MASTER'S THESIS

The value of personalized online reviews

How do personalization cues influence eWOM perceptions?

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Abstract

Due to the anonymous nature of electronic word-of-mouth (eWOM), readers of online reviews are known to look for certain cues to help them make assessments regarding the credibility of the source, which further dictates the review adoption. The authors argue that one such cue is the mention of a customer service representative in an online review (personalized review). An examination of 6.867 Trustpilot reviews confirms the existence of personalized reviews and indicates the prevalence of a positive valence among these reviews. Through a controlled experiment (N = 415), we observed no statistical difference between the perceived credibility and value of personalized reviews compared to non-personalized reviews. Personalization does, however, tend to increase the perceived credibility and value of online reviews. Furthermore, we observe that personalization significantly increases the influence of valence in assessments of review credibility and value. Through another controlled experiment (N = 479) on personalized reviews, we observe that a male reader will assign less credibility and less value to a negative review which mentions a male customer service representative. We observed the same effect in female readers when the negative review mentions a female. The opposite effect was observed in positive, personalized reviews. Perceived credibility and value of a review increased if the reader is of the same gender as the customer service representative, whereas the effect is more pronounced for male readers.

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Introduction

The importance of Electronic Word-Of-Mouth (eWOM) as a source of information is well established (Ladhari & Michaud, 2015; Liu & Park, 2015). Its benefits, such as ease of access to information and long-term availability makes it particularly valuable for information retrieval and making purchase decisions (Liu & Park, 2015). As it becomes easier to access real-time online product information written by other consumers, online reviews have grown substantially in popularity as a vital source of information about an item's perceived value (Hu, Liu & Zhang, 2008). Furthermore, online product reviews are the second most trusted source of information about brands, second only to recommendations from friends and families (Nielsen, 2012), whereas 52% of consumers always read online reviews to help them make purchasing decisions (Murphy, 2020). The reasons for seeking out and reading online reviews range from seeking guidance from previous customers, to easing the decision-making (Hennig-Thurau, Gwinner, Walsh, & Gremler, 2004). Customers read reviews both before and after purchasing a product or a service, to get a sense of how a potential service failure might be addressed (Burton & Khammash, 2010; Trustpilot, 2018). Furthermore, online product reviews have implications for management activities such as customer acquisition and reputation building (Hu et al., 2008).

Previous research has studied many aspects of online reviews and has provided useful insights into the elements that enhance or determine the value of a review. A valuable review is one that the reader is going to find helpful in making their purchasing decisions (Weiss, Lurie & Maclnnis, 2008), whereas, from a manufacturer's perspective, it is the expected effect of the review on sales (Ghose & Ipeirotis, 2007). There are many factors that influence review value, from the review content, which some scholars consider to be the most important aspect (Fang, Ye, Kucukusta, & Law, 2016; Ghose & Ipeirotis, 2007), to the credibility of the source (Chu & Kamal, 2008). For eWOM to be useful as a decision-making aid, the consumers must trust the reviewer (Xu, 2014). To make assessments regarding the credibility of the source, readers look for certain cues to help them do so faster (Cheung & Thadani, 2012). One such cue could be whether the reviewer mentions a customer service representative by name. However, to the best of the authors' knowledge, there is no research that investigates whether such a cue has an impact on how online reviews are perceived.

The presence of a customer-service representative mention in an online review could be an essential cue to investigate. Firstly, because the human interaction element in a customer-company interaction is of high importance when evaluating a service (Day & Bodur, 1978). Secondly, because customer-facing employees play a significant role in determining the outcome of service satisfaction (Brady, Cronin, & Brand, 2002; Bitner, Booms, & Tetreault, 1990), and are able, through their interactions, to make or break a brand (Roper & Davies, 2007).

We name the reviews, in which the reviewer has mentioned the name of the specific customer-facing employee, *personalized reviews.* Moreover, we propose that customers witnessing a customer service representative's performance indirectly, through reading a personalized review, will have an impact on the perceived value of the review.

More specifically, we investigate the effect of two mediating variables: causal attribution and credibility. Firstly, people are known to make causal attributions about online reviews, as they attribute them either to the writer of the review or to the company that is being reviewed (Cheung & Thadani, 2012). We, therefore, argue that personalization cues will influence the causal attribution of the review. Attribution is known to mediate the relationship between several cues present in online reviews and the review value (e.g., Chen & Laurie, 2013), and we suggest the same in the case of personalized reviews.

Secondly, the credibility of an online review refers to how confident the reader is in the reviewer's reliability, dependability, and integrity (Shin, Lee, & Hwang, 2017). Perceived source credibility is one of the three dimensions of online review value (Li et al., 2013), and is known to have a mediating effect on the review value (Chu, & Kamal 2008; Watts, & Zhang 2008). We, therefore, argue that personalization in an online review will influence the perceived credibility of the review and further mediate the relationship between personalization and review value. This paper, therefore, aims to extend previous research on online reviews, and answers the first research question: *How do personalization cues in online reviews influence attribution, credibility, and usefulness of the review?*

Furthermore, to investigate the effect of personalization in reviews, we consider two important moderators, valence, and gender of the customer service representative. Review valence is often referred to as sidedness, and it splits reviews into positive or negative (Cheung & Thadani, 2012). Previous research shows that eWOM can have varying effects on consumers' preferences and behavior, and implicitly, on sales, depending on whether a review is positive or negative (Chen & Laurie, 2013). Valence particularly influences the causal attribution and perceived credibility of online reviews (Cheung & Thadani, 2012).

In service settings, the gender of the customer influences performance evaluations (Fiske & Taylor 1991; Meyers-Levy & Loken, 2015). While men care that a transaction runs smoothly and the outcome is favorable, women focus on the process of service delivery, regardless of the outcome (Finsterwalder, Garry, Mathies & Burford, 2011; Iacobucci & Ostrom, 1993; Mattila et al., 2003). Furthermore, the gender of the customer service representative is also of importance in service settings. Evaluators understand and value an equal performance differently based on the gender of the individual whose performance is being assessed (Ellemers, 2018). In personalized reviews, the gender of the portrayed customer service representative is visible, and it might have an impact on the perceived credibility and value of the review. Based on this, the paper aims to extend previous research on online reviews and answers a second research question: *How does the gender of a service representative in a personalized review influence perceived credibility and review value?*

We tested our predictions in one correlational field study (N = 6.867) and two laboratory online experiments (N = 415) and (N = 479) respectively. The contributions of this research are three-fold. First, we show that personalized reviews indeed exist and therefore contribute to existing literature by uncovering a new phenomenon to investigate. Given the importance of customer-company interactions in a digital environment, it is of value to gather awareness and understanding of all potential cues that might contribute to a review's value both for customers and companies. In this paper, we gather awareness and further understanding of personalization in reviews.

Second, although we cannot show an initial difference between personalized and non-personalized reviews in affecting review value, we uncover that the effect of valence on source credibility and review value is primarily driven by personalized reviews. This questions previous literature on the effects of valence. Many scholars have shown that negative reviews are more valuable and more credible than positive ones (Cheung and Thadani, 2012; Greenleigh 2011; Schindler & Bickart, 2005), yet our research showed the opposite. Previous research has also not taken into consideration the influence of personalization in its stimuli development (Cheung and Thadani, 2012), although it represents a considerable portion of reviews in general.

Third, we contribute with knowledge about gender effects. This allows us to shed light on how the combination of the gender of the customer service representative, review valence, and reader's gender affects the perceived credibility and value of a personalized review. As service jobs are held by both males and females, we contribute by offering an understanding of how readers of online reviews perceive personalized reviews and implicitly service encounters based on their own gender and the employee gender.

The paper proceeds as follows. Chapter 2 summarizes the related literature. Chapter 3 describes the theoretical framework and research hypotheses. Chapter 4 describes the research setting, methodology, data collection, data analysis, and study-based discussions. Chapter 5 offers a discussion of theoretical contributions, managerial implications as we provide actionable recommendations for practitioners, and finally, we layout fruitful avenues for future research.

Literature review

2.1 Consumer communications

2.1.1 WOM and eWOM

Consumers are known to influence, mimic and learn from each other through various paradigms (Hawkins et al., 2004). One way is through the interpersonal influence of relaying past experiences of purchase to other potential customers, often referred to as Word-of-mouth (WOM) (Kim, Wang, Maslowska, & Malthouse, 2016). WOM is defined as communication between actors regarding an organization, brand, product, or service (Hawkins, Best, & Coney, 2004). Research into WOM communications in a marketing context dates to the 1960s (Arndt, 1967; Dichter, 1966), and has evolved substantially over time (Carl, 2006; Huete-Alcocer, 2017). Past research has shown that WOM influences consumer behavior (Daugherty & Hoffman, 2014; Huete-Alcocer, 2017). It has also been noted that consumers trust WOM more than advertisements and firm-initiated communications (Bone, 1995; Nielsen, 2012), and it can be a contributing factor in developing a successful business strategy (Cantallops, & Salvi, 2014).

Consumers are both internally and externally motivated to seek WOM information (Schiffman & Kanuk, 1978). One of these motivations is to try to reduce their risk and uncertainty (Schiffman, 1972). This is particularly important for intangible goods (Litvin, Goldsmith, & Pan, 2008) such as tourism and hospitality services, which are often considered to be high-risk purchases (Sotiriadis & Van Zyl, 2013).

With the ever-growing online presence of everyday consumers, an increasing number of them can seek advice and information about products and services before engaging in a transactional relationship with a firm (Lee, Park & Han, 2008). As a result, the relationship between consumers has evolved from personal spoken interactions into more paradigms, one of which is electronic word-of-mouth (eWOM) (Ladhari & Michaud, 2015; Zhang, Ye, Law, & Li, 2010).

To separate the two, i.e., WOM and eWOM, scholars have defined eWOM 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 institutions via the Internet"* (Hennig-Thurau et at., 2004, p.39). This definition expands on Westbrook's (1987, p.261) previous study, where he defines WOM as *"informal communications directed at other consumers about the ownership, usage, or characteristics of particular goods or services and/or their sellers.".* WOM and eWOM, while seemingly the same, present several differences among them.

2.1.2 Similarities and difference between WOM vs. eWOM

As our research will focus on reviews that are present on online review platforms, where the communication is in the form of eWOM, it is essential to recognize and expand on the core differences between traditional WOM and eWOM. Some scholars (e.g., Filieri & McLeay, 2014) do not differentiate between the two concepts, instead define eWOM merely as an online extension of traditional WOM. However, the concepts do differ in a few aspects.

Firstly, eWOM has an extra dimension, many-to-many communication, e.g., virtual pages, blogs, and chat rooms, while WOM tends to be a one-to-many or one-to-one communication (Cantallops & Salvi, 2014). The motivation of people to engage in WOM and eWOM also differ, mostly due to the many-to-many communication dimension of eWOM (Hennig-Thurau et al., 2004). This can be demonstrated by the fact that one of the motivations behind engaging in eWOM is a need to belong to a community and desire to add value to that community (Schmäh, Wilke & Rossmann, 2017).

Self-enhancement is a motivation that lies both behind WOM and eWOM. However, when it comes to eWOM, it takes the form of wanting to be viewed as a consumption expert or as an intelligent shopper by allowing a reviewer to signal connoisseurship and a level of social status that enhances one's self-concept (Hennig-Thurau et al., 2004). Remuneration, as a motivation, is another aspect that differentiates WOM from eWOM (Hennig-Thurau et al., 2004). Operators of online platforms sometimes offer an economic incentive for participation, which they can track, unlike with WOM (Balasubramanian & Mahajan, 2001). Finally, other motives to engage in both WOM and eWOM are that people want to save others from a negative consumption experience, to help other consumers with their buying decisions, or even help the company behind the products or services (Hennig-Thurau et al., 2004).

Huete-Alcocer (2017) proposed that WOM and eWOM differ on credibility, privacy, diffusion speed, and accessibility. Credibility in this context is *"the extent to which one perceives a recommendation as believable, true or factual"* (Cheung, Luo, Sia, & Chen, 2009, p.12). A possible difference in credibility stems from the relationship between the communicator and the receiver (Hussain, Ahmed, Jafar, Rabnawaz, & Jianzhou, 2017). Traditional WOM communication tends to be between closely related agents such as family, friends, and colleagues, and it happens through personal interactions while eWOM expands this relationship and includes anonymous sources from unknown agents (Hussain et al., 2017).

This difference between interactions also affects privacy (Lee & Youn, 2009). While WOM information is traditionally shared privately, eWOM mostly occurs between people who have little or no prior relationship with one another (Lee & Youn, 2009), and is most of the time not private and often spread anonymously (Huete-Alcocer, 2017). Despite the anonymity of reviewers, studies have shown that eWOM is a trustworthy and impartial source for reducing the risk of purchase (e.g., Hussain et al., 2017; Xie, Miao, Kuo, & Lee, 2011). In contrast, other studies have indicated that the anonymity of reviewers could reduce the credibility of the communication (Luo, Luo, Schatzberg, & Sia, 2013).

Lastly, eWOM and WOM differ significantly when it comes to their potential influence, accessibility, and speed of communication due to how they are published (Gupta & Harris, 2010). Traditional WOM tends to be spread slowly in interpersonal interactions, while eWOM benefits from the accessibility and reach of online platforms (Cheung & Thadani, 2012). While traditional WOM tends to disappear once spoken, eWOM can be accessed repeatedly after it has been published (Cheung & Thadani, 2012).

These differences illustrate the power of eWOM over traditional WOM and the opportunities and dangers it could represent to businesses (Cantallops, & Salvi, 2014; Dellarocas, 2003).

2.2 Online reviews

eWOM communication does not come only in the form of online reviews. eWOM communication can take other forms based on the channels that host it, such as online discussion forums, online consumer review sites, blogs, social networks, and online shopping sites (Cheung & Thadani, 2012). Schmäh et al. (2017) expanded further on this classification of eWoM channels by including media such as video and music streaming services, online travel agencies, online video games, and whistleblower websites. While all the channels where eWOM is found can include information about products and services, as well as the author’s experience, the most accessible form of eWOM communication remains online reviews (Cheung & Thadani, 2012).

Online reviews tend to be hosted on specific platforms such as online consumer review sites that are linked to the service providers or hosted on the company's own platform. In the latter category are Amazon, eBay, and other large online retailers (Lee et al., 2008). As customers seek information during their purchasing process, to minimize risk (Schiffman 1972), these reviews can affect decision making (Lee et al., 2008). Furthermore, online reviews are more easily accessible than online discussion forums and social networks so they can be accessed by a bigger portion of potential customers (Chatterjee, 2006).

Companies are also able to encourage their consumers to leave reviews, either on external or internal platforms, via various communications, such as email, and they do so to enhance their customer relationships (Hennig-Thurau et al., 2004; McAlexander, Schouten, & Koenig, 2002).

2.2.1 Impact of online reviews

2.2.1.1 The customer perspective

Due to the continuous evolution of media technologies in recent years, the nature, and effects of eWOM have gained rising attention from researchers (Chu & Choi, 2011; Dwyer, 2007). Online reviews have become a vital source of product information (Huang, Chen, Yen, & Tran, 2015). Furthermore, the importance and effects that online reviews have on user behavior are widely accepted by scholars (e.g., Huete-Alcocer, 2017; Schmäh et al., 2017).

The effects of online reviews on consumers are numerous. Online consumer reviews can affect attitudes towards products, and as the number and quality of negative reviews increase, these attitudes become unfavorable (Lee et al., 2008). These findings have been confirmed by Elwalda, Lü, and Ali (2016). Elwalda et al. (2016) also illustrated the positive influence that perceived usefulness of reviews can have on customers' purchase intention.

The effects of online reviews are so predominant that they can outweigh perceived trustworthiness, i.e., the general reputation of the online store which hosts those reviews (Utz, Kerkhof, & Van Den Bos, 2012). In other words, reviews can have more effect on consumers' perceived trustworthiness of an online store than the store's reputation (Utz et al., 2012). Online reviews can even lead to suboptimal decision making among consumers with low motivation to process information (Gupta & Harris, 2010). These consumers opt to use the information from the online reviews as a part of their limited research, to the extent that they become a significant factor in their decision making, rather than a complementary information source (Gupta & Harris, 2010).

Valence is a key driver when it comes to the impact of online reviews, and it affects a variety of mediating and moderating variables, such as credibility and review usefulness (Cheung & Thadani, 2012). Research has suggested that a single instance of negativity or positivity might not be that influential, but when in numbers, valence can play a big part in product judgment (Kim & Gupta's, 2012). Negative reviews are often perceived as more valuable than positive ones, a bias that is referred to as negativity bias (Baumeister, Bratslavsky, Finkenauer & Vohs, 2001). This bias can also be mitigated by a variety of cues within the review itself (Chen & Lurie, 2013; Hair, & Ozcan, 2018). We will dive further into these cues, the negativity bias, and the effects of valence in chapter 2.2.5.

2.2.1.2 The company perspective

As online reviews can have a positive impact on purchasing behavior and attitude, it is evident that they present an opportunity for companies (Cheung & Thadani, 2012), both in regard to communications, as well as revenue (Cantallops & Salvi, 2014). Nevertheless, only a few research papers have focused on the company's perspective on online reviews, and the opportunities that they present (Dickinger, 2011; Hills & Cairncross, 2010; Ye, Law & Gu, 2009).

In their literature review on hotel review research, Cantallops & Salvi (2014) identified several impacts of eWOM. The authors divided them into two main categories: communications and revenue. While focused on hotel reviews, many of the factors described in Cantallops & Salvi (2014) can be applied to general business activity. By analyzing the information that is presented in reviews, companies can build a competitive advantage through adjusted offerings, positioning, and by identifying needs (Cantallops & Salvi, 2014; Loureiro & Kastenholz, 2011). The information presented in online reviews can also be used to build up customer loyalty and as a monitoring tool for reputation and competitors (Loureiro & Kastenholz, 2011).

Regarding revenue management, online reviews can play a significant role. Ye, Law, and Gu (2009) showed a positive relationship between positive reviews and sales of hotel rooms, making them a vital part of every hotel operator's marketing strategy. Yacouel and Fleischer (2012) also showed, while controlling for multiple relevant covariates, that positive reviews had a positive effect on listed room prices. In other words, on average, positive reviews allow hotels to charge a premium, thus affecting the hotel's revenue management positively (Yacouel & Fleischer, 2012).

Finally, research has shown that online reviews can affect brand image (Chakraborty & Bhat, 2018), product development (Cantallops & Salvi, 2014), and willingness to recommend the service (Loureiro & Kastenholz, 2011). All these factors contribute to companies' core business activities, thus making it vital for companies to adopt a strategy on how to enlist and handle online reviews with the aim to mitigate negative reviews and capitalize on positive ones.

2.2.2 Reasons for leaving online reviews

Participation inequality exists in most online communities, and review platforms do not differ. Most users only observe and read reviews, while some rarely contribute, and very few actively contribute (Nielsen 2006). In their paper, Cantallops and Salvi (2014) estimated that only about

1% of consumers actively leave reviews, citing Nielsen's (2006) suggestion of 90-9-1 participation. What motivates this small group to share their opinion has been a subject of multiple research papers, both in traditional WOM research, and recently in the field of eWOM research. Park and Allen (2013) suggested that consumers usually write reviews to influence the decision making of other consumers, and to share their satisfaction or dissatisfaction with the service that they received. In a study on hotel reviews, Litvin et al. (2008) suggested that some consumers leave positive online reviews because they enjoy expressing their experiences and travelling expertise.

Hennig-Thurau et al. (2004) ran a comprehensive study based on several research papers that have previously investigated motives for WOM communication behavior. The aim was to identify the reasons that motivated consumers to participate and contribute in eWOM communication. Hennig-Thurau et al. (2004, p.48) results indicate that *"concern for other customers, extraversion/positive self-enhancement, social benefits, economic incentives, and to a lesser extent, advice seeking,"* were the primary motives for eWOM communication participation, both for participation and contribution.

Social benefit and concern for other customers refer to a focus-related utility, based on Balasubramanian & Mahajan's (2001) framework on the integration between social and economic activity within a virtual community. A focus-related utility *"assumes that "adding value" to the community is an important goal of the individual."* (Hennig-Thurau et al., 2004, p. 42). The social benefits motive stems from the need to be a part of a society. The *"concern for other customers"* motive is closely related to altruism, where the aim is to shield other consumers from making bad decisions, or guide them to a product or service that the reviewer had a positive experience with (Hennig-Thurau et al., 2004).

Self-enhancement and economic incentives fall within the approval utility of the Balasubramanian & Mahajan (2001) framework. This utility covers the consumer's satisfaction that occurs *"when other constituents consume and approve of the constituent's own contributions"* (Balasubramanian & Mahajan, 2001, p. 126). The Self-enhancement motive stems from the reviewers' desire to receive a positive recognition from others, e.g., in the form of a useful vote, a thank you comment, or another type of gratitude (Hennig-Thurau et al., 2004). Finally, the economic incentives motive refers to economic rewards, such as payments, or gifts from the platform operator, which is, in general, an important driver of human behavior (Hennig-Thurau et al., 2004).

2.2.3 Reasons for reading online reviews

Unlike the 90-9-1 participation inequality on the contribution side of online reviews, a vast majority of users read the reviews and use them to reduce their risk of purchase (Hussain et al., 2017). Reports from industry firms such as BIA/Kelsey suggest that up to 97% of consumers use some form of online media to research their local businesses, and Podium stated that 93% of consumers said that an online review affected their purchase decision (BIA/Kelsey 2018; Podium 2017).

In an industry study of 100 users of their platform, Trustpilot revealed a few reasons why their customers read reviews (Trustpilot, 2018) Consumers indicated that they read reviews to seek guidance from previous customers, to make decision making more manageable, to gauge the firm's reliability, to get a sense of how potential service failure might be addressed, and to get an insight into product quality (Trustpilot, 2018). Although quite broad, the results from Trustpilot only tell a partial story. The process and motivation for reading reviews is not a linear process, as is suggested by Trustpilot, but a more complicated process where themes, motives, and behaviors come together (Burton & Khammash, 2010). Some consumers read reviews before making a purchase to reduce their risk, some use them to gather information on how to use a particular product, while others try to justify their purchases by reading reviews post-purchase (Burton & Khammash, 2010).

The motive for seeking online reviews differs between industries because some require higher involvement than others, and because industries differ in levels of uncertainty. Travel-related services such as flights and hotels are often considered high-risk, and scholars have investigated the motives for reading reviews for these products in detail. Kim, Mattila, and Baloglu (2011) found three main reasons for reading reviews. These were risk reduction, optimizing value, and information gathering on new things in the marketplace (Kim et al., 2011; Xie et al., 2014). On top of that, Kim et al. (2011) noted that men and women differ in their motivations when reading online reviews. Women were more likely than men to seek online reviews, and to use them to lower their risk and attain the best value possible (Kim et al., 2011).

2.2.4 Review platforms

Online reviews generated by users have become an important decision aid in the process of purchase decision making for customers, which has encouraged the increased development of online review platforms (Siering & Janze, 2019). A study by Nielsen (2012) in which users from 56 countries have been surveyed, showed that, at the time, online reviews were the second most trusted source for information about brands, second only to recommendations from friends and families.

Online review platforms are complex socio-cultural and economic systems with different business models and technological affordances, they address different user segments and have a different power distribution in the online ecosystem (Xiang, Du, Ma & Fan, 2017). In their study about TripAdvisor, Yoo, Sigala, and Gretzel (2016) illustrate how the platform incorporates a wide variety of user data and information tools, and it represents many actors, resources, and, most importantly, business models, throughout the platform.

The platforms can be community-based sites such as TripAdvisor, which is the most visited holiday and travel portal in the world (Egger, Gula, & Walcher, 2016), or Yelp and even Lonely Planet. In the travel industry, they can also be transaction based OTAs (online travel agencies) such as Booking.com or Kiwi.com, where the reviews are incorporated onto the platform as eWOM (Gligorijevic, 2016). There are also online review platforms that are fostered by a company such as the shopping platform Amazon. In this case the reviews are usually hosted on the company website, which are environments fully controlled by the company and provides physical and social cues for the shoppers to process individually (Lee, 2012). In this last case, the purpose is more than to encourage purchases, it also contributes to making the company seem more human, which helps improve its perceived authenticity and approachability (Lee, 2012). While companies such as Amazon already make information about the products available to potential buyers, there often can be a difference between the information that the buyers and the sellers possess (Ba & Pavlou, 2002). This is referred to as information asymmetry, and it is one of the reasons why such platforms choose to not only offer their own information, but also open their platform for information from buyers in the form of reviews (Ba & Pavlou, 2002).

Lastly, some social media websites have company reviews as part of the platform. Platforms such as Facebook not only allow users to leave a review, but they also encourage social ratings in the form of likes or thumbs up meant to indicate to friends one's endorsement of a certain product or service (Aral, 2014). Trustpilot is another platform used for leaving reviews for products and services from all domains, and it allows users to review a company by leaving a one to five-star rating, as well as a written review (Johannsen, Hovy & Søgaard, 2015).

The online review platforms can also be characterized by a community fostering perspective (Egger et al., 2016). Among those websites that have community fostering as part of their core business are TripAdvisor, Yelp, and Zagat. Whereas websites such as Amazon, Booking.com or Hotels.com, on the other hand, feature reviews and ratings that users make use of, but they do not have a focus on fostering communities (Egger et al., 2016).

While they are widely used, online review platforms are highly criticized for their credibility. That is because the information that is posted there does not usually go through any rigorous editorial process to verify their truthfulness (Shanka & Marchegiani, 2012). The credibility of both the reviewer and the review itself are further discussed in chapter 2.5.

2.2.5 The review valence and its effects

Two of the most researched aspects of online reviews include the reviews valence, which is often referred to as sidedness and it splits reviews into positive or negative (Cheung & Thadani, 2012). Online consumers facing a large number of reviews assess the product quality by considering the valence of consumer product reviews, a tendency that is particularly apparent for experimental and credential products (Park & Nicolau, 2015).

Online reviews can be one-sided, meaning that they are either positive or negative, or two-sided. The two-sided reviews are those that include both positive and negative information about the service or product experience. Research suggests that customer communications that include both positive and negative information are perceived as being more complete (Kamins, & Assael, 1978), while also being perceived as more credible than the one-sided communications (Cheung et al., 2009; Doh & Hwang, 2009). This paper will, however, focus on one-sided reviews since positive reviews heavily outweigh negative reviews, suggesting that one-sided reviews are a lot more prominent than two-sided reviews (Greenleigh 2011). Extreme ratings (one star/five stars) were found by Foreman (2008) to be perceived as more helpful by readers, than reviews that had 2-3 stars. This implies that one-sided reviews are being perceived as more helpful than balanced ones that are two-sided and report on both positive and negative aspects of service. Pavlou and Dimoka (2006) demonstrated the same in their study that extreme positive or negative ratings were considered more informative than their counterparts.

Maheswaran and Sternthal (1990) point out that consumers perceive negative reviews as less ambiguous than positive ones when they have to judge a product. The prospect theory developed by Tversky & Kahneman (1979) explains the phenomenon. The theory states that people give higher value to the experience of loss than they do for the experience of pleasure which comes from gaining something the equivalent of what has been lost. When making choices, people are more influenced by a potential loss associated with each alternative, than a potential gain. This is consistent with the concept of negativity bias, which is further described in the next section.

2.2.5.1 The negativity bias

Looking at the negativity bias from a psychological perspective, Cacioppo, Gardner & Berntson (1997), define the negativity bias as the predisposition to avoid or withdraw from the face of threatening events in an effort for self-preservation. From an informational process perspective, negative information has a stronger influence on the individual’s judgement and choice, than positive information does (Skowronski, & Carlston, 1989). Taylor (1991) gathered several pieces of evidence that show that negative events evoke stronger and more rapid physiological, cognitive, emotional, and even social responses, than neutral or positive events do. In their paper about how negative information weighs more heavily on the brain than positive information, Ito, Larsen, Smith and Cacioppo (1998) found out that the negative bias mostly occurs at the stage of choice evaluation and information.

When it comes to online reviews, the valence of a review has an influence on the effects of a review (Cheung & Thadani, 2012). Daily, consumers are exposed to both positive and negative information regarding the experiences of fellow consumers (Lee & Youn, 2009). Unfavorable information is known to be more influential than favorable information (Fiske, 1980). Mizerski (1982), for example, found that unfavorable, as opposed to favorable, product information received from a brand's consumer leads to a stronger effect towards the brand's products. Negative reviews seem to affect readers' perception regarding the quality of a product because low-quality products are often characterized by negative attributes (Skowronski & Carlston, 1987). On the other hand, positive eWOM is often attributed to third parties and may fail to have an effect over the product's actual performance (Schindler & Bickart, 2005). Since the volume of positive online reviews outweigh negative ones, eight to one, they are in general perceived as less valuable individually, than the negative reviews (Greenleigh 2011). This negativity bias can however be mitigated through various cues in the reviews, even though negative reviews are typically attributed to the product/service performance rather than the reviewer (Mizerski 1982; Sen & Lerman 2007).

Chen and Lurie (2013, p.463) showed that positive reviews about a restaurant that included temporal contiguity cues, i.e., *"words and phrases indicating temporal proximity between product consumption and review writing"* were perceived as more valuable than negative ones. In other words, temporal contiguity mitigated the negativity bias, which was evident from their control group, which perceived negative reviews as more valuable than positive ones (Chen & Lurie, 2013). The mechanism for this mitigation was the reader's causal attribution about the reviewer itself (Chen & Lurie, 2013). Positive reviews with temporal contiguity cues were rather attributed to the product rather than the reviewer (Chen & Lurie, 2013).

Drawing on the work of Cheung and Thadani (2012), which suggested that reviews that are attributed to the reviewer rather than the product are less persuasive, and Yin, Bond, & Zhang' (2013) results which illustrate that perceived negative emotions decreased review helpfulness, Hair, & Ozcan, (2018) hypothesized that profanity and strong language cues in the reviews would mitigate negativity bias. This assumption, profanity would mitigate the negativity bias was confirmed in Hair, & Ozcan's (2018) research.

The frequency of reviews also heavily influences the negativity bias (Mizerski 1982). Social norms dictate people to provide more positive information about products (Mizerski 1982; Kanouse et al., 1972). Since positive information is more prevalent, it is less influential. Negative information, on the other hand, is more uncommon, which increases its influence (Mizerski 1982; Jones, Gergen, and Jones 1963). However, according to Lee & Hu (2005), customers who are dissatisfied are four times more likely to share their experiences. Service failure is often what drives negative online reviews. Service providers from all industries are concerned with the reactions of customers who are dissatisfied with a service failure (Black & Kelley, 2009). Hirschman (1970) points out three different responses of customers who experience service failure, exit, voice, or loyalty. While exit and loyalty imply staying or leaving an organization, voice refers to an attempt on behalf of the customer to *"change rather than escape from an objectionable state of affairs"* (Hirschman, 1970, p.30).

The valence of reviews, according to literature, is connected to the attribution of said reviews, which will be further defined and discussed in chapter 2.4.

2.3 Review value

2.3.1 Definition of review value

Online reviews play a key role for the consumer because, at a time when there are too many options for every single type of product or service, they help reduce uncertainty (Fang, et al., 2016). That is why consumers often rely on online reviews to form their purchase decisions (Fang et al., 2016). The definition of review value is generally agreed upon by scholars. Weiss et al. (2008) point out that the perceived value of information is related to the perception of the helpfulness of information received from others, in making a purchasing decision. The value of an online review is the likelihood that the reader of the review is going to use it to make their purchasing decisions (Weiss et al., 2008). Lastly, in their study on the value of online reviews, Fang et al. (2016, p.499) share a highly similar definition in which the value of a review is "*the helpfulness votes received, or its perceived helpfulness*". Ghose & Ipeirotis (2007), however, break down review value into two: from the point of the reader, which they define in terms of helpfulness in decision-making, as the previously mentioned authors, and from the point of the manufacturer defined as the expected effect on sales.

Pinpointing which reviews are most helpful is critical in overcoming the information overload created by a large number of available online reviews (Yin, Bond, & Zhang, 2011).

2.3.2 Review value influences

There are several factors that have been previously analyzed in literature in order to understand what influences the perceived value of online reviews. Many online review platforms offer the option of actively rating the usefulness of any specific review with the purpose of helping potential consumers to retrieve information easier and make decisions in a more efficient way (Hao, Li & Zou, 2009). However, for potential customers, it is not as easy. Ghose & Ipeirotis (2007) point out that the helpful votes of a review is not a useful feature for ranking recent reviews because these votes are being accumulated over time and therefore, cannot be used to place a review in a short or medium-term time frame. Therefore, there are other cues that readers search for to make their judgments of a review.

Based on the literature, there are three main factors that influence review value, and they are: review content, the reviewer himself, and the review reader. According to Fang et al. (2016) and Ghose & Ipeirotis (2007), the content of a review is the most essential factor that contributes to the value of a review. The authors find out that text readability, for example, influences the assigned value of a review. Text readability here being the written style of the review, how easily the review can be understood. Chen & Lurie (2013) investigated the presence of temporal contiguity cues in an online review. They observed that temporal contiguity cues increase the perceived value of positive reviews to a greater extent than they do for negative reviews (Chen & Lurie, 2013).

The valence of the review plays a significant role in the value perception of online reviews. In the case of service failure, which is usually described in negative reviews, the value of review is assessed differently by the readers (Black & Kelley, 2009). The research study by Black & Kelley (2009) shows that reviews that document a service failure are perceived as less helpful than reviews that do not document a failure. Readers perceive the reviews in which the provider has attempted a service recovery as no more helpful than the reviews that report failures with no recovery attempts, although consumers seem to be giving higher ratings to reviews that document an effective recovery (Black & Kelley, 2009).

Chen & Lurie (2013) found that positive online reviews are less valuable than negative ones. Whereas Fang et al. (2016) point out that it is not just negative reviews that are perceived as more valuable, but extreme sentiment, whether it is positive or negative, makes reviews more valuable. According to Hao et al. (2009), reviews with a higher positive orientation are also less likely to be rated for usefulness, possibly because of their weaker perceived diagnosticity as opposed to negative ones.

A distinctive feature of online reviews is that they are provided by anonymous individuals, which is why the characteristics of the reviewer play a big part in how a review is evaluated, and its perceived value. According to Xu (2014), for eWOM to be effective as a decision-making aid, the consumers must trust the reviewer. Fang et al. (2016) also found out that the perceived trustworthiness is an aspect that can affect the perceived value of reviews. The reputation of the reviewer is also a cue that readers look for to evaluate a review as reputation influences the affective and cognitive dimensions of reader trust (Xu, 2014). Bristor, (1990) points out the level of perceived expertise of the reviewer, which plays a particularly big role because the readers have little motivation to check the veracity of the information, they are being offered by retrieving their thoughts. The knowledge and competence of a reviewer, is however, most of the time hard to assess because of the limited access to personal attributes and background of the reviewer, which is why readers rely on either ratings or scores assigned to the reviewer either by the review platform or by other fellow-readers (Zhao, Wang, Guo & Law, 2015).

Lastly, the reader himself is also influencing the review value. For example, Weiss et al. (2008) also point out that the stage that the information seeker is in, whether they are in a learning or decision-making stage, has a great impact on the judgements of information value. Other characteristics of the audience also can influence the review value, when mediated by review message credibility. These characteristics include age, race, gender, education, and income (Greer, 2009).

2.3.3 Review value and emotions

Emotions have been the subject of multiple studies across numerous disciplines (Brosch, Pourtois & Sander, 2010), while three dimensions of emotions have consistently surfaced in most papers (Yin, Bond, & Zhang, 2013): valence, arousal, and power. Based on their valence, emotions can be divided into positive and negative emotions (Ulla, Zeb & Kim, 2015). Emotions enable the processes of communication and the sharing of private experiences with peers (Ulla et al., 2015). One of the emotions that contributes to evoking WOM is surprise (Derbaix & Vanhamme, 2003). Negative surprise can lead to negative WOM, whereas positive surprise can lead to positive WOM (Derbaix & Vanhamme, 2003).

The affective content of online reviews plays a significant role in defining their helpfulness (Yin et al., 2013). A study by Malik & Hussain (2017) finds that positive emotions: trust, joy and anticipation, and negative emotions: anxiety and sadness, have the highest perceived impact on helpfulness. Yin et al. (2014), examine the impact of anxiety and anger on online review helpfulness, as they are two of the most encountered emotions in online reviews. The reason for the prevalence of the two emotions stems from ambiguity regarding a product, the shipment times, or how refunds and returns would be handled by the provider, all of which enable expressed anxiety among reviewers (Yin et al., 2013). On the other hand, mishandled transactions and inadequate customer service are more likely to lead to anger (Yin et al., 2013).

Ulla et al. (2015) examine the effects of emotional contents of online reviews on the number of received helpfulness votes and find out that while positive emotional content has a positive effect, a negative emotional content does not affect perceived helpfulness of the review.

Our study will investigate both positive and negative reviews that follow a customer service interaction. As inadequate customer service interactions, which might be expressed in the form of a negative online review, are more likely to lead to anger (Yin et al., 2013) we focus on anger as a prevalent online reviews' emotion.

"Anger is an emotional state that motivates a person to alleviate personal harm attributed to others" (Yin et al., 2013, p.542). Anger appears in situations that are predictable and dictated by other individuals (Lerner & Keltner 2000) and is linked to less cognitive effort because angry people are generally more likely to engage in mindless, heuristic processing (Bond & DePaulo, 2008). According to the study by Yin et al. (2013), readers of a review can accurately assess the emotion in the review and make emotion-consistent inferences about the reviewer's effort. Angry reviews are associated by readers with a low effort, possibly due to their higher levels of arousal (Yin et al., 2013), and angry reviews are decreasing the perceived helpfulness of a review. A study by Kim & Gupta (2012) also shows that when negative WOM contains negative emotions, the review was perceived as less helpful and the reviewer as less rational. The information value and negative impact on product evaluations decrease when an online review contains negative emotions (Kim & Gupta, 2012). On the other hand, positive emotions expressed in online reviews do not have a significant influence on perceived value, or on product evaluations (Kim & Gupta, 2012).

2.4 Causal attribution

2.4.1 Attribution theory paradigm

As most online reviews are post-purchase actions, and our research will aim to manipulate such a review, we can look to Weiner's (2000) reflections on attributional thoughts about post-purchase consumer behavior. According to Weiner (2001), consumers attribute the responsibility of a service-failure within three interconnected dimensions of causality. These are *casual stability*, *causal locus*, and *casual controllability* (Weiner, 2001, p.384). Whom a consumer believes is responsible for a service-failure affects the probability of them returning to the same vendor or continuing to use their product (Folkes, Koletsky, & Graham, 1987), and in the case of online reviews, the probability of them using the service (Cheung & Thadani, 2012).

Casual stability refers to the attributional principle regarding how an individual evaluates satisfaction after receiving, or not receiving, the expected product or service (Weiner, 2000). In other words, stability refers to the consumer expecting that the service failure is only temporary, i.e., it is expected that things will be different the next time, and therefore leads to a stable outcome (Browning, So & Sparks, 2013). An example of this type of casual stability could be dissatisfaction with a mass-produced product, as the consumer can expect the next product to be the same as the one he was unsatisfied with. Repeated negative or positive experience can also contribute to casual stability, e.g., if a person is a regular customer of a restaurant and is repeatedly satisfied, a one-off bad experience can be attributed to a temporary lapse or an unstable cause, rather than a foreseen and stable outcome (Weiner, 2000). On the other hand, repeated service failures by a formerly stable performer will eventually lead to the customer reevaluating their position of the unstable factors and shift to expecting a stable negative outcome (Weiner, 2000). The quality of past performance is thus directly related to the causal attribution, and a positive past performance lessens the impact of service failure (Browning et al., 2013; Vázquez-Casielles, del Río-Lanza, & Díaz-Martín, 2007).

Locus of causality is a retrospective appraisal of who bears responsibility for a service failure (Poon, Hui & Au, 2004). In other words, was the firm itself responsible, or did the customer or another external factor cause the service-failure (Weiner, 2000). An example of this can be faulty electronics, such as a bad battery on a phone, where the manufacturer of the product is responsible. However, if the firm has to deal with an unexpected condition, such as an airline battling a storm, consumers can be more forgiving (Weiner, 2000). Customers are more likely to be dissatisfied with the firm if they believe it is responsible for the service failure (Folkes, 1988), and in turn, are less likely to continue their relationship with the firm (Browning et al., 2013).

Casual controllability refers to how much control the customer believes that the company has over the service yielded, and they are able to prevent a service failure in the future (Hui, Alan & Zhou, 2006; Weiner, 2000). A company with a good track record of delivering high-quality service can be expected to have full control over fixing a service-failure, even though it might bear full responsibility for the failure (Hess, Ganesan, & Klein, 2003). An example of that might be a mistake by a new employee or a faulty product batch in an otherwise repetitive satisfactory relationship between a firm and a consumer.

An important aspect for this research is that the causal attribution of the reviewer is only one side of the coin. The receiver of the persuasive communication, in our case, the online review, has to infer the motivation of the reviewer and further attribute the cause of the message (Folkes 1988). In the case of online reviews, it is harder for the receiver to adequately judge the motive of the source due to their anonymity, which is one of the key elements that determine the credibility of a message (Rieh & Danielson, 2007).

Although the perceived motivations of the reviewer to communicate is an important aspect, it is not the only factor that can influence how the receiver interprets the persuasive message and to whom they attribute the service success or failure (Cheung & Thadani, 2012). Studies on traditional WOM have used the attribution theory paradigm as a framework to understand the effect on the receiver's opinions (e.g., Curren & Folkes, 1987; Laczniak, DeCarlo, & Ramaswami, 2001; Mizerski, 1982). The same framework is shared among researchers that study eWOM and its influence on consumer behavior (e.g., Browning et al, 2013; Sen & Lerman, 2007; Vermeulen & Seegers, 2009).

2.4.2 Factors influencing causal attribution of online reviews

2.4.2.1 The role of the reviewer

From a firm perspective, it is evident that online reviews can be used to affect perceptions and influence sales (Amblee & Bui, 2011; Dellarocas, Zhang, & Awad, 2007). However, these online reviews are either valuable or a threat to the company only if they are attributed to the company or the product it produces, rather than to the communicator of the eWOM itself. Numerous factors can affect the receiver's attribution (Cheung & Thadani, 2012). One of which is that receivers of persuasive communication, such as word-of-mouth, must judge to what extent the message is affected by personal or situational causes (Folkes 1988). In other words, receivers might attribute a positive product review to the person who communicated it rather than the company based on the communicator being positive in general (Mizerski 1982), instead of the product exceeding set expectations (Chen & Lurie 2013).

As the traditional form of WOM is interpersonal, thus ensuring that the trustworthiness of the reviewer is assessable, and the identity of the communicator is known, therefore the receiver has an easier time evaluating the message (Herr, Kardes, & Kim, 1991). The same does not, however, apply to eWOM, in assessing the trustworthiness of the review, the reader must often make attributions (Cheung & Thadani, 2012). As it plays a critical role in the overall attribution and helpfulness of a review, the source credibility of online reviews is one of the most frequently investigated factors within the review literature (Cheung & Thadani, 2012). Furthermore, perceived source credibility is one of the three dimensions of review helpfulness (Li et al., 2013). Because online reviews are, to no small extent, written and shared by unknown individuals, it raises concerns about their credibility (Park & Lee, 2009; Park, Lee, & Han, 2007). Different aspects of eWOM credibility will be explored, in-depth in chapter 2.5.

Credibility is not the only factor influencing receivers' perception of communicator's online reviews (Cheung & Thadani, 2012). Other influencing factors include homophily, i.e., how similar the reviewer is to the receiver(Steffes & Burgee, 2009), where the information is coming from (Huang, Lurie, & Mitra, 2009), and expected underlying motivation for writing the review (Lee & Youn, 2009; Sen & Lerman, 2007). On the other hand, both the content of the review and internal factors of the receiver also influence the effect of online reviews, e.g., their perceived usefulness, consumer’s attitude, and purchase intent (Cheung & Thadani, 2012).

2.4.2.2 The role of the receiver

The effect of online reviews on consumers varies from person to person (Cheung & Thadani, 2012). Consumers are not a homogeneous group that responds the same to every stimulus. People differ in their motivation and ability to process information (Gupta & Harris, 2010), as well as their expertise (Park, & Kim, 2008) and their involvement (Park et al., 2007). Some consumers are more skeptical, while others are open-minded (Sher, & Lee, 2009). The gender of the reader is also influencing how the review is perceived. Women expect a woman to offer better service while men expect men to do the same, in settings where there is little information available about the potential service provider (Fischer et al., 1997). When reading online reviews, women are more easily influenced by relational information whereas men are more outcome focused (Mattila, Grandey & Fisk, 2003). These, and many more factors, influence how consumers respond to online reviews (Cheung & Thadani, 2012).

2.4.2.3 The role of the review

Finally, the message itself contributes to the effect it has on the receiver and how they interpret and attribute it (Huete-Alcocer, 2017; Schmäh et al., 2017). This does not only refer to the content of the message itself but also the sheer volume of reviews (Gupta & Harris, 2010) and the ratio between negative and positive reviews (Lee et al., 2008). There is a positive relationship between the number of reviews a product or service receives and its sales, as well as the consumers' purchase intentions (Cheung & Thadani, 2012).

2.5 eWOM credibility

As online reviews are mostly anonymous, or partially anonymous, in their case, the truth is in the eye of the beholder. Consumers who read the reviews have to make use of heuristic cues, and judgement calls on limited information to assess both the credibility of the person who wrote the review, as well as the message itself (Cheung & Thadani, 2012). These factors contribute to how credible the review is, which in turn affects review adoption (Cheung, Lee, & Rabjohn, 2008). Finally, review adoptions are positively related to purchase intent, so it is essential that companies that want to capitalize on positive reviews to be credible while not restricting participation too much (Cheung & Thadani, 2012).

2.5.1 Source credibility

Credibility is a type of trust and is defined by Ba & Pavlou (2002, p.246) as *"the belief that the other party is honest, reliable, and competent."* The credibility of an online review refers to how confident the reader is in the reviewer's reliability, dependability, and integrity (Shin et al., 2017). Credibility, the same as other people's opinions, or the length of the message, are heuristic cues applied to online reviews, meaning that they enable readers to use specific mental shortcuts or rules of thumb to make their decisions (Chaiken & Maheswaran, 1994).

Interpersonal communication is the interaction between four variables: the message, the communicator, the receiver, and the response (Hovland, 1948). From among the four, the source of the message (the communicator) is the most important element that determines the credibility of the message (Rieh & Danielson, 2007). The same applies to online reviews. The source credibility is of great importance as it is one of few factors that has been shown to directly affect the information usefulness, and credibility of the review itself (e.g., Cheung et al., 2009; Cheung et al., 2008; Sussman & Siegal, 2003), as well as its persuasiveness (Willemsen, Neijens, & Bronner, 2012). A message that is attributed to a highly credible source will result in a greater attitude change than a message whose source remains unidentified (Greenberg & Tannenbaum, 1961; Willemsen et al., 2012).

Flanagin & Metzger (2008) point out three different characteristics based on which credibility is assessed: believability, trustworthiness, and expertise. While perceived expertise refers to how capable a source is to make valid assumptions, perceived trustworthiness refers to the belief that a source's motivation for sharing information is none other than to communicate valid assertions (Hovland, Janis, & Kelley, 1954). Trustworthiness, as well as expertise, are important to message acceptance (Flanagin & Metzger, 2008).

Still, review sites allow anyone to leave a review about a product regardless of whether they are qualified or not to assess a product (Willemsen et al., 2012). So, readers look for specific cues to assess the credibility of what is often an anonymous source (Craciun, & Moore, 2019; Xie et al., 2011). Among these cues that help readers assess the credibility of the reviewer are identity cues (Sussman & Seigal, 2003). The identity of the source in an online setting plays a crucial role in online communications for two reasons, as identified by Sussman and Seigal (2003). Firstly, when the identity of the source of a piece of information is disclosed, the information exchange and acquisition will be more efficient (Sussman & Seigal, 2003). Secondly, source credibility is enhanced by source identity, which results in increased information credibility and usefulness (Sussman & Seigal, 2003). Most of the time, the only identity cue of a reviewer is their nickname, while the real name, a picture, or any other self-descriptions are not available on most review websites, which raises questions about the credibility of the reviewer (Kusumasondjaja, Shanka, & Marchegiani, 2012).

To reduce the perceived risk and uncertainty, and in order to accept or reject a review, readers look at specific identity elements that help them in the process, such as the profile picture of the reviewer (Xu, 2014). One such identity element is the reviewer's gender. Studies have shown the effect of gender stereotyping on source credibility (Armstrong & McAdams, 2009). A study by Timmers, Fischer & Manstead (2003) points out that readers of online reviews are rating female reviewers more negatively than males when they display emotional behaviors, pointing to gender-specific emotion stereotypes. Craciun & Moore (2019) also demonstrate the moderating effects of the reviewer gender on the credibility and helpfulness of emotional negative online reviews.

Another cue that assists readers to assess the credibility of a reviewer, and which enhances the perception of identity is the number of useful votes received on a review (Xu, 2014). Xu (2014) finds out that the number of helpful votes received by a reviewer is another way to evaluate the expertise and trustworthiness of the reviewer. A good reputation is a factor that influences reviewer credibility (Hu et al., 2008). When a reviewer is seen as having a good reputation their reviews can help decrease a product's uncertainty because they are already deemed by the market to have the necessary expertise to assess a product's quality (Hu et al., 2008). They are also seen as less likely to engage in opportunistic behavior in the form of accepting rewards for writing fake reviews (Hu et al., 2008).

Wang, Chan, Ngai & Leong (2013) measured perceived reviewer credibility based on the number of reviews posted by the reviewer. Likewise, Hu, Liu & Zhang, (2008) find out that the exposure of a reviewer plays a part in their perceived credibility. In the case of online reviews, review exposure refers to media exposure of the reviewer in the review community and the number of reviews that the reviewer has left on a specific platform (Hu et al., 2008).

According to Greenburg and Miller (1966), individuals are more resistant to persuasion when a source is considered to be low in credibility. This happens because the beliefs of an individual are immunized when confronted with low source credibility (Greenburg & Miller, 1966). Hass (1981) points out that the credibility of a source is harmed if it is not seen to fulfill two conditions. First, it must not be perceived as biased. Second, it must not communicate the message for any other purpose than to share information (Hass, 1981). When it comes to expertise, a source is considered to be an expert when it displays the *"correct knowledge"* (Hass, 1981, p. 143). Based on the discounting principle of attribution theory of Harold (1973), Willemsen, Neijens, & Bronner (2012) state that a user will discredit an endorsement that they think is attributed to non-product related factors, when the reviewer is thought to have left the review with the intent to persuade, and not to describe product performance.

The valence of the review can also be connected to the credibility of a reviewer, as pointed out by Kusumasondjaja et al. (2012). The authors examine how information regarding the identity of the reviewer, combined with the valence of a review affects the users' perception of the credibility of the review (Kusumasondjaja et al., 2012). The authors observed that when the reviewer's identity is disclosed, a negative online review is deemed more credible than a positive review (Kusumasondjaja et al., 2012). Negative reviews with a disclosed source were observed to be most credible (Kusumasondjaja et al., 2012). The same study also found out that when the reviewer identity is not identifiable, there is no difference between positive and negative reviews in terms of the reader's perception of the review credibility or trust towards the product being reviewed (Kusumasondjaja et al., 2012).

2.6 The value of the customer service representative

2.6.1 The unique nature of services

There are several differences between services and products, mostly resulting from their distinct nature as intangible, heterogeneous, and inseparable (Iglesias, Markovic, Rialp, 2018). When purchasing a good, there are not many surprises that consumers might stumble upon as its features can be touched, seen, and sometimes even tasted before consumption (Grace & O’Cass, 2004). On the other hand, services are high in experience qualities - characterized by being able

to be recognized only after purchase and during consumption, and credence qualities - attributes which may be impossible to evaluate even after the purchase and consumption (Grace & O'Cass, 2004; Iglesias, Markovic, Rialp, 2019). Researchers such as Grönroos (1990) and Parasuraman, Zeithaml, and Berry (1985) split service into two parts: the outcome - defined as what the customer receives, and the process - how the service is delivered to the customer.
Employees play a crucial role and are able, through their interactions, to make or break a brand (Roper & Davies, 2007). For example, a study by Hoffman, Kelley, and Rotalsky's (1995) showed that 15% of service failures were caused by the inappropriate behavior of the customer-facing employees, clearly pointing to the severity of their behavior, and the importance of the service employees.

Selling services usually entails a more significant number of interactions between the service employees and customers due to the lack of separation between the production and consumption processes (Grönroos 2006). This enhances the role of customer-facing employees in service settings (Iglesias et al., 2018). The problems faced by the marketers of services also differ from those of consumer goods, and they appear in the effort of trying to communicate an intangible offer, maintain standardization of service and delivery, and others alike, which make the service provision a complex task (Grace & O'Cass, 2004).

Studies show that a customer orientation coming from the service employees is likely to increase the customers' emotional commitment toward the services company represented by the service employee (Hennig-Thurau 2004). During service interactions, customers can have several emotions, whether positive or negative, and customers who experience positive emotions during an interaction tend to create bonds and relationships with the employee (Reynolds and Beatty 1999). A development of familiarity between customer and service employee increases the customer's emotional commitment towards the service provider and has a positive impact on customer retention (Hennig-Thurau 2004).

2.6.2 The role of the customer service representative

A service encounter is defined as the total period during which a consumer interacts with a specific service by Bitner et al., (1990), while Mohr & Bitner (1995) define it as a person-to-person interaction between a customer and an employee. The human element, most often experienced through a front-line employee, whether in the form of a salesperson, a customer service representative or other employees, is one aspect that seems to be a determinant to the outcome of service satisfaction when evaluating a service, as proven by several studies (Brady et al., 2002; Bitner et al., 1990). Service quality is defined here as the customer's overall impression of a service provider, which is often considered the same as the customer's overall attitude towards the company (Bitner, 1990).

When acquiring services, customers are fundamentally concerned with the completion of their task in a successful manner, and its efficacy, both of which are enabled by the front-line employee's helpfulness (Keh, Ren, Hill, & Li, 2013). Furthermore, what the employee does, how they speak, behave, is seen as an equivalent to how the company speaks, behaves, and is perceived (Bitner, 1990). An employee's actions, such as their courtesy, enables a bond between the customer and the retailer or service provider (Keh et al., 2013). The human interaction element in a customer and company interaction is of high importance when evaluating a service (Day & Bodur, 1978), while the satisfaction with the contact person is also known to heavily influence the satisfaction with said service (Crosby, & Stephens,1987). Pugh (2001) has shown that the connection created between a customer and the front-line employee is highly transferable towards the company. The author points that even something as unique as the display of emotion in the front-line employee would further be mimicked by the customers and is positively related to the customer's evaluations of the service quality (Pugh 2001).

Iglesias, Markovic & Rialp (2019) and Aggarwal, Castleberry, Ridnour & Shepherd (2005) emphasize one specific characteristic of the customer service representative that has a substantial and positive effect on the affective commitment that the customer develops toward the services brand or company. That characteristic is empathy and is defined as the ability to understand and appropriately react to the thoughts and feelings of those around us which, in a service setting allows a front-line employee to be helpful, and which in turn has a positive effect towards the brand or company (Iglesias et al., 2019). Empathy is a valuable trait as it can result in producing experiences that are rich in interpersonal concern and emotional contagion, a job that ultimately comes down to the customer-facing employees. According to Roper & Davies (2007), an employee's behavior during each interaction with a customer can make or break a brand, further emphasizing the strong effect of employees, such as front-line employees, towards the company and the brand they represent.

Hansen, & Danaher (1999) look at another aspect of a customer-facing employee encounter that has a strong effect over the brand they represent in the form of judgments of service quality and purchase intentions, and that is the performance consistency during service encounters. The study found out that an improvement in performance during such an encounter produces more positive evaluations towards the service and company than a decline or average performance. Bolton & Drew (1992) who argue in their study whether the service employees are indeed such a strong determinant to the perceived quality and value of the service itself, find out that the satisfaction resulting from a service encounter is more heavily weighted in determining the value of the service rather than the quality of the service (Bolton & Drew, 1992). The authors also find out that when quantifying the effect of a service encounter, the impact of service employees usually cannot compensate for service failures and disruptions (Bolton & Drew, 1992). The same is argued by Mohr & Bitner (1995) as the employee's effort and hard work are not recognized when customers do not get the outcome they want. Customer satisfaction is also directly connected to the service encounter and influenced by the consumer-facing employee (Bitner 1990; Mohr & Bitner 1995).

2.6.3 The gender of the customer service representative

Frontline service positions, including call center service representative ones, are far more likely to be filled by women, as a result of stereotypes such as their perceived role of emotionally expressive nurturers (Matilla, Grandey, & Fisk, 2003). Stereotyping implies ascribing characteristics to people based on their group membership (Oakes, Haslam & Turner, 1994), and while attitudes towards women's roles and rights have changed in time, stereotypes remain as strong today as they used to be (Hyde, 2014; Luoh & Tsaur, 2007). Moreover, that might as well be, as stereotypes play an essential role in human judgment (Luoh & Tsaur, 2007). Male and female evaluators understand and value an equal performance differently based on the gender of the individual whose performance is being assessed (Ellemers, 2018).

Social role theory proposes that the beliefs of social perceivers about social groups in society derive from their experiences with group members in their typical social roles (Koenig & Eagle, 2014). Because women, as opposed to men, are more prevalent in a specific type of job such as service jobs, perceivers assume that women possess the communal traits, such as helpfulness, social sensitivity, warmth, and nurturance that enabled them to profess that job (Eagly & Koenig 2006). Stereotypes prescribe how men and women should behave in different life domains and how they should generally be (Ellemers, 2018).

While assertiveness and performance are considered indicators of power in men, it is warmth and concern for others that women are positively associated with, reflecting the agency vs. caring behaviors (Ellemers, 2018). Anger is more acceptable for men, while other emotions such as sadness, fear, or happiness are more acceptable for women (Durik et al., 2006). Females are evaluated more favorably on warmth, empathy, and altruism than men, while men are evaluated more favorably in general ability and task performance (Ellemers, 2018). Therefore, stereotypes boil down to one central dimension for each gender: warmth for women, and competence for men (Ellemers, 2018; Fiske, Cuddy, Glick, & Xu, 2018; Ebert, Steffens, & Kroth, 2014; Fiske, 2010).

Previous research shows that, in service settings, women are more likely to rate employees of the same gender more favorably than those of the opposite gender (Mohr & Henson 1996). Fischer, Gainer, & Bristor's study (1997, p.382) points out that "*women have the highest expectations about positive relations in their service encounters with other women*". And while women would expect a woman to offer better service, men would expect men to do the same, in settings where there is little information available about the potential service provider (Fischer et al., 1997).

One possible explanation for this preference for the same gender might lie in the construct called homophily. According to Rogers & Bhowmik (1970, p.526), homophily is defined as "*the degree to which pairs of individuals who interact are similar with respect to certain attributes, such as beliefs, values, education, social status, etc*". Gender homophily refers to a preference for interactions with the same gender (Laniado, Volkovich, Kappler, & Kaltenbrunner, 2016). When they are given a chance to choose, people prefer to interact with other people who are similar to themselves (Brown & Reingen, 1987). Furthermore, in service settings, people might prefer to be served by people of the same sex as they might expect to feel more comfortable (Fischer et al.,1997). Laniado et al., (2016) find out that in dyadic relationships, there is higher gender homophily for women.

In service settings, women tend to try to maximize the interpersonal aspects of their relationships. They are more easily influenced by relational information, such as the service employee being described as helpful or thoughtful, especially when evaluating other women service representatives (Iacobucci & Ostrom, 1993). Women are less influenced by cues on service efficiency and accuracy. Men, on the other hand, are more outcome-focused and negative affective displays are not as detrimental to their satisfaction, as they are for women's satisfaction, resulting from a typical service encounter (Mattila et al, 2003) Men care that the transaction runs smoothly, and the outcome is favorable while women care about the process of service delivery, regardless of the outcome (Finsterwalder et al., 2011; Mattila et al., 2003; Iacobucci & Ostrom, 1993). Still, Mattila et al.'s study (2003) shows that in failed service encounters, men are highly influenced by negative displays, and are less satisfied with an incompetent employee and negative affective displays by the employee, than women are.

Women are more sensitive to emotional cues than men, are more likely to identify with the service employee and be empathic towards them (Fiske & Taylor 1991; Shemwell, Yavas, & Bilgin, 1999; Wharton & Erickson 1993). A tendency confirmed by more recent studies such as Meyers-Levy & Loken, (2015) which points out that females are more other-oriented whereas males are more self-oriented. Molina et al. (2013) show that women are more engaged in prosocial behavior than men.

Lastly, stereotypes play an important role in service settings, and an essential role in the perception of personalized reviews because of one main reason: when they need to assess unknown men and women, such as in a personalized gendered review, participants will rely on general gender-stereotypical expectations (Ellemers, 2018).

2.7 Personalized reviews

2.7.1 Definition and examples

Although people leaving reviews in which they mention a specific customer-facing employee by name is often happening and can be observed on different review platforms, these reviews have not been assigned a specific name yet and, to the best of our knowledge, they have not been the focus of any previous research. The focus of this research is to investigate several aspects of these types of reviews, so we assign a name and continue by calling them *"personalized reviews"*. Therefore, personalized reviews are those reviews in which the reviewer has mentioned the name of the specific customer-facing employee that they have interacted with.

To illustrate the difference between a non-personalized review and a personalized review, we look at excerpts from real-life reviews left by people who have been in contact with a company's customer service. The examples are from the review platform Trustpilot. The following review is a personalized review: *"Geoff was incredibly helpful and lovely on the phone and I was completely satisfied with the outcome of my enquiry. He even made sure that he took me off hold to let me know he would be a bit longer, in order to manage my expectations."* (Trustpilot, 2020a).

On the contrary, a non-personalized review would mention the customer service as a department or entity, or the company by name, and not mention the name of a specific person.
The following review is a non-personalized review: *"Excellent customer service. Kiwi responded to every mail you send to them even if it is the same topic. They also respond immediately on social media. I went to Lourdes from Paris. The first train ticket was not ready and after I saw all the bad reviews I got scared."* (Trustpilot, 2020).

2.7.2 The value of human cues

To understand why seeing a person mentioned in a review might make a difference for the reader, as opposed to a review in which a company, a department, or service employee is mentioned, it is of value to look at how people relate to people vs. companies How people interact with other people versus how they interact with companies, how they form human relationships vs. company relationships are all aspects worth investigating in this context. Marketers and scholars alike have been striving in the last decades to prove that brands can be perceived as humans, whether it was by assigning them personalities like those we assign humans (Aaker, 1997), or by defining types of relationships between a consumer and a brand similar to inter-human relationships (Keller, 2012). However, there are several differences between inter-human and human-company relationships. In their book, Malone & Fiske (2013) analyze how we relate to people and companies and point out that, like our primitive counterparts, today, we still judge people almost instantly, along with two categories of social perception known as warmth and competence. This criteria applies to all our relationships, including the way that we analyze and try to make sense of a brand or company. A study mentioned by Malone & Fiske (2013), however, points out that although we assess companies on the warmth and trust traits the same as we do people, we have a stronger tendency of deeming companies as the opposite - selfish, greedy and concerned with their immediate gain. We are harsher in assessing a company and its motives than we are a person. That might be because companies are perceived as mostly trying to sell us something (Malone & Fiske, 2013). At the end of the day, corporations are faceless abstract entities, whereas when interacting with people, we can encounter authentic emotions (Malone & Fiske, 2013).

We have a human need to trust and believe other humans who act authentically, we are hard-wired to respond to demonstrations of warmth. Our interactions with companies and brands lack concreteness and are instead dominated by abstractness, which further directs our general behavior (Malone & Fiske, 2013).

Brand personality, as defined by Aaker (1997) has been drawn from The Big Five scale of human personality. One of the main arguments for The Big Five being applicable to brands lies in the concept of animism and anthropomorphism both pointing to the tendency of people to humanize non-animated objects (Aaker, 1997). The reason behind animism and anthropomorphism lies in the need of humans to create a human connection where human connection is lacking (Epley, Waytz, & Cacioppo, 2007). Guthrie (1993) defines the concept of animism as the act of instilling life into objects when some motion or noise from the object is discerned, and he attributes this to a person’s wishful thinking. Anthropomorphism, as described by Epley et al. (2007), is the tendency of humans to assign humanlike characteristics, motivations, intentions, or emotions to real or imagined behavior of nonhumans. Epley et al. (2007) point out that the existence of a human element, even if it is the result of anthropomorphism, makes a difference in how a person interacts with an agent and whether that agent is worthy of respect and concern, as opposed to being treated merely as a nonhuman element, as an object.

Guthrie (1993) explains that not only are individuals susceptible to the availability of any human cue, but they are also very proficient in detecting its presence. Furthermore, Aggarwal, Pankaj, and McGill (2007) point out that when nonhuman information about companies is present, consumers show the tendency to process a piece of information cognitively and to overcome the anthropomorphic representations of a specific brand in their mind.

Guthrie's (1993) study regarding individuals' sensitivity to human cues and their sensibility to them, and Aggarwal et al.'s (2007) findings regarding nonhuman pieces of information about brands and the cognitive tendency that results, is a first indication of a possible difference in how the reader might perceive a personalized vs. non-personalized review.

2.7.3 Personalized reviews valence. An exploration.

As previously mentioned, to the best of our knowledge, personalized reviews have not been researched and there are no studies that could help us understand personalized reviews. Because of that, in the coming sections we take an exploratory approach to try to understand why people would leave personalized reviews and which valence of personalized reviews could be more prevalent. In doing so we combine concepts from psychology with existing research on online reviews.

The valence of personalized reviews, not unlike that of reviews generally, could be dictated by the reasoning behind leaving such reviews. Landis & Burtt (1924) observed that among other conversation topics, people like to talk about experiences, which might explain why people leave reviews in the first place. The same authors observed that people like to talk about personal relationships, which could explain why people take the action of leaving personalized reviews. In a personalized review the customer talks about the connection they made with a customer service representative, they talk about an interaction, or even a series of interactions with one individual. And this relationship is taken even further as the customer takes the action of leaving an online review where they write about how they feel about the representative and the help they were offered.

According to Berger (2014), one of the reasons why consumers share word of mouth is to shape the impressions that others have of them. Social interactions are explained by Goffman (1959) as a performance where people present themselves in a particular way to achieve the desired impressions. People communicate their desired identities while they avoid communicating undesired ones (Berger 2014). Based on the same thinking, a positive personalized review could depict a harmonious, positive experience, showing the customer praising the service representative, which might put the reviewer in a good light. On the other hand, leaving a negative personalized review, would be more likely to portray a customer who is willing to publicly shame an individual who is just doing their job. A person who might be perceived as not having any consideration for how their subjective assessment might affect the representative in real life, whether putting their job at risk, or their status.

Anger is the most common emotion associated with inadequate customer service experiences (Yin et al., 2013). Angry reviews are decreasing the perceived helpfulness of a review (Kim & Gupta (2012). A negative personalized review is likely to be perceived as showing an interpersonal conflict, which can be associated with anger (Brusman, 2015). According to Harris & Reynolds (2003), customers that display anger can be seen as violating social and moral norms.

Kanouse et al. (1972), and Mizerski (1982), imply that social norms dictate people to leave positive reviews. Positive personalized reviews could be motivated by a need of the customer to return the favor to a customer service rep who has met and potentially even surpassed their needs. This statement could be explained by social exchange theory. Social exchange, as defined by Blau (2017, p. 93), "*involves the principle that one person does another a favor, and while* *there is a general expectation of some future return, its exact nature is definitely not stipulated in advance*". It is unclear whether in real-life customer service reps are actively asking customers whose needs they have satisfied to mention their name when leaving a review but the customer might feel the need to return the favor, whether asked or not.

The action of leaving personalized reviews might also be rooted in the concept of altruism, or prosocial behavior, which dictates concern for others (Paul, Miller & Paul, 1993). In their paper about what motivates consumers to articulate themselves on the Internet, Hennig-Thurau et al. (2004) talk about how the customer's motivation for engaging in eWOM communications is based on trying to reciprocate the help given by a company, by offering something in return for a good experience. This should extend to when a consumer feels like a specific employee has gone out of their way to help them, and therefore positive personalized reviews should be driven in the same way, and possibly at an even higher rate. Equity theory could provide a similar explanation for leaving personalized reviews (Oliver & Swan,1989). Equity theory implies that individuals wish for fair and equitable exchanges. So, if a consumer feels like he/she has obtained a higher output/input ratio, from the interaction, than the employee who helped them, then they might feel like reciprocating. They might do so by offering the employee public praise which is visible to their employer and therefore equalizing the output/input ratio (Hennig-Thurau et al., 2004; Oliver & Swan, 1989).

While a lot can be drawn from literature on reviews in trying to explain the reasoning behind leaving positive personalized reviews, when it comes to negative personalized reviews, the implications are different. The implications of such a review are also towards the customer service representative that the customer has interacted with, not just the company they represent. Because of that, we further draw from literature regarding service encounters and customer facing employees to explore negative personalized reviews.

Service failure is often the beginning of a negative exchange happening between a customer and a customer service rep. In these cases, the customer might start with an aggressive complaint while the latter would be counterattacking and retaliating because they feel unfairly treated (Grandey, Dickter & Sin, 2004). In their paper about the effects of customers on call-center employees, Grandey, Dickter & Sin, (2004) show that customers are often the primary source of aggression when interacting with a customer service rep. The interaction might be characterized by interpersonal transgression (Leith & Baumeister, 1998). Even in situations where the customer service employee might be the beginner of an inappropriate behavior, potentially in the form of not being able, or not wanting to help, literature suggests that the customer might very likely still carry some blame.

Furthermore, emotional contagion in service encounters suggests that the customers often mimic the behavior of a customer service rep, and the opposite (Pugh, 2001). People exposed to poor attitudes from customer service representatives can lead to behaviors that are emotionally, psychologically, and even physiologically affected, and can surface in the form of expressed rage (Hunter, 2006). Therefore, in a heated discussion during which the customer is unhappy with the help and the responses that they are being offered, the customer is likely to also have had a less than desirable behavior.

Since in negative service encounters the customer is very likely carrying some blame, the customer himself might feel like he has strayed from normal socially accepted behavior, which is often connected to guilt and shame (Leith & Baumeister, 1998). Being guilt-prone, as per Leith & Baumeister (1998) would normally increase the likelihood of feeling guilty in a specific interpersonal conflict. The guilt feelings are likely to be joined by a tendency to consider and try to understand another person's point of view, in our case that of the customer service representative (Leith & Baumeister, 1998). So, when considering leaving a negative personalized review, could the customer feel guilt, which would make them more sensitive towards the service representative's perspective, and create empathy? Perspective taking would further lead the customer to try to create interpersonal outcomes that would be beneficial for the relationship (Leith & Baumeister, 1998). This mechanism suggests that people might avoid leaving negative personalized reviews altogether.

Still, people do have bad experiences and they might have specific needs, among which the need for venting (Berger, 2014). This need would then be likely to be satisfied by directing the negative review not to an individual but to the company, the service, or the customer service department as a team or department, towards whom there is no guilt in a service failure situation. It could be expected therefore that negative reviews from a customer who has also been in touch with a customer service rep would not mention individual names and instead would take a more company-focused approach.

2.7.4 The concreteness of personalized reviews. An exploration.

An interaction with a faceless company as opposed to a person lacks a quality that humans find very appealing, and that is called by psychologists “concreteness” (Malone & Fiske, 2013). Our interactions with companies lack concreteness and are instead dominated by abstractness. Companies are often perceived as a set of abstract logos and images without offering the concrete experience of their warmth and true intentions (Malone & Fiske, 2013). Based on these points by Malone & Fiske (2013), we explore the idea that personalized reviews, non-personalized reviews referring would be characterized by the same abstractness that companies generally are associated with, as opposed to reviews that concretely refer to a specific customer service representative.

According to Collins & Clément (2018) abstract descriptions are by definition more open to interpretation than concrete descriptions. Therefore, it is possible that abstract descriptions are perceived as having less evidentiary strength compared to concrete descriptions. Semin & Fiedler (1991) mention that abstractness implies less information about specific situations, it is therefore less verifiable and is more easily disputable than concrete information. Looking strictly at the abstract vs. concrete information literature, it could be inferred that a review mentioning a service or the customer service department of a company could be perceived as less valuable than a review that mentions a specific customer service representative by name. According to Goldstein & Scheerer (1941), there is a difference in behavior surrounding concrete and abstract information. Concrete information would limit the impact of the behavior to the specific circumstances in which it took place, whereas abstract information would generalize the impact of the behavior across time and situations.

While looking at the study by Freitas, Gollwitzer, & Trope (2004) regarding the influence of abstract and concrete mindsets, we can draw that a review mentioning the company would allow the reader to psychologically distance themselves from the situation and put themselves in an abstract mindset, whereas a personalized review would do the opposite. While in an abstract mindset, a reader would be adopting a deliberative mindset and consider potential pros versus cons of particular courses of action whereas in a concrete mindset they would be adopting an implementational mindset which would urge them to plan how to carry out an activity (Freitas et al., 2004). In other words, an abstract review, not mentioning a specific front-facing employee would put the reader in a deliberative mindset, whereas a more concrete review mentioning the employee's actions and behavior, could develop an implementational mindset (Freitas et al., 2004). A deliberative mindset implies not being decided about something, whereas an implementational mindset implies being decided about an issue (Gollwitzer, Heckhausen, & Steller, 1990). This would suggest that after reading a personalized review, the reader could be more likely to adopt an implementational mindset and be more likely to decide to engage in purchasing behavior based on the review.

Theoretical framework

3.1 Framework

This study explores the effects that personalization cues in online reviews have on the perceived value, credibility of the writer, and the reader's causal attribution. The research question that we aim to answer is:

> *How do personalization cues in online reviews influence attribution, credibility, and usefulness of the review?*

Drawing on literature review, the valence of reviews has a large impact on the outcome on perceived value and credibility. We expect this impact to be even more prominent in the personalized reviews as further elaborated in our hypothesis. Due to the lack of existence of previous research on personalized reviews, we draw mostly from review literature to hypothesize regarding the value of review, and theories that attribution and credibility will hold as mediators in that relationship.

We will apply attribution theory to explain the consumers' causal inference, as it explains in detail how consumers use their common sense, i.e. heuristic cues, to make judgement calls on limited information. According to that paradigm, readers determine the writer's motive and from there make causal inferences, which in turn affect the adoption of eWOM. Even though the accuracy of this judgment call might not be confirmed, it still influences the readers perception towards reviews' usefulness, and the credibility of its source. If the reader thinks that there are other factors than product/service reasons at play when the review was written they are more likely to perceive it non-believable, and thus consider it useless. By contrast, if the reader perceives the review as legitimate due to the perception that it only revolves around the service and product, they will consider it more useful.

As previously mentioned in chapter 2.5.1, the source credibility has a significant influence over the perceived value of a review, so we analyze if the same happens in the case of personalized reviews.

3.2 Hypothesis

People like to talk about personal relationships (Landis & Burtt, 1924), which could be one of the reasons why people leave personalized reviews. People also like to shape the impressions that others have of them by communicating their desired identities (Berger, 2014). Based on this thinking, leaving a positive personalized review might put a person in a good light, portraying them as someone showing gratitude to the customer service representative that helped them. On the other hand, leaving a negative personalized review might show a reviewer who publicly shames a service employee for merely doing their job, which could indicate an interpersonal conflict, which people tend to avoid (Brusman, 2015).

These same constraints do not apply to company reviews (non-personalized). This would suggest an increased volume of positive reviews and less volume of negative reviews when a review is personalized, tipping the scale towards positive valence for personalized reviews compared to non-personalized reviews. We thus formulate the following hypotheses.

H1: *Personalized reviews are more likely to be positively valanced than non-personalized reviews.*

Information receivers are known to make attributions about WOM communication (Grice 1975). They can attribute online reviews either to a product's attributes or to external factors such as specific characteristics of the reviewer (Sen & Lerman, 2007). According to Gilbert & Malone (1995), people are perceived to have more personal reasons to engage in positive WOM than negative WOM, and thus positive WOM is more likely to be attributed to the source, as opposed to the product experience. We adopt that line of thought and further assume that in the case of personalized reviews, the personal reason might be perceived as even stronger. This could happen because the positive personalized reviews portray an interpersonal relationship between the reviewer and the service representative. Thus, strengthening the attribution to the reviewer.

Willemsen, Neijens, & Bronner (2012) state that a reader is likely to discredit an endorsement which they think is attributed to non-product related factors. When the reviewer is thought to have left the review for other reasons than to describe a service's performance, such as with the intent to persuade, their intentions are questioned. This idea is based on the discounting principle of attribution theory of Harold (1973, p.113) that states that *"the role of a given cause in producing a given effect is discounted if other plausible causes are also present."*. As we assume that negative personalized reviews could be perceived to be written in anger, we infer that readers will put less trust in the reviewer's ability to truthfully describe their service experience. This is due to the interpersonal conflict that is portrayed in a negative personalized review. It might, therefore, be that if readers assume the review was written out of spite by an angry consumer, they will attribute it to other factors, such as specific characteristics of the reviewer and their mood (Sen & Lerman, 2007; Hovland, Janis, & Kelley, 1954).

Based on both existing review literature, and our assumptions regarding the reason why a customer would leave a personalized review, we formulate our second hypothesis as follows:

H2: *Personalized reviews are attributed to the reviewer to a higher degree than non-personalized reviews.*

To make sense of a piece of information for which the source is anonymous, the reader of a review is looking for specific cues that help him assess the value of a review (Huete-Alcocer, 2017). The credibility of the source is one of the heuristic cues applied to online reviews as it enables the readers to make their decisions (Chaiken & Maheswaran, 1994). Credibility is highly connected to attribution (Willemsen, Neijens, & Bronner, 2012). Our assumption in H2 is that a personalized review is more likely to be attributed to the reviewer than a non-personalized one. We could therefore assume that all personalized reviews would be rated as less credible. However, we expect the effect to be the opposite due to the personalization.

Customers who experience positive emotions during a service encounter tend to create relationships with the service representative (Reynolds & Beatty, 1999). Personalization in positive reviews could indicate a relationship between the customer and service employee. This might indicate consistency in the communication between the service provider and the customers, as the review mentions one specific customer representative, rather than a department. Consistency during a service encounter has a strong effect over a brand in the form of customer judgments of service quality, and their purchase intentions (Hansen, & Danaher, 1999). Therefore, we expect that:

H3a: *Positive personalized reviews are perceived as more credible than positive non-personalized reviews.*

A negative personalized review portrays an unhappy customer in an interpersonal conflict, whereas in a non-personalized review, it portrays merely an unhappy customer. Furthermore, people tend to associate interpersonal conflict with anger (Brusman, 2015). According to Harris & Reynolds (2003), customers that display anger can be seen as violating social and moral norms. These norms influence how consumers behave online and how their opinions are perceived (Harris & Reynolds, 2003). Research suggests that anger has a negative effect on the helpfulness and credibility of reviews (Yin et al., 2013). Craciun and Moore (2019) also showed that when anger is present in an online review, the source credibility is lowered. Based on these arguments, we introduce the following hypothesis:

H3b: *Negative personalized reviews are perceived as less credible than negative non-personalized reviews.*

The value of an online review is the likelihood that the reader of the review is going to use it to make purchasing decisions (Weiss et al., 2008).

The assumptions on which we base our next hypothesis are highly related to our previous hypothesis regarding credibility, as value and credibility are interconnected (e.g., Cheung et al., 2009; Cheung et al., 2008; Sussman & Siegal, 2003). The source credibility of online reviews is a critical contributor to the assessment of the value of a review (Cheung & Thadani, 2012). Perceived source credibility is one of the three dimensions of review helpfulness (Li, Huang, Tan, & Wei, 2013). Fang et al. (2016) point out that the perceived trustworthiness is an aspect that affects the perceived value of reviews, and a credible source would increase the value of a review.

Causal attribution is also known to influence the value of a review (e.g. Chen & Lurie, 2013). However, the discounting principle of Harold (1973) states that when participants are only submitted to one observation, the validity of attribution may be discounted. In our study, the participants will only be shown one single review. So, we assume that the causal attribution resulting from a single observation might also be more discountable (Kim & Gupta, 2012; Kelley, 1987). So, we will not connect our attribution hypotheses to our value hypotheses. But we will in turn draw them from our credibility hypotheses. Hence, we formulate the following hypothesis based on our previous assumptions on an increased credibility (H3a):

H4a: *Positive personalized reviews are perceived as more valuable than positive non-personalized reviews.*

As elaborated above, the presence of heightened emotions due to interpersonal conflict is expected to lower the perceived source credibility (Craciun & Moore, 2019), which in turn is expected to influence the adoption of negative personalized reviews (Cheung et al., 2008).

We therefore formulate the following hypothesis:

H4b: *Negative personalized reviews are perceived as less valuable than negative non-personalized reviews.*

In H4a we expect that positive personalized reviews are perceived as more valuable than positive non-personalized reviews. Yet, in H4b we expect that negative personalized reviews are perceived as less valuable than negative non-personalized reviews. However, according to H1, we do expect that most personalized reviews will be positive. Combining these expected predictions, we suggest the following hypothesis:

> **H4c:** *Consumers perceive personalized reviews as more useful than non-personalized reviews.*

When trying to assess the value of information, people make causal attributions to help them in the process (Friestad & Wright 1994); furthermore, review literature shows that attribution does partially mediate the relationship between a review and its value (e.g., Chen, Teng & Chiou, 2019; Chen & Lurie, 2013). Review literature also shows that credibility is another heuristic cue applied to online reviews to help readers make faster decisions about the trustworthiness of a review (Chaiken & Maheswaran, 1994). Source credibility is one of few factors that has been shown to directly affect the perceived information usefulness (e.g., Cheung et al., 2009; Cheung et al., 2008; Sussman & Siegal, 2003), as well as its persuasiveness (Willemsen, Neijens, & Bronner, 2012). Based on our previous assumptions on attribution and credibility, we propose that:

> **H5a:** *Causal attribution mediates the effect of personalization on the perceived value of online reviews.*

> **H5b:** *Perceptions of increased (vs. decreased) reviewer credibility mediates the effect of personalization on the perceived value of positive (vs. negative) online reviews.*

3.3 Conceptual model

To offer a detailed overview of our framework and hypothesis, we introduce and illustrate a conceptual model. As our literature review has covered, there are many factors involved when it comes to the response to an eWOM communication i.e., what determines if a consumer actually uses a specific review or not. Cheung & Thadani (2012) gathered many of the already defined factors in their literature analysis of eWOM research, showing that the stimuli, context, receiver knowledge and perceived attributions towards the reviewer, all influence the response in different ways. Schmäh et al. (2017) expand even further on this topic in their systematic literature analysis, highlighting relevant literature that could shed light on the status quo of eWOM research. Based on these existing literature analysis papers as a guide and our literature review, we proposed an expanded integrative model, based on Cheung & Thadani's (2012) model, and include personalization. The model, as seen in Figure 2 illustrates how we expect personalization cues to influence credibility, and further decision-making. Through our experiments we aim to investigate the moderation and mediation effects, as proposed in Figure 1.

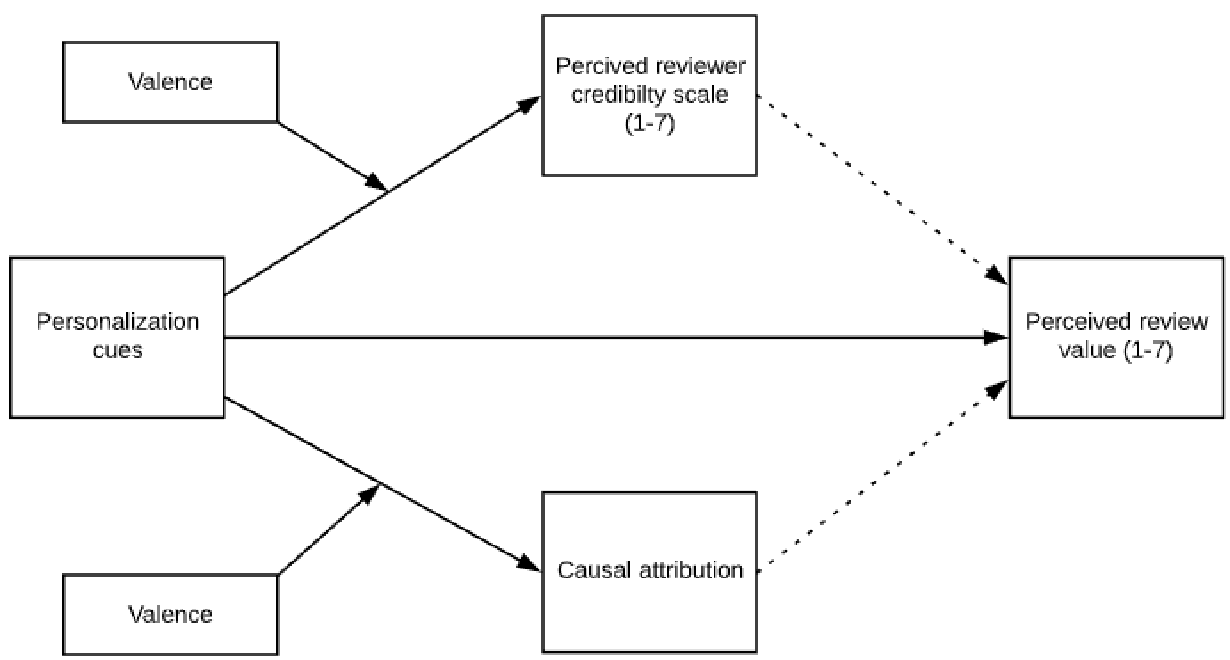

Figure 1: Expected mediation and moderation effects on review value

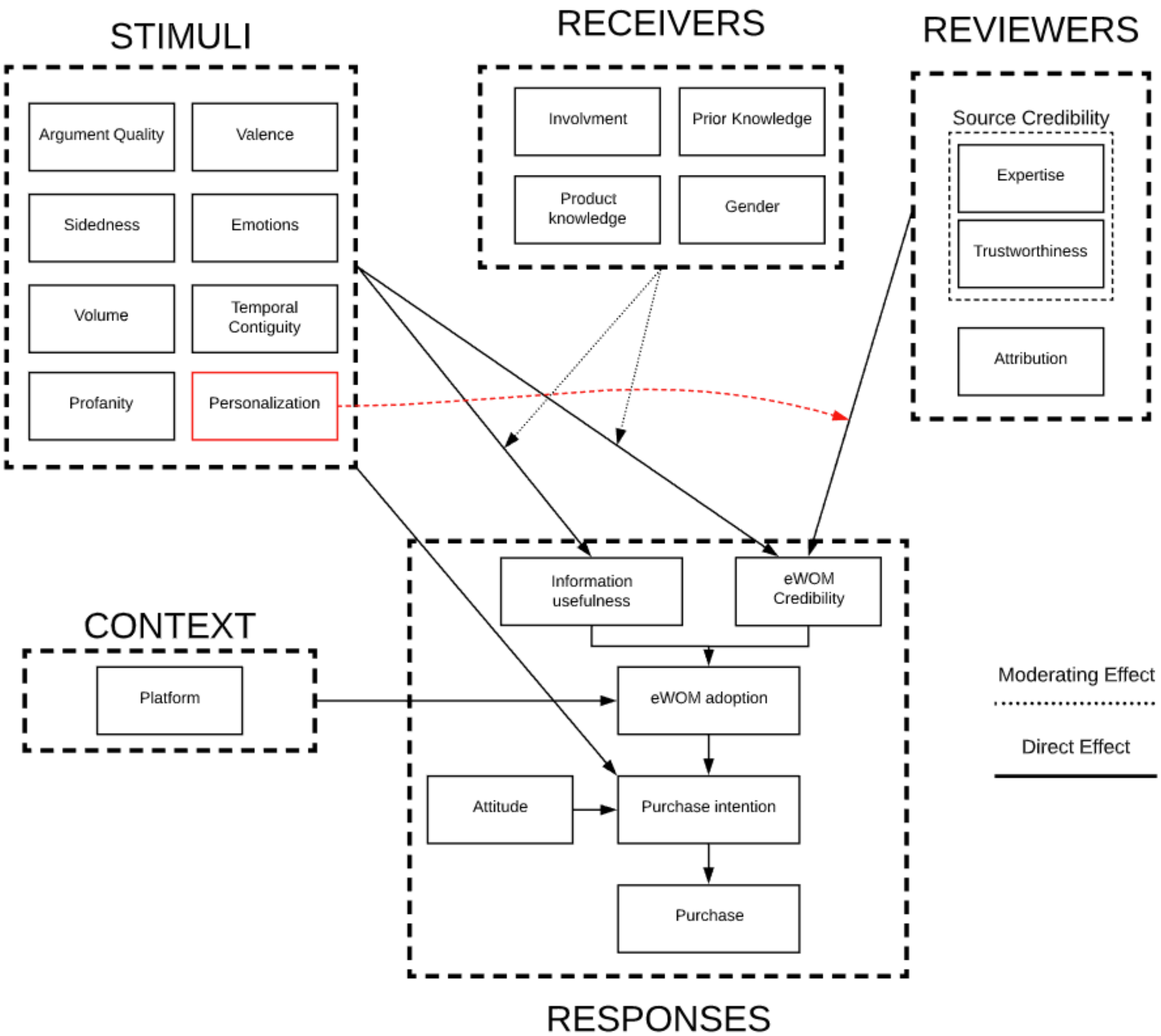

Figure 2: An expanded framework of the impact of eWOM factors on consumer response, adopted from Cheung & Thadani (2012).

Methodology

4.1 Research philosophy

To guide us in our quest to understand personalized reviews and lead us to our methodological choice, it is essential to define our research philosophy. This will influence the way we conduct our research and write our thesis. The paradigm is the worldview that helps us define the nature of the world, the place that we occupy in it, and our possible relationships to it (Guba & Lincoln, 1985). In this paper, we will employ a positivist paradigm, as it suits the nature of the research that we will conduct.

The following passage will describe the ontological, epistemological, and methodological assumptions of positivism which we will relate to the research of this paper.

The ontological level of positivism is realism (Lincoln & Guba, 1985). In a realist stance, the researcher's view of the nature of reality is external, objective, and independent of any social actors (Thornhill, Saunders & Lewis, 2009). The reality that exists is an apprehendable one and is driven by immutable natural mechanisms and laws (Lincoln & Guba, 1985). Knowledge of the way things are is in the form of time-free and context-free generalizations (Lincoln & Guba, 1985).

The epistemological level of positivism is that of dualism and objectivism (Lincoln & Guba, 1985). This paper's view of what constitutes acceptable knowledge is based only on observable phenomena. That is considered the only way to provide credible data and facts (Thornhill et al., 2009). The investigator and investigated object are assumed to be independent entities whereas the authors will study the object while neither being influenced by it nor by influencing it (Lincoln & Guba, 1985). Inquiry will take place as a one-way mirror with a focus on preventing influence on outcomes from any biases (Lincoln & Guba, 1985). Replicable findings will be considered to be true (Lincoln & Guba, 1985).

Lastly, the methodological question answers how the inquirer can go about finding out what they think can be known (Guba & Lincoln, 1994). The core of the positivist approach is to conduct experiments and test hypotheses. Our methodology for this thesis is experimental and manipulative. The purpose of our inquiry will be the explanation of a phenomena – personalization in online reviews, which will ultimately enable its prediction and control (Lincoln & Guba, 1985). We will take an explanatory deductive approach. First, we deduced hypotheses based on existing theories. The hypotheses are expressed in operational terms by indicating exactly how the variables will be measured (Thornhill et al., 2009). We will further create an experiment to verify the hypotheses, examining the specific outcome of our inquiry regarding attribution, credibility, and value of personalized reviews. We will be using controls to allow the testing of hypotheses. Sufficiently numerical sample sizes will be chosen to enble us to statistically generalize regularities in human behavior (Thornhill et al., 2009). Once verified, the hypotheses will be established as facts (Lincoln & Guba, 1985).

4.2 Study 1: The prevalence of personalized reviews in the field

4.2.1 Aim of the study

The aim of Study 1 is to help us confirm the existence of personalized reviews and find out their prevalence among online reviews. We also aim to answer H1 according to which we expect that personalized reviews are more likely to be positively valanced than non-personalized reviews. While several aspects from psychology would suggest this to be the case, we employ field data to confirm our assumptions. Lastly, Study 1 is meant to enable us to get a first glimpse, through field data, at the value of personalized online reviews, as observed through the assigned usefulness votes by readers of reviews. This will be done by either accepting or rejecting H4c.

4.2.2 Data collection

Study 1 examines the prevalence of personalized reviews and their valence on the Trustpilot platform. We choose this data source for two reasons. Firstly, because the meta-information presented on Trustpilot is more prevalent and more reliable than other platforms, whereas textual data is not length-restricted (Johannsen et al., 2015). Secondly, because of the high volume of reviews available on Trustpilot. According to Trustpilot (2020b), in any given month there are over 1.6 million reviews shared on the platform. Trustpilot is a third-party platform where the companies being reviewed have the option of taking over their review profile page by purchasing a service tier from Trustpilot and claiming their profile. Nonetheless, the companies who do claim their profiles have limited influence on which reviews are being showcased (Trustpilot, 2020b). Before leaving a review on Trustpilot, users must verify their identity with either Facebook or Google profiles, or their email address (Trustpilot, 2020c). Users both leave a rating in the form of stars, from one to five, and a written text.

We gather data from the profile of online travel agent (OTA) Kiwi.com. Kiwi.com offers a flight search with flight connections that include an insurance serviced by Kiwi.com. We choose Kiwi.com because it is easily observable that among the reviews left by users on their Trustpilot profile are also personalized ones. But also, because they are active in the travel industry and tourism-related content is the most shared and consumed by users (Miguens, Baggio & Costa, 2008).

We wrote a Python script that extracted 8.617 reviews about Kiwi on Trustpilot, out of which 1.750 were removed from the dataset as they did not include any review text and only a headline. The dataset contains all the reviews written about Kiwi on Trustpilot platform from 26th of June 2019 until 29th of February 2020. In our data set each review included the following parameters. The star rating of the review to determine its valence, on a five-point scale, where 5 is the highest rating, the number of reviews left by the participant, review text, both title and body, review date and the volume of useful votes that each review received. Appendix A shows a sample of a review on Trustpilot that showcases each variable that was extracted. The code for the Python script can be found in Appendix B.

4.2.3 Measures

One of our aims with Study 1 was to identify if there was any effect to be found from a personalized cue in an online review. We chose value as our dependent variable. The value was extracted by looking at “useful” votes each review received from users of Trustpilot. For our independent variable we used *review valence* and *personalization cues*. The valence was extracted through the star rating of the review, which is a 5-point scale, rating reviews from 1 to

5 stars, 5 stars being the highest rating possible. In our dataset, the average review was very positive (M = 4,37 out of 5). The overall distribution was that 84,8% of the reviews were positive (4 or 5 stars), 2,8% were neutral (3 stars) and only 12,5% of the reviews were negative (1 or 2 stars). This distribution in our dataset aligns well with the overall distribution of review ratings on Trustpilot according to previous research (Schoenmüller, Netzer, & Stahl, 2019).

Personalization cues are the given names, family names or nicknames of a customer facing employee that the reviewer mentions in an online review. Reviews that mention a person only by personal pronoun (e.g., he, she) and/or refer to the customer facing employee in a general way such as: “the customer service representative” or “the lady I spoke to” do not count as personalized reviews. Unless these are also accompanied by a name. We set this binary variable to 1 when a review contained the personalization cue, and to 0 when it did not.

Given the large number of reviews, hand coding of all personalization cues was not. One author read 1500 reviews and coded for the presence of personalization cues to capture names of Kiwi.is employees. We extracted 107 different names that were used in Kiwi’s reviews and inserted them into a text library together with a list of popular names around the world, namely in India and the US (see Appendix C). Names that matched airlines were only included with punctuation so they would not trigger specific airlines names rather than a personalized review. These were for example, Thomson as in Thomson Airways, Ryan as in Ryanair and Logan as in Loganair, Roy in Royal Air. Similar adjustments had to be made regarding service employees that shared names with cities and countries, e.g., Pari in Paris, Mia in Miami, Roman in Romania, Santi in Santiago, and Philip in Philippines. Finally, some names had to be removed, such as Sofia and Doha since they match city names, and also names that correspond to certain months such as June, April, and August.

Two interrater reliability checks were made to ensure the reliability of our data (Landis & Koch, 1977). First, 500 reviews that had not been read were checked and compared to the automatic output. The interrater reliability for our program was only Kappa = 0.591 ($p < 0,001$). Every name that was found in the 500 reviews was added to the list of names. A few hundred reviews, from each month in our data set were checked, and names were added to the list. Our second interrater reliability check resulted in a Kappa = 0.789 ($p < 0,001$) which is in the upper bounds of a substantial agreement between our system output and hand coded data (Landis & Koch, 1977). Out of the 6.867 remaining reviews, 909 (13,23%) were labeled as personalized by matching them to our library of names. Table 1 includes the descriptive statistics from Kiwi's Trustpilot data.

	Total	With personalized cues	Without personalized cues
N	6.867	909	5.958
Valence (1-5 stars)	4,25	4,18	4,71
Number of "Useful" votes	0,09	0,04	0,1
Word count	46,46	54,71	45,20
Number of reviews	1,15	1,47	1,52

Table 1
Kiwi's Trustpilot data - Descriptive statistics

4.2.4 Results

To check for H1, according to which we expect that personalized reviews are more positive than non-personalized reviews we ran a simple t-test on our sample data. Our results indicate that personalized reviews ($M_{personalized}$ = 4,71; SD = 0,87) are rated substantially more positive than non-personalized reviews ($M_{non\text{-}personalized}$ = 4,18; SD = 1,46). We can thus accept our hypothesis that those who post personalized reviews have a more positive image of the company than those who do not include the name of the person that they interacted with. It can be argued that it is not a good comparison to compare those who spoke to customer service and those who might not have had the same interaction with the company. We therefore opted to extract the average rating from reviews that mentioned customer service, and the outcome is even lower than an average review rating ($M_{customer\_service}$ = 4,03; SD = 1,58).

Looking at the analysis by Chen & Lurie (2013), that had a similar dataset, and the fact that we have a continuous count variable of review value, we look towards either Poisson regression or negative binomial regression to analyze the data (Cameron, Trived & Chester 1998). As the sample groups are vastly different in size and an overdispersion is present (M = 0,08; variance =

0,118), we opted to use a negative binomial regression to assess how the useful vote variable behaved in the Kiwi reviews on Trustpilot (Cameron et al., 1998). A negative binomial model was used to examine the relation of valence, review usage, word count, and possible effects of *personalization cues* on the number of useful votes.

Combined, our predictors accounted for a significant amount of variance in the model with a likelihood ratio of $\chi 2$ (4) = 1640,273; $p < .0001$. Review usage and *personalization cues* were not significant predictors of useful votes, ß = -0,008; SE = 0,021; p=0,692; CI[-,008 to .032] and ß = 0,126; SE = 0,1846; p=0,462; CI[-.236,.487] , respectively. Number of words in the review and its valence were significant predictors of useful votes ß = 0,001; SE = 0,0003; p=0,01; CI[.000 to .001] and ß = -1,053; SE = 0,0383; $p < 0,001$; CI[-1.128,-.978] respectively. Hence, as the amount of words increase and the valence of the review goes down, the more helpful votes it receives. These results would suggest that *personalization cues* are not a significant factor of value of reviews. We plan, however, on investigating the value of personalized reviews further, and will elaborate on the subject in the following discussion.

4.2.5 Summary and discussion

Our field experiment confirms the prevalence of personalized reviews as they represent 13,23% of the total reviews that were included in Study 1. The results allow us to accept hypothesis H1 according to which personalized reviews are more positive than non-personalized reviews. An explanation for these results might be that consumers who received exceptional service are more motivated to thank the person that help them, than those who only received acceptable service.

Alternatively, people might not be as likely to take the time to thank a company for the help, as they are when they feel an individual helped. People might also like to leave positive personalized reviews to signal expertise. Knowing the service representative by name could be observed as a proof of deeper knowledge of the company and the service they offer. Furthermore, it is understandable that people would not leave negative personalized reviews as it might put them personally in a bad light and show an interpersonal conflict. A negative non-personalized review, on the other hand, simply shows a dissatisfied customer.

We aimed to answer H4c through field data. However, the data available was not sufficient, as reviews on Trustpilot barely have usefulness votes. 93% of our data set had zero useful votes. We are therefore unable to either confirm nor deny H4c through Study 1.

Although our negative binomial regression did not suggest that personalization affects value, personalized reviews were clearly more positive than non-personalized reviews. The negative binomial regression analysis suggests that the amount of information presented in a review (word count) and the valence of it (rating) influences how people perceive the usefulness of a review. This would be in-line with previous research that shows a positive relationship between length of reviews and the effect on purchase (Maslowska, Malthouse & Bernritter, 2017), as well as negativity bias (Baumeister, Bratslavsky, Finkenauer, & Vohs, 2001).

It is worth mentioning the recent development on Kiwi's Trustpilot page which makes it clear that people who resonate with a negative review are more likely to use the useful vote button, than those resonating with a positive one. As Covid-19 hits Kiwi hard, average rating in March 2020 was 2,27 while in January and February it was 4,35 and 4,3 respectively. At the same time, useful votes in January and February combined were 355 while in March they were 1817. It is unlikely that the usefulness of reviews in the case of Kiwi has drastically changed while they are battling a force majeure due to a complete shutdown of air travel worldwide. We thus aim to investigate in our study 2, how consumers truly evaluate a personalized review, past the action of using a useful vote button as a sole indicator of value.

Even though we collected and analyzed a large dataset (N = 6.876), we are missing an understanding into the mind and motivations of the reader. We are unable to determine with certainty what effects personalization has on perceived value, source credibility and causal attribution, all factors that can influence decision making, and eWOM adoption (Cheung & Thadani, 2012). As personalized reviews exist, and there is a difference between them and non-personalized reviews, simply based on the ratings associated with them (and implicitly valence), we suggest a controlled experiment that addresses these limitations. We therefore propose a Study 2, in which we will proceed by manipulating a review on valence and personalization, based on the attributes that we observed in Study 1. We will test for various perceptions that the reader might hold, to assess the impact of personalization.

4.3 Study 2: Value, credibility, and attribution of personalized reviews.

4.3.1 Aim of the study

Study 2 builds on the knowledge that personalized reviews do indeed exist, and they are not a rare occurrence, as confirmed by Study 1. As people do leave personalized reviews, it is of interest to determine their value towards the customers who read them, and incidentally for the company itself. Study 1 also confirmed that personalized reviews differ on valence compared to non-personalized reviews, as they are more prevalently positive. We therefore propose Study 2 to investigate the value of personalized reviews in a controlled environment. In this study we aim to answer the question:

How do personalization cues in online reviews influence attribution, credibility, and usefulness of the review?

Study 2 addresses hypothesis H2 according to which we expect that personalized reviews are attributed to the reviewer to a higher degree than non-personalized reviews. Study 2 also aims to understand the effect of valence of personalized reviews on credibility and value of the review. Therefore, we will collect data that will allow us to either accept or reject H3a, H3b, H4a and H4b.

Study 2 will enable us to answer H3a according to which positive personalized reviews are expected to be perceived as more credible than positive non-personalized reviews; and its counterpart H3b which states that negative personalized reviews are expected to be perceived as less credible than negative non-personalized reviews. According to H4a, we expect that positive personalized reviews are perceived as more valuable than positive non-personalized reviews. We aim to confirm H4b according to which we expect negative personalized reviews to be perceived as less valuable than negative non-personalized reviews. Lastly, Study 2 aims to accept or reject H5a and H5b which investigate the mediation effects of attribution and credibility.

4.3.2 Data collection

To test our hypothesis H2 to H5, we hired 415 participants (57.1% males; M_{age} = 33.83; SD = 11,52) from the online survey platform mTurk. Each respondent was randomly assigned to one of four 2 (personalized cues: personalized vs. non-personalized) x 2 (review valence: positive vs. negative) between-subjects conditions. They were then presented with a short survey about the review they read.

Participants were first subjected to a message about the scenario in which the customer found themselves in to help the respondents to put themselves in the shoes of someone who is reading the reviews in real life. The customer was planning a holiday and had found tickets with an unfamiliar airline. To determine the trustworthiness of the company and get an insight into how they handle service failure, the participants look at online reviews. Participants were then shown one of four possible reviews. The stimuli can be found in Appendix D. Then the participants were asked a question about the usefulness of the review for their decision making. Afterwards followed a set of randomized questions about the reviewer credibility and causal attribution. Finally, the participants were subjected to a manipulation check on both valence and personalized cues. We also checked for online review usage as well as two questions related to credibility. All these factors were adjusted for and checked statistically in our results.

4.3.3 Stimuli development

The stimuli were based on the average length of our Study 1 sample and aimed to match a real personalized review. We manipulated valence and personalization between the reviews. The valence manipulation was done by using positive and negative adjectives. The personalization manipulation was done by either having a name of a specific customer service representative present in the review or only the company name. The stimuli can be found in Appendix D. All four reviews were about an airline booking, where a reviewer contacted the company to get help with a booking. A fictional name for the airline was chosen - Laris Airlines, to control for possible familiarity. We ran a few separate pre-tests on our stimuli to make sure that the manipulation would check out. Our initial stimuli was pre-tested on 43 participants, and both valence ($p < ,001$) and personalization ($p = 0,005$) were significant but we were unhappy with the variance of responses regarding the personalization manipulation ($M_{personalized} = 4,35$; $SD = 1,3$; $M_{non\text{-}personalized} = 2,96$; $SD = 1,66$) . We thus adjusted both the stimuli as well as our manipulation check questions and ran another pre-test on 98 participants. Our manipulation checked out ($p < ,001$) and our mean difference was acceptable ($M_{personalized} = 6,40$; $SD = 0,89$; $M_{non\text{-}personalized} = 3,47$; $SD = 2,35$). Finally, as we will address in our limitation, we noted many non-native English speakers in our pretests, and it was evident that they had a harder time interpreting the manipulation and the questionnaire. We thus opted to run our main study at a time where the pool of respondents would be predominantly located in the US. As our manipulation checks will show, this turned out to be a good choice, as the survey was written in English.

4.3.4 Measures

To capture *review value*, we looked to Chen & Lurie (2013) which adapted the questions from Sen & Lerman (2007). On a nine-point bipolar-scale from (1 ="very unlikely," and 9 - "very likely") we asked: "*Assuming that you were considering flying with Laris Airlines in real life, how likely would you be to use this review in your decision making*?". To assess the *causal attributions,* we drew from Chen & Lurie (2013) which adapted the questions from Frank & Gilovich (1989) and measured both reviewer and product attribution. *Reviewer attribution* was measures by asking participants the following question on a nine-point scale (1 - "minimal role," and 9 - "maximal role"): "*How large of a role do you think that the reviewer's personal factors (e.g., the reviewer's personality, traits, character, personal style, attitudes, mood) played a role in their decision to write this review?".* Product attribution was measured on the same scale with the following question: "*How large a role do you think service experience (e.g., service quality, service delivery) played in the reviewer's decision to write this review?".* To calculate the causal score, we subtracted the reviewer attributions from product attributions, leaving us with scores that indicated how much of the review was attributed to the product rather than the reviewer. Higher score meaning more attribution to product rather than reviewer and vice versa. This was based on Chen & Lurie (2013) who adapted it from Frank & Gilovich (1989).

Finally, we checked for the perceived *credibility of the source* by asking participants to rate the reviewer on six factors, on a seven-point scale. These factors were adapted from Chu & Kamal (2008) which based it on Choi & Rifon (2002). The factors were, “*believable/unbelievable*," "*credible/not credible*," "*trustworthy/not trustworthy*," "*dependable/not dependable*," "*reliable/unreliable*," and "*reputable/unreputable*". The scores were then averaged to get a measurement of a credibility score.

We drew from Chen & Lurie (2013) to check for valence manipulation, by asking participants on a seven-point scale to indicate how they perceived the review (1 = "*very negative*," and 7 = "*very positive*"). To make sure our personalized cue manipulation was noticed, we asked participants if they agreed or disagreed with the following statement: “*Think about the review you read. Did it mention the name of a service representative?*”

4.3.5 Results

4.3.5.1 Manipulation check

Both of our manipulations checked out. The 206 participants that were assigned a negative review (M = 2,22; SD = 1,571) indicated that they perceived it a lot more negatively than the 209 participants that were assigned a positive review (M = 6,14; SD = 1,109). The difference between groups was significant t(413) = 29,407, p < ,001. The 196 participants that were assigned a personalized review (M = 6,40; SD = 1,222) noticed the presence of the service representative compared to the 219 participants (M = 2,84; SD = 2,006) that were only presented with a company review. These results were also significant t(413) = 21,512; p < ,001.

While the interaction between valence and personalization was not significant (p = ,307) participants that were presented with a positive personalized review (M = 4,40; SD = 2,387) tended to perceive it more positively than those who were presented with a positive non-personalized review (M = 4,02; SD = 2,375), t(413) = 1,622; p =,106. This difference was driven by the fact that positive personalized reviews were generally perceived as more positive than the positive non-personalized reviews, while the negative reviews did not differ in perception.

4.3.5.2 Causal attribution

The first hypotheses that we assess pertain to the causal attribution by the reader of the review. We hypothesized that personalized reviews, regardless of valence, would be attributed to the reviewer rather than the company, for several reasons (H2). To determine if this is the case, we look at the interaction between valence and personalization on *causal attributions*. As previously mentioned, *the causal attributions score* was computed by subtracting reviewer attribution from company attribution, leaving us with a score that, when it increases, the attribution towards the product or service increases, and vice versa. We then subjected the causal attributions score to a 2 x 2 between subjects ANOVA (Analysis of variance). Below in Table 2, we have summarized the results, each group's means, standard deviation, and the ANOVA results from the four conditions. The interaction between personalization x valence is also presented graphically in Figure 3. Neither age (p = ,054) nor education (p = ,300) influenced our model.

	Positive reviews	Negative reviews
Personalized reviews	*n* = 102 (24,60%) Mean = 0,451 SD = 1,675	*n* = 94 (22,70%) Mean = 0,745 SD = 1,989
Non-personalized reviews	*n* = 107 (25,80%) Mean = 0,6542 SD = 1,776	*n* = 112 (27%) Mean = 1 SD = 2,05

Table 2a
Descriptive statistics
(Causal attribution)

Independent Variables	**Mean Square**	**F-value**	**p-value**
Review personalization	*5,431*	*1,538*	*0,216*
Valence of reviews	*10,563*	*2,991*	*0,084*
Personalization x Valence	*0,070*	*0,020*	*0,888*
Error	*3,531*		

Table 2b
ANOVA results of 2x2 experiment of personalization and review valence on causal attribution

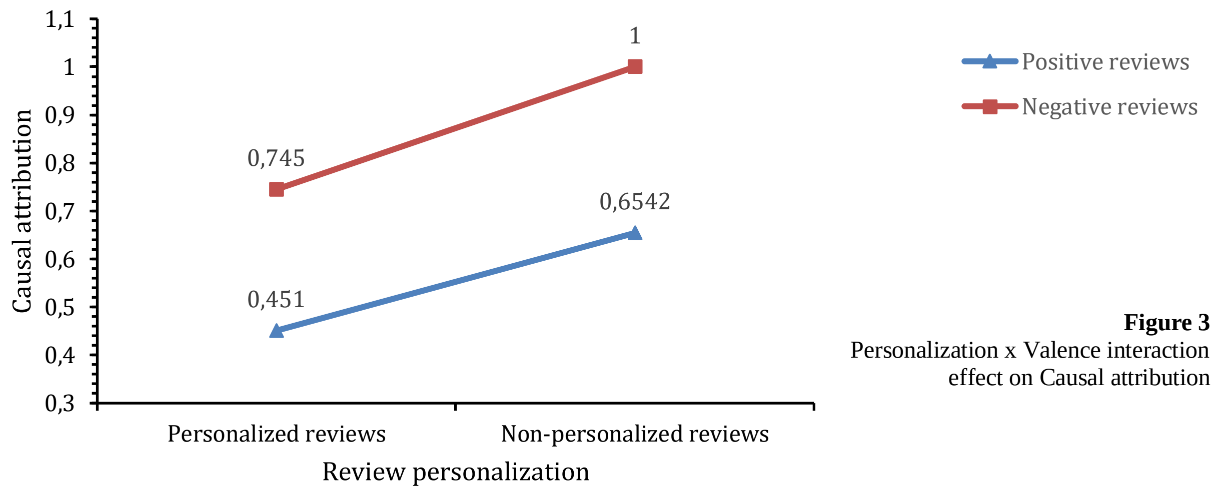

Figure 3
Personalization x Valence interaction effect on Causal attribution

Neither valence of review (F (1, 411) = 2,991; p = ,084) nor review personalization (F (1, 411) = 1,538; p = ,216) had a main effect. Moreover, the valence x personalization interaction on causal attributions was far from being significant (F (1, 411) = 0,07; p = ,888). It is worth noting that both valence and personalization showed a tendency, where personalized and positive reviews were attributed more to the reviewer than the company. But as none of the effects were significant, we reject H2. We also ran a check on the following covariates; usage of online reviews (p = ,156), review written for other reasons than relying information (p = ,439) and unreasonable preferences of reviewers (p = ,665), none of which had a significant impact on our model.

Although we did not hypothesize it, we checked to see if the gender of the participant would result in a difference in causal attribution. An independent sample t-test revealed that the gender of the reader does play a role in how they attribute the review. Males (M = 0,498; SD = 1,856) attributed the review more to the reviewer than females (M = 1,01; SD = 1,883), at a significant level t(413) = -2,77, p = ,006. Contrasting personalized and non-personalized reviews reveals that the difference is only significant in the case of non-personalized reviews (t(217) = -2,14; p=,034) but not in the personalized reviews (t(194) = -1,63; p=0,103). There is however a limitation to our study as the personalized reviews only had one gender, which we will address in our discussion, and in Study 3.

4.3.5.3 Perceived reviewer credibility

To test for hypothesis H3a and H3b we look at the interaction between valence and personalization on *perceived reviewer credibility*. The reviewer credibility score was computed by averaging the six items related to source credibility. In our survey we included two control questions which checked for unreasonable preferences of reviewers (p = ,209), as well as the participants' opinion on the statement that people might leave reviews for other reasons than to relay information (p = ,728). Neither of these covariates turned out to be significant but in our final model we included the covariant of usage of online reviews (p < ,001). We thus conducted an ANCOVA (see Table 3b) in which the dependent variable was the perceived reviewer credibility whereas the independent variables were valence and personalization. Usages of online reviews served as a covariant. The interaction between the four conditions is illustrated in Figure 4 and descriptive statistics can be found in Table 3a. Neither age (p = ,194), nor education (p = ,741) influenced our model.

	Positive reviews	Negative reviews
Personalized reviews	*n* = 102 (24,60%) Mean = 5,464 SD = 1,03	*n* = 94 (22,70%) Mean = 4,851 SD = 1,259
Non-personalized reviews	*n* = 107 (25,80%) Mean = 5,3 SD = 1,138	*n* = 112 (27%) Mean = 4,949 SD = 1,05

Table 3a
Descriptive statistics
(Perceived reviewer credibility)

Independent Variables	**Mean Square**	**F-value**	**p-value**
Review personalization	*0,001*	*0,001*	*0,980*
Valence of reviews	*20,398*	*17,772*	*0,000*
Personalization x Valence	*0,789*	*0,688*	*0,407*
Error	*1,148*		

Table 3b
ANCOVA results of 2x2 experiment of personalization and review valence on perceived reviewer credibility

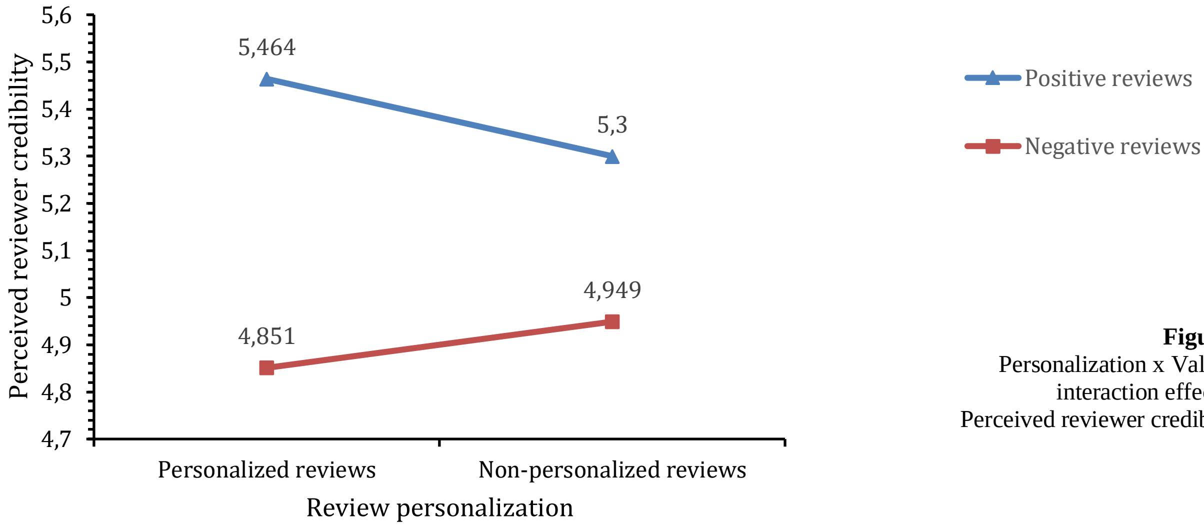

Figure 4
Personalization x Valence interaction effect on Perceived reviewer credibility

We hypothesized that positive personalized reviews would be perceived as more credible than non-personalized reviews (H3a), and that negative personalized reviews would be perceived as less credible than non-personalized reviews (H3b).

Review personalization (F (1, 410) = 0,001; p = ,980) did not have a main effect on credibility whereas valence (F (1, 410) = 17,772; p < ,001) did. The valence x personalization interaction on perceived reviewer credibility showed a tendency but was not significant (F (1, 410) = 0,688; p = ,407). This leads us to reject both H3a and H3b. If we look to the main effect of valence, and contrast our conditions with a pairwise comparison, while also including our covariant, we note that positive personalized reviews (M = 5,409; SE = ,106) and negative personalized reviews (M = 4,876; SE =,111) differ at a significant level (p < ,001). However, the same effect is noted in the non-personalized reviews, although at a less significant level (p = ,014).

4.3.5.4 Perceived review value

Finally, hypothesis H4a and H4b can be confirmed or rejected by a look at the interaction between valence and personalization on *perceived review value*. We also ran a check on the following covariant; usage of online reviews (p < ,001), preconception that people might have other reasons than relying information for leaving reviews (p = ,837), and unreasonable preferences of reviewers (p = ,814), so our model includes usage of online reviews as a covariant. We conducted an ANCOVA (see Table 4b) in which the dependent variable was review value, and the independent variables were valence and personalization. The interaction between the four conditions is illustrated in Figure 5 and descriptive statistics can be found in Table 4a. Neither age (p = ,982) nor education (p = ,408) influenced our model. The Levene's test for equality of variance resulted in a violation. Although ANOVAs (Analysis of variance) are generally expected to be fairly reliable towards such a violation (Ito, 1980) we will employ non-parametric tests to confirm our significant findings (Colliander, Söderlund, & Marder 2019; Marder, Erz, Angell, & Plangger, 2019). For t-test we will use report results according to Levene's test outcome, as it is built into the t-test.

	Positive reviews	Negative reviews
Personalized reviews	*n* = 102 (24,60%) Mean = 5,42 SD = 1,375	*n* = 94 (22,70%) Mean = 4,65 SD = 1,938
Non-personalized reviews	*n* = 107 (25,80%) Mean = 5,27 SD = 1,425	*n* = 112 (27%) Mean = 5,07 SD = 1,675

Table 4a
Descriptive statistics
(Perceived review value)

Independent Variables	**Mean Square**	**F-value**	**p-value**
Review personalization	*0,810*	*0,320*	*0,572*
Valence of reviews	*28,222*	*11,147*	*0,001*
Personalization x Valence	*1,920*	*0,758*	*0,384*
Error	*2,735*		

Table 4b
ANCOVA results of 2x2 experiment of personalization and review valence on perceived reviewer credibility

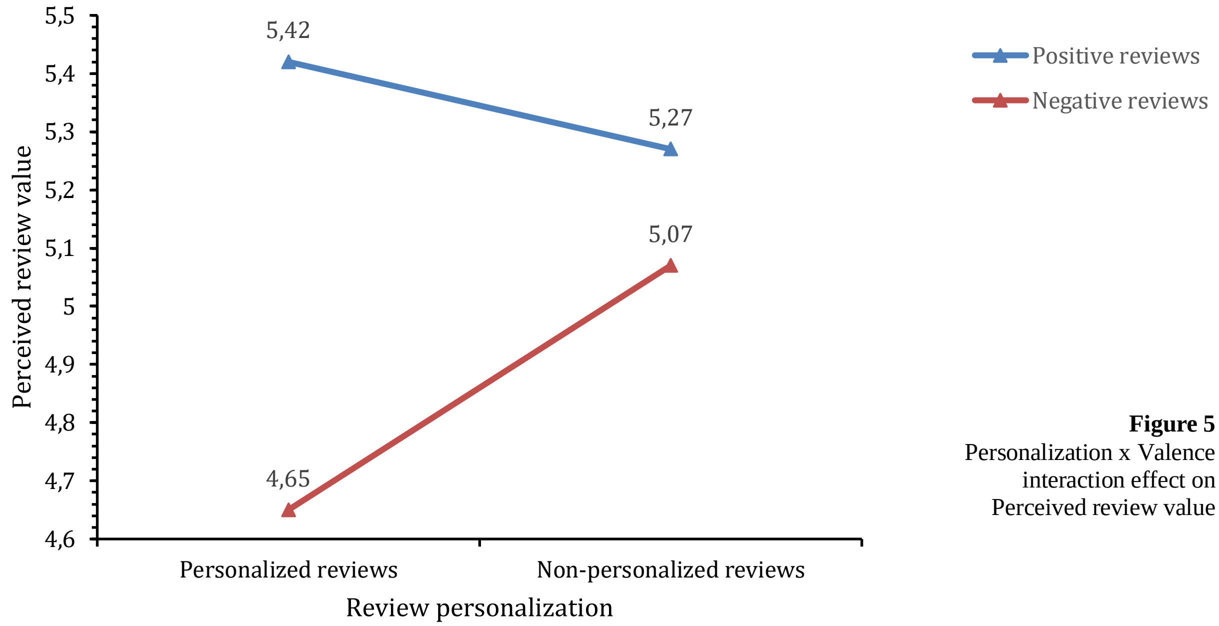

Figure 5
Personalization x Valence interaction effect on Perceived review value

Similarly, in perceived reviewer credibility there is a tendency to be observed. We hypothesized that positive personalized reviews would be perceived as more valuable than non-personalized reviews (H4a), and that negative personalized reviews would be perceived as less valuable than non-personalized reviews (H4b).

Review personalization (F (1, 410) = 0,082; p = ,774) did not have a main effect on value, while valence had a main effect on value (F (1, 411) = 34,206; p < ,001), supported by an additional Mann-U Whitney test (U = 17151,000; p = 0,004). The valence x personalization interaction on perceived review value had a tendency but was not a significant effect (F (1, 411) = 1,469; p = ,226). This leads us to reject both H4a and H4b. But if we look to the main effect of valence, and contrast our conditions with a pairwise comparison, we note that positive personalized reviews (M = 5,42; SD = 1,375) and negative personalized reviews (M = 4,65; SD = 1,938) differ at a significant level (p < ,001), supported by an additional Mann-U Whitney test (U = 3801,000; p = 0,01). This effect is not significant among non-personalized reviews (U = 4800,500; p = 0,121).

Interestingly, our research contradicts previous studies on online review value (Chen & Lurie, 2013). Generalized negativity bias, which Chen & Lurie (2013) based their hypothesis on, suggests that negative reviews, i.e. consumer information, are rarer and thus considered more valuable (Baumeister, et al., 2001). Yet in our results, positive non-personalized reviews (M = 5,27; SD = 1,425) are perceived to be more valuable than negative ones (M = 5,07; SD = 1,675), close to a significant opposite effect (p = ,091).

4.3.5.5 Mediation and moderation modeling

We hypothesize that attribution and credibility would mediate the relationship between personalization and review value. We thus ran a few statistical models to see if personalization, valence, or a combination of both variables, would influence attribution, credibility, or review value. As we have covered in previous sections the interaction between personalization and valence was not significant on any of our dependent variables. We thus reject our hypothesis that perceptions of decreased product attributes mediate the effect of personalization on the perceived value of online reviews (H5b). We also reject the assumption that perceptions of increased (vs. decreased) reviewer credibility mediates the effect of personalization on the perceived value of positive (vs. negative) online reviews (H5c).

We did however reveal that valence played a role and was a significant predictor of both credibility and value, especially in the personalized reviews. We also noted that perceived credibility and review value behaved similarly in positive and negative reviews. It is evident from literature review that source credibility is a key factor in eWOM adoption (e.g., Cheung et al., 2009; Cheung et al., 2008; Sussman & Siegal, 2003), but research is at odds on how valence influences that relationship (Lim, & Van Der Heide, 2015, cf. Kusumasondjaja et al., 2012) Based on that we opted to investigate if perceived credibility mediates review value.

We collapsed our data to investigate the role that *valence* and *credibility* play, regardless of personalization of reviews. We ran PROCESS v.3.4 - Model 4 in SPSS to check for a possible mediation (Hayes, 2013). Valence was set as an independent variable (1 = positive, 0 = negative). *Credibility* was selected as a mediator, with *review value* as the dependent variable and review usage was controlled for. The model was applied to all four conditions from 415 responses. Results from PROCESS exports can be found in Appendix E and are illustrated in Figure 6.

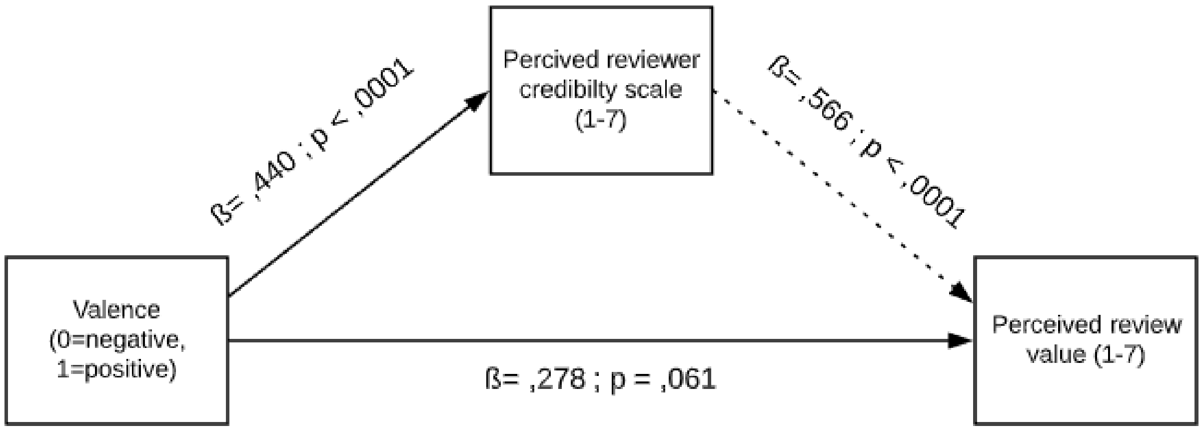

Figure 6: Indirect effect of valence via perceived reviewer credibility.

For our reviews, perceived source credibility mediated the relationship between valence and perceived review value (ß= ,301; SE=0,8 95% *CI*[0,16 to 0,47]. The direct effect of valence was not significant (ß= ,256; p = ,088) and CI crossed zero. The total effect of valence on value was significant, (ß= ,513; p = ,0006; 95% *CI*[0,24 to 0,88]. When isolating total effect for personalized reviews (ß= ,656; p = ,0051; 95% *CI*[0,20 to 1,11] and non-personalized reviews (ß= ,387; p = ,072; 95% *CI*[-0,03 to 0,81] the total effect results were significant, albeit marginally, for personalized reviews. We will thus address that in our third study and investigate if credibility mediates valence in personalized reviews.

4.3.6 Summary and discussion

As Study 1 suggested, personalized reviews differ from non-personalized reviews. Personalized reviews were more positive than non-personalized according to Study 1, while they were also perceived as more positive, than positive non-personalized reviews, by our participants in Study 2. Our aim for the research however was to answer the following research question:

How do personalization cues in online reviews influence attribution, credibility, and usefulness of the review?

As our literature review reveals, all three factors might be affected by the presence of personalization in the stimuli (Cheung & Thadani, 2012).

Causal attribution was addressed by subtracting the reviewer attribution from the company attribution. Our results indicated that personalized reviews were attributed more to the reviewer than the company, but not at a significant level. We therefore reject H2 which assumes that personalized reviews, regardless of valence, would be attributed to the reviewer to a higher degree than non-personalized reviews.

Perceived source credibility was measured with a six-item scale adapted from Choi & Rifon (2002). Although not significant, positive personalized reviews were seen as more credible that non-personalized positive reviews. As the results were not statistically significant, we reject H3a, which suggested that personalized cues in a positive review influence source credibility.

According to H3b, we expected that negative personalized reviews would be perceived as less credible than negative non-personalized reviews. As previously mentioned, a reviewer who leaves a negative review in which they blame an individual directly might portray a person in an interpersonal conflict, a person who is directing their anger at an individual who is just doing their job. We expected the personalization to decrease the credibility of the reviewer more so than in a non-personalized review, as the review can more easily be perceived as the result of the reviewer's mood or personality traits. Our results however, show no statistical difference between the credibility assigned to a reviewer who leaves a personalized review and the credibility assigned to a reviewer who leaves a non-personalized review. We hence reject H3b.

We also examined the interaction between valence and personalization and whether it would affect source credibility. While we observed a tendency of valence being a bigger factor in personalized reviews than non-personalized ones, both types of reviews were significantly influenced by valence.

Given that there is not a consensus on how credibility influences eWOM adoption we also opted to investigate, regardless of personalization, if credibility would mediate the relationship between valence and perceived review value. Our PROCESS model (shown in Appendix E) revealed that credibility does indeed mediate the relationship, and that valence has a positive effect on value, confirming Lim et al.'s (2015) results.

Perceived review value was measured as the likeliness of participants to use the review in their decision-making. While the interaction between *personalized cues* and valence was clear, it was not significant, leading us to reject the notion that *personalized cues* had an effect on review value compared with non-personalized reviews. We therefore reject H4a and H4b.

The lack of difference in perceived credibility and value of a personalized, as opposed to non-personalized review might be explained by the fact that people perceive the customer service representative as one and the same with the company. Whether a review mentions a customer service representative or a company by name, might not create any difference in the mind of the reader. Bitner (1990) points out that the service encounters with a front-line employee is considered to be the actual service by the customer, leaving no room for differentiation between, for example, the front-line employee as an individual, and the company that they represent. What the employee does, how they speak, behave, is seen as an equivalent to how the company speaks, behaves, and is perceived. In short, the employee is the company, and their actions have a direct effect on the service quality (Bitner, 1990). In conclusion, although we do observe a tendency, our findings suggest that the name of a customer service representative in a review might not be a heuristic cue that readers of reviews use to more easily assess the credibility of a review.

Study 2 had a limitation regarding the gender of the service representative, as we only presented customer service representatives with one gender (male) in the personalized reviews (Mynamestats, 2019). The reviews portrayed a male, Alex, who was referred to by the pronoun "he".

"I called to inquire about my flight booking. I spoke to Alex who made me feel very calm during our conversation. ***He*** *was helpful and I'm so happy with how* ***he*** *handled the situation and quickly solved my issue with my Laris Airlines booking. I feel very lucky that I got to speak to Alex,* ***he*** *made what could have been a stressful situation into a pleasant one. It was the best experience."*

Data analysis revealed that men and women differed on how they perceive the positive personalized review. Similar trends were observed with value, attribution, and credibility. Although they were not significant, we suggest a further study to address this limitation in Study 3. An optimal further study would include a 2x2x2 experiment where the gender of the service representative, valence, and personalization would all be manipulated. But due to time constraints, as well as the fact that both the gender aspect, and enhanced effects of valence were only present in the personalized reviews, we opt to conduct a 2x2 experiment where we will manipulate the gender of the service representative and valence, focusing only on personalized reviews.

4.4 Study 3: Personalized reviews and gender

4.4.1 Aim of the study

The aim of Study 3 is to address the gender limitation present in Study 2. Study 2 only presented customer service representatives with one gender (male) in the personalized reviews. However, McColl-Kennedy, Daus, & Sparks (2003), point out that people's perceptions are influenced by the gender of the service provider, and even by the match between the customer and service provider gender. Frontline service positions are more likely to be filled by women, often due to their roles as emotionally expressive nurturers fueled by stereotypes (Matilda, Grandey & Fisk, 2003). Still, service jobs are generally occupied by both men and women so it is of value to companies to understand how customers and employees respond to, and perceive service encounters based on their gender (Snipes, Thomson, & Oswald, 2006).

We noted in Study 2 that male participants tend to perceive the personalized reviews as more valuable than females, regardless of valence. This tendency between the genders was not noted in our control group. Gender of the participant further affected credibility between our control and manipulation, although not significantly. This study would therefore benefit from investigating the moderation of the gender of participants. However, due to time constraints, we focus only on addressing the gender limitation of Study 2 as it portrays only males in the manipulation.

In Study 2, gender of the participant also influenced attribution, but similarly between our control and our manipulation. Furthermore, attribution did not mediate the relationship between personalization and value. Finally, attribution did not influence credibility nor value in our control group. Thus, we opt to only investigate credibility and value in Study 3.

We aim to find out whether the gender of the customer service representative in the personalized review is what caused the discrepancy in perceived value and credibility by respondents of the two genders. To address this, participants will be presented with personalized online reviews where the customer service representative is portrayed as both female and male.

Therefore, the research question that we aim to answer through Study 3 is:

How does the gender of a service representative in a personalized review influence perceived credibility and review value?

4.4.2 Hypotheses

While attitudes towards women's roles and rights have changed in time, stereotypes remain as strong today as they used to be, particularly in service settings (Hyde, 2014; Luoh & Tsaur, 2007). In the word of online reviews, which are often characterized by anonymity, people often use heuristics or shortcuts to help them assess the reviews (Cheung & Thadani, 2012). Gender stereotypes are particularly helpful in a situation when there is a need to make quick estimates of how unknown individuals are likely to behave, or in an effort to understand how groups of people differ from each other (Ellemers, 2018). This could indicate that, in a personalized review, the reader might be even more likely to assess the performance of the customer service representative through the lens of their gender and therefore make assumptions on the credibility of the reviewer, and helpfulness of the review.

While there are stereotypically higher expectations of men in their competence and task performance domains, women are consistently evaluated more favorably than men in terms of warmth, empathy, and altruism, even when these evaluations are unfounded (Ellemers, 2018).

Based on the main stereotypical trait of women as being helpful (Ellemers, 2018) we expect that a positive personalized review will be considered as credible when it mentions a woman, as it confirms the stereotype. However, a person who holds the universal stereotype that women are helpful, and reads a review portraying a woman as unhelpful in a service setting might be more likely to deem it non-credible. A negative personalized review that mentions a female might therefore result in a decreased credibility of the reviewer. This could happen if the review presents a situation that is in dissonance with the beliefs held by the reviewer (Brehm & Cohen, 1962).

In the case of a negative personalized review that mentions a male we do not expect the same effect. Although males hold the stereotype of being competent in most cases, anger is more acceptable for men, than it is for women (Durik et al., 2006). A negative personalized review portraying personal conflict, which is often associated with anger, would be less likely to decrease the credibility of the reviewer, we assume. That is because the customer service representative mentioned is a male, and males are known to be more anger-prone, making the review more believable, than if a woman was mentioned. Therefore, we formulate our first hypothesis as follows:

H6a: *Expressing a failed service interaction in a personalized review, lowers the perceived credibility of the review more when it mentions a female customer service representative, than when it mentions a male.*

A valuable review, as previously mentioned in our paper is highly affected by its credibility. In H6a we expect the reviewer to be perceived as less credible when the review mentions a female than when it mentions a male. Drawing from that, we also expect that the value of a negative personalized review mentioning a woman will be diminished. We thus formulate our next hypothesis:

H6b: *Expressing a failed service interaction in a personalized review, lowers the perceived value of the review more when it mentions a female customer service representative, than when it mentions a male.*

Based on the results that credibility mediated the relationship between valence and value of personalized reviews in Study 2 we expect the same effect to be present in our third study, as we only assess personalized reviews. The mediation is also of interest as some literature suggests that credibility does not play a role in this relationship (Cheung, Lee, & Thadani, 2009) while others suggest a positive relationship between credibility and adoption (value) (Chu, & Kamal 2008; Watts, & Zhang 2008). We thus hypothesis the following and illustrate the mediation in Figure 7.

H7: *Perception of reviewer credibility mediates the role of valence on perceived value.*

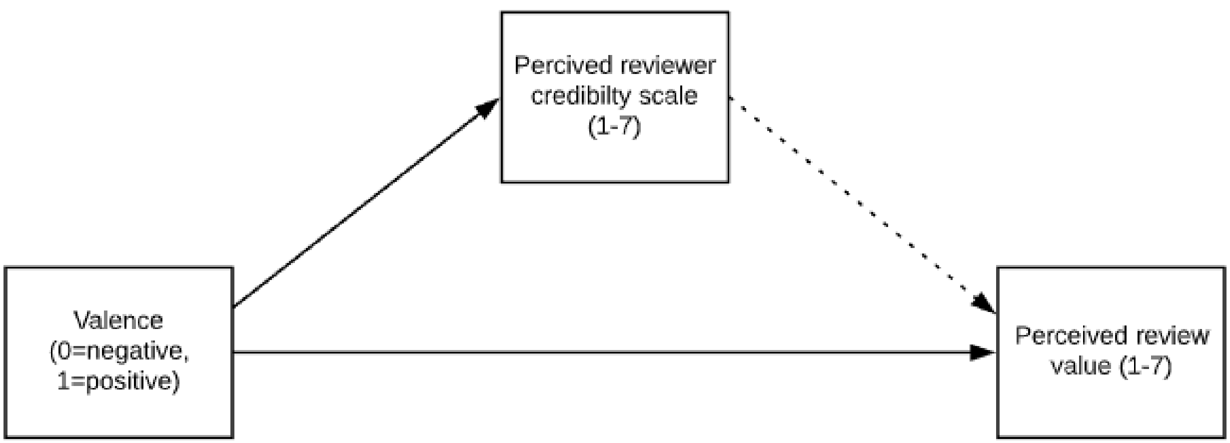

Figure 7: Expected indirect effect of valence via perceived reviewer credibility.

By taking the same stereotype-based approach as in the first two hypotheses, we expect that positive personalized reviews mentioning females will not have any effect over the credibility nor value of a review. They are expected to show no effect due to the normality of helpfulness associated with females. We expect that due to the competence expected from males due to stereotypes, a positive personalized review mentioning a male will also have no effect and result null.

4.4.3 Participants, procedure, and measures

For Study 3, we hired 493 participants from the online survey platform mTurk. After cleaning missing and faulty responses, we were left with 479 valid responses (58.7% males; M_{age} = 33,26; SD = 9,92). Each respondent was randomly assigned a personalized review that had gender cues (male vs. female) and was either positively or negatively valanced, in a between-subjects design. Afterwards each participant was presented with a short survey about the review they read.

Participants were subjected to the same message regarding the situation they were to consider themselves in, as in Study 2. The stimuli can be found in Appendix F. Participants were also subjected to the same questions as in Study 2, except causal attribution was not checked and two control questions were removed. As online review usage was a factor in Study 2, we kept that control in.

Review value was captured with the same questions as in Study 2. *Credibility of the source* was measured again by the same six factors as in Study 2.

4.4.4 Results

4.4.4.1 Manipulation check

Both of our manipulations checked out. The participants that were assigned a negative review ($M_{negative}$ = 2,16; SD = 1,458) indicated that they perceived it a lot more negatively than the participants that were assigned a positive review ($M_{positive}$ = 6,21; SD = 0,991). Although the assumption of equal variance was violated by a Levene's test the difference between groups was significant $t(431,4) = -35,7$, $p < ,001$. The participants that were assigned a male review (M_{male_review} = 5,77; SD = 1,549 vs M_{female_review}= 1,97; SD = 1,623) agreed that it contained a male service representative and likewise for female reviews (M_{male_review} = 2,41; SD = 1,717 vs M_{female_review}= 6,30; SD = 1,3). The results were significant for the male review $t(477) = 26,2$; p <

,001 and although the assumption of equal variance was violated for the female reviews, the results were significant t(437,6) = -27,9; p < ,001.

4.4.4.2 Perceived credibility

To test for hypothesis H6a we look at the interaction between gender of the service representative and valence on *perceived reviewer credibility*. The reviewer credibility score was computed by averaging the six items related to source credibility. In our survey we included control questions on review usages which had an impact on our model (p < ,001). We thus conducted an ANCOVA (see Table 5b) in which the dependent variable was the perceived reviewer credibility, the independent variables were gender of the service representative and valence. Usages of online reviews served as a covariant. The interaction between the four conditions is illustrated in Figure 8 and descriptive statistics can be found in Table 5a. Neither age (p = ,670), nor education (p = ,626) influenced our model.

	Positive reviews	Negative reviews
Reviews including a male service representative	*n* = 111 (23,17%) Mean = 5,423 SD = 1,101	*n* = 125 (26,09%) Mean = 4,524 SD = 1,532
Reviews including a female service representative	*n* = 123 (25,67%) Mean = 5,505 SD = 0,782	*n* = 120 (25,05%) Mean = 4,812 SD = 1,309

Table 5a
Descriptive statistics
(Perceived reviewer credibility)

Independent Variables	**Mean Square**	**F-value**	**p-value**
Gender of service representative	*2,354*	*1,778*	*0,183*
Valence of reviews	*70,697*	*53,397*	*0,001*
Service gender x Valence	*2,374*	*1,793*	*0,181*
Error	*1,324*		

Table 5b
ANCOVA results of 2x2 experiment of service rep and review valence on perceived reviewer credibility

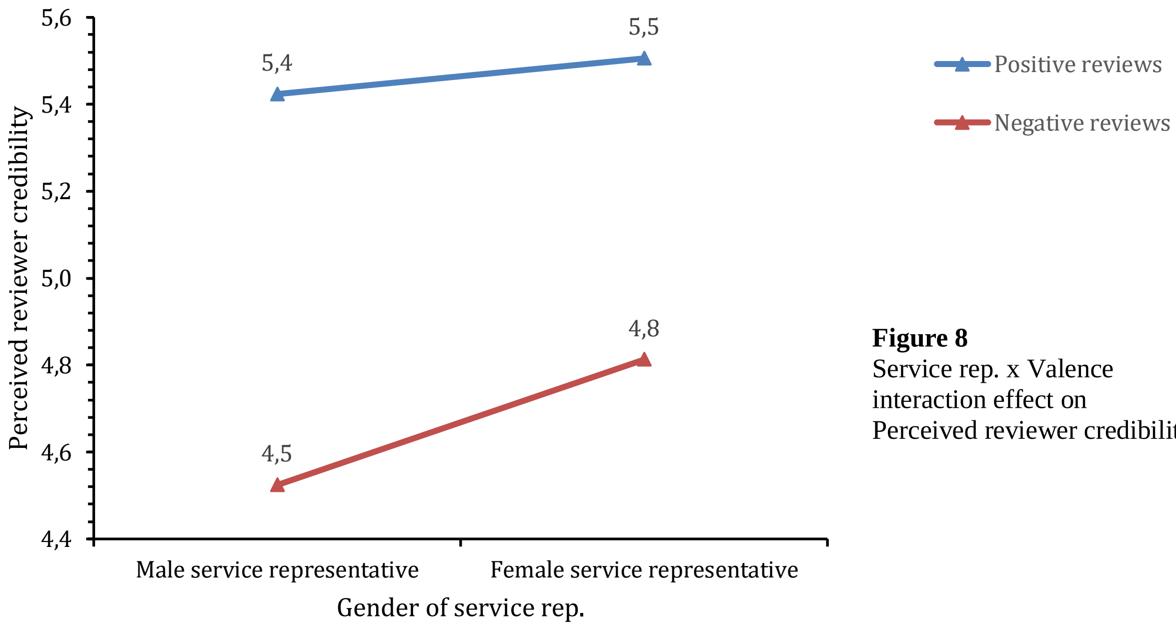

Figure 8
Service rep. x Valence interaction effect on Perceived reviewer credibility

We hypothesized that expressing a failed service interaction in a personalized review, lowers the perceived credibility of the review more when it mentions a female customer service representative, than when it mentions a male (H6a). Although not significant, our results however, point in the opposite direction. They suggest that when expressing a failed service interaction with a male representative in a personalized review, the reviewer's credibility is lowered ($M_{negative\_male\_review}$ = 4,52; SE = 1,53 vs $M_{negative\_female\_review}$= 4,81; SD = 1,31). This difference between service representatives was not noted in the positive reviews ($M_{positive\_male\_review}$ = 5,42; SD = 1,1 vs $M_{positive\_female\_review}$= 5,51; SD = 0,78). Valence had a main effect on credibility ($F (1, 474) = 53,397$; $p < ,001$), confirmed by a supplementary Mann-U Whitney test ($U = 18951,000$; $p < ,001$). The interaction between gender of the service representative and valence is also not significant, yet shows the tendency towards lowered reviewer's credibility, when expressing a negative interaction with a male ($F (1, 474) = 2,374$; $p = ,181$). We thus reject hypothesis H6a.

Since gender of the reader did play a role in our study 2, we opt to run a three-way ANCOVA on a sample of 479 participants to examine the effect of valence, gender of reader and gender of service representatives on perceived reviewer credibility. Review usage was controlled for as it had a significant influence on the model ($p < 0{,}001$). There was a significant three-way interaction, $F(1, 470) = 9{,}078$; $p = {,}003$. Results of the three-way ANCOVA can be found in table 5c.

Independent Variables	Mean Square	F-value	p-value
Gender of service representative	*2,377*	*1,817*	*0,178*
Valence of reviews	*65.528*	*50,106*	*0,001*
Reader gender	*1.192*	*0.911*	*0,340*
Service gender x Valence	*0.795*	*0.608*	*0.436*
Service gender x Reader gender	*0.007*	*0.005*	*0.943*
Reader gender x Valence	*0.137*	*0.104*	*0.747*
Service gender x Valence x Reader gender	*11.872*	*9.078*	*0.003*
Error	*1,308*		

Table 5c
ANCOVA results of 2x2x2 experiment of service rep gender, reader gender and review valence on perceived reviewer credibility

In order to interrupt and untangle this three-way interaction between valence, reader, and service representatives, we opted to split our dataset by the readers gender and ran a 2x2 ANCOVA on the gender of service representatives and valence, with review usage as a covariant. Our results show that when a male is reading the reviews, the interaction between the gender of service representatives and the reviews valence is significant $F(1, 276) = 34{,}562$ ($p = 0{,}003$), while female readers do not exhibit a significant interaction between the gender of service representatives and the reviews valence $F(1, 193) = 2{,}192$ ($p = 0{,}204$).

Both genders follow the same pattern. Both believe the reviewer more when their own gender is shown in a positive light ($M_{positive\_male\_reader\_to\_male\_rep} = 5{,}64$; $SE = 0{,}12$ vs $M_{positive\_male\_reader\_to\_female\_rep} = 5{,}39$; $SE = 0{,}09$; $p = 0{,}092$) and ($M_{positive\_female\_reader\_to\_female\_rep} = 5{,}65$; $SE = 0{,}11$ vs $M_{positive\_female\_reader\_to\_male\_rep} = 5{,}09$; $SE = {,}18$; $p = 0{,}01$). Similarly, assign less reviewer credibility when the review describes a failed service interaction by their own gender

($M_{negative\_male\_reader\_to\_male\_rep}$ = 4,34; SE = 0,18 vs $M_{negative\_male\_reader\_to\_female\_rep}$= 4,9; SE = 0,15; p = 0,021) and ($M_{negative\_female\_reader\_to\_female\_rep}$ = 4,7; SE = 0,20 vs $M_{negative\_female\_reader\_to\_male\_rep}$= 4,8; SE = 1,43; p = 0,718). In other words, the effects of valence on the gender of the service representative becomes more pronounced when a male is reading the review than a female. An illustration of this effect can be seen in Figure 9.

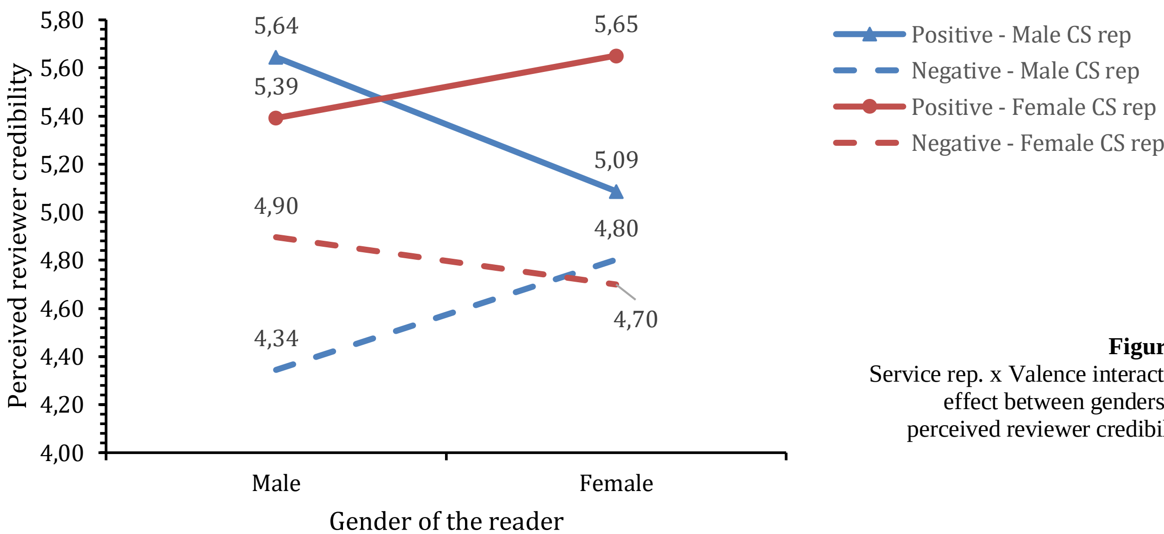

Figure 9
Service rep. x Valence interaction effect between genders on perceived reviewer credibility

4.4.4.3 Perceived review value

Like the last section we test the interaction between gender of the service representative and valence on *perceived review value* to test for our H8b hypothesis. As we expect credibility to mediate the effect between valence and value of personalized reviews, it can be expected that the interaction on review value will be similar as on credibility. The review value was measured on a 7-point scale, by asking participants how likely they would be to use the review in their decision-making. Review usage was also controlled for as it influenced our model ($p < ,001$). We thus conducted an ANCOVA (see Table 6b) in which the dependent variable was the perceived review value, the independent variables were gender of the service representative and valence. The interaction between the four conditions is illustrated in Figure 10 and descriptive statistics can be found in Table 6a. Neither age (p = ,545), nor education (p = ,817) influenced our model.

	Positive reviews	Negative reviews
Reviews including a male service representative	*n* = 111 (23,17%) Mean = 5,45 SD = 1,33	*n* = 125 (26,09%) Mean = 4,42 SD = 1,98
Reviews including a female service representative	*n* = 123 (25,67%) Mean = 5,59 SD = 1,14	*n* = 120 (25,05%) Mean = 4,61 SD = 1,79

Table 6a
Descriptive statistics for each of our four experimental conditions

Independent Variables	**Mean Square**	**F-value**	**p-value**
Gender of service representative	*,404*	*,171*	*0,679*
Valence of reviews	*101,392*	*43,021*	*0,001*
Service gender x Valence	*1,663*	*,706*	*0,401*
Error	*2,357*		

Table 6b
ANCOVA results of 2x2 experiment of service rep and review valence on perceived reviewer credibility

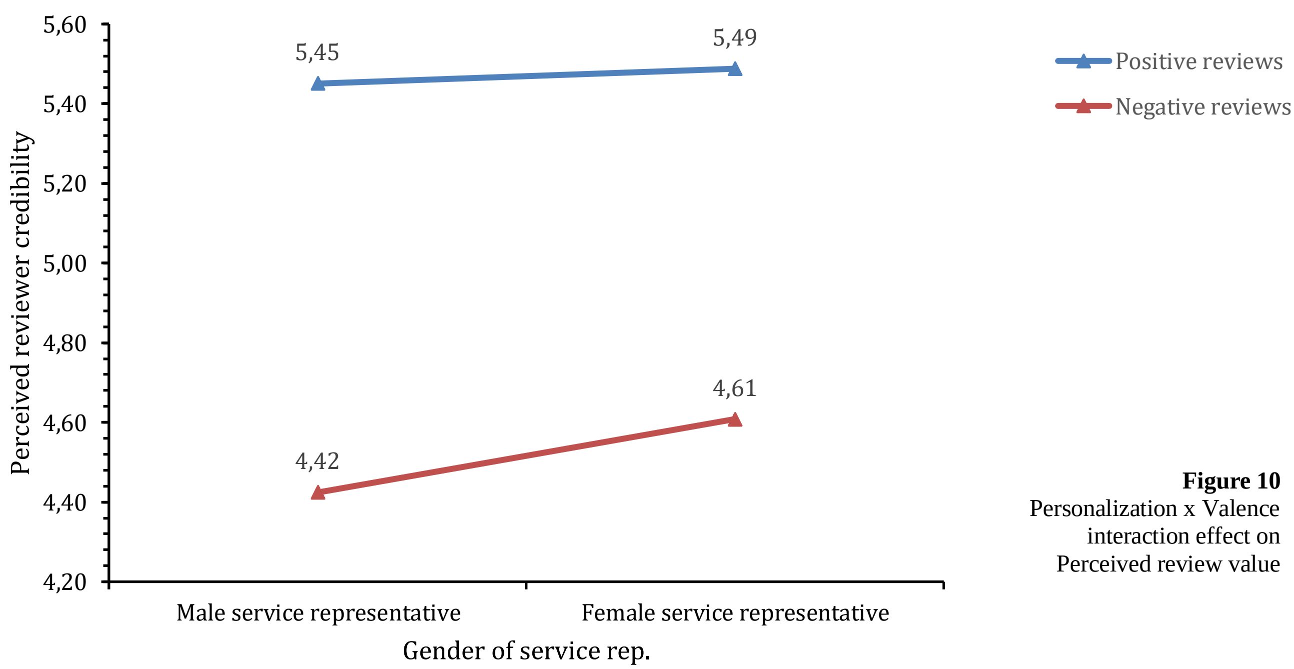

Figure 10
Personalization x Valence interaction effect on Perceived review value

We hypothesized that expressing a failed service interaction in a personalized review, lowers the perceived value of the review towards readers when it mentions a female customer service representative, than when it mentions a male (H6b). As expected, the results were similar to those from our perceived credibility analysis. A failed service interaction with a male representative in a personalized review lowered the value of the review the most ($M_{negative\_male\_review}$ = 4,42; SD = 1,98 vs $M_{negative\_female\_review}$= 4,61; SD = 1,79). This difference between service representatives was not noted in the positive reviews ($M_{positive\_male\_review}$ = 5,45; SD = 1,33 vs $M_{positive\_female\_review}$= 5,49; SD = 1,14). The interaction between gender of the service representative and valence is also not significant, yet shows the tendency towards lowered reviewer's credibility, when expressing a negative interaction with a male ($F(1, 474)$ = 0,706; p = ,401). We thus reject hypothesis H6b.

We also opted to investigate a possible three-way interaction with the readers gender as the third factor. Review usage was controlled for as it had a significant influence on the model (p < 0,001). There was not a significant three-way interaction, $F(1, 470)$ = 6,625; p = ,094.

4.4.4.4 Mediation and moderation modeling

Based on our results from study 2, we will first look at our hypothesized mediation of source credibility. We ran PROCESS v.3.4 - Model 4 again in SPSS to check for a possible mediation (Hayes, 2013). Valence was set as an independent variable (1 = positive, 0 = negative). *Credibility* was selected as a mediator, with *review value* as the dependent variable and review usage was controlled for. The model was applied to all four conditions from 479 responses. Results from PROCESS exports can be found in Appendix G and are illustrated in Figure 11.

For our personalized reviews, perceived source credibility mediated the relationship between valence and perceived review value (ß= ,484; 95% *CI*[0,32 to 0,66]. The direct effect of valence was also significant (ß= ,438; p = ,0009; 95% *CI*[0,18 to 0,69]). The total effect of valence on value was significant, (ß= ,922; p < ,0001; 95% *CI*[0,64 to 1,20].

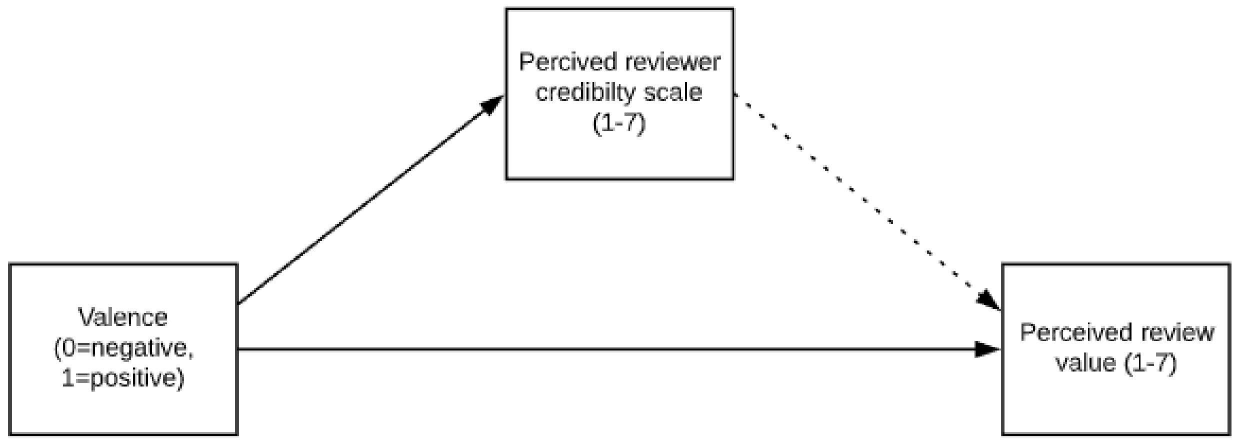

Figure 11: Mediation model of perceived reviewer credibility in personalized reviews

Given that the three-way interaction between valence, gender of the reader and the gender of the service representative were significant we should get a significant model by adding them to our previous observation. Below is an illustration of the model (Figure 12), and Table 7 containing coefficients, standard errors, p-values, and boot intervals.

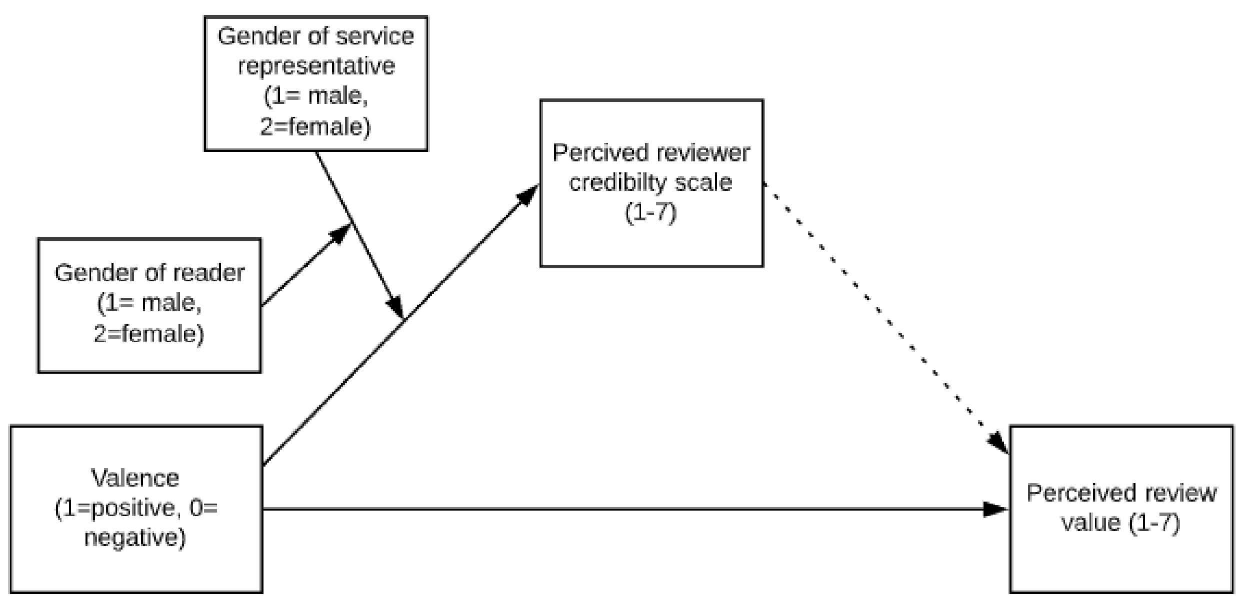

Figure 12: Moderated mediation model of perceived reviewer credibility on perceived review value.

Table 7. Results of the conditional process model (PROCESS, model 11) with review value as dependent variable.

	Mediator variable model (Perceived reviewer credibility)			
Predictor variables ($R^2 = ,22; p < ,001$)	**B**	**SE**	**t**	**P**
Constant	-2,45	2,54	-,96	,3367
Gender of service representative	3,67	3,70	3,24	,0013
Valence of review	11,98	1,62	2,27	,0234
Gender the reader	0,87	,47	1,89	,0642
Service gender x Valence	-7,22	2,32	-3,12	,0019
Reader gender x Valence	-2,00	,68	-2,93	,0036
Service gender x Reader gender	-0,63	,30	-2,11	,0357
Service gender x Valence x Reader gender	1,28	,43	3,01	,0027

	Dependent variable model (Y) (Perceived Review Value)			
Predictor variables ($R^2 = ,35; p < ,001$)	**B**	**SE**	**t**	**P**
Constant	0,49	0,35	1,39	,1652
Credibility	0,63	0,05	11,64	<,0001
Valence of review (direct effect)	0,44	0,13	3,35	,0009

		Conditional indirect effects of X on Y		
Service gender	**Reader gender**	**B**	**SE**	**Boot 95% CI**
Male	Male	,75	0,17	**[0,43 to 1,09]**
Male	Female	,30	0,16	[-0,01 to 0,63]
Female	Male	,24	0,11	**[0,04 to 0,74]**
Female	Female	,60	0,15	**[0,33 to 0,91]**

Note: *Significant conditional indirect effects in bold.*

Using PROCESS model 11, we examined the conditional indirect effects of this proposed moderated mediation. Results are presented in Table 7 and indicate that credibility significantly mediates the association between valence and value for men reading reviews about both female and male service reps, (ß= ,75 ; SE = ,17; 95% *CI*[0,43 to 1,09]) & (ß= ,24 ; SE = ,11; 95% *CI*[0,04 to 0,74]), but only female readers that read reviews about females (ß= ,60 ; SE = ,15; 95% *CI*[0,33 to 0,91]). Credibility does not mediate the association between valence and value when a female reads a review about male service representative (ß= ,30; SE = ,16; 95% *CI*[-0,01 to 0,63]).

4.4.5 Summary and discussion

Both Study 1 and Study 2 indicated that personalized reviews are differently perceived than non-personalized reviews. The results of Study 2 showed that valence had a more pronounced effect on credibility and value in personalized reviews, than in non-personalized ones. Study 2 also indicated that readers had a different perception of personalized reviews based on their gender. Based on these findings and a limitation of Study 2 according to which we only showed personalized reviews which mentioned a male customer service representative, we formulated Study 3. Through Study 3 we proposed a second research question and explored related literature to hypothesize on expected outcomes. Our second research question was as follows:

How does the gender of a service representative in a personalized review influence perceived credibility and review value?

Through our examination of relevant gender literature in service settings, we expected that readers would assign less credibility (H6a) and less value (H6b) to a review if it described a woman, as opposed to a man, negatively. Also, drawing from literature and the results of Study 2, we assumed that credibility would mediate the relationship between valence and value in personalized reviews. A brief discussion of our dependent variables and the mediation analysis follows.

Perceived source credibility was measured with a six-item scale borrowed from Choi & Rifon (2002). The study results do not confirm our expectations according to which readers would assign less credibility if the review described a woman negatively, than if it would describe a man negatively. We, therefore, reject H6a. Although not statistically significant, the results indicate that the review readers had the least trust in reviewers who spoke badly about a male. This difference between genders was not noted in our positive reviews. The anonymous nature of online reviews, together with the literature on gender stereotypes, could explain our results. When evaluating a review, the reader has access to limited information about the reviewer and must draw on heuristics or shortcuts to help them assess the reviews (Cheung & Thadani, 2012). One of the only available cues in the personalized reviews is the gender of the customer service representative.

Stereotypically, there are higher expectations of men in competence and task performance domains, than of women (Ellemers, 2018). Witnessing a review that negatively portrays the performance of a male service employee might not comply with the general perception of males. This could result in assigning the "blame" for a negative review to the reviewer, not the customer service representative, and thus, the company, and questioning the credibility of the reviewer. The pro-male evaluation bias might also provide an explanation (Nieva & Gutek, 1980). The concept states that males are being rated as higher in performance than women, even in situations where the performance is equal (Nieva & Gutek, 1980).

Although not hypnotized, we ran a three-way ANCOVA to see if the reader's gender would influence perceived credibility, and our results were statistically significant. After untangling the effect, we concluded that the representative's gender has more influence on male readers than it does on females, although the direction of the effect is the same for both genders. Both genders assigned the most credibility to reviews positively portraying their own gender. Both genders assigned the least credibility to reviews negatively portraying their own gender.

The concept of homophily could explain these results. Gender homophily refers to a preference for interactions with the same gender (Laniado, Volkovich, Kappler, & Kaltenbrunner, 2016). People prefer to interact with other similar people (Brown & Reingen, 1987). In service settings, people might prefer to be served by people of the same sex as they might expect to feel more comfortable (Fischer et al.,1997). This might translate into preference and empathy for the same sex.

According to literature, the effect of homophily is more pronounced in women than in men (Laniado et al., 2016), our studies, however, would suggest the opposite. Our results show that males assigned less credibility to a higher degree when the same gender was negatively portrayed than females do. This would suggest the existence of a stronger empathy of males towards their own gender. While stereotype theory shows that it is females who showcase empathy, more so than males (Ellemers, 2018), that might not reflect how each gender behaves, in reality.

Perceived review value was measured as the likeliness of participants to use the review in their decision-making. Readers tend to be less likely to rely on negative reviews that mention a male rather than a female, for their decision-making. This is the same tendency as was noted in our source credibility results. In Study 2, we show that perceived credibility is a mediator of the relationship between valence and value. So, it is not surprising that less value is assigned to less credible reviews. This leads us to reject our hypothesis according to which expressing a failed service interaction in a personalized review would lower the perceived value of the review more when it mentions a female customer service representative, than when it mentions a male (H6b).

Our results show the relevance of the customer service representative identity information in a review for shaping credibility and helpfulness evaluations.

Lastly, we hypothesized that credibility would mediate the relationship between valence and review value. The results from Study 2 confirmed the mediation regardless of personalization. When we contrasted personalized and non-personalized reviews, the effect of our model was more significant in personalized reviews. Many scholars have investigated this relationship, some with other mediators between source credibility and purchase intention, while others have focused only on the effect of source credibility on adoption. Weitzl, Wolfsteiner, Einwiller, & Wagner (2016) were unable to show a direct effect of source credibility on purchase intention.

However, they showed that source credibility positively influenced perceived argument quality, and that perceived argument quality also mediated the relationship between source credibility and purchase intention (Weitzl et al., 2016). Kusumasondjaja et al. (2012) showed that negative reviews were perceived significantly more credible than positive ones. Furthermore, if a source was known, then the negative reviews were even more credible than other forms of reviews (Kusumasondjaja et al., 2012). Lim & Van Der Heide (2015) showed the opposite, what positive reviews were perceived to be more trustworthy than negative ones, but were unable to confirm a mediation effect by source credibility on the relationship between valence and attitude towards a restaurant. Previous literature analysis suggested that source credibility is a key factor in eWOM adoption, so our mediation analysis is even more interesting, given the conflicting results from previous research (Cheung et al., 2012).

Our mediation analysis revealed the same results as Study 2, that perceived source credibility mediates the relationship between valence and perceived value. The direct effect of valence on perceived source credibility is in line with Lim, & Van Der Heide's (2015) results. Our research also managed to confirm the mediation between these variables, which Lim, & Van Der Heide (2015) expected to be present. Although the direct effect of valence contradicts other findings (Kusumasondjaja et al., 2012), the mediation effect is in line with previous review literature (e.g., Cheung et al., 2012).

Furthermore, a three-way interaction between the gender of the service representative, valence, and the gender of the reader was significant. This allowed us to confirm a moderated mediation effect of these factors and perceived credibility on review value. After untangling the results, we confirmed that credibility significantly mediates the association between valence and value for men reading reviews about both female and male service reps. However, the mediation is only significant when female readers read reviews about females, but not when a female reads a review about male service representatives. In other words, the perceived credibility did not significantly influence the assigned review value by female readers when they read a positive or a negative review about a male service representative.

The results could be explained by the differences between males and females in how they perceive their gender counterparts. Alternatively, they could be explained by the difference in how males and females assess service performance.

The study data was also analyzed to check for a possible three-way interaction by adding readers' gender as a second moderator. However, the results were not were not statistically significant.

Implications, limitations, and further research

5.1 Implications

5.1.1 Theoretical

This paper expands theory in four ways. Firstly, we enhance the current literature by introducing a new phenomenon in the form of a new type of review cue. Previous research has not taken into consideration the influence of personalization in its stimuli development (Cheung & Thadani, 2012). Not only do we observe the existence of personalized reviews but also show that when leaving a personalized review, people are most likely to leave a positive one. This sets a foundation to further research, which might focus on understanding the motivation behind leaving personalized reviews, and the reason for their prevalently positive valence.

Secondly, we uncover that personalized reviews primarily drive the effect of valence on source credibility and review value. We contribute with new findings which contradict several previous papers and findings on online reviews and the effect of valence. While previous literature shows that negative reviews are more valuable and more credible than positive ones (Cheung and Thadani, 2012; Greenleigh 2011; Schindler & Bickart, 2005), we find the opposite through our results.

Thirdly, we contribute with knowledge about gender effects and show how gender shapes credibility and helpfulness evaluations. We particularly shed light on how the combination of the gender of the customer service representative, review valence, and reader's gender affects the perceived credibility and value of a personalized review. While there are several pieces of research on the role of gender in online reviews, they mostly focus on either the gender of the reviewer and how that shapes the impressions of the reader (e.g., Craciun & Moore, 2019). There is also research showing the influences of the gender of customer service representatives on performance evaluations in service settings (e.g., Meyers-Levy & Loken, 2015). Nevertheless, to the best of our knowledge, no research investigates the gender of the customer service representative and its relevance and impact in reader evaluations of online reviews. The paper furthers knowledge on the role of gender when indirectly evaluating the performance of their own and opposite gender, both in positive and negative service settings.

Finally, we show that credibility mediates the relationship between valence and value, an observation that pervious research had either not manage to confirm (Lim & Van Der Heide, 2015) or showed the opposite effect of valence (Kusumasondjaja et al., 2012). Our results indicate that positive reviews are perceived more credible than negative ones, contradicting Kusumasondjaja et al., 2012, especially among personalized reviews. This effect of valence and mediation of credibility raises questions about the consensus within review literature that negative reviews are more valuable than positive ones, a consensus which Wu (2013) too has questioned.

5.1.2 Managerial

Companies are generally known to engage in proactive efforts to increase the volume of positive reviews and decrease that of negative reviews. This focus is understandable on behalf of companies as online reviews are the second most trusted source for information on a product or service. While our studies found no statistical difference between personalized and non-personalized reviews when it came to attribution, perceived credibility, or value, personalized reviews did show tendencies of being perceived as both more credible and more valuable. Based on this, if given a chance to influence their reviews that customers leave for their products or services, companies should try to encourage people to refer to the service employee who helped them. Our study also unearthed another relevant finding which should hold value to companies.

The finding is that positive, personalized reviews were perceived as more positive than positive non-personalized reviews. Companies might want to encourage the mention of a customer service representative in a review because the review will be perceived as more strongly positive than a non-personalized review. According to our findings, positive reviews are both more credible and more valuable than negative reviews.

Our findings from Study 3 show a correlation between the gender of the customer service representative, review valence, and gender of the reader. We also show the relevance of the customer service representative identity information, particularly their gender, in a review for shaping credibility and helpfulness evaluations. This might be particularly relevant for companies whose target market is only one of the two genders. For example, a product that addresses males might have mostly males reading reviews to help them make purchasing decisions. Since males were shown to assign more value to a positive review mentioning a male, it might be a good consideration on behalf of the company to encourage the mention of male customer service representatives in an online review. The same applies to women. A product addressing a woman, and whose reviews would thus be mostly read by women will be more impactful regarding perceived value, if a woman service representative is mentioned. In their efforts to influence how their online reviews are influencing adoption, companies could keep these matters in mind, if they choose to encourage personalized reviews.

5.2 Limitations & future research discussions

This study is not without its limitations. There are several limitations that might have influenced the results of our study, and that might also give a clue towards future research on personalized reviews.

Starting with the first study, we acknowledge a limitation in the fact that the field data has been gathered from among a single company's review list - Kiwi.com. While the choice for Kiwi.com was their prevalent personalized reviews, the same volume of personalized reviews might not be present in the reviews of other companies. It is unclear whether Kiwi.com has a customer service strategy in place that encourages its customers to leave personalized reviews, although it would seem so at first glance. Study 1 should have assessed the reviews of several companies in order to make its results more easily generalizable.

Study 1 also gathers data from Trustpilot. While there are several benefits to gathering data from Trustpilot, as opposed to other platforms (Johannsen et al., 2015), it is merely one platform. Data gathered from several platforms might have allowed for a more holistic look at the prevalence of personalized reviews, which might have, in turn, influenced the results for our hypothesis. Lastly, one of the main limitations of the study is also likely a result of the platform used, and it is a lack of data for our second hypothesis H4c, which allowed us to neither accept or deny it, due to the lack of useful votes presented on reviews on Trustpilot.

Participants both in Study 2 and in Study 3 were recruited through MTurk, which was an obvious choice for these studies as it presents several benefits. MTurk has been shown by recent studies to be as reliable as data gathered from students populations, while its data is considered to outperform that from other competing marketing research panels (Kees, Berry, Burton, & Sheehan, 2017; Peer, Brandimarte, Samat, & Acquisti, 2017). The participants on MTurk are known to be highly attentive (Thomas & Clifford, 2017), as also shown by our own data based on attention checks, and they are also more diverse than alternative samples (Casler, Bickel, & Hackett, 2013). Nonetheless, the participants in MTurk are experienced in answering surveys, and their repeated participation can have effect on how they respond. During our stimuli development and manipulation checks Study 2, we launched the experiment at different hours only to realize that based on the time zones our answers were either prevalently from the Indian population, or from Eastern Europe. The results from our tests showed this to be less than optimal as, based on the results, the participants had a harder time interpreting the manipulation and the questionnaire. Study 2 has been released at a time fitting with the US time zone and has had mostly participants from the US. While this was preferred due to language proficiency, as our manipulation checks prove, a more diverse sample would have been preferred.

Our studies focus only on services and the travel industry, so our results might not be applicable to products and other industries, which limits their generalizability, especially as the impact of online reviews can be more powerful in the travel industry that in other industries (Öğüt & Taş, 2012).

In our manipulation, we used the name Laris Airline to control for familiarity and preconceived opinions. However, being confronted with a no-name airline, in an industry where airlines are normally spending significant efforts and budgets to create brand awareness, might have influenced the perception of the participants as they might have perceived the airline to be lacking reputation or experience due to its perceived newness.

Study 2 and Study 3 tested the effects of personalized reviews. During our Study 1, when we read about 1500 reviews to code for the presence of personalization cues, we noticed that personalized reviews also tend to have a different text composition than non-personalized reviews. We noticed that personalized reviews tend to be longer in the number of characters than non-personalized ones. For example, positive reviews referring to a company tend to say that the service was "*excellent*", the "*process was easy*", the service was "*great*". (Trustpilot, 2020d). Whereas reviews mentioning a specific employee tend to include more details, explain exactly the help that was received. A real-life example is: "*Thanks to John M for very quickly sorting out and correcting my phone number, and sending me an email to inform me that the matter was resolved. Thank you John M, you are a valuable employee!!*" (Trustpilot 2020d). Another example shows the same need to be more concrete about the help received when referring to a customer-facing employee as opposed to a company: "*Finn was excellent. He listened and resolved our concerns efficiently and quickly. I cannot praise him enough.*" (Trustpilot, 2020d).

Clearly, in real life, personalized reviews differ from non-personalized reviews in the type of wording used, in the length of the message, and in the form of how emotions are expressed. The level of objectiveness vs. subjectiveness in the content of a review is another difference between personalized vs. non-personalized reviews (Ghose & Ipeirotis, 2007). Nonetheless, in our study, we had to keep the reviews in the manipulation the same, to test only for the effects of personalization and valence. This is a limitation that would encourage future research to examine personalized reviews from a text analysis perspective.

Study 2, which investigates the perceived credibility of personalized reviews, also presents limitations due to the manipulation. Our manipulation did not include any names of the reviewer, no platform indicated expertise or any other clue as to the source of the review, although these elements, however, are visible on most platforms, Trustpilot included. Therefore, making it quite difficult for the reader to evaluate the reviewer's credibility on a very limited number of heuristic cues, which might explain why valence played such a big role in the results for personalized reviews. We thus suggest that source credibility may be more useful in capturing review value when there is more information available on the reviewer. These cues would anchor certain factors, such as anonymity and expertise, that were not captured by simply asking participants directly about the source credibility. A future study could look at adding these credibility cues and see the influence of personalization on credibility when the usual credibility cues are present, as they often are in real life.

Kim & Gupta's study (2012), which focuses on the discounting principle of attribution credibility, shows that the validity of attribution based on a single observation should be discounted. This might particularly apply to online reviews, which are usually in a stream of many reviews of both valances. The reader is rarely presented in real life with only one single review of a product or service. Kim & Gupta (2012) suggest that the participants could discount a specific relationship between variables because they were only being shown one review. It might have been more beneficial to show more than one review at a time, to get more valid data when testing for personalization in online reviews.

Our results from Study 2, while they do not show a lot of statistical difference between personalized and non-personalized reviews, do show a few tendencies. For example, positive personalized reviews are perceived as more credible than non-personalized reviews. Future studies could try to find out why that is and gain a deeper understanding of the mediation effect of credibility. The same applied for negative personalized reviews, which have a tendency to be seen as less credible than non-personalized reviews. Future research is encouraged to try to understand the "why" of personalized reviews.

Study 3 focuses on the gender of the customer service representative portrayed in personalized reviews. We hypothesized based on assumptions built on gender stereotypes, which have been proven to exist still, particularly in service settings (Hyde, 2014). Nonetheless, we did not control for those specific stereotypes in our study. While some people might indeed hold the preconception that women are helpful, friendly, and warm, and men are more anger-prone and competent, the stereotypes might not be held by all participants. Broad differences in gender stereotypes of different nationalities have been observed (Niemann et al.,1994). To get accurate results, we could have based our stereotypes on the geographical location of the respondents. We, in turn, counted on general stereotypes to argue our hypothesis and their universal truth. Perceptions of service quality may also vary across cultural groups (Furrer, Liu & Sudharshan, 2000).

Study 3 was based on our results from Study 2, which showed a difference in perception between males and females on personalized reviews. Nonetheless, time constraints did not allow us to look into the gender of the respondent as a moderator in our hypothesis formulation, and we did instead choose to focus on the gender of the customer service representative and the valence of personalized reviews. We did, however, look at the obtained data and try to understand the influence of the gender of the respondent afterward. Future studies could address the relation between the gender of the respondents and the gender of the customer service representative in personalized reviews. Many studies also show that the gender of the reviewer can play a role in the perception of a review, its credibility, and value (e.g., Luoh & Tsaur, 2007; Otterbacher, 2010). Otterbacher (2010) points out a difference in perception of reviews written by men and those written by women. Women's reviews receive fewer feedback votes than those by men and are also seen as being less useful than those written by men (Otterbacher, 2010).

Study 2 and Study 3 manipulated the review valence as positive vs. negative. While it is shown that neutral reviews are likely to have no significant differences in consumer evaluation (Chiou & Cheng, 2003), future research could also include neutral reviews to match real-life situations more accurately.

While we are investigating how personalization influences the attribution, credibility, and value of reviews, future research is encouraged to try and answer the question, "why do people leave personalized reviews". While our own study tries to gather information from psychology, from different thought streams and theories, combined with previous review literature to understand this, to a large degree, our study is based on assumptions, which poses another limitation of our study. Future research should try to understand and test the mechanisms behind leaving a personalized review as opposed to a non-personalized one.

It would also be valuable to understand whether any companies are actively directing their customers to mention the name of the customer service representative that has helped them through different techniques. Furthermore, how much more likely are people to leave a review, or a positive review, when the customer service representative does indeed urge the customer to mention that they were the ones who helped, by name. The relationship between the customer and the customer service representative that might fuel the personalized reviews would also be worth understanding better. Understanding this could have substantial managerial implications and might set a new practice to try to generate more positive online reviews. Little is known as of now about personalized reviews, yet Study 1 shows their significant existence. While in our paper we try to test a few effects, we do not aim to understand why those effects happen. The "why" in our paper is missing, which constitutes ample opportunity for future research. There are many questions left unanswered, and this thesis puts a good foundation for further research, and most importantly, it justifies a future focus on this topic.

In the current review literature, the main types of review attributions are attribution to reviewer and attribution to the company. There is, however, literature that suggests that, in service encounters, the customer service representative is sometimes perceived as an individual, a separate entity than the company that they represent. (Aggarwal et al., 2005; Lynn & Grassman, 1990). Given that personalization brings a new element to reviews, while also adding a new actor - the customer service representative, future research is encouraged to test whether, in the case of personalized reviews, a customer service representative attribution could arise.

In conclusion, the presence of personalized cues does have an influence on review perception and impacts other factors, such as valence, which affect review adoption. As personalized reviews are widespread among online reviews, gaining a better understanding of the reviewers' motivation to write such reviews, and the readers' perception of them can be valuable, both for practitioners are well as to broaden theoretical knowledge.

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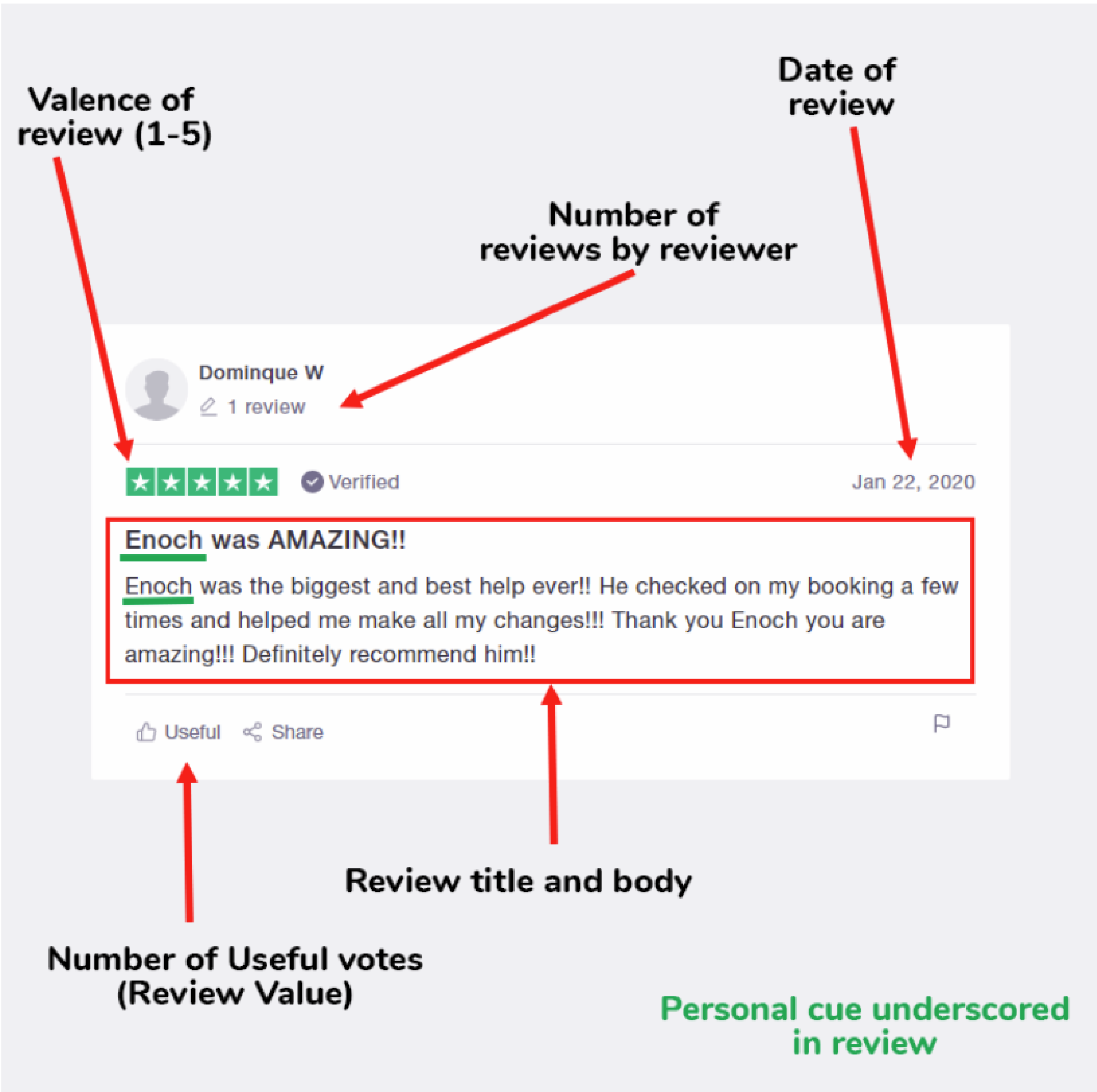
Appendix A

Review taken from Trustpilot.com/reviews/5e6a5b8a3c93ae091806a1fb



Appendix B

```
from bs4 import BeautifulSoup as soup  # HTML data structure
from urllib.request import urlopen as uReq  # Web client
import json #to parse scripts
import time #to parse scraping
import io   #to read/write csv
# Name the output file to write to local disk
out_filename = "trustpilot_kiwi.csv"
# Header of csv file to be written
headers = "Ratings|Date|Number of Reviews|Useful votes|Review Text|Review Length|Review Word Count \n"
# Opens file, and writes headers
f = io.open(out_filename, "w", encoding="utf-8")
f.write(headers)
# How many pages do we want to scrape
# Trustpilot has 20 reviews per page
number_of_urls = range(1, 500)

for x in number_of_urls:
    # Defines the company webpage that we want to scrape
    page_url=("https://www.trustpilot.com/review/kiwi.com?page=" + str(x))
    print(page_url)
    # Opens the connection and downloads html page from url
    uClient = uReq(page_url)
    # Parses html into a soup data structure to traverse html
    page_html = uClient.read()
    uClient.close()
    # HTML parsing
    page_soup = soup(page_html, "html.parser")
    # Grabs each review
    containers = page_soup.findAll("article",{"class":"review"})
    # Loops through each review and grabs attributes about each review

    for container in containers:
        #Parses initials <script>'s with json
        inner_review_html = container.script.text
        review_rating_json = json.loads(inner_review_html)
        inner_publish_html = container.section.div.div.div.select("div")[1].script.text
        publish_date_json = json.loads(inner_publish_html)
        # Defines rating
        review_rating = review_rating_json["stars"]
        # Defines publishing date
        publish_date = publish_date_json["publishedDate"]
        # Number of reviews
        number_of_reviews = container.aside.a.div.select("div")[1].div.span.text
        # Text of review and length and word count
        review_text = container.findAll("div", {"class": "review-content__body"})[0].text.strip().replace('\n', ' ').replace('\r',
'').replace('                  ',';')
        review_text_length = str(len(review_text))
        review_text_words = str(len(review_text.split()))
        # Define usefulness
        useful_string = container.select("brand-find-useful-button")
        useful_count = (str(useful_string)[55:56])
        # Writes out csv file
        f.write(str(review_rating) + "|" + publish_date + "|" + number_of_reviews + "|" + useful_count + "|" + review_text + "|" +
review_text_length + "|" + review_text_words + "\n")
    time.sleep(2) # seconds
f.close()
```

Appendix C

Aadhya	Aria	Chavvi	Eylül	Hitesh	Kamya	Manuel	Omisha
Aadi	Ariel	Cheeny	Eymen	Hosna	Karan	Manya	Omkaar
Aahana	Arin	Cheryl	Faiza	Hosniya	Karen	Marcell	Omya
Aalia	Arjon	Chloe	Fajr	Hredhaan	Karim	Margaret	Oni
Aanya	Arjun	Chris	Falak	Hritik	Kashika	Maria	Onkar
Aaradhya	Arnav	Chris!	Falan	Hugo	Kashvi	Mariana	Onveer
Aarav	Artem	Chris,	Falguni	Hussein	Katharina	maricel	Opal
Aarna	Arthur	Chris.	Faqid	Ibrahim	Katherine	Marie	Orinder
Aarnav	Artyom	Chris?	Faraj	Ida	Kathleen	Marilyn	Osha
Aarohi	Arunima	Christian	Faras	Idika	Kathryn	Marisol	Owen
Aaron	Arya	Christina	Farhan	Idris	Kavya	Mark	Owi
Aarush	Aryan	Christine	Farida	Ijaya	Kaye	Martha	Pablo
Aayush	Ashima	Christopher	Fariq	Ikbal	Kayla	Martim	Pahal
Abdallah	Ashley	Christy	Faris	Ikshita	Keith	Martin	Palak
Abdel-Rahman	Ashraqat	Cielo	Farisha	Imaran	Kelly	Martina	Pallavi
Abdul	Ashutosh	Cristina	Farzeen	Inah	Kenneth	Mary	Pamela
Abeer	Asima	Cynthia	Fatheha	Indali	Kevin	Marya	Panini
Abhimanyu	Atharv	Daksh	Fatin	Indrajit	Khaled	Maryam	Paolo
Abhiramnew	Aulivia	Daksha	Fatma	Ira	Khushi	Matalia	Pari
Abhishek	Aurora	Dakshesh	Finn	Irati	Kiaan	Maté	Pari!
Abigail	Ava	Dalaja	Fitan	Isaac	Kiara	Matilde	Pari,
Adam	Avni	Dalal	Fiyaz	Isabela	Kim	Matteo	Pari.
Aditi	Aya	Dalbir	Forum	Isabella	Kimberly	Matthew	Pari?
Aditya	Ayaan	Damini	Frado	Isha	Kirill	Mattia	Parth

Advaith	Ayaz	Damyanti	Frances	Ishaan	Krish	Matviy	Parul
Advay	Ayush	Dan	Francesco	Ishani	Krisha	Maxim	Patricia
Advik	Ayushman	Dan!	Frank	Ishanvi	Krishan	Maximilia n	Patrick
Advika	Azaan	Dan,	Frank!	Ishita	Krishna	Meera	Paul
Adweta	Azad	Dan.	Frank,	Ishwar	kristi	Megan	Pavani
Adya	Azra	Daniel	Frank.	Isla	Kristin	Megha	Peter
Agastya	Bachittar	Danielle	Frank?	Ivan	Kristy	Meghana	Philip
Ahana	Baghyawa ti	Daniil	Frankie	Jack	Kyle	Meher	Philip!
Ahmed	Bahadurjit	Danilo	Fwarren	Jacob	Kyra	Melissa	Philip,
Ahmet	Bakhshi	Darika	Gabriel	Jacqueline	Laban	Mia	Philip.
Ahxel	Balendra	Darpan	Gabriele	Jade	Ladli	Mia!	Philip?
Airasia	Balhaar	Darsh	Gagan	Jagat	Laia	Mia,	Pihu
Akshara	Baljiwan	David	Gamalat	Jagdish	Lajita	Mia.	Polina
Akshay	Balvan	Davide	Gamila	Jagrati	Laksh	Mia?	Pranav
Alan	Balveer	Dayamai	Ganga	Jagvi	Lakshay	Michael	Praneel
Alejandro	Banjeet	Dayita	Garima	Jai	Lakshit	Michelle	Pranit
Aleksande r	Barbara	Deborah	Gary	Jainew	Lakshmi	mico	Pratyush
Alessandr o	Beatriz	Debra	Gaurang	Jairaj	Lalit	Miguel	Pratyusha
Alexander	Ben	Deepa	Gaurangi	Jairaldine	Lara	Mike	Premita
Alexandre	Bence	Denise	Gaurav	Jalsa	Larry	Mikey	Prenav
Alexis	Benjamin	Dennis	Gauri	Jam!	Laura	Mikhail	Prisha
Alfonso	Berat	Devansh	Gaurika	Jam,	Lauren	Miko	Puja
Ali	Betty	Dhriti	Gautam	Jam.	Laurence	Miraç	Qabil
Ali!	Beverly	Dhruv	Gautami	Jam?	Lawrence	Miray	Qadim
Ali,	Bhagyasri	Diana	Gayathri	James	Lea	Mishka	Qarin
Ali.	Bhanumati	Diane	Geet	Jamica	Lea!	Mitali	Qasim

Ali?	Bhavani	Dime	Geetika	Janaki	Lea,	Mitesh	Qayanat
Alice	Bhavini	Divya	Genilyn	Jane	Lea.	Moez	Qiyara
Alissa	Bhavna	Diya	Gentili	Janet	Lea?	Mohamed	Quasar
Allen	Bilal	Dmitri	George	Janice	Leena	Mohamme d	Queeni
Alli	Billy	Dominik	Gerald	Januja	Lekha	Murad	Quincy
Allie	Bimala	Donald	Giorgia	Janya	Leo	Mustafa	Qushi
Alma	Bina	Donna	Girik	Jasmine	Leon	Myra	Rabhya
Alvaro	Binita	Doris	Girindra	Jasmit	Leonardo	Nachiket	Rachana
Amaira	Bishakha	Dorothy	Girish	Jason	Leonor	Nahia	Rachel
Amanda	Bobby	Douglas	Giuia	Jatin	Levente	Naira	Rachit
Amandeep	Bradley	Dylan	Glen	Jaylen	Libni	Naksh	Rachita
Amandyf	Brandon	Ealek	Gloria	Jazmin	Lili	Nakul	Radha
Amaya	Brenda	Ecrin	Gopal	Jean	Linda	Nancy	Rafael
Amber	Brian	Edward	Grace	Jeet	Lipika	nara	Raghav
Amelia	Brijesh	Edwin	Gracie	Jeevika	Lisa	Nara	Rahol
Amen	Brinda	Ekaja	Gregory	Jeff	Liza	Natalie	Rajata
Amol	Brittany	Ekalinga	Greta	Jeffrey	Lochan	Nathan	Rajeshri
Amrita	Bruce	Ekani	Gunbir	Jeffry	Logan	Naveen	Raksha
Amruta	Bryan	Ekansh	Guneet	Jennifer	Logan!	Navya	Ralph
Amy	Carl	Ekanta	Habiba	Jenny	Logan,	Nayantara	Ranbir
Ana	Carol	Ekantika	Haizea	Jeremy	Logan.	Neel	Randy
Anaisha	Carol!	Ekapad	Halim	Jerry	Logan?	neha	Ranveer
Ananya	Carol,	Ekaraj	Hamza	Jesse	Lohit	Netra	Raul
Anastasia	Carol.	Ekavir	Hanna	Jessica	Lolita	Nicholas	Raveena
Anastasya	Carol?	Ekbal	Hannah	Jhalak	Lopa	Nicole	Rayaan
Anay	Caroline	Ekiya	Hardik	Jhanvi	Lorenzo	Nidra	Raymond
Anaya	Carolyn	Ekta	Harinakshi	Joan	Lori	Nihal	Rebecca
Andrea	Catherine	Ela	Harini	Joao	Louis	Niharika	Reem

Andrew	Chaaya	Elias	Harish	Joe	Louise	Nikhel	Rehaannew
Andriy	Chai	Elif	Harita	John	Luca	Nikit	Reyansh
Ane	Chaitaly	Elizabeth	Harold	Johnny	Lucas	Nikita	Richard
Angel	Chaitanya	Elizaveta	Harry	Johny	Lucie	Nilesh	Ridhi
Angela	Chakradev	Ella	Harsada	Jon	Lucky	Nilima	Rishi
Angelica	Chakradhar	Emilia	Harshada	Jon	Luisa	Nisha	Riya
Anglica	Chakrika	Emily	Harshida	Jonathan	Luka	Nitara	Robert
Anika	Chaman	Emir	Harshil	Joseph	Lyssa	Nitesh	Rodrigo
Aniruddha	Chameli	Emir!	Harshita	Joshua	Maanas	Noa	Rogelo
Anirudh	Champak	Emir,	Hasnaa	Joyce	Maanav	Noah	Roger
Anirudha	Chanakya	Emir.	Hassan	Juan	Madhav	noni	Rohan
Anmol	Chanchal	Emir?	Heather	Judith	Madhavi	Nora	Roman!
Ann	Chandani	Emma	Heena	Judy	Madison	Nylsia	Roman,
Anna	Chandran	Enoch	Helen	Jules	Magdahlin	Odika	Roman.
Ansh	Chandresh	Eric	Hema	Julia	Maha	Oeshi	Roman?
Anthony	Charan	erjon	Hemal	Julie	Mahika	Ojas	Ron
Anushka	Charita	Eshana	Hemang	Juliete	Mahmoud	Ojasvi	Ronald
Anvi	charles	Ester	Hemangini	Julius	Manan	Oliver	Ronik
Anya	Charlie	Eta	Hemani	Justin	Manbir	Olivia	Ronik
Anzar	Chasmum	Ethan	Henry	Kabir	Manjip	Omaja	Ronith
apurv	Chatresh	Eugene	Hiral	Kajal	Manon	Omar	Rose
Araan	Chatura	Evelyn	Hiranur	Kalpit	Manthan	Omer	Rowan
Zora	Zoya	Zsofia	Zuri	Zuri!	Zuri,	Zuri.	Zuri?
Roy	Triya	Solomia	Wishi	Selim	Virginia	Teerth	Zaida
Roy!	Tulsi	Sophie	Wriddhish	Semi	Vivaan	Tejas	Zara
Roy,	Turvi	stella	Wridesh	Shahbaz	Vladislav	Teresa	Zarna

Roy.	Tyler	Stephanie	Yachana	Shahd	Wafiya	Terry	Zashil
Roy?	Ubika	Stephen	Yadavi	Shaimaa	Wahab	Theresa	Zayan
Rudranew	Ucchal	Steven	Yagnesh	Shanaya	Waheeda	Thomas!	Zayyan
Rushil	Udant	Suha	Yahvi	Sharon	Waida	Thomas,	Zeba
Russell	Udarsh	Suhana	Yash	Shaurya	Wajeeha	Thomas.	Zehaan
Ruth	Udyati	Suhani	Yashawini	Shirley	Wakeeta	Thomas?	Zehra
Ryan!	Umang	susan	Yashica	Shivansh	Walter	Timothy	Zenia
Ryan,	Umbraj	Susanna	Yashoda	Shravya	Warda	Sami	Vanya
Ryan.	Unnati	Susannah	Yashodhar a	Shreya	Warinder	Sammy	Vasana
Ryan?	Unni	Suzan	Yassin	Shun	Warjas	Samuel	Vasatika
Saanvi	Upadhriti	Swapnil	Yasti	Siddesh	Watika	Sandeep	Vasudha
Sagar	Upasna	Sweetie	Yatan	Siddharth	Wayne	Sandra	Vedant
Sahana	Upkaar	Taha	Yatin	Simon	Wazir	Santi!	Vedhika
Sahar	Upma	Tamanna	Yauvani	Simran	Widisha	Santi,	Veer
Saira	Urishilla	Tanay	Yochana	Sneha	William	Santi.	Veronika
Saksham	Urmi	Tanish	Youssef	Sofya	Willie	Santi?	Viaannew
Samaira	Utkarsh	Tanmayi	Yug	Sarah	Vihaan	Sara	Victoria
Samaksh	Uxue	Tanuja	Yusuf	Sarthak	Viktoria	Toni	Zeynep
Samantha	Vaishnavi	Tanveer	Yuvraj	Sathvikne w	Vinaya	tony	Zivah
Samar	Vamakshi	Tanvi	Zachary	Saumya	Vincent	Tripti	Zlata
Samarth	Vamika	Tarak	Zaha	Scott	Vinea	Trisha	Zoe
Samesh	Vansha	Tareq	Zaid	Sean	Viraj	Triveni	Zoey
Zuzanna							

Appendix D

Personalized positive review

"I called to inquire about my flight booking. I spoke to Alex who made me feel very calm during our conversation. He was helpful and I'm so happy with how he handled the situation and quickly solved my issue with my Laris Airlines booking. I feel very lucky that I got to speak to Alex, he made what could have been a stressful situation into a pleasant one. It was the best experience."

Personalized negative review

"I called to inquire about my flight booking. I spoke to Alex who made me feel very anxious during our conversation. He was not helpful and I'm so unhappy with how he handled the situation and failed to solve my issue with my Laris Airlines booking. I feel very unlucky that I got to speak to Alex, he made what could have been a pleasant situation into a stressful one. It was the worst experience."

Non-personalized positive review

"I called to inquire about my flight booking. I spoke to Laris Airlines who made me feel very calm during our conversation. They were helpful and I'm so happy with how they handled the situation and solved my issue with my Laris Airlines booking. I feel very lucky that I got to speak to them, they made what could have been a stressful situation into a pleasant one. It was the best experience."

Non-personalized negative review

"I called to inquire about my flight booking. I spoke to Laris Airlines who made me feel very anxious during our conversation. They were unhelpful and I'm so unhappy with how they handled the situation and failed to solve my issue with my Laris Airlines booking. I feel very unlucky that I got to speak to them, they made what could have been a pleasant situation into a stressful one. It was the worst experience."

Appendix E

Model 4: Valence as the independent (1 = positive, 0 = negative). *Credibility* was selected as a mediator, with *review value* as the dependent variable. Review usage was controlled for.

Run MATRIX procedure:

**************** PROCESS Procedure for SPSS Version 3.4.1 ****************

Written by Andrew F. Hayes, Ph.D. www.afhayes.com
Documentation available in Hayes (2018). www.guilford.com/p/hayes3

****

Model: 4
Y: Value
X: Valence
M: Credibility

Covariates:
Preference

Sample
Size: 415

****

OUTCOME VARIABLE:
Credibility

Model Summary

R	R-sq	MSE	F	df1	df2	p
,2291	,0525	1,2415	11,4128	2,0000	412,0000	,0000

Model

	coeff	se	t	p	LLCI	ULCI
constant	4,4308	,2520	17,5816	,0000	3,9354	4,9262

Valence	,4722	,1094	4,3154	,0000	,2571	,6872
Preferen	,0844	,0427	1,9759	,0488	,0004	,1684

****

OUTCOME VARIABLE:

Value

Model Summary

R	R-sq	MSE	F	df1	df2	p
,4620	,2134	2,2224	37,1716	3,0000	411,0000	,0000

Model

	coeff	se	t	p	LLCI	ULCI
constant	1,6000	,4461	3,5868	,0004	,7231	2,4769
Valence	,2560	,1497	1,7103	,0880	-,0382	,5501
Credibil	,6448	,0659	9,7825	,0000	,5152	,7744
Preferen	,0034	,0574	,0590	,9530	-,1095	,1163

************************** TOTAL EFFECT MODEL ****************************

OUTCOME VARIABLE:

Value

Model Summary

R	R-sq	MSE	F	df1	df2	p
,1740	,0303	2,7332	6,4304	2,0000	412,0000	,0018

Model

	coeff	se	t	p	LLCI	ULCI
constant	4,4571	,3739	11,9197	,0000	3,7220	5,1921
Valence	,5604	,1623	3,4521	,0006	,2413	,8795
Preferen	,0578	,0634	,9122	,3622	-,0668	,1824

************** TOTAL, DIRECT, AND INDIRECT EFFECTS OF X ON Y **************

Total effect of X on Y

Effect	se	t	p	LLCI	ULCI
,5604	,1623	3,4521	,0006	,2413	,8795

Direct effect of X on Y

Effect	se	t	p	LLCI	ULCI
,2560	,1497	1,7103	,0880	-,0382	,5501

Indirect effect(s) of X on Y:

	Effect	BootSE	BootLLCI	BootULCI
Credibil	,3045	,0799	,1566	,4717

*********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:
95,0000

Number of bootstrap samples for percentile bootstrap confidence intervals:
5000

------ END MATRIX -----

Appendix F

Male service representative - Positive review

"I called to inquire about my flight booking. I spoke to Alex who made me feel very calm during our conversation. He was helpful and I'm so happy with how he handled the situation and quickly solved my issue with my Laris Airlines booking. I feel very lucky that I got to speak to Alex, he made what could have been a stressful situation into a pleasant one. It was the best experience."

Male service representative - Negative review

"I called to inquire about my flight booking. I spoke to Alex who made me feel very anxious during our conversation. He was not helpful and I'm so unhappy with how he handled the situation and failed to solve my issue with my Laris Airlines booking. I feel very unlucky that I got to speak to Alex, he made what could have been a pleasant situation into a stressful one. It was the worst experience."

Female service representative - Positive review

"I called to inquire about my flight booking. I spoke to Maria who made me feel very calm during our conversation. She was helpful and I'm so happy with how she handled the situation and quickly solved my issue with my Laris Airlines booking. I feel very lucky that I got to speak to Maria, she made what could have been a stressful situation into a pleasant one. It was the best experience."

Female service representative - Negative review

"I called to inquire about my flight booking. I spoke to Maria who made me feel very anxious during our conversation. She was not helpful and I'm so unhappy with how she handled the situation and failed to solve my issue with my Laris Airlines booking. I feel very unlucky that I got to speak to Maria, she made what could have been a pleasant situation into a stressful one. It was the worst experience."

Appendix G

Model 4: Valence as the independent (1 = positive, 0 = negative). *Credibility* was selected as a mediator, with *review value* as the dependent variable. Review usage was controlled for.

**************** PROCESS Procedure for SPSS Version 3.4.1 ****************

Model: 4
Y: Value
X: Rev_Vale
M: Credibil

Covariates:
Rev_usag

Sample
Size: 479

****
OUTCOME VARIABLE:
Credibil

Model Summary

R	R-sq	MSE	F	df1	df2	p
,4408	,1943	1,3286	57,3906	2,0000	476,0000	,0000

Model

	coeff	se	t	p	LLCI	ULCI
constant	2,6586	,2759	9,6358	,0000	2,1165	3,2008
Rev_Vale	,7724	,1054	7,3263	,0000	,5652	,9796
Rev_usag	,3407	,0451	7,5467	,0000	,2520	,4294

****
OUTCOME VARIABLE:
Value

Model Summary

R	R-sq	MSE	F	df1	df2	p
,5888	,3466	1,8333	84,0056	3,0000	475,0000	,0000

Model

	coeff	se	t	p	LLCI	ULCI
constant	,4925	,3543	1,3901	,1652	-,2037	1,1887
Rev_Vale	,4379	,1306	3,3519	,0009	,1812	,6946
Credibil	,6267	,0538	11,6405	,0000	,5209	,7325
Rev_usag	,1864	,0561	3,3219	,0010	,0761	,2967

****************** DIRECT AND INDIRECT EFFECTS OF X ON Y ******************

Total effect of X on Y

Effect	se	t	p	LLCI	ULCI
,9220	,1403	6,5736	,0000	,6464	1,1976

Direct effect of X on Y

Effect	se	t	p	LLCI	ULCI
,4379	,1306	3,3519	,0009	,1812	,6946

Indirect effect(s) of X on Y:

	Effect	BootSE	BootLLCI	BootULCI
Credibil	,4841	,0886	,3180	,6618

*********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:
95,0000

Number of bootstrap samples for percentile bootstrap confidence intervals:
5000

NOTE: Variables names longer than eight characters can produce incorrect output.
Shorter variable names are recommended.

------ END MATRIX -----

Model 11: Valence as the independent (1 = positive, 0 = negative). Service representative and reader gender as moderators. *Credibility* was selected as a mediator, with *review value* as the dependent variable. Review usage was controlled for.

Run MATRIX procedure:

**************** PROCESS Procedure for SPSS Version 3.4.1 ****************

Model: 11
Y: Value
X: Review Valence
M: Credibility
W: Rev_Gend
Z: Gender

Covariates:
Rev_usag

Sample
Size: 479

****
OUTCOME VARIABLE:
Credibil

Model Summary

R	R-sq	MSE	F	df1	df2	p
,4657	,2169	1,3078	16,2743	8,0000	470,0000	,0000

Model

	coeff	se	t	p	LLCI	ULCI
constant	-2,4481	2,5453	-,9618	,3367	-7,4497	2,5536
Review Valence	11,9751	3,6965	3,2396	,0013	4,7114	19,2387
Review Gender	3,6740	1,6157	2,2739	,0234	,4991	6,8490
Int_1	-7,2272	2,3152	-3,1217	,0019	-11,7766	-2,6778
Reader Gender	,8726	,4704	1,8551	,0642	-,0517	1,7970
Int_2	-1,9951	,6818	-2,9263	,0036	-3,3349	-,6554

Int_3	-,6268	,2975	-2,1068	,0357	-1,2114	-,0422
Int_4	1,2838	,4261	3,0129	,0027	,4465	2,1212
Rev_usag	,3355	,0458	7,3296	,0000	,2455	,4254

Product terms key:

Int_1 : Review Valence x Review Gender

Int_2 : Review Valence x Reader Gender

Int_3 : Review Gender x Reader Gender

Int_4 : Review Valence x Review Gender x Reader Gender

Test(s) of highest order unconditional interaction(s):

	R2-chng	F	df1	df2	p
X*W*Z	,0151	9,0777	1,0000	470,0000	,0027

Focal predict: Review Valence (X)

Mod var: Review Gender (W)

Mod var: Reader Gender (Z)

Test of conditional X*W interaction at value(s) of Z:

Reader Gender	Effect	F	df1	df2	p
5,0000	-,8081	8,7488	1,0000	470,0000	,0033
6,0000	,4758	2,1164	1,0000	470,0000	,1464

Conditional effects of the focal predictor at values of the moderator(s):

Rev_Gend	Reader Gender	Effect	se	t	p	LLCI	ULCI
1,0000	5,0000	1,1914	,1922	6,1983	,0000	,8137	1,5691
1,0000	6,0000	,4801	,2390	2,0088	,0451	,0105	,9498
2,0000	5,0000	,3834	,1953	1,9629	,0502	-,0004	,7671
2,0000	6,0000	,9559	,2233	4,2809	,0000	,5171	1,3947

****

OUTCOME VARIABLE:

Value

Model Summary

R	R-sq	MSE	F	df1	df2	p

,5888	,3466	1,8333	84,0056	3,0000	475,0000	,0000

Model

	coeff	se	t	p	LLCI	ULCI
constant	,4925	,3543	1,3901	,1652	-,2037	1,1887
Rev_Vale	,4379	,1306	3,3519	,0009	,1812	,6946
Credibil	,6267	,0538	11,6405	,0000	,5209	,7325
Rev_usag	,1864	,0561	3,3219	,0010	,0761	,2967

****************** DIRECT AND INDIRECT EFFECTS OF X ON Y *****************

Direct effect of X on Y

Effect	se	t	p	LLCI	ULCI
,4379	,1306	3,3519	,0009	,1812	,6946

Conditional indirect effects of X on Y:

INDIRECT EFFECT:

Rev_Vale -> Credibil -> Value

Rev_Gend	Gender	Effect	BootSE	BootLLCI	BootULCI
1,0000	5,0000	,7467	,1680	,4334	1,0946
1,0000	6,0000	,3009	,1607	-,0115	,6310
2,0000	5,0000	,2403	,1103	,0370	,4739
2,0000	6,0000	,5991	,1497	,3261	,9119

Index of moderated moderated mediation

Index	BootSE	BootLLCI	BootULCI
,8046	,2938	,2684	1,4294

Indices of conditional moderated mediation by W

Gender	Index	BootSE	BootLLCI	BootULCI
5,0000	-,5064	,1836	-,8828	-,1638
6,0000	,2982	,2136	-,1008	,7330