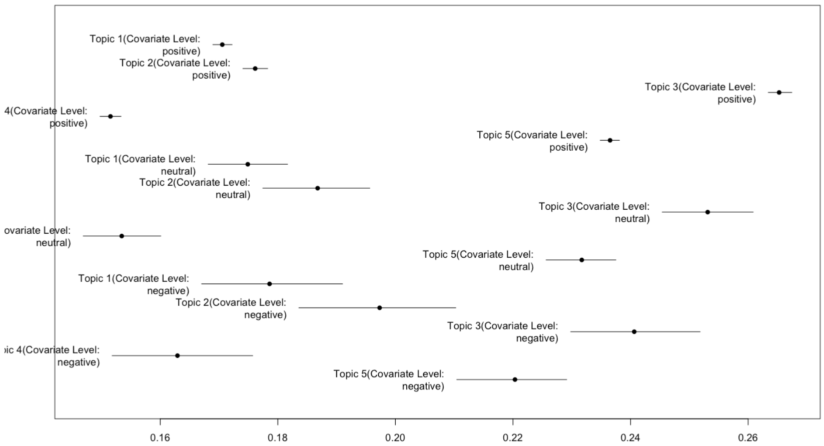

Figure 42: Correlation between topics and sentiment polarity

As it is shown in **Figure 43** correlation among topics has also been inspected. Results show that topics three, four and five are related but separated from the other two. Whereas topic one and two are correlated. It means that according to the way the algorithm finds them, topics three, four and five are discussed in the reviews and appear together, but they do not appear with topic one and two that are discussed in the reviews and appear together.

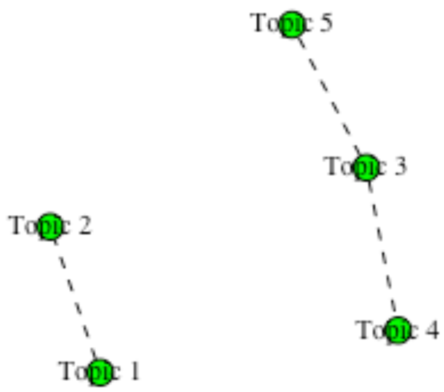

Figure 43: Topic correlation

6.5.2. Product eWOM

Bag of Words

The first step in the Bag-of-Words approach has been the identification and replacement of *n*-grams such as "Ultra Boost", "Adidas Supernova", "road runner", "lifetime", etc. This operation has been carried on by joining words that otherwise the algorithm might interpret separately leading to mistrustful results.

Then a network of bigrams has been analyzed. The network graph has been created using the `ggraph` function. It shows that words such as "shoes", "comfortable", "size" and "running" form common centers of nodes, which are often followed by adjectives like "perfect", "excellent", "larger", "normal", etc. All the adjectives associated with central nodes are merely positive showing a positive attitude towards the product.

To get text mining and Bag-of-Words approach, both the Document-Term-Matrix (DTM) and the Term-Document-Matrix (TDM) have been generated. The creation of DTM has led to the possibility of inspecting word frequency represented in **Figure 44.**

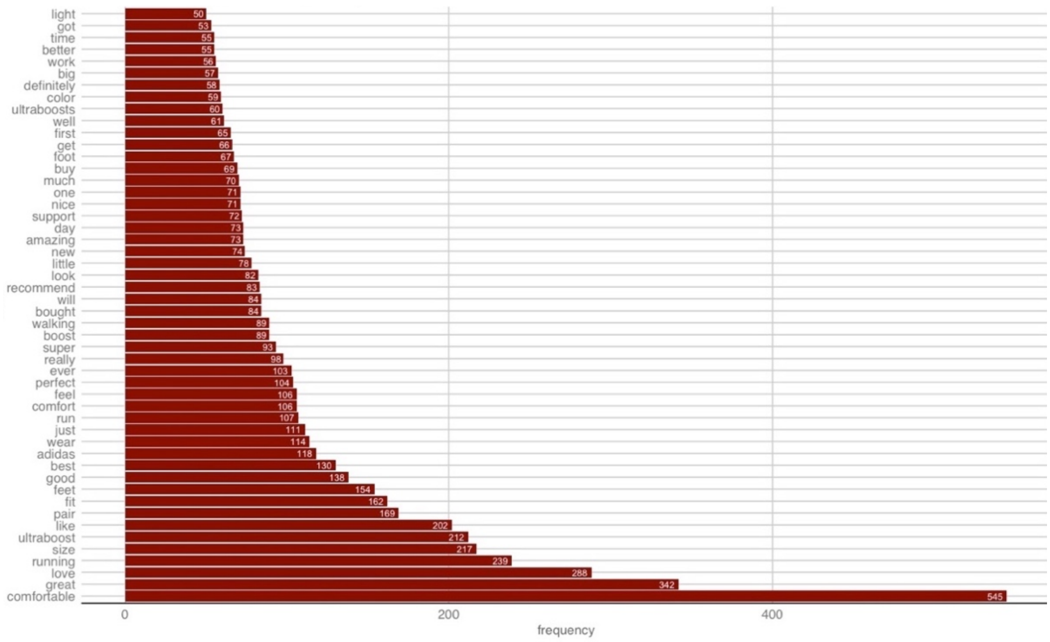

Figure 44: Words frequency for product eWOM

The above graph demonstrates that consumers focus a lot on the comfortability of the shoes (e.g. "comfortable" $f = 545$, "comfort" $f = 106$), on the emotions that they feel when wearing them (e.g. "love" $f = 288$) and their propensity to endorse the product (e.g. "recommend" $f = 82$).

Word frequency across datasets has also been inspected to look over possible differences.

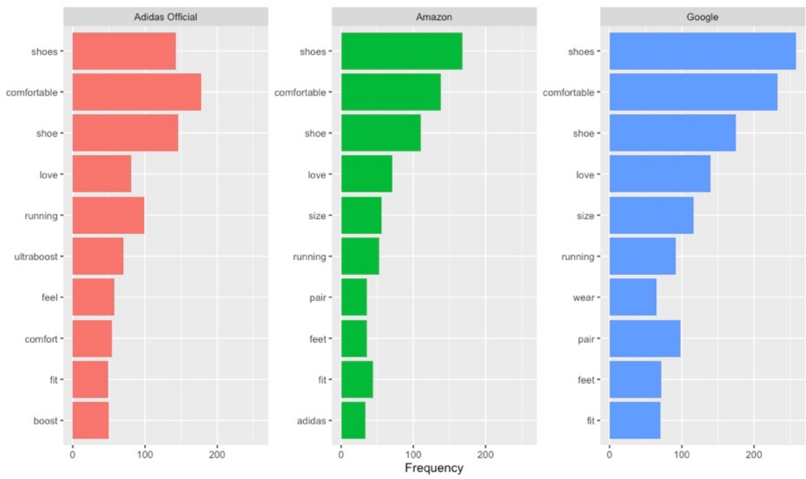

Figure 45: Words frequency across datasets

In all three datasets people pay attention to the comfortability of the shoes and on expressing their positivity towards the product using the word "love" in particular. It is worth to highlight that in the *Google Dataset* the two concepts have a higher frequency (*f* = 240*)* compared to the *Amazon* (*f* = 140*)* and *Adidas Datasets (f* = 170*)*.

A wordcloud has been generated using the function `wordcloud`. In this specific case, the word "comfortable" is the biggest one and is the only one in violet meaning that it is the most prominent word in the entire dataset. Other words such as "love", "great" and "like" are highlighted. The results suggest that in the *Shoes_Dataset* corpus positive terms have a greater weight than negative ones.

Figure 46: Shoes_Dataset wordcloud

It is worth to calculate the word frequency for each word across the entire *Shoes_Dataset* versus within each dataset namely *Adidas Official*, *Google* and *Amazon* since three different datasets have been analyzed. This procedure allows to compare strong deviations of word frequency within each dataset as compared to across the entire *Shoes_Dataset*. **Figure 47** shows the results of such analysis.

Figure 47: Frequency for each word across the three datasets versus within each dataset

Words that are close to the line in these plots have similar frequencies across all the datasets. For example, words such as “shoes”, “recommend”, “love” and “quality” are fairly common and used with similar frequencies across the three datasets. Words that are far from the line are words that are found more in one set of texts than another. Words standing out above the line are common across the series but not within that review webpage. On the contrary, words below the line are common in that particular dataset but not across all of them. For example, “arch” stands out above the line in the *Adidas Official Dataset* meaning that the word is fairly common across each one of the three datasets but is not often used in the *Adidas Official* one. In contrast, a word below the line such as “amazon” in the *Amazon Dataset* suggests that the term is common in this dataset but far less common across all of them.
A correlation test has also been carried on (using the functions `cor` and `cor.test`) to get a whole understanding of how similar or different these sets of word frequencies are. Results illustrate a high correlation for all three datasets. In particular, the Pearson’s correlation coefficients are $\rho = 0.962$ for the *Adidas Official Dataset*; $\rho = 0.975$ for the *Amazon Dataset* and $\rho = 0.987$ for the *Google Dataset*. The high correlations, all of them statistically significant ($p.value < 0.001$), suggests that the relationship between word frequencies is highly similar across the entire *Shoes_Dataset*.
After the identification of the key terms that appear in the corpus, association between terms has been analyzed. In particular the one related to “material”. The correlation has been set to 0.20 and a dot plot has been drawn to better illustrate the associations (**Figure 48**). The words connected with “material” are mostly positive. It is worth to notice that the eco-aspect of the shoes emerges from the association analysis. Indeed, when dealing with the shoes materials, reviewers tend to notice and speak about the fact that the product is made of recycled material for example they use the words “recycled” (association of 0.228) and “eco-style” (association of 0.328).

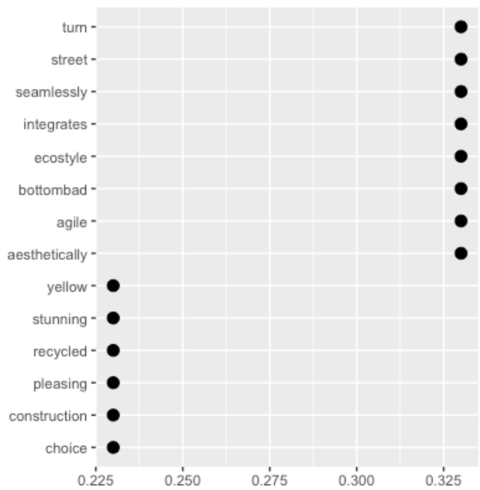

Figure 48: Association with word "material"

After that, cluster analysis has been performed clustering the Term-Document-Matrix (TDM) with the purpose of discovering relative significant words.

The *elbow method* has been applied for determining the ideal number of clusters and according to the computation, the ideal number is four.

The method `cosine` has been used to calculate the matrix distance and the method `ward.D` to develop a hierarchical clustering. **Figure 49** shows the resulting dendrogram graph.

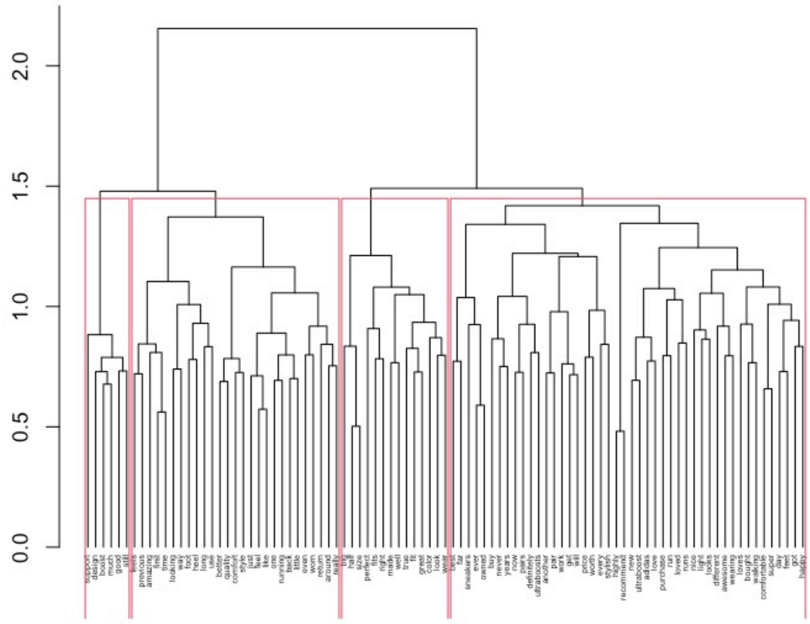

Figure 49: Dendrogram of the TDM

The top five words defining each cluster have been inspected through the library `textmineR`. The results underline a huge discrepancy in clusters size composition. Specifically, the first cluster represents the 77% of the TDM whereas the fourth one represents only the 0.9%.

It is worth to notice that the words for cluster one, three and four are similar and positive. On the contrary cluster two contains words more relating the size and functional aspects of the shoes.

Table 17: Most frequent words for each cluster in product dataset

Cluster	Size	Top words
1	714	boost, ultra, good, feel
2	58	size, big, toe, sizing
3	148	comfortable, shoes, great, love, walking
4	8	great, shoes, pair, comfortable, love

Sentiment Analysis at document level

The first analysis carried on to inspect reviews sentiment is at the document level. First of all, sentiment score has been calculated using the function `get_sentiment` and the "`nrc`" lexicon as an analysis method. Emotion distribution has been plotted as shown in **Figure 50**. It comes out that the highest value is represented by the "positive" emotion, whereas the negative one is much lower. Two other important emotions emerging from the data are "trust", "joy" and "anticipation" that suggest positive feelings within people.

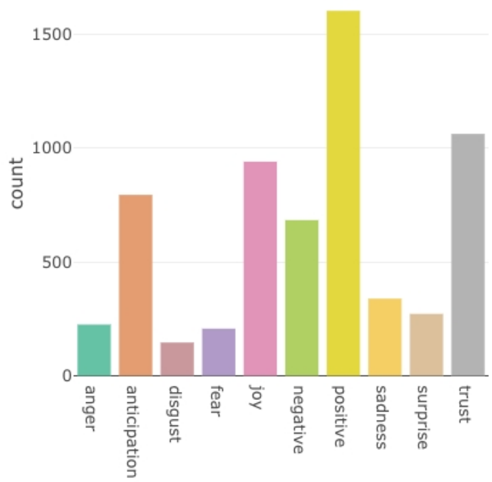

Figure 50: Shoes_Dataset emotion distribution

Considering the extremely positive review scores, the relationship between positive sentiment and gender has been examined. Indeed, women tend to perceive higher value for eco-friendly products thus exhibiting higher positive sentiment scores as previous cited literature states.

The *p-value* for the dummy variable *sexMale* is significant ($\beta = -0.44,\ p < 0.01$), suggesting that there is a statistical evidence of a difference in average positive sentiment between genders.

The estimates are $b_0 = 1.96032$ and $b_1 = -0.44277$ leading to a prediction of average positive sentiment of 1.96032 for females and a prediction of $1.96032 - 0.44277 = 0.65355$ for males.

Running also the ANOVA analysis for the relationship between gender and sentiment, it comes out that there is a significant difference in the mean between males and females individuals ($F(1{,}718) = 9.78,\ p = 0.001834, M = 35.201$).

The fact that the coefficient for *sexM* in the regression output is negative indicates that being a male is associated with a decrease in positive sentiment relative to females thus confirming the hypothesis that women perceive more favorably an eco-friendly product.

Table 18: Regression analysis between positive sentiment and gender

Coefficients:					
	Estimate	Std. Error	t value	Pr (> |t|)	
Intercept	1.96032	0.09757	20.091	< 2e-16	***
sexM	-0.44277	0.14157	-3.128	0.00183	**

Table 19: ANOVA table for the relationship between gender and positive sentiment

Response:	pos.sent					
	Df	Sum Sq	Mean Sq	F value	Pr (> F)	
sex	1	35.2	35.201	9.7817	0.001834	***
Residuals	718	2583.8	3.599			

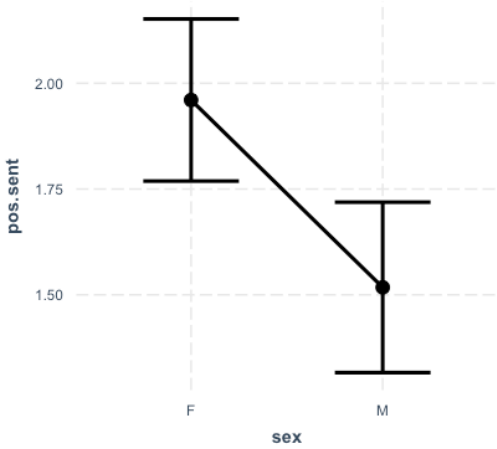

Figure 51: Regression scatterplot males vs females

Sentiment Analysis at sentence level

Developing the sentiment analysis at the sentence level, *Sentiment Score* distribution has been plotted as it is shown in **Figure 51**. The graph exhibits an extremely polarized sentiment score whose distribution is positive skewed shifting towards one. This means that, on average, users' sentiment is extremely positive. In particular, the figure illustrates that a lot of users are slightly positive and fewer strongly positive. Moreover, it underlines that negative sentiment expressed by users is slightly negative with no case of extremely negative scores.

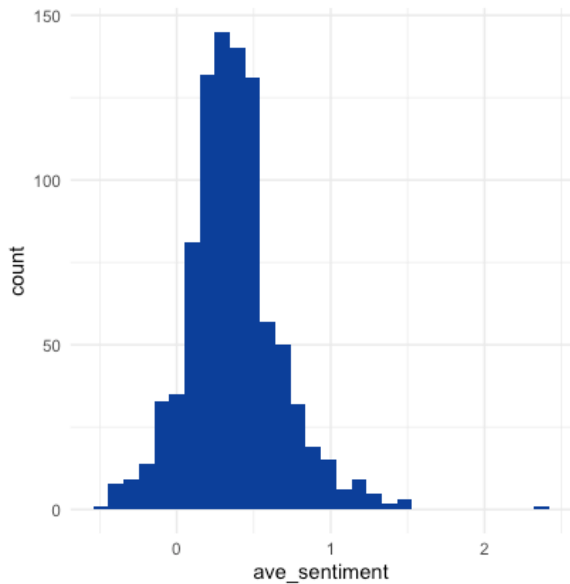

Figure 52: Sentiment score distribution for product eWOM

In the present case, the role played by the three datasets and the role played by gender should be considered. So, two additional graphs have been plotted using the library `ggplot2`. **Figure 53** illustrates the differences between positive and negative sentiment score across datasets. It points out that *Adidas Official Dataset* contains the highest values both for negative and positive polarity, the *Google Dataset* contains the lowest values for positive scores and *Amazon Dataset* has got the lowest values for negative scores.

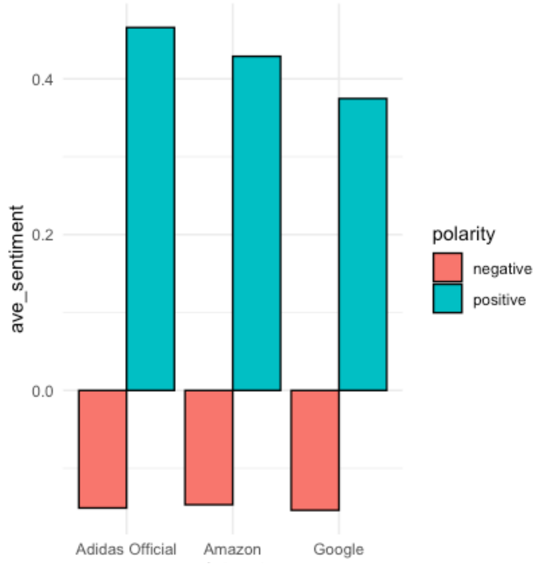

Figure 53: Positive and negative sentiment across datasets

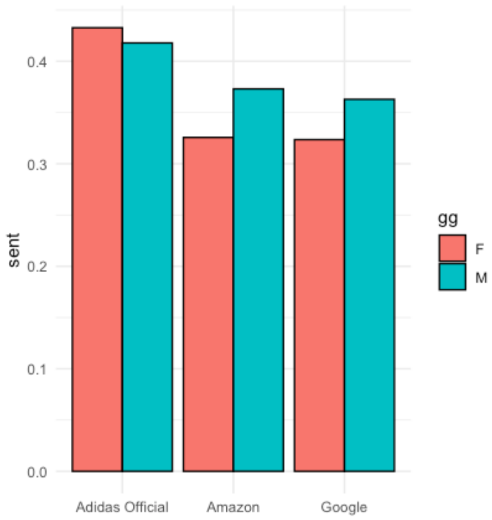

Figure 54: Sentiment differences between women and men across datasets

Figure 54 presents sentiment differences between females and males across the three datasets. To build such a graph anonymous observations have not been considered. The picture exposes to view that for the *Adidas Official Dataset* the average sentiment for females is higher than for males, an assumption that is not true for the other two datasets. However, the overall mean for females (μ = 0.3817) results to be slightly higher than for males (μ = 0.3644).

The sentiment trend over time has been inspected as well. As it is possible to notice, the sentiment keeps on its positive value. It is not stable for the whole years of observation. It exhibits an increase till the end of 2019, then a decrease in the first period of 2020 and then a raise in the last part of 2020 and the beginning of 2021.

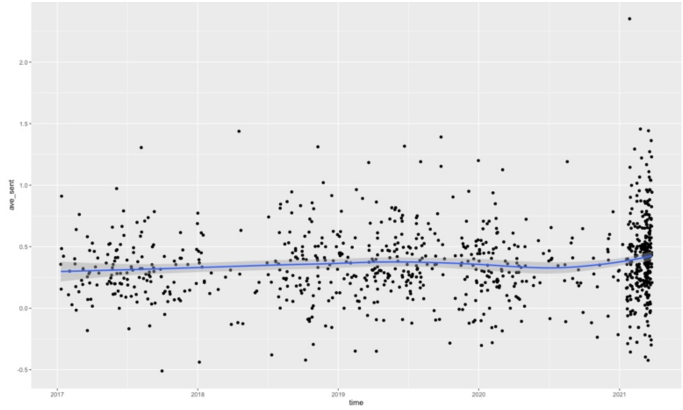

Figure 55: Sentiment trend across years for product eWOM

Sentiment Analysis at aspect level

Another brick in the research is to analyze sentiment by aspects. Boxplots have been generated to inspect differences among aspects.

All the boxplots show a positive tendency. There are some outliers defined by the "moustaches" of the graphs. The medians of "material" ($M_{material} = 0.27$; $\mu_{brand} = 0.25$), "price" ($M_{price} = 0.32$; $\mu_{price} = 0.49$) and "quality" ($M_{quality} = 0.49$; $\mu_{quality} = 0.53$) are quite different from one another. The graph shows that the highest level is represented by "quality". Considering also the outliers, the range goes from a value higher than 2.0 to a value of lower than -0.2. For what concerns the symmetry or asymmetry of the distribution, "quality" exhibit symmetric distribution (the median is in the center of the box). The boxplots of "material" and "price" show a positive-skewed distribution because the upper quartile is farther from the median than the lower quartile.

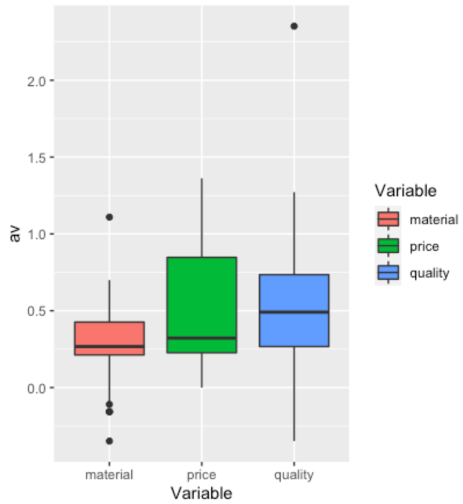

Figure 56: Boxplots of the sentiment for material, quality and price

Topic Model

In order to proceed with the analysis, the library `stm` has been loaded and dataset has been adjusted. Then a new corpus has been created using `textProcessor` function.

Empty documents have been dropped and some words removed (1,348 words out of 2,576 terms; 1,348 out of 14,799 tokens due to frequency). Finally, the corpus contained 927 documents, 1,228 terms and 13,451 tokens.

The second step has been the identification of the ideal number of topics. It has been done using the function `searchK` and setting the search range between two and fifteen. Moreover, gender variable has been considered as metadata to include during the search.

The choice of the ideal topic number has been based on two values: exclusiveness (how specific a topic is) and coherence (what a topic is about). The value that maximizes both values has been identified to be six. Indeed, this number is the nearest to the upper-right corner of the graph where the maximization of the two variables occurs.

To inspect the topic content, topic proportion has been calculated. Topics five and four have a likelihood higher than 20%. This means that more than 40% of the corpus will be described by topic two and five. The other topics are all less relevant in the discussion with values that range between 10% and 20%.

Two wordclouds have been generated to better understand what the most relevant topic are about.

Figure 57: Wordcloud of topic four

Figure 58: Wordcloud of topic five

Figure 57 shows that shoppers concentrate more on the brand. Specifically, they speak about "Adidas" and "Ultraboost shoes" in a positive way, describing them as "great". Additionally, if looking carefully at the wordcloud, it is possible to notice that they relate the product and the brand to the "environment" and the "future". They classify the product as a very good one for walking and running focusing on the environment. **Figure 58** emphasizes that people concentrate more on the shoes particularly on their comfortability. They define them as "awesome", "beautiful" and that wearing them is like walking on "clouds".

Function `lableTopics` has been used to detect the most relevant keywords for each topic. The following list summaries what has been found using the *highest probability* method:

- **Topic one**: it is about the shoes price (defined as worth), quality (defined as good) and look (defined as awesome).
- **Topic two:** it is about the use that buyers make of the shoes. They employ them for running and they infer that the shoes give stability.
- **Topic three:** it is about how people feel when running with "Ultraboost" shoes. Then some writers suggest using the shoes if someone has toes problems.
- **Topic four:** it is about the brand and its involvement in the environmental cause, the comfortability of the shoes and how many pairs people have bought.
- **Topic five:** it is about the sentiment that people have towards the product. Indeed, they state that they love the shoes.
- **Topic six:** it is about the spread of positive eWOM. People recommend the shoes to others finding them as perfect and nice.

To help to extract more insights, reviews have also been inspected using `findThoughts` function. **Figure 58** shows examples related to topic four and five.

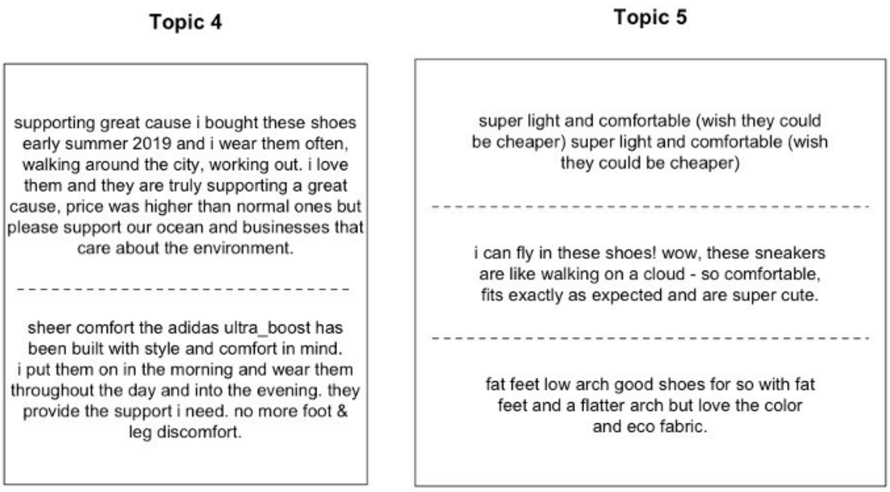

Figure 59: Reviews about topics four and five

Reviews from topic four underline the fact that users have bought the shoes in order to support a brand that is involved in a great cause: the saving of the oceans. Additionally, they underline the fact that Adidas is truly involved in the environmental cause. Also in reviews from topic five the eco-style of the product emerges. This result is in line with the assumption that using a partnership may increase the possibility that users appreciate the recycled aspect of the product.

After that, correlation between topics and metadata has been analyzed. It allows to understand how topics are influenced by the presence or absence of covariates. In this particular case, gender has been considered as an influencing factor.

The function `estimateEffect` has been used to carry on the computation. Besides, it has been found that both males ($\beta = -0.04,\ p < 0.05$) and females ($\beta = -0.06,\ p < 0.001$) are significantly correlated with topic three with a negative score coefficient. This means that in the corpus of reviews both men and women do not speak about topic three, whereas anonymous writers show positive correlation. Topic one is significantly negatively correlated with females ($\beta = -0.04,\ p < 0.05$), whereas topic two is significantly positively correlated with them ($\beta = 0.04,\ p < 0.05$) Thus they will not speak about topic one, but about topic two. Topic five is positively correlated with both men ($\beta = 0.04,\ p < 0.05$)and women ($\beta = 0.05$, $p < 0.001$).

The below graph gives a visual representation of what previously explained.

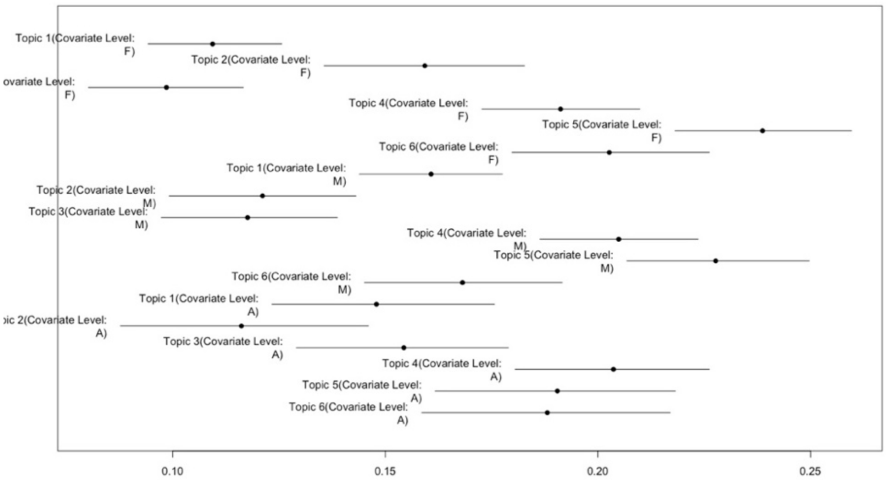

Figure 60: Correlation between topics and gender

Considering the results of correlation analysis, the relationship among topic one, two and five and gender have been inspected. It has been found that topic two is more discussed by females. Whereas topic five by anonymous writers and females as well.

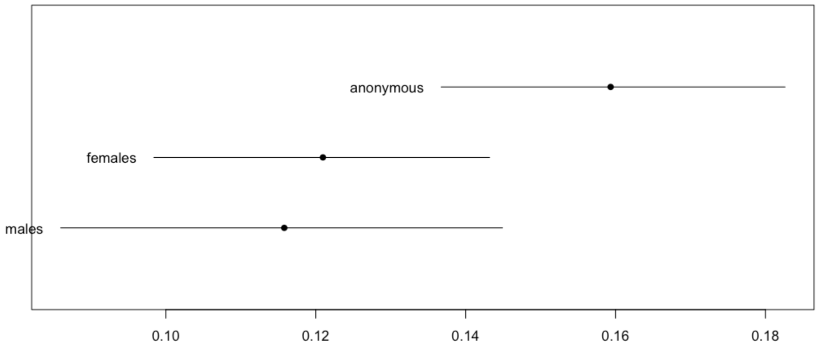

Figure 61: Topic two by gender

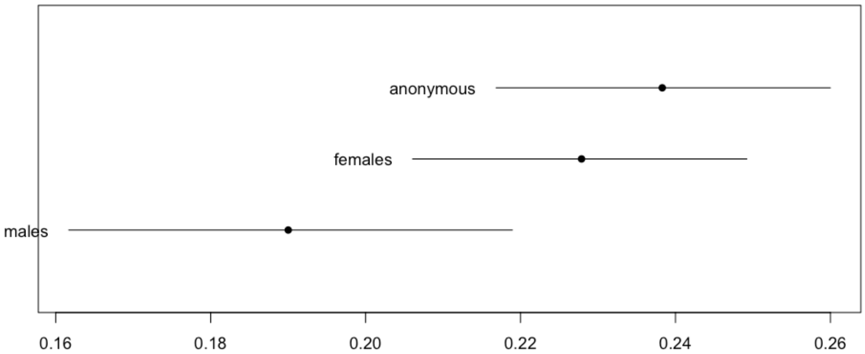

Figure 62: Topic five by gender

Analyzing the output of function `lableTopics` and **Figure 60**, the most important words for males have been found to be: comfortable, love, shoes, like, walking, supe, feel. On the contrary, for females, the most important words result to be: stability, feet, ankle, shoe, like, run.

An additional aspect to investigate is the correlation among topics as displayed in **Figure 63**.

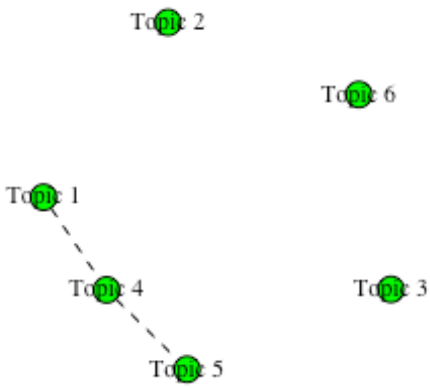

Figure 63: Topics correlation for product eWOM

Results show that topics two, six and three are independent and topics one, four and five are correlated. It means that according to the way the algorithm finds them, topics two, six and three are discussed in the reviews but do not appear together, whereas topics one, four and five are discussed in the reviews and appear together.

6.6. Discussion

The mere purposes of this second study were to examine how a brand and its products are perceived when the company engages in a co-branding strategy with an environmental association by directly scrape reviews about both the brand and the product. The analysis has been developed based on the findings of the conceptual model tested in the first part of this work that departs from the literature relating to green marketing, Corporate Social Responsibility and Word-of-Mouth.

The findings reveal that both the product and the brand show extremely positive polarized sentiment scores meaning that people tend to perceive “Adidas” and “UltraBoost Parley shoes” in a very favorable way.

From Bag-of-Words (BoW) study emerges that people tend to love Adidas and they use mostly positive words when speaking or writing about it. The environmental concern of the brand emerges as well. Indeed, many writers focus on the fact that Adidas has engaged in a collaboration with Parley for the Oceans thus helping the planet. According to reviewers, this collaboration gives a *plus* to the brand differentiating it from competitors.

For what concerns the product, people find them comfortable and of great quality. They tend to associate UltraBoost materials with ecological aspect without considering the shoes as having low features. This result strengthens the assumption that a partnership may allow consumers to perceive a fashion product made of recycled materials as very good in its characteristics. The examination of the use of words in three different webpages has led to the result that no extreme differences occur, so people are not influenced by the review platform in which they write.

Sentiment Analysis reinforces the findings obtained from the BoW. The sentiment at document, sentence and aspect level is positive and shifts towards one both for the brand and for the product. From the analysis carried to verify the evolution of sentiment during the years it emerges that sentiment increases across the time span with two main spots, one in 2015 (year of the announcement of “Adidas X Parley” project) and the other one in 2017 (UltraBoost Parley shoes reaching the market).

Regression Analysis underlines that culture does not affect sentiment towards the brand. A result that does not validate previous studies. Indeed, it is possible to notice that there is no difference in sentiment score between individualistic and collectivistic cultures. Whereas gender influences sentiment towards the product. Specifically, females perceive more favorably the product leading to the spread of a more positive eWOM compared to males. Considering Perceived Value (PV), regression outcome demonstrates that the relationship between PV and sentiment is significant and positive. So, PV positively influences sentiment. This result confirms the literature according to which the more positively consumers value circular fashion offerings, the more likely to engage in positive attitudes (e.g. spread of information) towards the company and the products they will be (Ki, Park, & Ha-Brookshire, 2020).

Quality and price of the brand and the product exhibit positive sentiment with quality being more important and showing higher sentiment scores than price.

Topic model analysis reveals that when speaking about Adidas in general, people tend to focus on price, quality and how the brand makes them feel, in this particular case stylish and cool. They speak also about Adidas eco-friendly aspect by underling that buying its products may help to create a better planet. Most of the reviewers suggest others to buy Adidas meaning that the brand exhibits a high level of positive eWOM. Considering covariates, topics are almost equally distributed across the years. Furthermore, brand positive polarity reviews show a positive correlation with the most prominent topics in the dataset (topic three and five).

On the other hand, when dealing with the product, people focus even more on ecological characteristics. They stress the fact that UltraBoost shoes are made of recycled material and buying them allow to help an environmental organization (Parley), thus enhancing the planet. They also focus on the comfortability of the shoes and on the use, they made when wearing them.

From the results, it emerges that when dealing with companies engaged in a co-branding strategy, people tend to spread more favorable eWOM, an outcome that is in line with literature stating that green partnerships can be instrumental in carrying out environmental strategies of firms and generate performance gains and reputational gains (Sadovnikova & Pujari, 2017). However, from topic modeling, it emerges that people tend to treat more about ecological features when writing reviews about the product rather than about the brand. Indeed, when dealing with the brand they especially focus on how cool, cute, trendy it is and on the so-called "impression management", so how good the brand makes them look in the eyes of others.

All in all, findings from this second study confirm the hypothesis that a co-branding strategy may influence positive eWOM about a brand and a product.

Chapter VII: Final Remarks

7.1. General Discussion

The fashion industry is now in the eye of the storm for what concerns sustainability because of the huge impact that such a business area has on the environment. As a result, new business models have emerged providing an increasing relevance of circular economy in the worldwide spotlight. However, to realize the full potential for inner loops in circular economy consumers, should change their perceptions and behaviors towards circular products and services (Mugge, 2018). Consumers need to perceive ample benefits and limited risks in refurbished/remanufactured products (Mugge, 2018), while companies have to reassure customers about their products and advertising with a clear and faithful promise that they are following ethical principles since they have to deal with the possible consumers' distrust due to the practice of greenwashing (Chen, Lin, & Chang, 2014). So communication may play a critical role in influencing consumers' perception towards circular products and brands operating with such a business model, thus influencing consumers' behavior by breaking adoption barriers (Mugge, 2018).

The study developed in this paperwork aims at fulfilling the before mentioned issue by considering co-branding strategies as powerful communication tools to allow products made of recycled materials to be endorsed.

The literature regarding green marketing and the Internet word-of-mouth (eWOM) has far not addressed the potential of using green co-branding as a strategy to enhance positive discussions among consumers on product and brand dedicated virtual platforms. Though it has been hypothesized that green alliances might lead to an increase of perceived recycled product value, a decrease in the perception of the greenwash effect and an increase in positive eWOM. Additionally, research on green marketing has not taken into account the influence of gender and culture in the above-cited relationships.

With some of the proposed hypotheses supported and the data mining study, that allows to have a deeper understanding of the phenomenon, the results reveal a set of interesting findings.

The combined analysis of experimental study and text mining approach shows that when a company engages in a co-branding strategy with pro-environmental NGOs, consumers perceive the product made of recycled materials as higher in value and they do not perceive that the brand is trying to mislead them by means of false, unclear, untruthful green claims thus leading to a positive eWOM regarding the brand and the product. This way perceived product value and greenwash effect work as mediators of the direct relationship between co-branding strategy and positive eWOM.

From text mining analysis it emerges that quality and price (two essential aspects of perceived product value) of the brand and the product exhibit positive sentiment with quality being more important and showing higher sentiment scores than price.

Topic model analysis reveals that when speaking about the brand, people tend to focus on price, quality and how it makes them feel. They speak also about the brand eco-friendly partnerships by underling that buying its products may help to create a better planet. Most of the reviewers suggest others to buy the brand products meaning that it exhibits a high level of positive eWOM.

When dealing with the product, people focus even more on ecological characteristics. They stress the fact that the product is made of recycled material and buying it allows to help an environmental organization, thus enhancing the planet.

Results about culture stand in contrast with the ones by Eom, Kim, Sherman, & Ishii (2016) and Yalcinkaya (2008), who show that cultural differences have an impact on the adoption and diffusion of products coming from a closed-loop business model. They highlight that individualism influences the extent to which people's environmental concern predicts pro-environmental behaviors because of individualistic cultures score high results in expressing internal values and ideas. Indeed, both from the experimental study and the text mining examination, it emerges that collectivistic and individualistic cultures do not affect the relationship between the use of co-branding strategy and the recycled product value perception.

On the other hand, an interesting pattern arises when comparing results from the experimental study and the text mining approach about gender differences. In fact, if considering the moderation analysis carried on in the first part of the present work, no strongly significant variations emerge between females and males in the product value perception as well as in the spread of positive product eWOM.

For what concerns brand eWOM, it seems that a slightly significant difference comes out standing in line with previous literature which considers females as more other-oriented, comprehensive in selecting data, sensitive to detailed information, more easily persuaded when ads generate sympahty, and favor equity-based allocations that benefits others and the self (Meyers-Levy & Loken, 2015; Fang, Wen, George, & Prybutok, 2016), thus being more inclined to spread positive information about a brand that engages in green partnerships and uses circular economy as a business model.

Instead, when regressing data coming from the dataset extracted from the product reviews webpages, it emerges that gender influences sentiment towards the product. Specifically, females perceive more favorably the product leading to the spread of a more positive eWOM compared to males.

All in all, this study extends the current understanding about how co-branding strategy, perceived recycled product value and greenwash effect influence the exchange of positive information about the product and brand among online users. More importantly, the present findings extend the green marketing line of research by suggesting that the impact of green co-branding can influence both the overall company image and the perceived performance of the company products, such that the products are perceived to have superior performance and value as well as a lower greenwash effect. Besides, women show the tendency to give more value to the items created in a co-branding agreement. Positive eWOM derives from this attitude.

7.2. Managerial Implications

From the obtained results, it is possible to draw some practical and interesting implications for managers in charge of marketing campaigns that endorse fashion products made of recycled elements.

As fashion companies have to convince consumers that their recycled products are truly made of refurbished materials, they should incorporate co-branding strategies in their plans. Such partnerships might lead to an increase in the company's overall performances because brand names perform as signals of quality and linking two (or more) brand names may have win-win outcomes. In particular, it enhances consumers' product quality perceptions when product quality is not readily observable (Rao, Qu, & Ruekert, 1999).

Partnerships with environmental activist groups, research institutions, and NGOs might furnish firms with environmental knowledge as well as carrying out firms' environmental strategies and generate economic gains. Collaborations may provide the organization with environmental skills and competence, access to environmental technologies, greater influence over its environmental inputs/outputs, presence in green markets and other benefits unavailable to the organization alone (Crane, 1998). They stimulate image transfer from ecological and environmental purposes of a cause to a brand, increase public awareness of a cause and brand, willingness to buy products and improve brand image (Huertas-Garcìa, Lengler, & Consolaciòn-Segura, 2017).

This study aims at giving to marketers an overview of what kind of outcomes this very powerful tool might have. Scraping data from review platforms allows to have a first-hand understanding of the possible implications of using alliances to endorse recycled products. A tool that is becoming more and more important in an era in which consumers search for a lot of information and exchange insights about companies and products. A tendency that is amplified by the extensive use of the Internet and the accumulation of big data.

On the other hand, this dissertation gives contribution to emerging research on how to introduce and communicate circular offers to users in a successful way and it complements extant research on co-branding and expands knowledge regarding the strategic nature of partnerships to increase positive eWOM.

Managers should consider the potential that partnerships might have in spreading positive information among consumers, thus enhancing brand image. With this awareness in mind the design of green communication campaigns is driven, the consumer perceptions of fashion products made of recycled materials is improved and the sprawl of worthwhile information through eWOM is increased.

7.3. Future Research

Although the current work gives a clear contribution to research on the effects of co-branding, perceived product value and greenwash on eWOM, it has also some limitations.

The first one being that only one fashion product has been included in the research: shoes. Future research could focus on a broader range of fashion products to test the model described in this work.

Secondly, only one kind of communication format has been used to convey the environmental strategy of the organization. In reality, the information consumers are confronted with is less structured, more complex, and can differ in valence, emphasis, repetition over time, and tone, which might lead to different situations than the one used in the experiment. So, future research might look for different forms of communication to test the model.

To avoid the problem of the so-called "artificial situation" created by the experiment, text mining has been used to extract information from a real-life case involved in green partnerships. However, reviews have been scraped only on review platforms. But it should be interesting to analyze the sentiment that consumers show on social media platforms in order to extract more information.
The relationship between individualistic and collectivistic cultures does not perfectly match the individualistic-collectivistic traits at the cultural level since individualistic cultures may be characterized also by individuals with collectivistic ideals; vice versa collectivistic cultures may be marked also by individuals with individualistic ideals. As a result, a deeper analysis addressing the issue is necessary.
Finally, only one fictitious brand and cause has been considered in the experimental analysis as well as only one real brand has been analyzed in the text mining part. Examining more brands and causes would enrich results.

7.4. Conclusions

Fashion companies are facing two major problems when presenting green and circular economy efforts to their public. The first one is related to the company's ability to motivate consumers to choose products positioned at their ethical attributes over products positioned on self-benefit attributes (Peloza, White, & Shang, 2013). Indeed, even if the demand for circular economy products is increasing, consumers are still reluctant to shop for them leading to inconsistency between demand and purchase intention (Ki, Chong, & Ha-Brookshire, 2020).
The second problem is linked to the difficulty of fashion firms to ensure company transparency and truly sustainable performance. The main trouble in today's green marketing landscape is the lack of consumers' confidence in companies' communication of environmental information (Martìnez, et al., 2020) that is dealing with greenwashing. It leads customers to experiment confusion rising questions of trust and confidence in the company and its products and may result with the loss of buyers' enthusiasm to engage in eco-friendly behavior. In this respect, to get the gap less wide and improve on a large-scale people's tendency to assume a sustainable behavior, it is necessary to create suitable green brand strategies (Groubor & Milovanov, 2017).
However, current understanding of how managers can best begin greening their firms' marketing efforts is far from comprehensive. There is the necessity to discern the way to successfully communicate circular offers to users and to identify facilitating conditions that may influence the successful implementation of circular strategies (Ferasso, Beliaeva, Kraus, Clauss, & Ribeiro-Soriano, 2020).
A possible answer is the use of co-branding strategies to enhance consumers' perception of product value (Chernev & Blair, 2015) as well as to reduce the perceived consumer risk related to an innovation, new technology and environmental communication (Crane, 1998). Translated into the circular economy and eco-friendly field, partnership as a green marketing strategy is a powerful tool to allow changes and the spread of more environmentally safety behaviors.

With reference to the marketplace and the call for more research into the outcomes of corporate green strategies, the main focus of the present study is to point out the influence that green co-branding strategies have on perceived product value, perceived risk or greenwashing and link the results to an important social change, that is the worldwide spread of digital technologies and the birth of the big data phenomenon.

Consumers' decision-making process and firms' strategies have undergone a wide process of transformation after the birth, development and sprawl of social media platforms, blogs and e-commerce websites.

By sharing thought leaders and other buyers' opinions with a wide range of audience, the Internet not only has greatly affected people's ideas about different topics but it has also created awareness, spread ideas and beliefs, increased engagement and allowed firms to extract information about what customers' think and believe about offerings. So, the Internet and digitalization may nourish circular economy and sustainable practices in the way that it enables the dissemination and sharing of huge volumes of information about this phenomenon. The Internet working virally can amplify and broaden certain practices dissemination (Chalamon, Guiot, & Chouk, 2012) allowing individuals from all over the world to talk, share opinions and spread eWOM.

So, the current work has tried to extend this area of research with new knowledge considering eWOM from the perspective of green co-branding strategy, perceived recycled product value, greenwashing, gender and culture.

This combined study adds to a growing corpus of research showing several interesting results: (1) it provides academicians with an overall view of the relationship between circular economy, business models and consumers' behavior on the Internet; (2) it addresses an issue of considerable practical importance (co-branding as a way of enhancing companies CSR actions); (3) if consumers believe that the company is engaged in a true alliance with a pro-environmental organization they will perceive a fashion product made of recycled materials in a more positive way, breaking the adoption barriers that are a strong obstacle in the choice of circular economy products; (4) it gives practitioners and scholars an overview of how green co-branding could act as an antecedent of positive eWOM; (5) it highlights the key role of gender in approaching circular economy and the role that co-branding might have in enhancing its adoption between males and females; (6) it shows that reviews about a brand that engages in a partnership with a pro-environmental organizations and its products made of recycled materials tend to be mostly positive.

However, it has also been found that culture does not affect inner loops business models leading to a call for more detailed research on the role of culture.

The main conclusion that can be drawn is that co-branding strategies are an effective means of obtaining and increasing the reputation of a company and its products. This is even more true when the product comes from the circular economy. Furthermore, the use of this type of strategy results in an increase in the positive sentiment of users towards the brand, as it is demonstrated by the analyzed year trend in the text mining phase.

Appendix

Appendix Table A: Nationality frequencies and relative frequency

Country	Frequency	Relative Frequency	Country	Frequency	Relative Frequency
Albania	2	0.07%	Lithuania	2	0.07%
Algeria	2	0.07%	Luxemburg	1	0.04%
Argentina	39	1.43%	Macedonia	2	0.07%
Australia	101	3.70%	Malawi	2	0.07%
Austria	4	0.14%	Malaysia	3	0.11%
Belgium	1	0.04%	Mauritania	1	0.04%
Belize	1	0.04%	Mexico	44	1.61%
Bolivia	8	0.29%	Morocco	8	0.29%
Bosnia Herezegovina	2	0.07%	Namibia	1	0.04%
Brazil	11	0.40%	Netherlands	9	0.33%
Bulgaria	2	0.07%	New Zealand	9	0.33%
Canada	183	6.70%	Nigeria	1	0.04%
Chile	29	1.06%	Norway	2	0.07%
China	1	0.04%	Pakistan	1	0.04%
Colombia	5	0.18%	Panama	4	0.14%
Costa Rica	11	0.40%	Peru	6	0.22%
Croatia	2	0.07%	Philippines	8	0.29%
Czech Republic	1	0.04%	Poland	3	0.11%
Denmark	1	0.04%	Portugal	12	0.44%
Dominican Republic	8	0.29%	Puerto Rico	1	0.04%
Ecuador	6	0.22%	Qatar	1	0.04%
Egypt	17	0.62%	Romania	7	0.26%
Estonia	1	0.04%	Russia	5	0.18%
Finland	2	0.07%	San Marino	1	0.04%
France	13	0.48%	Saudi Arabia	16	0.59%
Georgia	2	0.07%	Serbia	2	0.07%
Germany	11	0.40%	Singapore	4	0.14%
Greece	11	0.40%	Slovakia	1	0.04%
Guatemala	11	0.40%	Slovenia	1	0.04%
Guyana	2	0.07%	South Africa	9	0.33%
Hungary	1	0.04%	Spain	18	0.66%
India	41	1.50%	Sweden	2	0.07%
Iran	1	0.04%	Switzerland	4	0.14%
Ireland	19	0.70%	The Bahamas	1	0.04%
Isle of Man	1	0.04%	Tunisia	1	0.04%
Israel	2	0.07%	Turkey	3	0.11%
Italy	40	1.47%	Ukraine	3	0.11%
Jordan	2	0.07%	United Arab Emirates	21	0.77%
Kosovo	1	0.04%	United Kingdom	182	6.67%
Kuwait	1	0.04%	United States of America	1,700	62.30%
Latvia	1	0.04%	Uruguay	5	0.18%
Lebanon	5	0.18%	Venezuela	5	0.18%
Liberia	11	0.40%	Vietnam	1	0.04%

Appendix Table B: VIF values of survey data variables

	co_branding	PV	GW	culture	sex
VIF	1.323613	1.312448	1.032200	1.037952	1.038379

Appendix Table C: Results of parallel mediation for product eWOM

Variables	Predictors	label	B	SE	z	p	β
PeWOM	PV	b	0.688	0.049	13.961	<0.001	0.652
PeWOM	GW	d	-0.054	0.028	-1.959	0.050	-0.070
PeWOM	co_branding	e	0.257	0.106	2.426	0.015	0.108
PV	co_branding	a	1.040	0.106	9.785	<0.001	0.461
GW	co_branding	c	-0.346	0.169	-2.051	0.040	-0.111

Appendix Table D: Results of parallel mediation for brand eWOM

Variables	Predictors	label	B	SE	z	p	β
BeWOM	PV	b	0.861	0.070	12.312	<0.001	0.626
BeWOM	GW	d	-0.086	0.035	-2.429	0.015	-0.086
BeWOM	co_branding	e	0.591	0.130	4.511	<0.001	0.191
PV	co_branding	a	1.040	0.110	9.438	<0.001	0.461
GW	co_branding	c	-0.346	0.169	-2.051	0.040	-0.111

Appendix Table E: Results of sex moderation analysis for brand eWOM

Variables	Predictors	label	B	SE	z	p	β
PV	co_branding	a1	1.018	0.138	7.403	<0.001	0.449
PV	sex	a2	-0.169	0.108	-1.563	0.118	-0.075
PV	co_branding:sex	a3	0.077	0.154	0.498	0.618	0.030
BeWOM	co_branding	c1	0.709	0.150	4.713	<0.001	0.231
BeWOM	sex	c2	0.630	0.110	5.715	<0.001	0.205
BeWOM	co_branding:sex	c3	-0.304	0.157	-1.942	0.050	-0.088
BeWOM	PV	b	0.862	0.055	15.667	<0.001	0.636

Appendix Table F: Results of sex moderation analysis for product eWOM

Variables	Predictors	label	B	SE	z	p	β
PV	co_branding	a1	1.018	0.138	7.403	<0.001	0.449
PV	sex	a2	-0.169	0.108	-1.563	0.118	-0.075
PV	co_branding:sex	a3	0.077	0.154	0.498	0.618	0.030
PeWOM	co_branding	c1	0.370	0.123	3.018	0.003	0.156
PeWOM	sex	c2	0.331	0.090	3.679	<0.001	0.140
PeWOM	co_branding:sex	c3	-0.242	0.128	-1.893	0.058	-0.091
PeWOM	PV	b	0.686	0.045	15.291	<0.001	0.658

Appendix Table G: Results of culture moderation analysis for product eWOM

Variables	Predictors	label	B	SE	z	p	β
PV	co_branding	a1	0.893	0.147	6.055	<0.001	0.395
PV	culture	a2	-0.371	0.093	-3.999	<0.001	-0.163
PV	co_branding:culture	a3	0.241	0.179	1.347	0.178	0.093
PeWOM	co_branding	c	0.636	0.112	2.547	0.011	0.121
PeWOM	PV	b	0.678	0.053	12.694	<0.001	0.648

Appendix Table H: Results of culture moderation analysis for brand eWOM

Variables	Predictors	label	B	SE	z	p	β
PV	co_branding	a1	0.893	0.201	4.451	<0.001	0.395
PV	culture	a2	-0.371	0.152	-2.435	0.015	-0.163
PV	co_branding:culture	a3	0.241	0.237	1.020	0.308	0.093
BeWOM	co_branding	c	0.636	0.109	5.825	<0.001	0.206
BeWOM	PV	b	0.845	0.049	17.265	<0.001	0.621

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LUISS

Dipartimento
di Impresa e Management

Cattedra: Big Data Analysis

Summary:

"When RE-cycled becomes RE-viewed"
The effect of green co-branding, perceived product value, perceived greenwashing on eWOM

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Thesis purpose:

With consumers' increasing awareness of environmental problems, many firms are striving to improve their environmental positions by presenting their efforts to the public. This phenomenon has doubled since the spread of the Internet. So, firms are applying green marketing strategies to gain competitive advantages especially in the fashion industry because of the influence daily fashion production and consumption practices have on environment, society, and economy. The linear economy "take-make-use-throwaway" system has adverse effects on the environment. To avoid this process there has been a growing demand for changing to a circular economy in the fashion business though the difficulty to make it accepted. Indeed, lots of products made of recycled materials are still perceived as lower in quality. Not all green marketing claims accurately reflect firms' environmental conduct and can be viewed as "greenwashing". Greenwashing both affects a company's profitability and results in ethical and brand image harm.

The growing digitalization of the economy has opened new opportunities. The fashion industry is more characterized by the use of digital platforms and digital marketing strategies. Thus, eWOM is becoming one of the main tools to gain strong competitive advantages. There is a lack of research in understanding what strategies might be used to allow the spreading of products made using circular economy systems. Therefore, this research examines how the use of a green co-branding strategy between a fashion company and an environmentally concerned organization can increase perceived recycled product value and reduce the perceived greenwashing effect leading to both product and brand positive eWOM.

The current work tries to extend this area of research with new knowledge considering eWOM from the perspective of green co-branding strategy, perceived recycled product value, and greenwashing, culture and gender.

Thesis development:

For long, producers and consumers have adopted a "linear economy" model that implies the extraction of a large number of non-renewable resources. Recently firms and consumers are trying to change towards new, more conscious systems. In other words, they are drifting from linear economy to a model that considers the finite nature of resources and thus endorses a restorative economic system.

Since the fashion industry is the second world polluter, many fashion companies are striving to improve their environmental positions. Consumers have become the lever of change and companies have to identify the fundamental principles to better exploit it. However, consumers still perceive lots of products made of recycled materials as lower in quality. Additionally, not all green marketing claims reflect firms' environmental conduct and can be viewed as "greenwashing". Greenwashing may not only affect a company's profitability but it might result in ethical and brand image harm.

Taking into consideration the literature about all the possible approaches to make firms circular economy efforts to be accepted and adopted, it has been found that many firms rely on strategic partnerships (Wassmer, Paquin, & Sharma, 2014) to enhance consumers' perception of product value (Chernev & Blair, 2015) as well as to reduce the perceived consumer risk related to innovation, new technology, and environmental communication (Crane, 1998). Translated in the eco-friendly field, partnership as a green marketing strategy is a powerful tool to allow changes and the spread of environmentally safe behaviors.

Another important aspect is the appearance of new opportunities due to economy digitalization especially in the fashion industry. Thus, eWOM is becoming one of the main tools to gain strong competitive advantages.

The conceptual framework described in this writing has been developed from the literature related to fashion circular economy and green marketing taking into consideration the gaps in such field. As a matter of facts, there is the need to find a successful strategy to let closed loops business models being accepted in the fashion world and to enhance the perceived value of circular economy outcomes. Moreover, firms should try to find a way to decrease the recent phenomenon of Greenwashing making consumers less suspicious.

Two other important consumers' aspects have been taken into consideration: culture and gender. Cultures differ in what drives environmentally friendly actions. Specifically, individualism influences the extent to which people's environmental concern predicts pro-environmental behaviors because individualistic cultures score high results in expressing internal values and ideas (Eom, Kim, Sherman, & Ishii, 2016). For what concerns gender, it might play an important role in determining purchases. When shopping, females and males show different needs and decision-making processes (Fang, Wen, George, & Prybutok, 2016), in particular when dealing with green fashion products (Gazzola, Pavione, Pezzetti, & Grechi, 2020).

The causal analysis, whose hypothesis have been investigated using a randomized between-subject experimental study, demonstrates that the use of a co-branding strategy may increase the possibility that consumers might spread positive word-of-mouth about the product and the brand among relatives as well as on the Internet. This is an essential finding because of the increasing importance and effectiveness of the world wide web to create awareness and interest for recycled products.

The model tested highlights that co-branding strategy between a fashion company and an NGO increases the way a recycled product is valued, and it enables the spread of positive eWOM.
For what concerns Greenwash Effect, it has been found that co-branding reduces its perception. Besides, the lower level of greenwash discernment allows the spread of positive eWOM. However, the strength of the influence of greenwash as a mediator of the model is not as impactful as the one of perceived product value. All in all, results are in line with the overall literature.
According to the model tested and unlike what literature maintains, culture does not influence the relationship between co-branding strategy and perceived recycled product value. This implies that being part of a collectivistic or individualistic culture does not influence the way a recycled product is perceived. The outcome of the model suggests that gender does not have a relevant influence on perceived product value while it has a slight influence on brand eWOM.
The causal study described above allows the examination of the cause-effect relationships among the aforesaid variables. On the other hand, qualitative studies facilitate qualified descriptions of the market functions and ways of approaching a specific market (Medeiros, Duarte Ribeiro, & Nogueira Cortimiglia, 2016). A qualitative study has been developed for such reasons and to have a deeper understanding of the topic, a projection in today's world as well as to address the need for further understanding of how companies might implement sustainability into their business models and which strategy they might adopt to make their products accepted (Groubor & Milovanov, 2017). The concept of eWOM is deeply linked to the worldwide spread of digital technologies and the birth of the big data phenomenon. With the sprawl of social media platforms, blogs, and e-commerce websites, consumers' decision-making process and firms' strategies have changed. People are more affected by the opinions of thought leaders and other buyers shared through the Internet that, working virally, can amplify and broaden certain practices dissemination (Chalamon, Guiot, & Chouk, 2012) allowing individuals to talk and trade with one another.
The mere purposes of this qualitative study were to examine how a brand and its products are perceived when the company engages in a co-branding strategy with an environmental association by directly scraping reviews about both the brand and the product. The analysis has been developed from the findings of the conceptual model tested in the first part of this work that departs from the literature relating to green marketing, CSR and Word-of-Mouth.
The work has been carried on by applying data mining techniques to a real case: the "Adidas X Parley" partnership. After having realized the importance of plastic pollution caused by the fashion industry, Adidas has decided to use recycled plastics in the production of Adidas items. This was the beginning of a project by Adidas to eliminate new plastic from its supply chain. The sportswear brand has created a partnership with "Parley for the Oceans" making a new entire line of sportswear products by turning plastic into raw material. The analysis departs from the conceptual framework described in the first part of the reserach, opinions from Internet users have been extracted using Data Scraping, Sentiment Analysis and Topic Modeling to fully understand the issue. Sentiment Analysis and Topic Modeling have been used to get consumers' opinions about the product and the brand allowing to monitor eWOM among buyers, brand reputation, and performance.

Data collection has been performed applying Web Scraping activity that is used for extracting data from websites by copying gathered data into a local database for later analysis.
To perform web scraping, Data Miner has been employed on four webpages: *Influenster*, *Amazon*, *Adidas Official* and *Google Reviews*. After that, data cleaning, Bag-of-Words and sentiment analysis as well as topic modeling have been performed.
The findings reveal that both the product and the brand show extremely positive polarized sentiment scores meaning that people tend to perceive “Adidas” and “UltraBoost Parley shoes” in a very favorable way.
From Bag-of-Words (BoW) study emerges that people tend to love Adidas and they use mostly positive words when reviewing it. The environmental concern of the brand emerges as well. Indeed, many writers focus on the fact that Adidas has engaged in a collaboration with Parley for the Oceans thus helping the planet. According to reviewers, this collaboration gives a plus to the brand differentiating it from competitors.
For what concerns the product, people find it comfortable and of great quality. They tend to associate UltraBoost materials with ecological aspect without considering the shoes as having low features. This result strengthens the assumption that a partnership may allow consumers to perceive a fashion product made of recycled materials as very good in its characteristics.
The examination of the use of words in three different webpages has led to the result that no extreme differences occur, so people are not influenced by the review platform in which they write.
Sentiment Analysis reinforces the findings obtained from the BoW. The overall sentiment is positive and shifts towards one, both for the brand and for the product. From the analysis carried to verify the evolution of sentiment during the years it emerges that sentiment increases across the time span with two main spots, one in 2015 (year of the announcement of “Adidas X Parley” project) and the other one in 2017 (UltraBoost Parley shoes reaching the market). Regression Analysis underlines that culture does not affect sentiment towards the brand. Gender influences sentiment towards the product. Specifically, females perceive more favorably the product leading to the spread of a more positive eWOM compared to males. Considering Perceived Value, regression outcome demonstrates that PV positively influences sentiment. This result confirms the literature as well as the finding of the causal study in the first part of the work.
Topic model analysis reveals that when speaking about Adidas in general, people tend to focus on price, quality and how the brand makes them feel.
They speak about Adidas eco-friendly aspect by underling that buying its products may help to create a better planet. Most of the reviewers suggest others to buy Adidas meaning that the brand exhibits a high level of positive eWOM.
When dealing with the product, people focus even more on ecological characteristics. They stress the fact that UltraBoost shoes are made of recycled material and buying them allows to help an environmental organization , thus enhancing the planet.
From the results, it emerges that when dealing with companies engaged in a co-branding strategy, people tend to spread more favorable eWOM, an outcome that is in line with literature stating that green partnerships can be instrumental in carrying out environmental strategies of firms and generate performance and reputational

gains (Sadovnikova & Pujari, 2017). From topic modeling it emerges that people tend to treat more about ecological features when reviewing the product rather brand. Indeed, when dealing with the brand they especially focus on how cool, cute, trendy it is and on the so-called “impression management”.

All in all, findings from this second study confirm the hypothesis that a co-branding strategy may influence positive eWOM about a brand and a product.

Consclusions:

Fashion companies are facing two major problems when presenting green and circular economy efforts to their public. The first one is related to the company's ability to motivate consumers to choose products positioned at their ethical attributes over products positioned on self-benefit attributes (Peloza, White, & Shang, 2013). Indeed, even if the demand for circular economy products is increasing, consumers are still reluctant to shop for them (Ki, Chong, & Ha-Brookshire, 2020).

The second problem is linked to the difficulty of fashion firms to ensure company transparency and truly sustainable performance. The main trouble in today's green marketing landscape is the lack of consumers' confidence in companies' communication of environmental information (Martìnez, et al., 2020) that is dealing with greenwashing which leads customers to experiment confusion and the loss of enthusiasm to engage in eco-friendly behavior. In this respect, to get the gap less wide and improve on a large-scale people's tendency to assume a sustainable behavior, it is necessary to create suitable green brand strategies (Groubor & Milovanov, 2017).

As fashion companies have to convince consumers that their recycled products are truly made of refurbished materials, they should incorporate co-branding strategies in their plans thus leading to an increase in the company's overall performances because brand names perform as signals of quality and linking more brand names may have win-win outcomes.

Partnerships with environmental activist groups, research institutions, and NGOs might furnish firms with environmental knowledge as well as carrying out firms' environmental strategies and generate economic gains. Collaborations may provide the organization with environmental skills and competence, access to environmental technologies, presence in green markets and they stimulate image transfer from ecological and environmental purposes of a cause to a brand, increase public awareness of a cause and brand, willingness to buy products and improve brand image (Crane, 1998; Huertas-Garcìa, Lengler, & Consolaciòn-Segura, 2017).

The combined analysis of experimental study and text mining approach shows that when a company engages in a co-branding strategy with pro-environmental NGOs, consumers perceive the product made of recycled materials as higher in value and they do not perceive that the brand is trying to mislead them thus leading to positive eWOM. This way perceived product value and greenwash effect work as mediators of the direct relationship between co-branding strategy and positive eWOM.

All in all, this study extends the current understanding about how co-branding strategy, perceived recycled product value and greenwash effect influence the exchange of positive information about the product and brand among online users. The findings extend the green marketing line of research by suggesting that the impact of green co-branding can influence both the overall company image and the perceived performance of the company products, such that the products are perceived to have superior performance and value as well as a lower greenwash effect. Besides, women show the tendency to give more value to the items created in a co-branding agreement and positive eWOM derives from this attitude.

This study aims at giving to marketers an overview of what kind of outcomes this very powerful tool might have. Scraping data from review platforms allows to have a first-hand understanding of the possible implications of using alliances to endorse recycled products. A tool that is becoming more and more important in an era in which consumers search for a lot of information and exchange insights about companies and products.

This dissertation gives also contribution to emerging research on how to introduce and communicate circular offers to users in a successful way, it complements extant research on co-branding and expands knowledge regarding the strategic nature of partnerships to increase positive eWOM.

With reference to the marketplace and the call for more research into the outcomes of corporate green strategies, the main focus of the present study is to point out the influence that green co-branding strategies have on perceived product value, perceived risk or greenwashing and link the results to an important social change, that is the worldwide spread of digital technologies and the birth of the big data phenomenon.

Consumers' decision-making process and firms' strategies have undergone a wide process of transformation after the birth, development and sprawl of social media platforms, blogs and e-commerce websites. By sharing thought leaders and other buyers' opinions with a wide range of audience, the Internet not only has greatly affected people's ideas about different topics but it has also created awareness, spread ideas and beliefs, increased engagement and allowed firms to extract information about what customers' think and believe about offerings. So, the Internet and digitalization may nourish circular economy and sustainable practices in the way that it enables the dissemination and sharing of huge volumes of information about this phenomenon.

This combined study adds to a growing corpus of research showing several interesting results: (1) it provides academicians with an overall view of the relationship between circular economy, business models and consumers' behavior on the Internet; (2) it addresses an issue of considerable practical importance (co-branding as a way of enhancing companies CSR actions); (3) if consumers believe that the company is engaged in a true alliance with a pro-environmental organization they will perceive a fashion product made of recycled materials in a more positive way, breaking the adoption barriers that are a strong obstacle in the choice of circular economy products; (4) it gives practitioners and scholars an overview of how green co-branding could act as an antecedent of positive eWOM; (5) it highlights the key role of gender in approaching circular economy and the role that co-branding might have in enhancing its adoption between males and females; (6) it shows that reviews about a brand that engages in a partnership with a pro-environmental organizations and its products made of recycled materials tend to be mostly positive.

Although the current work gives a clear contribution to research, it has also some limitations: only one fashion product has been included in the research, only one kind of communication format has been used to convey the environmental strategy of the organization, reviews have been scraped only on review platforms (it should be interesting to analyze the sentiment that consumers show on social media platforms), a deeper analysis addressing the cultural differences is necessary, only one fictitious brand and cause has been considered in the experimental analysis as well as only one real brand has been analyzed in the text mining part.

However, it has also been found that culture does not affect inner loops business models leading to a call for more detailed research on the role of culture.

The main conclusion that can be drawn is that co-branding strategies are an effective means of obtaining and increasing the reputation of a company and its products. This is even more true when the product comes from the circular economy. Furthermore, the use of this type of strategy results in an increase in the positive sentiment of users towards the brand, as it is demonstrated by the analyzed year trend in the text mining phase.

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