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The effect of different types of online sales channels on online product review valence

Author: Tara Kamer

Student ID: 471548

Supervisor: Dr. M. van Crombrugge

Co-reader: Dr. K. Gruber

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Abstract

As companies move to digital, e-commerce is getting a fundamental place in the retail sector. This transformation was accelerated by the recent COVID-19 pandemic and now having a digital presence for retail businesses carries more importance than ever. When answering to this transformation, manufacturers have choices to make. They can either take digital sales into their hands by providing an online direct sales channel or partner with well-established third-party marketplaces like Amazon. While providing a direct online channel keeps brand communications in control, huge marketplaces like Amazon provides more traffic and sales to the products while sacrificing this control over electronic word of mouth. In this study, we analyze whether this sacrifice is worthy for the firms with respect to online product reviews which is an element of electronic word of mouth. We study how online product review valence changes when the direct online sales channel and indirect online sales channel are compared. We also take into account product description length, review volume, and review valence as possible variables that affect this relationship. Our findings show that contrary to the expectations of this study, the indirect channel does not result in a more negative review valence when compared with the direct channel. Additionally, we find significant evidence on the positive moderation by volume and positive mediation by variance on the review valence. Thus, with the results of our study, we encourage brand managers to rethink their sales channel portfolios and consider partnering with e-commerce giants like Amazon.

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1 Introduction

With developing technologies and situations, brands and consumers are vastly transforming into the digital. This digital transformation accelerated by the COVID19 pandemic is bringing new choices to both sides of the sales transactions. Now sellers have a crucial choice to make when deciding on their sales channel portfolios and consumers can opt for the channel they want to use. The current move towards online sales because of COVID19 is seen as the “tipping point” for this transformation which will shift the buyer-seller dynamics permanently (Sides & Skelly, 2021). This means there is a shift to online sales channels which will be a permanent shift rather than a temporary trend. Manufacturers need to adapt to this situation and respond effectively by finding the right channel portfolio that works best for their brand image. Many brands are following a “bricks-and-clicks” combination while opting for multichannel environments (Agatz et al. 2008). This means integration of online sales channels to the traditional brick-and-mortar one. Having a complementary channel portfolio provides better customer service and enhances the overall value proposition of the manufacturer (Wallace et al., 2004). Also, this diverse channel portfolio can include downsides as well. The most important concern points include cannibalization and channel conflicts (Webb, 2002). A manufacturer can compete with its own channel and cannibalize sales (Tsay et al., 2004). Thus, multi-channel management becomes a crucial point for the brands and firms. They should follow the digital transformation by providing online sales channels to their consumers however this should be done carefully in order to not damage the brand.

When a brand is building an online presence, there are multiple choices of sales channels that can be used. They can have an online direct channel supplied by the manufacturer itself. Also, they have a choice to enter the marketplaces like Amazon and eBay to reach a greater audience. Additionally, they can supply an online retailer to add their product to their product assortment. Having a presence in multiple channels would seem logical for manufacturers since it provides as many touchpoints with the consumers as possible. But this is not the case for every manufacturer. A recent example from Nike illustrates this. Nike made a deal with Amazon to sell their products to them, and prevent unlicensed products sold by third parties thus hoping to direct sales to their channel (Forbes, 2020). The expected outcome never happened so Nike pulled its products from Amazon and focused on its own channel to have a more direct relationship with the consumers (Bloomberg, 2020). These unlicensed products were a threat to Nike and its brand image. According to Forbes (2020), it was affecting the first-party sales. Also, these counterfeit products were getting more online product reviews than the original products thus making the original products harder to find on the marketplace. Nike had a lack of control over counterfeit products as well as the accumulating reviews under the counterfeit products.

Although problems may arise with online channel integration, it is a fact that in some specific markets, online channels have become a disruptive development (Christensen and Raynor, 2003). Many firms responded by changing their business models (Sorescu et al. 2011). This rise in the online channel popularity and the internet in general, lead to brands no longer having the control over all communications about their brand (Yu et al., 2018). Now with the new era, user-generated content influences the brand image almost to the point that it is replacing the traditional media (Bruhn et al., 2012). This study focuses on and analyzes a form of user-generated content which is the online product reviews. Online sales channels often include a review section for consumers to rate and comment on the product. Reviews about a product coming from previous purchasers can both benefit and harm the image of the brand (Lin & Xu, 2017; Craig et al., 2015). However, especially on e-commerce platforms like Amazon, reviews from consumers are uncontrolled and uncensored from the brands' perspective. Hence, deciding on an online channel portfolio is a crucial strategy for brands and their image.

This study will focus on how the sentiment of online product reviews changes across online channels and what the drivers of this difference are. This paper will aim to answer the following research question and the sub-questions to understand this effect:

How does the review valence differ between the direct online sales channels and third-party e-commerce platforms?

- How does the review sentiment in online product reviews differ across the online channel of the manufacturer and e-commerce platforms?

- How would product description moderate review sentiment difference across the online channel of the manufacturer and e-commerce platforms?

- How do review volume, and review variance moderate and/or mediate this review sentiment difference across the online channel of the manufacturer and e-commerce platforms?

This paper aims to study how different types of online channels can influence the review valence of the same products. Findings are relevant to all firms that want to make decisions when digitally transforming. Understanding the drivers of review valence specific to an online sales channel will bring value to the firm by having control over the conversation. We provide empiric evidence on whether or not review valence differs between channels and the reasoning behind this difference.

This section is followed by possible contributions to the research field. We continue with a literature review section where we take a look at the research that has already been done. We then present our conceptual framework where we have the variables that we use in this study with the corresponding theories. To continue, we show how we scraped and prepared our data with its descriptive statistics. Next, we continue with the methodologies used in our paper. Lastly, we present the results of these analysis and conclusion and a discussion of these results.

2 Contribution

Prior literature on multichannel found that there exist many differences between sales channels. Alba et al. (1997) compared multiple traditional channels such as supermarkets, department stores, and online channels like internet retailers. They summed the dimensions differing in sales channels as follows: providing alternatives for consideration, screening alternatives from the consideration set, providing information, order and fulfillment. Avery et al. (2012) focused on the differences between offline and online channels. Their empirical study included how online, catalog and brick-and-mortar channels differ considering experiential and conspicuous capabilities. For example, conspicuous capabilities included assortment depth, transaction costs, and sales support whereas experiential capabilities included recognition of retailer, shopping experience, and easiness. However, they did not include a comparison between direct online sales channels and online retailers. Also, they did not explore online product reviews as one of the capabilities. Maier and Wieringa (2021) investigated how marketplaces impact retailers' websites. Although they were focusing on sales, they included marketplaces in their study to compare with retailers. They observed assortment depth differences across these channels. They involved marketplaces in their study however, online product reviews was not investigated and direct online channels were not included in this study.

In this research stream, some studies focused on direct and indirect channel differences. Hendershott and Zhang (2006) built a model to analyze sales and price differences between direct and indirect channels while accommodating the fact that there are transaction cost differences between the channels. Rodriguez and Aydin (2015) modeled the channel choice of a consumer as a function of assortment and prices offered by both direct and indirect channels. So, prior studies mentioned transaction cost, price, and assortment depth differences amongst direct and indirect channels. Our study includes a form of multichannel difference that has not been highlighted by mentioned studies: electronic word-of-mouth.

Consumer reviews have been the subject of several studies and our study contributes to this area of research also. A study by Chevalier and Mayzlin (2006) stated there are more and longer reviews on the online marketplace when compared with a retailer. However, this study didn’t include a direct online sales channel when observing consumer reviews. Also, our study adds a new aspect of product reviews which is the variance amongst ratings. Yang et al. (2021) concluded in their studies that providing consumer reviews on a manufacturer’s online channel is not beneficial in case the review is not favorable. The study has a dual-channel framework, but they compare a direct online channel with a brick-and-mortar retail channel. Until now, no study elaborated on product reviews as differences between direct and indirect online channels. This paper will contribute by having empirical proof on how product reviews differ amongst channels thus giving a guideline to brands on online sales channel selection.

3 Literature Review

The theme of this research is to how direct and indirect channels differ when we focus on the valence of online product reviews. Therefore, we unify 3 research streams: research on (i) online product reviews, (ii) the impact of online product reviews, and (ii) how firms use online product reviews. In the first section, we focus on what online product reviews are. Next, we analyze the impact of online product reviews on purchase behaviors and attitudinal measures. Lastly, we focus on how firms can make use of online product reviews for better positioning of the brand concerning review valence.

3.1 Online product reviews

This paper focuses on online product reviews to understand the relationship between the type of the online marketplace and review valence. Thus, we start with a brief understanding of online product reviews. Online product reviews are a fundamental part of the electronic word of mouth (eWOM) that is available on the internet. Hennig-Thurau et al. (2004) defined Electronic Word of Mouth as any positive or negative statement done by potential, actual or former customers about a product or service via the Internet. They stated that eWOM can take place in many forms such as web-based opinion platforms, discussion forums, boycott websites, news groups etc. eWOM is user-generated content that includes online product reviews as well as social media interactions and discussions on forums (Homburg, Ehm, & Artz, 2015). This paper focuses on online product reviews which is one of the many aspects of eWOM.

Online product reviews have a place in majority of the online marketplaces nowadays to help consumers to form an opinion where they cannot touch, or smell products like in traditional retail shops (Park, Lee, and Han, 2007). By providing mentioned information to consumers, these reviews tend to decrease customers' choice risk (Cui et al., 2012; Zhu & Zhang, 2010). This is also an example where reviews work as an informant as Park, Lee, and Han (2007) mentioned their dual role as an informant and as a recommender. Product reviews as recommenders include the recommendations of previous users about the product. Both roles attach importance to product reviews for the topics of consumer choices and customer decision-making journey. Mentioned role of product reviews made product reviews and their impacts on the firms and brands a popular research stream.

3.2 Impact of online product reviews

The larger part of the research on online product reviews focuses on their impact on purchase behavior. Within this stream, Chevalier and Mayzlin (2006) found in their seminal paper that the improvement of a review of a product also improves the sales of the product. Their study focused on online book reviews and found out that when reviews of books improve, sales increase relatively. Also, they concluded that the impact of one-star reviews is higher than the five-star reviews on sales. Their finding was followed by other studies looking at the characteristics of online product reviews on purchase intention. Dellarocas et al. (2007) added the influence of volume of ratings to the sales and enhancement of this effect in the early period of the product. Park et al. (2007) found that the quality of the online reviews has a positive impact on the purchasing decisions of the consumers. Clemons et al. (2006) added in their findings that the variance of ratings is significantly correlated with the sales of a product. To continue, Hu, Koh, and Reddy (2014) concluded in their research that review sentiment has a direct effect on sales where review ratings indirectly impact through the sentiments. Discussed characteristics of the online product reviews are scientifically important moderating factors when we are discussing the effect of online product ratings on sales of a product as stated in the studies above mentioned. Low valence reviews may imply low sales for the brands and products thus the reasons need to be understood by brands.

Another stream of research focuses on the differences amongst products and their impact on online reviews. Sen and Lerman (2007) found that while making purchase decisions about a utilitarian product consumers give more importance to negative reviews when compared to the hedonic products. Cui et al. (2012) compared the effect of review valence on search versus experience goods and found out they have a more enhanced effect on the sales of search goods. Their study also found that the volume of reviews is more important than review valence when experience goods are examined. Hence, product differences have a moderating role when it comes to the review ratings.

The next research stream we focus on covers the impact of online reviews on attitudinal measures. Customer reviews decrease the importance of brand image in consumers' decision-making process (Kostyra et al., 2016). Therefore, understanding the impact of reviews is crucial for brands. The study by Bambauer-Sachse and Mangold (2011) provided support for negative online product reviews having a detrimental effect on consumer-based brand equity. Lin and Xu (2017) also stated in their findings that review valence has an influence on brand attitude next to purchase intention. Beneke et al. (2016) added to this stream by concluding negative reviews have a detrimental effect when it comes to brand equity and purchase decisions. Also, they added high quality reviews are more influential than low-quality reviews for brand equity. All in all, previous study findings illustrate online product reviews have a crucial place for the brand image and online presence by impacting the customer decision journey.

Although the previous literature diligently researched online product reviews and their importance, there is an absence of research on the effect of sales platform differences on online reviews. Many studies are present about channel selection in dual and multi-channel sales contexts. Tahirov and Glock (2022) described in their study that if a manufacturer sells its products through its website or company-owned stores, this is a use of a direct sales channel. If a manufacturer sells the products through an intermediary which can be retailers, wholesalers, etc.., the manufacturer uses indirect sales channels. In the case of manufacturer encroachment, indirect channels often see this move as a threat thus creating a channel conflict (Webb, 2002). Rodríguez and Aydın (2015) modeled consumers' channel preferences as a function of price and assortment depth to elaborate on channel selection. Also, research by Chiang and Li (2009) also confirmed this and also stated accessibility, which is defined by the authors as a channel allowing consumers to examine the product during the consumers' evaluation process, is also a factor in channel preference. Some aspects that differ from channel to channel like price and assortment are studied in the literature in the context of channel selection however there is a lack of literature on how online product reviews differ among the online sales channels.

3.3 Online product reviews and firms

The mentioned importance of the online product reviews suggests that firms should understand what the drivers are of the review valence. This section will discuss how firms can position themselves to have an impact on the review valence. Godes et al. (2005) described four different roles can a firm play when the topic is online product reviews which is a type of electronic word of mouth. They are observer, moderator, mediator, and participant. They define social interactions as actions taken by consumers that impact others' expected utility out of the product or service. The firm as an observer only collects the social interaction information. The firm as a moderator fosters these social interactions whereas the firm as a mediator manages. Lastly, as the most active role, the firm as a participant plays a role in social interactions. Considering this framework, firms can position themselves in these non-mutually exclusive roles in order to manage online reviews and influence their valence.

Although solely being an observer is not a strategy for moderating the effect of the online product reviews, firms can observe online reviews to gain insights into the consumers and their thought processes about a brand or a product (Godes et al., 2005). Next two possible approaches by firms, moderator and participant, can have a direct effect on online product reviews. The firm as a moderator basically starts by hosting the conversation on the firm's platform (Godes et al., 2005). As a moderator, firms can have an influence on the review valence. Eelen et al. (2017) suggested brands need to encourage even their loyal consumers that have a positive experience to engage in electronic word of mouth. Thus, firms need to incentivize consumers to leave online comments. Burtch et al. (2018) resulted in their experimental paper that monetary incentives result in a larger number of reviews. A recent study by Garnefeld et al. (2020) concluded incentives like monetary rewards increase the chance of leaving a positive comment for the consumer. Although the effect of this on review valence tends to be mixed since for some consumers review valence is affected negatively since they avoid feeling manipulated. Lastly, a firm as a participant in social interaction is defined by Godes et al. (2005) as participating in the conversation about the brand directly and in general anonymously. Zhuang et al. (2018) presented in their findings that adding positive reviews and deleting negative reviews in an online context has an inverted U-shaped effect on sales. He, Hollenbeck, and Proserpio (2022) found a significant but short-term increase in the average rating of the products on Amazon when firms buy fake and highly rated product reviews. However, they continue their findings by adding that, after firms stop buying fake reviews, ratings again decrease, and the number of one-star reviews increases. To prevent this from occurring, Amazon has an anti-manipulation policy for customer reviews (Amazon 2022). If they detect suspicious behavior, they can suspend or terminate the relationship brand and pursue a lawsuit if found fraudulent. This does not conclude that regulations prevent fraudulent situations. As Walsh (2022) covered in his article on Forbes, Amazon sued two companies for selling fake product reviews to firms. Whether positive or negative, firms can impact online product revies by positioning themselves accordingly. Understanding aspects of online product reviews that may affect review valence can help brands to finalize their strategies and focus on the important characteristics of product reviews to increase brand value and sales.

4 Conceptual Framework

After we take a look at the previous literature on online product reviews and sales channels, we now continue with our conceptual framework. The framework is visualized below in Figure 1. We first start with explaining the expected main effect and continue with our moderation and mediation variables. Lastly, we mention our control variable for this study.

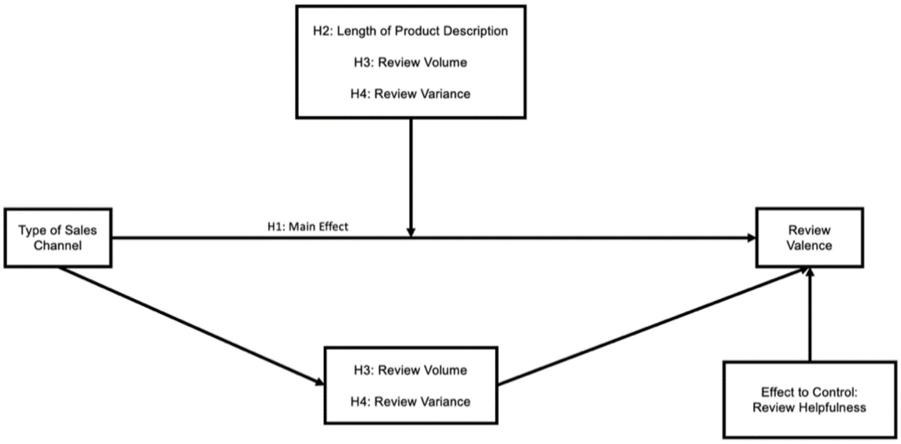

Figure 1: The conceptual framework

4.1 Main Effect

The main effect this paper studies is the relationship between online product review valence and the type of online sales channel. The first hypothesis is that review valence for the same selected product will be higher in the direct online channel when compared with the third-party marketplace. This hypothesis is based on previous research made in the field. In a seminal paper by Dick and Basu (1994), they concluded that word of mouth is a result of customer loyalty. In an electronic word-of-mouth context, Eelen et al. (2017) claimed that a customer identifies with the brand and this "self-brand" connection enhances their brand loyalty. When customers are identifying with a brand, they develop a desire to help that brand. Furthermore, they added that loyal consumers of the brand are more likely to leave a review. This study expects that the brand loyalty effect has a higher impact on reviews in the direct online channel rather than in third-party marketplaces. This outcome is expected because we expect brand loyalty and thus desire to help the brand have a stronger impact on direct online channels compared to third-party marketplaces. Dellarocas and Narayan (2010) argued in their studies that people with extremely positive and extremely negative opinions tend to contribute more to online reviews than those with moderate opinions. Since it is proven that brand loyal consumers are more likely to leave a review due to self-brand connection, we expect them to be on the positive side of this extremeness when leaving reviews to help the brand. To further support this idea, we can look at the work done by DeAngelis et al. in 2012. They stated that a stronger connection between the self and a brand may enhance their tendency to engage in positive word of mouth about that brand. Since we expect consumers to have a stronger self-brand connection on the direct online channel, we hypothesize review valence in the direct online channel would be higher when compared to an online marketplace. We expect brand loyal consumers to purchase and leave a review from the direct online channel rather than marketplaces since they are already decided to buy the specific brand that they are loyal to and don't need the brand options that a marketplace offers.

H1: *Review valence on the same product is more positive in direct online sales channels when compared with the third-party online channels.*

4.2 Moderating/mediating variables

After we hypothesize that reviews are more positive in direct online sales channels compared to third parties, we wanted to understand the moderating and/or mediating factors of this relationship. This study focuses on the online product review attributes such as length of the product description, review volume, and review variance. Because our main effect is based on brand-loyalty and self-brand identification, we consider aspects of an online shopping environment that can alter these concepts for the consumer when leaving a review. We consider product description as a first important moderating effect since product descriptions can cause a stronger connection with the consumer in online channels (Rose et al., 2012). Similarly, we select review volume as the second effect since word-of-mouth behavior relates to helping the brand (Sundaram et al., 1998). Finally, we select review variance because as stated above consumers have more potential to leave a review when they have extreme opinions (Dellarocas and Narayan, 2010) thus creating variance. Additionally, variance and volume of the product reviews are easy measure and obtain for market researchers. As Sun (2012) stated in his paper about online review variance, market researchers can easily calculate this value. Understanding how these values change over sales channels and impact the brand is not costly and beneficial for the brands.

This section continues with the explanation of these moderators/mediators and hypotheses. We will handle the product description variable as a moderator only whereas we will operationalize review volume and review variance variables as both moderators and mediators separately. This approach of using variables as both moderator and mediators has been used in many studies before (e.g., Dunkley et al., 2000, Eertmans et al., 2005, Holman and Wall, 2002, Lewis and Kliewer, 1996).

4.2.1 Length of Product Description

The first effect we elaborate on is the length of product descriptions. This refers to the writing that introduces the product to the consumer. This can be either named as "about this product" section or an untitled section where the consumer is first introduced to the product via the means of textual information.

Rose et al. (2012) stated in their study that customers experience an online brand through incoming sensory data. They elaborated this data as text-based information, images, and audio. Cleff et al. (2018) tested and found significant results for cognitive brand experience having a positive effect on brand loyalty. Rose et al. (2012) suggests one of the ways a retailer has a connection with a consumer in online channels is through text-based information provided. For our study, we will focus on text-based information that accompanies the products as a part of cognitive information which is the product descriptions. Product descriptions offer information to consumers, and we assume their length is correlated with their level of detail and the amount of extra information that descriptions provide to consumers. Thus, increasing the incoming sensory data from the website. Also, with the product descriptions manufacturer has the chance to connect with the potential customers and improve their perceived customer experience as Rose et al. (2012) suggested. Since our main hypothesis expects a brand-self connection to have a positive impact on review valence, we expect connecting with consumers through product descriptions to have a positive impact on review valence in indirect channels where the brand loyalty and self-brand connection are hypothesized as missing.

Sheth and Venkatesan (1968) researched repetitive consumer behaviors and found out that consumers were seeking less information when purchasing repetitively over time. Our main effect suggests brand loyalty being higher in direct channels thus this paper expects these repetitive buyers also shop from the direct channels. We expect direct channels won't be impacted by above-mentioned effect as much as an indirect channel where we hypothesize to have less loyalty and self-connection with a brand. Extra information given by the textual data can remedy this lack of loyalty and connection according to mentioned theories. So, we expect consumers have more positive reviews in the indirect channels as the product description length increases.

H2: *The difference in review valence for the same product across the online direct channel and online third-party marketplace is smaller when products have longer descriptions.*

4.2.2 Review volume

Second effect we introduce is the review volume. This refers to the number of reviews that are written by consumers for a specific product. This variable will be analyzed in from a moderation and mediation perspectives. Below we present theories for both sides.

4.2.2.1 Moderation

Godes and Silva (2009) concluded that review valence decreases with the ordinality thus the volume of the product reviews. Order effect is explained as the decrease in consumer's ability to assess previous reviews and when previous reviewers are different, more reviews lead to more purchase errors thus concluding in lower review valence in future. In line with this effect, as the number of reviews increases, review valence starts to get more negative.

Leaving a product review has a connection to motivational factors like self-presentation, helping others, and helping the brand (Barasch and Berger, 2014; Chen and Kirmani, 2015;

Cheung and Lee, 2012; Hennig-Thurau et al., 2004). De Angelis et al. (2012) argued that a stronger connection between the self and a brand increases the possibility to engage in positive word of mouth about the brand. Thus, brand loyal consumers expected to have positive reviews to help the brand because of their self-brand connection. We expect these loyal consumers to judge the product in a positive manner and not need other people's opinions when stating their reviews. However, indirect channels are expected to have non-loyal consumers in our experiment. Reviews made before them represent more value to non-loyal consumers since they justify their purchase and decrease their uncertainty about a product (Korfiatis et al., 2012). So, we expect indirect channels to get a higher impact through the order effect. This study expects larger volumes in indirect channels to cause negative review valence due to the ordinality effect thus increasing the difference in review valence between direct and indirect channels.

H3: *The difference in review valence for a product across the online direct channel and online third-party marketplace is larger when product reviews have a higher volume.*

4.2.2.2 Mediation

This paper expects higher traffic in third-party marketplaces when compared to direct online channels due to the fact these marketplaces include more options for each product category by carrying multiple brands and becoming a resource for comparison for consumers. According to a study done by Similarweb in 2021 Amazon had six times more traffic than Walmart and their share of traffic cannot even compare with the direct channels of the manufacturers. We expect this traffic would result in more sales and a higher quantity of product reviews in marketplaces as Chatterjee in 2001 stated in his study that the number of reviews is directly related to the sales of a product. As discussed before there is an expected negative effect of high volume on review valence due to ordinality effect since consumers more inclined to make mistakes when assessing previous reviews to make a decision (Godes and Silva, 2009). Since indirect channel is expected to have higher quantity of reviews due to high traffic, order effect is expected to be present in indirect channels whereas direct channel is expected to have brand loyal consumers who make more positive reviews (De Angelis et al., 2012) to help the brand because of their self-brand connection.

H4: Indirect online channel causes lower review valence via review volume.

4.2.3 Review variance

Final effect we analyze is the review rating variance. This is the star rating variance of the reviews of a product. This variable will be analyzed from both a moderation and mediation perspectives. Below we present theories for both sides.

4.2.3.1 Moderation

Wu and Huberman (2008) concluded in their paper that later opinions show a significant difference when compared with earlier opinions thus creating a review valence difference. The reasoning behind this difference is consumers contribute their ideas by writing an online review when they can add additional value to the conversation. Schlosser (2005) concluded in her study that, when customers are posting a review, they tend to adjust their own evaluation according to previous reviews. So, following reviewer is influenced by the early reviews that they are exposed to. Schlosser explained the discussed behavior of the reviewer by the differentiation effect. Commentators can have a desire to differentiate themselves by providing extremely rated reviews to be seen as more competent and expert. For example, this behavior was studied in Amabile (1983) and concluded that negative evaluators are seen as more intelligent and expert on the subject compared to positive evaluators in an offline environment. As before mentioned, brand loyal consumers that have a connection with the brand tend to have a desire to help the brand (Eelen et al., 2017). We expect to see the reviews in the direct channel adding more positive aspects to the reviews as the conversation goes along whereas, in the indirect channel, we expect to see the effect Wu and Huberman (2008) and Schlosser (2005) mentioned. Thus, indirect channel causes review variance to increase due to differentiation effect and thus review valence to decrease.

H5: *The difference in review valence for a product across the online direct channel and online third-party marketplace is larger when product reviews have a higher variance.*

4.2.3.2 Mediation

Heterogeneity amongst online reviews creates a lack of consensus in opinions about a product. Many researchers suggested this lack of consensus can create uncertainty for the consumer (Ellsberg 1961; Hogarth 1989; Meyer 1981). Consumers often consider their own experiences as well as others' experiences when deciding what to buy and also what to recommend to others. (Etkin and Sela, 2015). A product having highly varied reviews will increase the uncertainty and thus expected to lower the future review valence of the prospective reviewers. This effect is expected since as Li & Hitt (2008) defined online reviews reflect post-purchase evaluation of the purchased product. And since consumers are impacted both by their experiences and others', review valence is expected to decrease as the variance increases due to the lack of consensus. Brand loyal consumers that we expect to see in direct channels are expected to already have positive opinions about the brand and they know what to expect so we expect to see a common consensus amongst the reviews. The indirect channel is expected to have a lack of consensus due to missing connection and loyalty with the brand thus review variance is expected to be higher in indirect channels. This leads to indirect channels having lower review valence.

H6: Indirect online channel causes lower review valence via review variance.

4.3 Control effect

Review helpfulness is the control variable for this study. It is known that review length and helpfulness score have a linear relationship (Mudambi and Schuff, 2010). Also, they pointed out that when experience goods are in focus, reviews with extreme ratings are less helpful than the reviews with average ratings. Cao et al. (2011) also add that negative reviews are found more helpful by the consumers when compared with neutral ones. This strong and known relationship between review valence and review helpfulness won't add additional knowledge to our study as a moderating factor since review helpfulness is decided after review valence. Including review helpfulness scores as a control variable helps to indicate extreme reviews that tend to get high helpfulness scores.

5 Data

This section introduces our data source and preparation. We also present in this section how we operationalized the variables we are using in this study. Lastly, we include descriptive statistics of the dataset.

5.1 Data Sources

To test the hypothesis stated in the conceptual framework we need to scrape online product reviews from one direct sales channel and one online third-party marketplace. Next to a wide number of literature focusing on books (Berger et al. 2010; Chevalier & Mayzlin 2006; Li and Hitt 2008) and movies (Dellarocas et al. 2004; Duan et al. 2008; Zhang and Dellarocas 2006) for consumer reviews, a number of studies focused on consumer electronics where they used online product reviews of digital cameras as their data (Cui et al., 2012; Luan et al., 2016). Godesan and Ipeirotis (2005) also included digital cameras but alongside with other consumer electronics such as audio/video players and DVD players (Hu et al., 2014). After a search on many consumer electronics websites, we select Logitech as the brand in our empirical setting. We select the direct online web store of Logitech for our direct sales channel. There are two practical reasons behind this decision. First and most important, Logitech is one of the few consumer electronics websites that allowed web scraping. Second, they combine the reviews of different colored products under one review page. This approach is also used by Amazon when grouping product listings. Logitech reported sales revenues of 5.25 billion U.S. dollars in 2021. 784.5 million U.S. dollars of this revenue was made from keyboard and keyboard-and-mouse combination sales (Statista, 2021). Because keyboards had a great share in the revenues of Logitech, we focus on the keyboards when scraping product reviews. For the third-party online marketplace, we select Amazon. Product reviews on Amazon are used in several pieces of literature in the past (Chevalier & Mayzlin, 2006; Olagunju et al., 2020).

For gathering the online product reviews from both websites, we use web scraping. To have English-written reviews and a customer sample with a similar, we scrape from US websites of both Logitech and Amazon. Web scraping uses the URLs of the websites and corresponding HTML nodes for the information we want to scrape from the website. We make use of for loops to scrape all pages that contained reviews. Scraping data from Amazon is done by the rvest package in R by Hadley Wickham. However, scraping data from the website of Logitech is not possible with this method since the website uses JavaScript. After an exhaustive search of the possible solutions, we continue with using Parsehub. Parsehub is a free-to-use, no-code software that makes web scraping available also for JavaScript websites.

5.2 Preparation of Data

To have a final dataset that has all common keyboard models with the reviews and channels that are scraped, we have done some data preparation. After the initial scraping of the data, web-shop of Logitech has 300 total reviews for 18 keyboard models. Amazon has 16 Logitech keyboard models available, and the total number of scraped reviews is 10881. When we look at the models more closely, 2 models are not exactly present on Amazon. First model is K380 model. Amazon only has the Macintosh version of the keyboard whereas the Logitech web shop has both Windows and Macintosh. Second model is MX Mini. Amazon doesn't have Macintosh specific model. To have the same products when comparing the reviews, we deleted these 2 models from the Logitech dataset.

After we scrape from both sales channels, we deal with structural cleaning. Review text and ratings both had initial sentences before them. For example, review text starting with a phrase "Review by XXX on DD/MM/YY review stating" and review rating scraped as "ID Verified Reviewer 4.0 star rating". Additionally, from both channels, we scrape product descriptions for each product. We take "About this item" section as the product description on Amazon. For direct channel, this process was less straightforward. Products have visuals and text that incorporates these visuals. Luckily, editorial sections about products started with a brief description of them, which we use as a description length variable in our study.

After initial cleaning and formatting, both datasets are combined, and the final data set includes 16 common keyboard models in both channels. Total review count adds up to 11151 observations where we have 10881 reviews from Amazon and 270 reviews from Logitech's website.

5.3 Variables

5.3.1 Dependent Variable

This study is building an experiment to find out how product reviews are differing when different sales channels are compared. Our experiment uses sentiment scores as dependent variable with respect to prior literature. Hu et al. (2014) stated that review valence has an impact on sales through review sentiment rather than review star rating. Thus, to have a complete understanding of the sales channel effect on brands and manufacturers we use sentiment scores as dependent variables. We name this variable as *Review Valence.*

To prepare the sentiment scores, we use the final merged dataset. For calculating sentiment scores, we use sentimentr library that is available in R (Rinker 2021). Sentiment analysis is the process of extracting emotional information from a text (Kwartler, 2017). We focus on the review text when we are calculating the sentiment scores. Sentimentr package gives us the balance between accuracy and speed for optimum results. Sentimentr function allows us to calculate a score that corresponds to the emotions from the review texts. This is a dictionary-based algorithm to give positive and/or negative values that indicates a sentiment. Used function defaults to an elevated version of Jockers & Rinker's augmented Hu & Liu (2004) data tables that contain positive and negative sentimental words and their corresponding value. For each corresponding positive word that the function finds in the review, review gets +1 while gets -1 for the corresponding negative words. Again, with this function, we account for the valence shifters that impact the meaning of the words. There are 4 categories of valence shifters: negators, amplifiers, de-amplifiers, and adversative conjunctions. Negators are the adverbs that are used to negate the meaning of the sentence. For example, if we have “I do like this keyboard.” as our example sentence, “I do not like this keyboard.” would include a negator. Amplifiers are used to intensify the meaning mentioned in the sentence. Our previous example would become “I very like this keyboard.”. De-amplifiers work opposite to amplifiers which would decrease the intensity. For example, “I barely like this keyboard.”. Lastly, adversative conjunctions outperform the previous clause that they follow. An example would be “I do like this keyboard, but it is too expensive.”. These valence shifters also affect the sentiment scores. For example, for negation words, the score that a word gets changes signs. Also, for each amplifier sentiment score is impacted by +/- 1.8. In the end, a sentiment score is calculated for each review by summing up positive and negative sentiment words and their valence shifters. Sentiment score calculated is recorded under the variable named *Review Valence*$_{ijk}$. *Review Valence*$_{ijk}$ is the sentiment score for review *i* in sales channel *j* where product *k* is observed. *j* represents the type of sales channel (direct or indirect). *k* represents the product models that were selected for the study and takes 16 different values.

5.3.2 Independent Variables

Type of Sales Channel$_{jk}$ and its impact on the review ratings are the main effect of our study. *Type of Sales Channel*$_{jk}$ is the sales channel type *j* where product *k* is sold. *Type of Sales Channel*$_{jk}$ takes value of 0 if product *k* is sold in the direct sales channel and 1 if product *k* is sold in the indirect sales channel. We coded this variable manually when merging the datasets of scraped data from Amazon and Logitech together.

We continue with the introduction of the moderating/mediating variables. *Description Length*$_{jk}$ refers to the number of words in the product description section on the sales channel *j* belonging to product *k*. For a chosen product, we have 2 values of description length one referring to the direct channel and the other referring to the indirect channel. Next, we have *Volume*$_{ijk}$. *Volume*$_{ijk}$ is the number of reviews posted before the observed review. It is the cumulative sum of previous reviews for review *i* in sales channel *j* for product *k*. For every review made for each product on each sales channel, the accumulative quantity of reviews is recorded. This process is done after ordering the reviews in the observed channel of the specific product in an oldest-first chronological order and counting the cumulative number of reviews accordingly. Also, *Variance*$_{ijk}$ variable is calculated in a similar manner. *Variance*$_{ijk}$ is the cumulative variance of prior reviews for review *i* in sales channel *j* for product *k*. For each review in the observed sales channel for the specific product, we calculate the cumulative variance of star ratings after ordering the reviews from oldest to newest. Since our theory suggests the next review is impacted by the previous *Volume*$_{ijk}$ and *Variance*$_{ijk}$, we made sure each review shows values based on the prior reviews' volume and variances.

5.3.3 Control Variable

Helpfulness Score$_{ijk}$ variable is very straightforward for Amazon. *Helpfulness Score$_{ijk}$* is the helpfulness score calculated for individual review *i* in sales channel *j* for product *k*. On Amazon, this value is stated below review text as "X people found this helpful." However, on the Logitech's website, this is not the case. There is a voting system presented to visitors of the websites. They can vote thumbs-up if they find the vote helpful and thumbs down if they find the review not helpful. To have a value that we can use in our study, we subtract the thumbs up votes from thumbs down votes and have a variable that we can use for review helpfulness. Although this produces a value for our variable, this method also results in some negative values where a review is rated as not helpful more than it is rated as helpful. This situation is not valid for Amazon and the lowest value available for Amazon reviews is 0. To account for this scaling difference, we recode all negative values for review helpfulness to 0.

5.4 Descriptive Statistics

To have a better understanding of our final dataset created, we focus on fundamental descriptive statistics for variables that we use in our paper. Below Table 1 and Table 2 show descriptive statistics specific to sales channels. Table 1 and Table 2 show direct sales channel and indirect sales channel respectively.

Logitech (Direct Channel)

	Mean	St. Dev.	Min	Max
N = 270				
Dependent				
Review Valence$_{ijk}$	0.098	0.224	-1	1
Independent				
Volume$_{ijk}$	18.600	18.917	1	76
Description Length$_{jk}$	30.215	13.262	2	49
Variance$_{ijk}$	1.841	1.438	0	8
Type of Sales Channel$_{jk}$	0	0	0	0
Control				
Helpfulness Score$_{ijk}$	3.385	8.064	0	89

Table 1: Descriptive statistics for the variables used in the paper specific to direct sales channel

Amazon (Third-Party Marketplace)				
Statistic	Mean	St. Dev.	Min	Max
N = 10,881				
Dependent				
Review Valence$_{ijk}$	0.182	0.240	-1.278	2.024
Independent				
Volume$_{ijk}$	1,399.340	1,188.783	1	3,977
Description Length$_{jk}$	102.984	45.182	0	234
Variance$_{ijk}$	1.635	0.485	0	8
Type of Sales Channel$_{jk}$	1	1	1	1
Control				
Helpfulness Score$_{ijk}$	1.152	14.920	0	1,154

Table 2: Descriptive statistics for the variables used in the paper specific to indirect sales channel

Starting with the observation numbers that are scraped from the sales channels (N), we notice that Amazon has more reviews compared to the direct online channel. We start analyzing the descriptive statistics with the dependent variable. For the *Review Valence$_{ijk}$* in Amazon, we observe more extreme values as minimum and maximum. This indicates people share more extreme opinions on the indirect channel. *Review Valence$_{ijk}$* on direct channel have a range of -1 to 1 while Amazon reviews have -1.278 to 2.024. Although *Review Valence$_{ijk}$* in direct channels seems like they are bounded but this is just a coincidence. Moving on with the independent variables, in the direct channel average *Volume$_{ijk}$* of reviews per product is 18.6 whereas it is 1399.34 in Amazon thus the difference in our total observations. For each product, Amazon has significantly more reviews compared to direct channel. *Description Length$_{jk}$* provided for the product have a higher mean of 102.98 on Amazon when compared with the mean of the direct channel which is 30.125. Lastly, the *Variance$_{ijk}$* of review ratings across a product is slightly higher in the direct channel than the Amazon marketplace. We can conclude there were more extreme star ratings on the direct channel thus the increased variance over the star ratings.

Before continuing with any analysis, we want to check our data for the correlation between the variables. If there is a high correlation between two variables, results can be misleading due to a multicollinearity problem. Below Figure 2 is the matrix for variable correlations.

Figure 2: Correlation matrix including the variables of this paper

Figure 2 shows us the correlation coefficients between variable couples. We take a look into the correlation coefficient between the length of *Description Length*$_{jk}$ and the *Volume*$_{ijk}$ since it has the highest absolute coefficient in Figure 2. There is a negative correlation coefficient of -0.25. This implies the number of reviews in a product differs according to description length. However, from the above analysis of descriptive statistics, we know Amazon has longer product descriptions when compared to the direct channel thus we believe this correlation is affected by the sales channel variable also. We can actually see this from the correlation coefficient between *Description Length*$_{jk}$ and *Type of Sales Channel*$_{jk}$ as well. Also worth mentioning is the correlation between *Volume*$_{ijk}$ and *Variance*$_{ijk}$. We have a positive correlation coefficient between these 2 variables implying as the number of reviews increase, variance also increase. In sum, all variables have low correlation between each other implying that we don't need to worry about multicollinearity in our dataset.

6 Methodology

In this section, we are going to continue with the methodologies used in this paper to test the hypothesis stated in the conceptual framework. For both analyses all variables are standardized by subtracting the variable mean from each value, because the variables are measured on different scales.

6.1 Moderation Analysis

First, for our moderation analysis, we are going to start with an ordinary least squares (OLS) model. Below is the initial model stated in Equation 1.

$$Review\ Valence_{ijk} = \beta_0 + \beta_1\ Review\ Helpfulness_{ijk} + \beta_2\ Volume_{ijk} + \beta_3\ Variance_{ijk} + \beta_4\ Description\ Length_{jk} + \beta_5\ Type\ of\ Sales\ Channel_{jk} + \beta_6\ Type\ of\ Sales\ Channel_{jk} * Volume_{ijk} + \beta_7\ Type\ of\ Sales\ Channel_{jk} * Variance_{ijk} + \beta_8\ Type\ of\ Sales\ Channel_{jk} * Description\ Length_{jk} + \varepsilon_i \quad (1)$$

After our initial OLS model, we need to honor the nested structure of the data collected for this paper. Variables like *Review Valence*$_{ijk}$, review *Volume*$_{ijk}$, and review *Variance*$_{ijk}$ are measured at an individual review level, whereas *Type of Sales Channel*$_{jk}$ and *Description Length*$_{jk}$ measured at a sales channel-product level. In our analysis, we use low-level data to explain something happening at a higher level of data. We want to explain the change in review valence for an individual by using the marketplace which the specific product is sold in. Our data is hierarchical and has 2 levels: individual product review level and marketplace level for every selected product model. Level 1 which is review-based level includes our dependent variable *Review Valence*$_{ijk}$ and independent variables like review *Helpfulness Score*$_{ijk}$, *Variance*$_{ijk}$, and *Volume*$_{ijk}$. Level 2 which is based on sales channel includes *Type of Sales Channel*$_{jk}$ and *Description Length*$_{jk}$. Table 3 provides a summary of this. We assume Level 1 information is nested in Level 2. Ordinary Least Squares (OLS) assumes the error terms being independent of the variables. For the data of our study, this assumption does not hold. We have individual observations nested in different groups in our data. Using the interpretation of OLS for our moderation analysis, will lead to underestimation of coefficients and overestimation of the coefficient significance (Moulton 1990).

<u>Level 1 (i)</u> Review	*Review Valence*$_{ijk}$ *Review Helpfulness*$_{ijk}$ *Volume*$_{ijk}$ *Variance*$_{ijk}$
<u>Level 2 (j)</u> Sales Channel	*Type of Sales Channel*$_{jk}$ *Description Length*$_{jk}$

Table 3: Levels of used variables

Hofmann (1997) presented three options to deal with hierarchical data. First approach is to disaggregate the data in a way that each lower-level unit has a score representing a higher unit variable. Problem with this approach is that we cannot make sure of independence in individual observations since they can have group-level similarities due to similar stimuli within groups. Second approach he mentioned is to aggregate the lower-level units and analyze the relationships at an aggregate level. Disadvantage of this approach is to not take into account potentially meaningful low-level variance in the outcome. Last approach discussed is the hierarchical linear models. Above mentioned disadvantages of the previous models can be avoided with this method. Hierarchical linear models and multilevel models are two interchangeable words and broadly can be called as mixed models (Garson, 2013). Hitt et al. (2007) stated in their study that most management problems involve a multilevel phenomenon and they suggested multilevel models to address them. Multilevel models account for the variance in the dependent variable at the lowest level of analysis by considering all levels of information (Steenbergen and Jones, 2002). Multilevel modelling method deals with hierarchical data and has one response variable from the lowest level and explanatory variables from all existing levels (Hox, 2013). Since it has a hierarchical way of handling the data, regression equations used also have a hierarchical sense.

Considering the suitability of multilevel models to our data structure we select and continue with this method. Also, we choose random intercept model out of available multilevel models. The intercept here represents the mean of the dependent variable which is the sentiment scores. This type of model incorporates the random effect of the clustering variables at higher-level (Garson, 2019). We now build a multilevel model that we use in the paper to tackle our hierarchically structured data in line with the overview provided by Hofmann (1997). We show the equation for the lowest level of data which is the individual review level.

$$Review\ Valence_{ijk} = \beta_{0jk} + \beta_1\ Review\ Helpfulness_{ijk} + \beta_2\ Volume_{ijk} + \beta_3\ Variance_{\ ijk} + \beta_4\ Type\ of\ Sales\ Channel_{jk} * Volume_{\ ijk} + \beta_5\ Type\ of\ Sales\ Channel_{jk} * Variance_{ijk} + r_{ijk}\ (2)$$

Review Valence$_{ijk}$ is the review valence we measure with the sentiment scores calculated. The intercept β_{0jk} is discussed in Equation 3. It is affected by the higher level which is the sales channel level. In this equation we have the variables measure in review level as well as the cross-level interaction terms. These interaction terms include variables from the 2 different levels hence they are called as cross-level. In the end, we add the residual r_{ijk} which is the error term of this level.

$$\beta_{0jk} = \gamma_{0k} + \gamma_1\ Type\ of\ Sales\ Channel_{jk} + \gamma_2\ Description\ Length_{jk} + \gamma_3\ Type\ of\ Sales\ Channel_{jk} * Description\ Length_{jk} + u_{jk}\ \ (3)$$

When we continue with level-2 analysis, we use the intercepts and slopes from Equation 2 as our dependent variable. γ_{0k} is the second level intercept term. Level 2 also has its residual u_{jk} which is the error term representing the variation in this sales channel level. This equation includes only the variables from the higher level. Also, here we introduce the sales channel and description length interaction term that we hypothesize to influence review valence.

6.2 Mediation Analysis

Theories presented in the conceptual framework suggest review variance and review volume can have a mediation aspect to our main effect. To have a well-rounded analysis we will now continue with the methodology of a mediation analysis for these two variables: $Volume_{ijk}$ and $Variance_{ijk}$. Even though a study done by Krull and MacKinnon in 2001 states that using single-level models with clustered data for assessing the mediating effect underestimates the standard error of the effect, we will continue with a mediation analysis. Also, to reduce this error, we will use parallel mediation where shared variances between mediators are accounted (Hayes 2017).

Our study utilizes Zhao et al. (2010) approach for testing for mediation. Zhao et al. stated only requirement needed to establish an indirect effect is a significant indirect effect *a x b* by a bootstrap test. They suggest one should simply run a Preacher-Hayes script to generate Bootstrap Results for Indirect Effects to determine whether there is mediation or not. They stated this can be done by looking at the bootstrapped confidence interval and analyzing whether this interval includes 0. If not, we can conclude there is mediation. After this step, Zhao et al. (2010) suggested classifying the type of mediation. They presented 5 typologies complementary, competitive, indirect-only, direct-only, and no-effect mediations.

In our study, we follow the framework suggested by Zhao et al. in 2010 to have a more updated approach to mediation analysis. Below, equations 4, 5, and 6 show the parallel mediation approach that we use with the used variables of this paper. Below i_{M1}, i_{M2} and i_Y represent the intercepts of the equations where e_{M1}, e_{M2} and e_Y are the residuals of the linear models. c' represents the coefficient relating independent variable adjusted for the mediator where a relates independent variable to the mediator. This approach is operationalized in R environment by the PROCESS macro by Andrew Hayes. We use a 95% confidence interval, and we detect mediation if zero is not in the range for the 5000 times bootstrapped confidence interval.

$$Volume_{ijk} = i_{M1} + a_1\ Type\ of\ Sales\ Channel_{jk} +\ e_{M1}\ \text{(4)}$$

$$Variance_{ijk} = i_{M2} + a_2\ Type\ of\ Sales\ Channel_{jk} +\ e_{M2}\ \text{(5)}$$

$$Review\ Valence_{ijk} =\ i_Y + c'\ Type\ of\ Sales\ Channel_{jk} +\ b_1\ \ Volume_{ijk} + b_2\ Variance_{ijk} +\ e_Y\ \text{(6)}$$

7 Results

7.1 Moderation Analysis

In this section, we first check the assumptions of the used model. Afterward, results are presented for the moderation analysis. First reported results are the output of the OLS regression whereas the second results are the results of multilevel regression.

7.1.1 Assumptions Check

Before we present the results of the moderation analysis, we continue with an assumption test for our moderation analysis. We start with the initial OLS model we build. Multilevel models also require the same assumptions as OLS regressions. We start with the independence assumption where data points in our data must be independent of each other. We conduct a Durbin-Watson test to test this assumption. This test has no correlation among residuals as the null hypothesis and autocorrelation as the alternative hypothesis. Our result has a p-value of 0.012 which is less than 0.05 thus we reject the null hypothesis. This is not an unexpected result since we already have discussed the nested structure of our data and the importance of adding a multilevel regression model to our study. Next, we continue with the multicollinearity assumption. We already checked the data for multicollinearity in the descriptive statistics section. Correlation coefficients of the variables are analyzed to see if there is a multicollinearity issue. For our data multicollinearity assumption holds as well. Next, we need to check for the linearity of the model. The relation between dependent and independent variables must be linear. Residual plots are used to check for this assumption. Below, we present the residual plot in Figure 3.

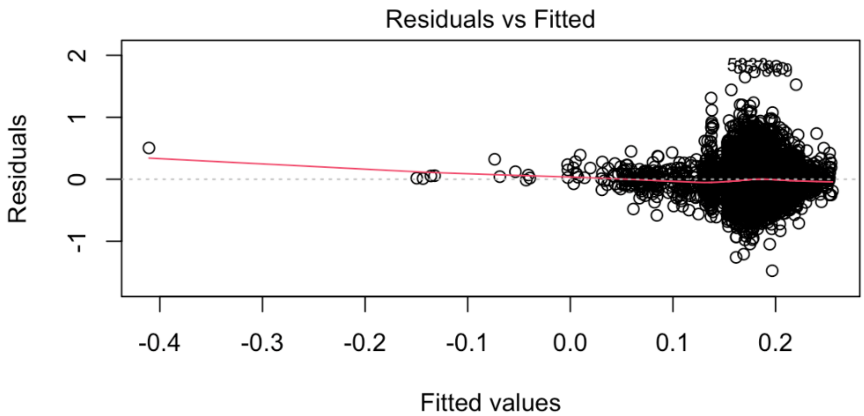

Figure 3: Residuals vs Fitted for moderation model

All residuals should have the same interval around the 0 line for us to say the linearity assumption holds. Although there are outliers that makes this process hard to understand, we clearly don't see any relationship that can be fitted to this graph also. We can say linearity assumption also holds for our model. Lastly, we check for the normality. Residuals should be distributed normally according to this assumption. We plot a Q-Q plot below to check for this assumption in Figure 4.

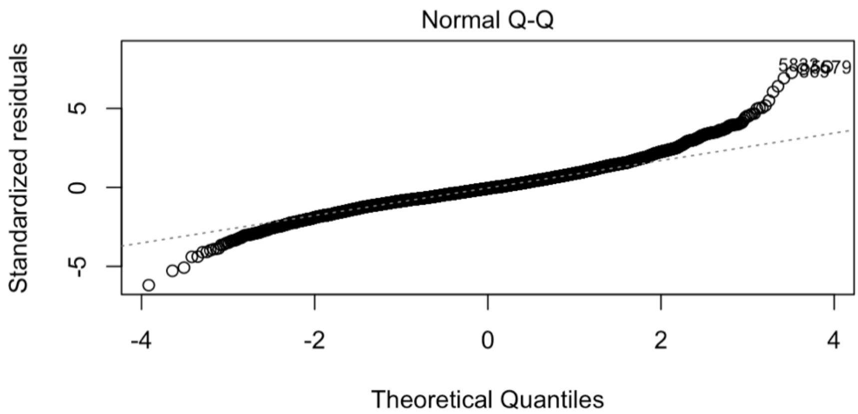

Figure 4: Normal Q-Q Plot for moderation model

To confirm that normality assumption holds, we need to see residual points following the dashed line. We can again see the above-mentioned outliers however, the general trend in the graph allows us to say that the normality assumption holds. We also plot the last 2 graphs for the multilevel regression model and conclude assumptions hold.

7.1.2 Results

7.1.2.1 OLS Results

Although we already stated our data violates the independency assumption, we share the results of OLS regression to have an initial idea about the relationship of the variables. We should keep in mind that this process can overestimate the importance of the variables thus next section will continue with multilevel regression. Below is the output of the OLS model in Table 4.

	Dependent variable:
	Review Valence$_{ijk}$
Type of Sales Channel$_{jk}$	10.792**
	(4.867)
Volume$_{ijk}$	-8.711**
	(4.182)
Variance$_{ijk}$	-0.080***
	(0.023)
Description Length$_{jk}$	-0.416*
	(0.236)
channel$_{jk}$: description$_{jk}$	0.400*
	(0.236)
channel$_{jk}$: volume$_{ijk}$	8.693**
	(4.182)
channel$_{jk}$: variance$_{ijk}$	-0.005
	(0.026)
Review Helpfulness$_{ijk}$	-0.032***
	(0.009)
Constant	-10.783**
	(4.867)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 4: OLS regression output

We start to comment on the results with the main effect. We observe a significant effect of *Type of Sales Channe*$_{jk}$ on the *Review Valence*$_{ijk}$ (β = 10.792, $p < 0.05$). However, we were expecting a negative effect here since our main hypothesis stated direct channels were expected to have positive review valence compared to indirect channels. Thus, we reject the H1. Since we reject the main hypothesis, we also reject the following ones since we justify the moderation effects with the theory coming from H1. Nevertheless, to gain more insight we take a look at the effects of the moderation variables on the main effect.

First moderation effect we focus is the *Description Length*$_{jk}$. We see this moderation variable having a positive significant impact on review valence (β =0.4, $p < 0.1$). This means as the product descriptions in indirect channel get longer, the difference in review valence between the direct and indirect channel increases. Although we reject the main effect, with the moderation of description length we were expecting exactly this effect. So, description length is moderating the effect of channel on review valence with the expected positive sign. However, since the main effect between channel and valence is positive, this moderation makes the valence difference between channels larger and not smaller as we were expecting in our framework thus rejecting H2. *Volume*$_{ijk}$ variable also has a significant impact (β =8.693, $p < 0.5$). We observe a positive impact meaning as the number of reviews increases in the indirect channels, review valence increases. There is a moderation effect however this is the opposite effect that was expected thus we reject H3. Lastly, *Variance*$_{ijk}$ is insignificant in this model thus we directly reject H5.

As before discussed, using a linear regression with a nested data structure can overestimate the significance of the variables thus this study continues with the presentation of the multilevel regression results.

7.1.2.2 Multilevel Regression Results

To test and have results on how our selected variables affect the dependent variable as a moderator, we will continue with the multilevel regression analysis. We start with building null models for each level. These null models will be an indicator to see how much variance in sentiment scores of the reviews is explained at each level.

Level	Variance
Level 1 (i)	0.99027
Level 2 (j)	0.07886

Table 5: Variance of levels in the null model

Above Table 5 shows the variance of each level in the null model where there are only the residuals. To further elaborate on the variation in sentiment score at each level, we will use the above variances to calculate Intraclass Correlation (ICC). This is a descriptive statistic that is special to measurements that are made on units in a group. It ranges from 0 to 1 and a high ICC indicates high similarity between the values in the same group whereas a low ICC means values in the same group are not similar to each other. ICC is calculated by dividing the random effect variance (variance we calculated above for Level 2) by the total variance which we can easily calculate by summing the random effect and residual variance (variance of Level 1). Below is the calculated ICC.

Level	ICC
Level 2 (j)	0.074

Table 6: ICC score for Level 2

Level 2, where we observe sales channel difference, captures approximately 7.5% of the total variation in sentiment scores. Explained variation within the group is lower than expected. However, we continue with using multilevel regression since we have a hierarchical structure in our data and OLS would not account for this data structure.

We continue our analysis by building the model mentioned in our methodology. To capture the leveled aspect in our data, we model the regressions in a leveled sense also. When building Model 1, we add the Level 1 variables without cross-level interaction terms to the Equation 2. For Model 2, we add Level 2 variables to Model 1 again leaving out the interaction terms. Finally, Model 3 includes all variables and the sales channel level interaction term and from Level 2. Lastly, Model 4 includes all variables and cross-level interaction terms for all levels. We exclude description length and sales channel interaction term in the last model since it is insignificant in the previous model. Below Table 6 is the output of all 4 models build.

	Dependent variable:			
	sentiment_score			
	(1)	(2)	(3)	(4)
Type of Sales Channel$_{jk}$		0.3363***	0.5578	8.956 .
		(0.067)	(0.3476)	(4.570)
Volume$_{ijk}$	-0.0414**	-0.0415**	-0.0417**	-7.676 .
	(0.0130)	(0.013)	(0.013)	(4.044)
Variance$_{ijk}$	-0.0759***	-0.0756***	-0.0746***	-0.08***
	(0.0135)	(0.013)	(0.0135)	(0.0232)
Description Length$_{jk}$		0.004	-0.1466	0.0049
		(0.021)	(0.2236)	(0.02)
channel$_{jk}$: description$_{jk}$			0.1499	
			(0.2226)	
channel$_{jk}$: volume$_{ijk}$				7.635 .
				(4.044)
channel$_{jk}$: variance$_{ijk}$				0.0045
				(0.028)
Review Helpfulness$_{ijk}$	-0.0318***	-0.0317***	-0.0317***	-0.0321***
	(0.0094)	(0.0094)	(0.0094)	(0.0094)
Constant	-0.1845	-0.3572***	-0.5869 .	-8.982*
	(0.1221)	(0.0769)	(0.3495)	(4.569)
Note:		***p < 0.001, **p < 0.01, *p < 0.05, . p < 0.1		

Table 7: Multilevel regression output of Model 1-5

We will focus on Model 2 and Model 4 for assessing our hypothesis. First, we start by looking at the main effect. Both Model 2 (β =0.3363, $p < 0.001$) and Model 4 (β =8.956, $p < 0.1$) show significant coefficients for the *Type of Sales Channel$_{jk}$*. Also, both models have a positive coefficient for this variable. This means online product reviews in an indirect sales channel have more positive reviews when compared with the direct channel when we keep all other variables constant. Therefore, we reject H1.

Although we rejected our main effect, we will continue analyzing the moderating effects. We expected the direct channel to have more positive reviews whereas our data presented us that in fact reviews were more positive in indirect channel. At this point, we will reject the remaining hypotheses H2, H3 and H5 since we reject the main effect. However, analyzing the moderation variables while keeping in mind that we rejected the main effect can help us to understand how our selected variables affect the relationship between channel and review valence. To interpret moderators, Model 3 and Model 4 are used. From Model 3 we can see that there is no significant moderating effect of $\textit{Description Length}_{jk}$ allowing us to reject H2. Model 4 shows a significant moderation of $\textit{Volume}_{ijk}$ on the main effect (β =7.635, $p < 0.1$). This moderation variable has a positive coefficient meaning as volume increases over indirect channel, review valence also increases. H3 expected a larger difference in review valence over sales channels when review volume is higher. This statement is in line with the findings however our selected theories in the conceptual framework expected a negative effect of review volume on the review valence due to the order effect. Next, we see no significant moderation for the $\textit{Variance}_{ijk}$ variable and rejecting H5. Finally, our control variable $\textit{Review Helpfulness}_{ijk}$ shows a significance with a negative coefficient in every model (β = -0.032, $p < 0.001$). This shows more helpful reviews tend to have a lower sentiment score. This aligns with our expectation of negative reviews are found more helpful by the consumers when compared with neutral ones (Cao et al. 2011) so $\textit{Review Helpfulness}_{ijk}$ was worth controlling because of the already found literature on its impact of it on review valence.

Also, a significant thing to note here is that in linear regression we find a significant effect of moderation by the $\textit{Description Length}_{jk}$. This significance is no longer present in the multilevel regression so we can conclude linear regression can indeed overestimate the significance of the variables thus multilevel regression was needed for the analysis of our data. Additionally, we can see the same effect in the moderation variable for $\textit{Volume}_{ijk}$. In linear regression, output suggested $p<0.05$ whereas in multilevel regression we see $p<0.1$ in Model 4.

7.2 Mediation Results

As the previous literature suggests *Volume*$_{ijk}$ and *Variance*$_{ijk}$ are observed to have a direct effect on review valence. To have a more well-rounded analysis, we continue with a mediation analysis where we can account for this direct effect of selected independent variables on our dependent variable. This section starts with an assumption check for the mediation analysis and continues with the presentation of the results.

7.2.1 Assumptions Check

For the results to hold we need to check for assumptions. Main method used for building a mediation analysis is OLS. So, we look at the assumptions of linear regression. To do this, we extract the models used in PROCESS macro and build the same regressions. Then we use these models to check for the assumptions. We check the assumptions for all 3 models that we used. Below we only report the review variance variable, but we have similar results for the rest of the models as well. We already reported independence and multicollinearity assumptions in the previous assumption check for the moderation analysis thus we continue with the remaining. First assumption we check is the linearity assumption where the relation between dependent and independent variables should be linear. To check for this assumption, we plot the residuals vs fitted graph.

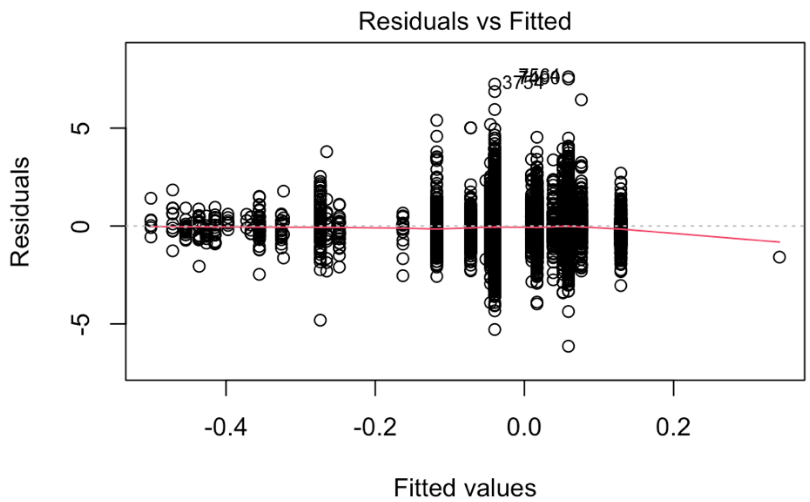

Figure 5: Residuals vs Fitted for mediation model for review variance

In Figure 5, there is no clear pattern in the plot. Line shows an almost straight trend which shows linearity assumption holds for our model. One thing to notice here, we can see the nested nature of our data here as well. Data points are grouped in several natural clusters because of the leveled data.

Next, we check for normality assumption. Residuals should be distributed normally according to this assumption. Normal Q-Q plot is used to check for this assumption.

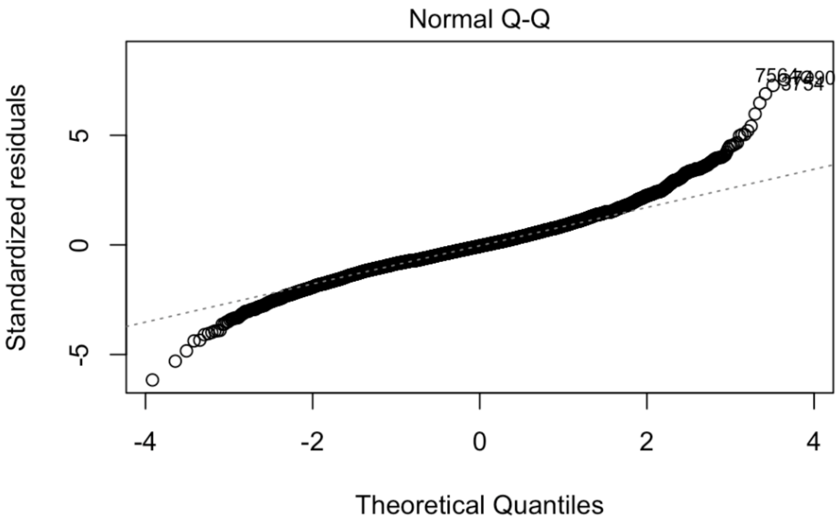

Figure 6: Normal Q-Q Plot for mediation model for review variance

In Figure 6, we are looking to see residual points following the dashed line which is valid in our case. Other than a few outlying data points, Q-Q plot shows normality assumption also holds. As mentioned, the same plots are plotted for review volume and similar results have been achieved thus we continue with presenting the results.

7.2.2 Mediation Results

We use a parallel mediation model to present our results. With parallel meditation, we test each proposed mediator while accounting for the shared variance between them (Hayes 2017). This is especially important in our case since we have a nested data structure. Below is the output of PROCESS macro for a paths of both volume and variance mediator.

Outcome Variable: *$Volume_{ijk}$*				
	coeff	p	LLCI	ULCI
constant	-1.1236	0.0000	-1.2410	-1.0063
Type of Sales $Channel_{jk}$	1.1515	0.0000	1.0327	1.2703
Review $Helpfulness_{ijk}$	-0.0367	0.0001	-0.0550	-0.0185

Table 8: Path a of the mediation analysis for outcome variable volume

Outcome Variable: *$Variance_{ijk}$*				
	coeff	p	LLCI	ULCI
constant	0.3805	0.0000	0.2614	0.4996
Type of Sales $Channel_{jk}$	-0.3900	0.0000	-0.5106	-0.2694
Review $Helpfulness_{ijk}$	-0.0153	0.1061	-0.0338	0.0033

Table 9: a path of the mediation analysis for outcome variable variance

Above tables show that p-values of a-path are significant. Table 8 and Table 9 shows *Type of Sales $Channel_{jk}$* significantly predicts *$Volume_{ijk}$* (β =1.1515, $p < 0.001$) and *$Variance_{ijk}$* (β = -0.39, $p < 0.001$). As we move from the direct channel to the indirect channel, review volume increases whereas the review variance decreases. Review volume increase was expected in our framework due to the high traffic over online marketplaces. However, our framework expected an increase also for the review variance. Here we observe that this is not the case for the collected data. This might be a result of high number of reviews averaging in an average point and extreme values become unimportant in online marketplace due to high volume of reviews compared to direct channel. We continue with the b and c' path of the analysis.

Outcome Variable: *Review $Valence_{ijk}$*				
	coeff	p	LLCI	ULCI
constant	-0.3169	0.0000	-0.4380	-0.1958
Type of Sales $Channel_{jk}$	0.3247	0.0000	0.2021	0.4474
$Volume_{ijk}$	-0.0119	0.2288	-0.0312	0.0075
$Variance_{ijk}$	-0.0888	0.0000	-0.1078	-0.0697
Review $Helpfulness_{ijk}$	-0.0316	0.0008	-0.0501	-0.0131

Table 10: b and c' path output of the mediation analysis

When we look at the b path of the mediation, *$Variance_{ijk}$* has a significant effect on review valence (β = -0.0888, $p < 0.001$) however this case does not hold for review volume. As review variance increases, review valence tends to decrease according to b path of the mediation. As we presented in the conceptual framework, high variance amongst product reviews may create uncertainty for the consumer and affect their post-purchase judgement towards the product. This founding from the empirical setting is in line with the expected impact from our framework. Our direct effect c' which is the effect of channel on review valence also has a significant effect as seen from Table 10 ($\beta = 0.3247$, $p < 0.001$). This paper expected a negative effect of indirect channel on review valence thus this result is leading us to reject the main hypothesis H1. There is a significant effect of type of sales channel on review valence however it is positive so our theory on brand loyalty and self-brand connection on direct channels does not hold up. We continue with analyzing the bootstrapped indirect effect. Below is the output of the result in Table 11.

Indirect effect(s) of X on Y

	Effect	BootSE	BootLLCI	BootULCI
TOTAL	0.0209	0.0190	-0.0151	0.0590
$Volume_{ijk}$	-0.0137	0.0114	-0.0357	0.0090
$Variance_{ijk}$	0.0346	0.0151	0.0056	0.0656

Table 11: Bootstrapped results for indirect effects

Above, bootstrapped confidence interval of $Variance_{ijk}$ does not include zero inside the range thus we can conclude a positive mediation of variance to direct effect ($\beta = 0.3346$, CI [0.0056, 0.0656]). However, bootstrapped confidence interval of $Volume_{ijk}$ (CI [-0.0357, 0.0090]) includes zero thus no mediation. After this mediation analysis, we again turn back to our last two hypotheses about review volume and review variance. Since $Volume_{ijk}$ has no significance as an indirect effect, we reject H4 from a mediation perspective. For $Variance_{ijk}$, there is a mediation effect on the direct effect, however, we theorized high variance would lead to a lower review valence over the indirect channel, which is not the case, so we reject H6.

8 Conclusion and discussion

This paper analyzes the differences of online product reviews between direct online sales channels where the manufacturer owns the sales channel over indirect online sales channels where third parties own the sales channel and offer many brands in their portfolio. We attempted to explain this difference in the online sales channels by focusing on online product reviews. While doing this, we investigated the impact of product description length, review volume, and review variance on this review valence difference over channels. This study includes two analyses: moderation and mediation.

In moderation analysis, we aimed to understand the main effect of channel type on review valence, and which chosen variables are moderating this relationship. Our tested moderating variables included product description length, review volume, and review valence. We conducted both linear regression and multilevel regression to honor the nested structure of our data. For the main effect, we reject H1. There is a significant relationship but not the one we expected in our study. One can argue that either there is another underlying theory and argumentation, or our data had flaws. First, our main expectation might be wrong so brand loyal consumers are not exclusively using direct channels and prefer the easiness that comes from the marketplaces such as faster ordering due to having a profile or fast shipping. Second, theory can be valid under different circumstances when it comes to the data. One thing we see as a limitation here is the difference in the number of reviews scraped from the channels. Direct channel had 270 total reviews whereas the indirect channel had 10881 which most probably affected the results. Nonetheless, this scenario is a very realistic one for firms since their review systems are not as famous as Amazon.

Although we reject the main hypothesis, there are some conclusions to draw from the moderation analysis. Product description length had a significant effect as a moderator on linear regression results whereas this effect diminished in multilevel. Thus, showing using multilevel regression is a must in our data structure to not overestimate the significance of the variables. Also, the review volume moderator had a significant positive effect meaning as the review volume in the indirect channel increased, the review valence also increased. Not in line with our argumentation, however, it might be a result of reviews getting close to an average since we had significantly more reviews in the indirect channel when compared with the direct channel.

In mediation analysis, we aimed to understand if the main effect of online sales channels on review valence is mediated by review volume and/or review variance. Review volume was insignificant as a mediator. In the analysis, we find a significant effect of sales channel type on review volume however we don't find a significant effect for the impact of review volume on valence. It is true that the indirect channel has more reviews than expected. Impact of volume on variance may be lacking because of the high review volume difference between channels due to our scraped data. Review variance had a positive mediating effect on the relationship between sales channel and review valence. As review variance increases on the indirect channel, review valence also increases where our framework expected a reverse effect. We again reject the hypotheses but open a new door for further research to be examined because there is a significant mediating effect.

It is worth mentioning the limitations of this study for further improvement by other researchers. First, as we mentioned we had significantly more reviews for the indirect channel when compared with the direct channel. Also, for data-specific limitations, there is a notable issue with scraping the data. To identify products on Amazon there is a unique product code named ASIN where we can easily understand the different products. However, this is not the case for the direct channel of Logitech. Logitech provides only the model names of the keyboards thus matching over the two platforms is done by hand. This made the data collection part of this study labor and time intensive. For the methodologies, we make use of multilevel regression since we reject the independence assumption of linear regression. Also, multilevel models deal with the nested data structure that we have since data is collected on three levels: review, sales channel, and product. From multilevel models, we use random intercept models where we ignore the heterogeneity between the predictors and the dependent variable. Lastly, mediation analysis is based on OLS regressions, and we reject independence of errors assumption for our data. For further research, this analysis can be moved to multilevel as well for more accurate results.

All in all, since we reject our hypotheses there are many paths to follow for further research. Our main hypothesis founded on brand loyalty and self-brand connection did not hold up for our data. This can be tried again with a different set of data to see if this result still holds up. Also, for moderation, we still recommend including product description length and review volume as variables since some significant results were found. For mediation, review variance can be further researched due to significant results.

As a concluding remark, from the output of this research, we would suggest firms not be hesitant to branch out to independent sales channels. As we see from the results, review valence does not decrease over the independent channel, and on the contradictory, there is an increase. This may be a result of review volume being high since it was a significant moderating effect. Also, higher variance over independent channels can be a mediator for this relationship.

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