Journal of Business Research 150 (2022) 147–164

Contents lists available at ScienceDirect

Journal of Business Research

journal homepage: www.elsevier.com/locate/jbusres

Perceived usefulness of online customer reviews: A review mining approach using machine learning & exploratory data analysis

Madhumita Guha Majumder [a], Sangita Dutta Gupta [b], Justin Paul [c,d,e,f]

[a] Prin. L.N. Welingkar Institute of Management Development and Research, Bangalore, India
[b] BML Munjal University, India
[c] University of Puerto Rico, San Juan, PR 00907, USA
[d] Henley Business School, University of Reading, UK
[e] Indian Institute of Management (IIM), India
[f] International Journal of Consumer Studies, (A Rank, ABDC Australia), Australia

ARTICLE INFO

Keywords:
Online customer review
Electronic word of mouth
Peripheral
Sentiment analysis
Text mining

ABSTRACT

Online customer reviews, considered as electronic word of mouth, have become very useful in the era of e-commerce as they facilitate future purchase decisions. The present study discusses the central and peripheral sources of influence, such as the content of the review, star rating, review length, and the total number of votes on the perceived usefulness of the review. It analyses reviews from Amazon.com on three products, namely, a videogame, digital music, and a grocery item. Using text mining, the study uncovers sentiment polarity, identifies sentiment patterns, and finally, analyses the perceived usefulness of reviews under the moderation effect. The study establishes that the impact of the central route is not significant for search goods. The study concludes that peripheral sources have a significant impact on the search products. Our study provides insights on how marketing strategies can be formulated by online retailers based on the product type.

1. Introduction

In recent years, digital transformation has impacted how business is conducted posing new managerial challenges (Bresciani et al, 2021; Del Giudice et al, 2020; Galindo-Martin et al., 2019; Chakraborty & Paul, 2022). It has also revolutionized the way companies conduct business using big data analytics, artificial intelligence, and social media networks (Gunawan & Huarng, 2015, Rialti et al, 2019; Erevelles et al., 2016; Purohit, Arora & Paul, 2022). Marketing activities of many companies have been impacted by big data (Erevelles, 2016). Firms with greater big data analytics have performed better (Ferriera, 2019). Digital transformation has brought about changes in the buying behavior of customers. Online purchasing has become extremely important in last two years because of the pandemic. Many customers have started to purchase online, and they prefer online shopping to traditional in-store shopping, as it is convenient, flexible, and cost-saving. Adoption of digital technologies have changed the way information being shared by the consumers (Baima et al., 2022). So, digital transformation has impacted business performance of many companies (Ferraris et al., 2019; Ferreira et al., 2019). It has also created great opportunities for companies to expand their business and increase visibility (Magni et al., 2021).

However, customers face difficulties in online purchasing because of limited information (Dimoka et al., 2012). Customers overcome such limitations through online reviews, which provides them information that facilitates their future purchases. These reviews aid in purchase decisions because they describe user experience rather than the features of the product (Chen & Xie, 2008; Dellarocas, 2003). According to Kaemingk (2020), 97% of consumers research online about the product they intend to purchase, 93% of consumers go through the reviews before making a purchase decision, and most of the consumers are ready to pay 31% more for the same products if they are convinced about the positive aspects of reviews. Therefore, a product with good online reviews acts as good electronic word of mouth (eWoM) which impacts the purchase decisions of existing as well as potential customers. As this turns out to be a novel way to generate eWoM, most online shopping websites encourage customers to share their views. Amazon, one of the largest online retailers, provides abundant customer reviews on almost all products that it sells on its e-commerce platform (Mishra et al., 2018; Forman et al, 2008). Even though online ratings do not have a direct

E-mail addresses: madhumita_gm@yahoo.com, madhumita.majumder@welingkar.org (M. Guha Majumder), Sangitadgpt@gmail.com (S. Dutta Gupta), justin.paul@upr.edu (J. Paul).

https://doi.org/10.1016/j.jbusres.2022.06.012
Received 23 September 2021; Received in revised form 1 June 2022; Accepted 5 June 2022
Available online 16 June 2022
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impact on the sales of a product, they have a huge indirect impact on sales through review sentiments. Sentiments, however, have a direct impact on sales. (Hu et al., 2014). These sentiments, along with the presence of ample information on the product, may overwhelm future customers (Godes & Silva, 2012). Sometimes they are unable to understand which reviews are actually useful (Yin et al., 2014). The presence of numerous reviews, including unhelpful ones, causes information overload which affects the cognitive capabilities of consumers, and as a result, the impact of reviews goes down in consumer's mind while making a purchase decision. So, information overload needs to be reduced (Baek et al., 2015). It is important, therefore, to identify the most helpful reviews. Siering et al (2018) applied signaling theory to develop such a research model. Many online retailers have introduced a social voting system that allows readers to vote for helpful reviews (Ghose & Ipeirotis, 2011). Naturally, these reviews are considered equally by all readers (Pan & Zhang, 2011). Therefore, it is beneficial to study what factors make a review useful perceived by the users (Baek et al., 2013; Ghose & Ipeirotis, 2011; Mudambi & Schuff 2010; Purnawirawan et al., 2014). The present study tries to determine the impact of various factors, including review content, review depth, star rating, and the total number of votes received, on the perceived usefulness of reviews. The reviews for three products, namely, a videogame, a grocery item, and digital music were selected for these estimations from Amazon.

According to consumer psychologists, customers' perceptions and decision-making are highly influenced by helpful product reviews (Chakravarti et al., 2006; Li et al., 2013). Zablocki et al. (2019) point out that emotional content within online reviews impacts product attitudes. Research reveals that users' evaluation of information may be based on the Elaboration Likelihood Model (ELM) of persuasion (Baek et al. 2013; Cheung & Thadani, 2012). It emphasizes two informational paths which affect perceived usefulness – the *central* route and the *peripheral* route. While the central route represents the content of the review itself, the peripheral route represents the peripheral source of influence, such as source identity, reviewer's rating, review length, etc. (Bhattacherjee & Sanford, 2006; Cheung & Thadani, 2012). However, studies so far have produced mixed results as far as the determinants of perceived review helpfulness are concerned (Hong et al, 2017).

The present study addresses this research gap. It adopts a comprehensive ELM framework, incorporating both central and peripheral aspects which influence the perceived usefulness of reviews for potential customers. The main contribution of the study is that it provides insights about the impact of the central and peripheral routes on the product type, namely search and experience goods.

Previous studies have attempted to understand the helpfulness of reviews and contributing factors such as review rating (Cao et al., 2011; Ghose & Ipeirotis, 2007; Mudambi & Schuff, 2010), word count (Baek et al., 2012; Kim et al., 2006; Mudambi & Schuff, 2010), creditability of reviewers (Baek et al., 2012; Forman et al., 2008), subjectivity and readability (Ghose & Ipeirotis 2007). Multiple studies including Siering and Muntermann (2013), Wu (2013) and Yin et al. (2016) found a positive relationship between review depth and review helpfulness, whereas Racherla et al. (2012) established a negative relationship between the two. A positive relationship was established between the star rating and review helpfulness by a few studies (Wu, 2013; Huang et al., 2015; Ullah et al., 2015; Yan et al., 2012); however, negativity between the two was also established by other researchers (Chua & Banerjee, 2015; Zhang & Tran, 2010; Zhou & Guo, 2015; Guo & Zhou, 2016). After identifying the inconsistencies and contradictions in the previous research, the present study attempts to evaluate the impact of various factors on the perceived usefulness of reviews using the central and peripheral routes, and contributes to the development of new perspectives about online reviews. The study is also adding to the literature of customer knowledge sharing (CKS). More the online reviews are considered useful, more the customers are willing to share knowledge about products and services on social media (Baima et al., 2022). So, insights from this study can be useful for understanding knowledge sharing behavior of customers.

The unique feature of the present study is that it adopts a hybrid methodology, combining an exploratory study and a hypothesis-driven deductive approach. Conducting a sentiment polarity analysis of review content is also an exclusive contribution of the study, in comparison with similar studies which also tried to develop relationships between various aspects of reviews and their helpfulness. Three critical hypotheses emerged from the exploratory analysis, which also helped the authors identify 'Product Type' as the moderator in the hypothesis-driven model. The findings from this study can help e-commerce retailers formulate strategies by understanding the importance of both central and peripheral routes of persuasion in the perceived usefulness of a product.

The paper is structured as follows. The second section establishes the theoretical background of the paper. The section after that reviews existing literature leading to identification of research gap and hypotheses development. Methodology is discussed in section 4. The section after that discusses the results and discussion. The penultimate section discusses the implications and future scope for research. The last section concludes the paper.

2. Theoretical foundation

Online customer reviews are an important part of eWoM (Mishra et al., 2018). Customers often face difficulties in making the right online purchase decisions. So, they seek information about their potential purchases through online reviews by other customers (Choi and Leon, 2020). Online customer reviews, therefore, have a significant influence on purchase decisions. Electronic Word of Mouth (eWoM) has been revolutionized by the emergence and popularity of social media and user-generated content. However, information overload can sometimes overwhelm customers. It is important therefore, that online retailers identify the most helpful reviews among the large number posted online by customers (Baek et al., 2015). Customers tend to attach more value to the reviews posted by existing customers (Lin et al., 2017) rather than the information provided by vendors (López-López & Parra, 2016). Information Economics or the Economics of Information is helpful to understand the role played by online customer reviews in purchase decisions. Often, there is information asymmetry and customers make purchase decisions without complete information about the quality of the product or the available alternatives. It is not always easy to get useful information. It can be time-consuming and at times, costly. So, there is always a tradeoff between the cost and the benefit of search (Stigler, 1961). There is also a close connection between information and uncertainty (Nelson, 1970). eWoM can solve this problem because information gathered through online customer reviews can reduce uncertainty to a large extent. Helpful reviews have a significant influence on the purchase decision of the customers who can enhance their knowledge by finding cues based on the cue-summation theory (Severin, 1967).

The dual-process theory of external information systems is appropriate as a theoretical foundation for studies related to online customer reviews. Jahoda (1959) stated that social influence decides how an individual is influenced by others, for example, online reviews by experienced customers can be a social influence on potential purchases by new customers (Cialdini, 2009). According to the dual process theory suggested by Deutsch and Gerard (1955), social influence can be categorised into two - informational and normative. The influence exerted on an e-commerce cite by experienced customers through online reviews can be classified as normative social influence.

Normative social influence is influenced by the strength, immediacy, and number of sources (Latane, 1981). The importance of the influential group is measured by strength. In case of online reviews, the experience of the customers is considered an important influence on potential purchases. Immediacy denotes proximity which is facilitated for online

reviews by the internet. The number of sources refer to the number of people who can influence purchase decisions. The average ratings tend to increase with an increase in the number of reviewers, which in turn influences potential customers. The Elaboration Likelihood Model (ELM) in the dual process theory states that both context and content of information are important to impact the perception of the recipients. So, both central and peripheral routes are important to influence the perceived usefulness of a product in an online purchase (Bhattacharjee and Sanford, 2006). The study also considers attribution theory and affect-as-information theory to understand the impact of the central route, that is, the content of the review on the perceived usefulness of a product.

3. Literature review and hypothesis development

An online customer review (OCR) is a form of content generated by users and has a significant impact on the purchase decisions of customers (Lin et al., 2017). It reduces purchase risk (Bruce et al. 2012). It also acts as one of the sources of evaluation of alternative products (Kim, 2014). Online retailers encourage customer reviews because they facilitate future purchase decisions. However, the high number of such reviews triggers customers to look for 'helpful reviews' (Yi Chen et al, 2020). The present study examines what factors contribute to such helpfulness which influences the prospects.

3.1. Review usefulness

Berthon et al. (2008) define online reviews as specific comments through which reviewers aim to communicate to future customers about the product. As it is not possible for consumers to experience products beforehand, their purchase decision making is largely guided by consumers who have already purchased the product. However, too many reviews may clutter their decision-making process, therefore, they prefer to consult only the useful reviews. Online reviews are useful when customers' perceived understanding about the quality and performance of the product is clear (Li et al., 2013). This is referred to as perceived usefulness. High-knowledge customers react differently to negative online reviews compared with low-knowledge customers (Chiou et al. 2018). The valence of online reviews, that is whether reviews are predominantly positive or negative, influences the perceived usefulness of a product (Purnawirawan et al, 2015). The review content complements the descriptions and features of the product, reduces uncertainties regarding potential purchases; and thus exerts influence on purchase decision-making through e-word of mouth (Cheung & Thadani, 2012; Chevalier & Mayzlin, 2006; Mudambi & Schuff, 2010). Studies (Hollebeek et al., 2014; Saboo et al., 2015) have shown that customer engagement with brand intensifies while reading reviews.

As online customer reviews reduce purchase risk (Bruce et al., 2012) and help evaluate alternative products (Kim, 2014), online retailers are encouraged to capture such experiences from users. The present study has adapted the *number of helpful votes* as the primary measure of review usefulness as suggested by previous research (Cao et al., 2011; Forman et al., 2008; Mudambi & Schuff, 2010; Zhang & Tran, 2010).

3.2. Review content

Content-based reviews and their sources have a significant influence on review helpfulness (Li et al, 2013). Studies based on the attribution theory have shown that the impact of messages mediated through causal attribution towards product/store/personal trait is immense (Chiou et al., 2018). It essentially explains customers' behavioral responses towards products. Weiner (1986) developed a three-stage structured framework of attribution theory: a person must observe the behavior of the other person; the observer must believe that the behavior is intentionally performed, and finally the observer must determine what causes compel such behavior. Therefore, customers' judgement towards the usefulness of online reviews may be affected by the causal inferences explained in the attribution theory.

The affect-as-information theory postulates that one evaluates his/her affective reactions (positive or negative) to judge whether the environment in question is good or bad in nature. Affective conditions have two parts: *affective valence*, which essentially says how good or bad the environment is; and *affective arousal*, which denotes its significance or urgency (Clark & Isen, 1982). Khare et al. (2011) have argued that review valence and review volume are two important cues that influence the perceptions of review usefulness. The present study has adapted the valence approach to assess how reviews are accepted by readers.

User-generated content essentially indicates reviewers' sentiments which could be positive, negative, or neutral and these sentiments reflect their attitude towards the product (Hu et al. 2014). Following the attribution theory and affect-as-information theory, this study focuses on the content of reviews. and hypothesizes the following:

Hypothesis 1. *The content of a review has a positive effect on the perceived usefulness of the review.*

3.3. Review ratings

Pan and Zhang (2011) mention that reviewers' textual comments are usually accompanied by star ratings taken on a 5-point scale, 1 being extremely negative and 5 being extremely positive. Reviewers' overall ratings are expected to reveal their experiences about the quality of the product (Hu et al., 2008), which in turn captures the overall attitude of a reviewer towards the product. As demonstrated by the cue-summation theory (Severin, 1967), customers gather knowledge about a product or service from various cues of information. Naturally, users' star ratings are considered to be very helpful in the purchase decisions of future customers (Lalehan and Kim, 2016). Multiple studies have shown that extreme ratings are very useful in customers' purchase decision-making process (Forman et al., 2008; Pavlou and Dimoka, 2006; Korfiatis et al., 2012).

Osgood and Tannenbaum (1995) point out that there should be consistency between people's thoughts and actions. It is expected that the sentiments expressed by reviewers should match with their respective ratings for the product. Therefore, star rating was included as one of the independent variables to observe whether ratings have a similar impact on perceived usefulness and to assess the consistency of reviewers' attitudes. Rating extremity has been considered as review valence (Forman et al. 2008, Ghose & Ipeirotis 2011), while average rating has been considered as an indication of indifference (Cao et al. 2011). The present study has adopted the concept of review valence while integrating the star rating in the model. Based on the above discussion, the study formulates the following hypothesis.

Hypothesis 2. *The star rating has a significant impact on the perceived usefulness of a review.*

3.4. Review length

It is suggested that reviews should be comprehensive and should provide useful information to facilitate decisions (Filieri, 2015; Zheng et al., 2013)**.** Research shows that the length of review is one of the key predictors of review performance (Mudambi & Schuff, 2011; Schindler & Bickart, 2012). Short reviews may not be perceived well, whereas long reviews may be better analyzed by the users. Further, Korfiatis et al. (2012) established that readers get more information in lengthy review and the quality of such reviews are better than shorter reviews. This could be attributed to the level of cognitive effort which is related to length of reviews. The study of Mudambi and Schuff (2010).

shows that there is a high positive correlation between the review usefulness and the number of words that a review contains. Therefore, it's established that the length of a review plays a key role in the perceived usefulness of reviews. Further, Ghasemaghaei *et al.* (2017)

show that lower star ratings are associated with longer reviews. Guided by their findings, a correlation test was conducted between review length and star ratings to observe that the correlation is not significant ($r = -0.013$, $p = 0.627 > 0.05$). This led the researchers to incorporate review length as an independent variable to estimate its impact on perceived usefulness, with the following hypothesis being formulated:

Hypothesis 3. *Review length significantly influences the perceived usefulness of a review*.

3.5. Number of votes

Wu (2017) suggests that the effectiveness of a review is determined by product quality & the ability that it attracts customer's attention. Product popularity for experience product is assessed by number of votes that the review has received (Cui et al., 2012). Highly popular products are perceived as highly credible and as a result, reviews are perceived as highly useful, as emotions are attached with such kind of products. Bansal and Voyer (2000) suggest that a reviewer's experience in reviewing a product may be judged by the number of votes received. The acceptability of a review is greater when the expertise and trustworthiness of a reviewer is high (Kim & Na, 2007). Studies (Cheung & Ho, 2015) have shown that the acceptance of a review is subject to the number of votes it receives. As the authors were curious about the peripheral route of review usefulness, it was logical to consider the experience and expertise of reviewers to determine the usefulness of reviews. Further, research suggests (Cheung & Ho, 2015) that the number of votes a review receives could be a proxy variable to measure the experience of reviewers. Based on the above discussion, the present study developed the following hypothesis.

Hypothesis 4. *The total number of votes received by a review has a positive impact on its perceived usefulness of reviews*.

3.6. Product type

The economics of information advocates the importance of the product type in customers' purchase decision-making process (Mudambi & Schuff, 2010). It postulates that customers must have full information on product quality, seller quality, and the available alternatives. However, seeking information is costly and time-consuming. The total cost of a product increases since it includes the product cost as well the search cost (Nelson, 1970). Search denotes the physical as well as the cognitive search for a product. Nelson (1970, 1974) found that the nature of the product plays a key role in determining the search cost. He defines *search* and *experience* goods as two major categories of products: if a customer can get the information about the product quality before the purchase, it is considered as *search* goods, while *experience* goods are those which must be purchased or experienced to evaluate them. There are several products, however, which are of mixed type and therefore, fall in the continuum of pure search and pure experience products.

Nelson (1974) further emphasizes this classification based on whether product quality can be evaluated by search or by experience. Objective explanations of attributes are required for search goods whereas experience goods call for subjective explanations of attributes (Huang et al., 2009). Experience goods must be sampled to take a call and that sampling essentially turns out to be the purchase of the product. For example, a 30-second video clip of an online lecture allows a customer to collect some pre-purchase information and even to experience the lecture virtually; however purchasing is required for access to the entire lecture/topic.

Although customers search for reviews for their products, it is quite obvious that the nature of information available on these two categories of products is different, since search products reveal more objective information while experience products carry subjective information. The valence of an online review is moderated by the product type. (Xia & Bechwati, 2008). Customers can get valid information in case of search products before using them. However, only sensory experience helps in evaluating the performance of experience products (Nelson, 1970).

There may be an interaction between product type and review content, as reviewers opine differently for different products. Choi and Leon (2020) pointed out that product intangibility moderates the effect of review. Reviews for experience goods may reveal sentiments unique or personal to the reviewer only. In contrast, the sentiments of reviewers for search products are very product-oriented and objective as customers for search goods look for more factual information about the product (Mudambi & Schuff, 2010).

Driven by the above arguments, three products are chosen for this study: a *grocery item* as a search product, a *videogame* as an experience product, and *digital music* as a mixed category product. An experience product is an item in which customer interacts with the product, which results in certain emotions and feelings (Desmet & Hekkert, 2007). Schmitt (1999) opines that experiences are the main deliverables of experience goods. Dyck et al. (2003) opine that videogame is a product which brings novel interaction between the user and the product. The study considers the videogame as an *experience* product, because videogame customers look for experiencing alternate realities and the thrill of problem-solving through interactive experience. Nelson (1970) characterizes the search products as those products, information of which can be gathered though information search. As the purchase of grocery products are driven by specific requirements, customers typically look for the availability of a particular brand, the price of the product and the rating of the brand while shopping online. It is on these grounds that the present study considers it as *search* product. According to Bhattacharjee et al. (2009), digital music may be considered as a product for which customers look both for product experience as well as prior information about the product while searching. This prompted the authors to consider 'digital music' as a mixed product which lies in the middle of the search and experience product continuum scale.

As review content is driven by the nature of products, we propose 'Product Type' as a control variable to evaluate the following hypothesis:

Hypothesis 5. *Product type moderates the effect of review content on perceived usefulness of reviews*.

Fig. 1 represents the conceptual model of the present study based on the five hypotheses developed above.

4. Research methodology

The studies (Biancone et al., 2016; Cardamone et al., 2012) suggest that value-relevance investigation may be adopted to test the hypothesis, as in this method, analysis reveals the relevant information from a given set of data (Secinaro et al., 2021). The hypotheses of the present study have been tested using the above approach. Further, to examine the impact of product type as moderator, we have adopted dummy variable technique (Secinaro et al., 2021), in which we have created two dummy variables, one for 'Videogame' and the other for 'Digital Music', while 'Grocery' has been considered as reference category. The study attempts to measure the effectiveness of online reviews through peripheral versus central route, therefore, we adopted a statistical quantitative approach to research as it is more scientific, focused, and acceptable as compared to qualitative study.

4.1. Data Collection

The study is based on online reviews of three products, namely, a videogame, digital music, and a grocery item from Amazon.com. Even though many reviews are available on all three products, we concentrated only on the most recent ones available. We chose the two experience products in such a way that reviews are subjective and difficult to compare with those of other similar products. We chose the grocery item as our search products as awareness about these items is high and these

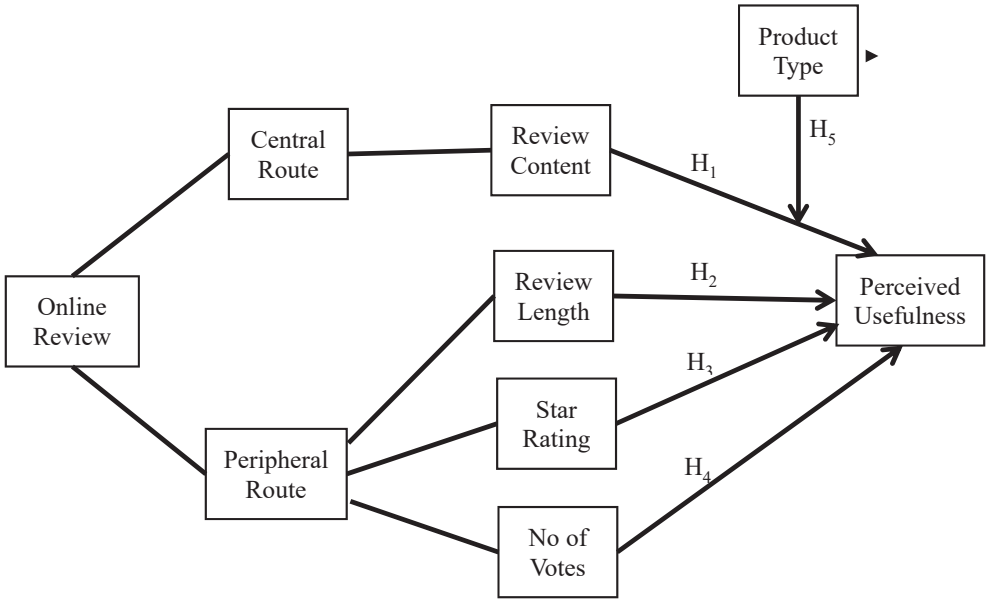


Fig. 1. Conceptual Model.

products are easily comparable.

For each product, we obtained the following information from each review page:

The text of the review
The overall star rating (on a 5-point scale)
The number of people that voted against the question: "Was this review helpful to you (yes/no)?"
Number of people who voted in favour (those who said 'yes' to the above question)
The word count, extracted from the review text to capture the length of each review.

After eliminating the reviews which did not garner any vote either in favour or against as to their helpfulness, our final sample size worked out to 1364 as shown in Table 1.

While building the empirical model, the study has adopted the minimum sample size requirement of Green (1991) and Tabachnick et al. (2007) which indicates 50 + 8k should be the minimum sample size, where k is the number of predictors in the study. As we have 4 predictors in the model, the required sample size is 92, So the study has met the sample size requirement.

4.2. Operationalization of variables

As depicted in Fig. 1, the outcome variable is the perceived usefulness of reviews and this is derived from the total of helpful votes received for each review. Four independent variables were selected including review length, review content, total votes received, and the overall star rating. The details of the operationalization of variables are given in Table 2.

Table 1
Sample Size.

Product	No of Observation
Digital Music	379
Grocery	408
Videogame	577
Grand Total	1364

Table 2
Operationalization of Variables.

Variable	Variable Type	Data Collected	Data Type	Collection Method
Perceived Usefulness (Cao et al. 2011; Forman et al. 2008; Mudambi & Schuff 2010; Zhang & Tran 2010)	Dependent Variable	No. of helpful votes	Continuous	Collected from Amazon website
Review Length (Mudambi and Schuff, 2011; Schindler and Bickart, 2012)	Independent Variable	No of words extracted from text review	Numeric	Derived from Reviews
Review Content (Clark and Isen, 1982; Khare et al. 2011)	Independent Variable	Compound sentiment	Numeric	Derived from Reviews
Total Votes Received (Cheung and Ho, 2015)	Independent Variable	Total Votes	Numeric	Collected from Amazon website
Star Rating (Osgood and Tannenbaum, 1995)	Independent Variable	Overall	Numeric	Collected from Amazon website

4.3. Data analysis

The analysis was carried out in four phases:

Phase 1: Determination of the proportion of positive, negative, and neutral opinions using sentiment analysis.

Phase 2: Exploration of the distribution of review sentiments using Exploratory Data Analysis.

Phase 3: Identification of a logical pattern using the Text Mining Algorithm.

Phase 4: Estimation of the perceived usefulness of reviews using a Multiple Regression Model.

Phase 1: Determination of the Proportion of Positive, Negative, and Neutral Opinions Using Sentiment Analysis.

To extract the positive, negative and neutral aspects of reviews,

Sentiment Analysis was performed, also known as Opinion Mining, as part of Natural Language Processing (NLP) on the Python platform. Sentiment Analysis is a computational method of extracting positive and negative polarity from a text, and is often used to understand customers' sentiments attached to online reviews (Archak et al., 2011; Pang & Lee, 2008). There are two approaches to extract sentiments from a text: polarity-based and valence-based. The polarity-based method only classifies a piece of text into positive and negative categories; whereas the valence-based method considers the intensity of the sentiment. For example, the polarity-based approach would classify both 'bad' and 'horrible' as negative categories, whereas 'horrible' would be considered as more negative in the valence-based approach. We adapted Valence Aware Dictionary and sEntiment Reasoner (VADER), a lexicon and rule-based sentiment analysis tool to extract sentiments. A lexicon is a list of lexical words representing positive or negative sentiments. The analysis produces positive, negative, and neutral scores representing the proportion of reviews that falls under these categories. Finally, it provides the compound score, a metric that calculates the sum of all the lexicon ratings after normalizing them between −1 (most negative) and + 1 (most positive). This compound score finally categorizes the sentiments of review text as follows:

Compound Score $\geq 0.05 \Rightarrow$ Positive Sentiment.

Compound Score $\leq -0.05 \Rightarrow$ Negative Sentiment.

$-0.05 <$ Compound Score $< 0.05 \Rightarrow$ Neutral Sentiment.

A sample extract of positive, negative, neutral, and compound sentiments is presented in Table 3.

The first review in Table 3 indicates that it contains 4.4% negative, 53.8% neutral, and 41.9% positive sentiments. As the compound score for the same review turns out to be 0.9794 ($\geq$0.05), the overall sentiment of the review is considered extremely positive. Further, the intensity of review sentiment of the first review in Table 3 is greater compared to that of the second or third ones, as revealed by the composite scores of 0.9531 and 0.4019 respectively. Similar interpretations were drawn for negative sentiments as well. We have thus transformed the unstructured review data into a structured format and the review valence, measured by the composite score, was considered as a measure of review content in the model.

Phase 2: Exploration of the Distribution of Review Sentiments Using Exploratory Data Analysis.

The objective of this exploratory study is to examine the pattern of positive, negative, and neutral review sentiments and whether these sentiments are consistent with the reviewers' star ratings. We have used key visualization tools, including histogram and box plot, to explore the distribution of positive, negative, and neutral review sentiments of customers. The histogram is a frequency distribution graph for continuous data that represents the shape of the distribution for a single variable and also facilitates the identification of outliers in the distribution. A box plot represents a five-point summary of distribution, including allowable minimum value, first quartile, median, third quartile, and allowable maximum value of the distribution. We have adapted this tool to explore bivariate distributions to investigate the positive, negative, and neutral sentiments of reviews across star ratings. Further, as discussed in section 3.5, customers' sentiments are different for different types of products. We developed three more hypotheses driven by the exploratory data analyses of sentiment distributions. The hypotheses are stated below and we conducted an Analysis of Variance (ANOVA) to test these hypotheses:

Hypothesis 6. *The proportion of negative sentiment in reviews varies across products*.

Hypothesis 7. *The proportion of positive sentiment in reviews varies across products*.

Hypothesis 8. *The proportion of neutral sentiment in reviews varies across products*.

Phase 3: Identification of a Logical Pattern Using the Text Mining

Table 3
Identification of sentiment category.

Review Text	Negative	Neutral	Positive	Compound	Sentiment Category
This is a great CD. I thoroughly enjoyed it. I'd give it all five stars except for one small sour note on this effort… The trilogy that started off is the best I've ever heard. … Feelings #34 is a great track as well… I listen to it every night…	0.044	0.538	0.419	0.9794	Positive
Cat at his best. These songs have been played hundreds of times over the years and still have not lost their ability to move people's emotions. I know I've played them, listened to them, analyzed them, discussed them with friends, sung along with the recordings, and sang them together with friends. They are part of my youth, part of my life, and will forever be a part of me …	0.04	0.651	0.309	0.9531	Positive
Aptitudes and skill(s) of the fifth album categorises the Rock music to attract the new generation and to make a long-lasting position in the library shelf.	0	0.881	0.119	0.4019	Positive
	0.298	0.702	0	−0.5256	Negative

(*continued on next page*)

Table 3 (*continued*)

Review Text	Negative	Neutral	Positive	Compound	Sentiment Category
I was disappointed when I got this CD and it didn't work. Can I get a refund? It acts as if there is no information on it.					
Horrible Quality can hardy hear it !!!!!	0.427	0.244	0.329	−0.2023	Negative
The whining in this song makes me crazy. It sounds like Coldplay's Chris Martin getting raped in a maximum-security prison shower. A-awe-awe-all! terrible!	0.415	0.404	0.18	−0.7506	Negative

Algorithm.

Text mining is a process to extract knowledge from unstructured text data (Kao & Poteet, 2007). It has been defined by researchers as one of the key data mining techniques. Standard data mining techniques are used to extract logical patterns from structured data, while text mining is a process of knowledge discovery and a technique for identifying logical patterns from unstructured data (Kano et al., 2009). The text-mining algorithm extracts features such as characters, words, terms, concepts, and sentiments from a body of text (Feldman & Sanger, 2006; Grimes, 2007). The algorithm follows a standardized process consisting of various steps including tokenization, lemmatization, stemming, dictionary generation, part-of-speech tagging, word sense disambiguation, phrase recognition, and feature generation (Protaziuk et al., 2016).

Using the text-mining algorithm, we have extracted various categories from the review data. Documents from the text are assigned to pre-existing categories; the present study uses the categories defined in the '*customer satisfaction*' library, as these reviews express essentially customers' satisfaction about a product.

After pre-processing the data, the extraction process follows the steps given below:

- First, interesting words and phrases are extracted from each document; these words and phrases collectively are known as '*Terms*'.
- A '*Concept*' is formed by grouping all the relevant terms that have already been extracted.
- Combinations of a few concepts which reveal the key ideas, knowledge, and attitudes expressed in the text are known as '*Categories*'.
- Once the categories are identified, certain patterns were identified.

Phase 4: Estimation of the Perceived Usefulness of Reviews Using a Multiple Regression Model.

Finally, the study has adopted multiple regression technique to test the five hypotheses, hypothesis 1 through hypothesis 5. The technique essentially has estimated the linear relationships between perceived usefulness as the dependent variable and the four independent variables, namely, review length, review content, star rating, and the total number of votes received. As mentioned in Table 2, independent variables of the model have been derived from the reviews of the customers. Review length is the number of words which has been extracted from the review. Review content essentially represents the sentiments of the reviewers embodied in the reviews. Total number of votes that a review has received and the star rating pertaining to a review have been taken in actuals. We have considered product type as the control variable as described in the research conceptual model. We have estimated two models using the Ordinary Least Square Method:

Model 1: Effect of all predictors on perceived usefulness of a review.

Perceived Usefulness $= \beta_0 + \beta_1$ Review Content $+ \beta_2$ Review Length $+ \beta_3$ Star Rating $+ \beta_4$ Total Votes Received $+ \varepsilon_1$.

Model 2: Effect of all predictors on perceived usefulness of review in the presence of 'product type' as a moderator.

To incorporate 'Product Type' as a moderator, we have created two dummy variables, namely Digital Music and Videogame, using the following dummy codes:

1. Digital Music: If Product Type = Digital Music, then Digital Music = 1, or else = 0
2. Videogame: If Product Type = Videogame, then Videogame = 1, or else = 0

As a result, Grocery is now the reference category in Model 2. We have estimated the second model as follows:

Perceived Usefulness $= \beta_0 + \beta_1$ Review Content $+ \beta_2$ Review Length $+ \beta_3$ Star Rating $+ \beta_4$ Total Votes Received $+ \beta_5$ Digital Music $+ \beta_6$ Videogame $+ \beta_7$ Review Content*Digital Music $+ \beta_8$ Review Content*Videogame $+ \varepsilon_2$.

5. Results & discussion

5.1. Evaluation of positive, negative, and neutral sentiments in customer reviews

Customer reviews were analyzed using sentiment analysis to extract sentiments about the products. The descriptive statistics of these sentiments are presented in Table 4. On an average, customers expressed only 8.3% negative opinions as against the 30.3% of positive opinions. It is further revealed that on an average, customer attitude towards a product is typically positive as the average compound score was determined as 0.685 ($\geq$0.05).

5.2. Exploratory data analysis of review sentiments

In order to examine the distribution of the three categories of sentiments, we visualized histograms of positive, negative, and neutral sentiments which are depicted in Figs. 2–4 respectively.

As evidenced from the three figures above, we conclude that the proportion of negative sentiment follows a positively skewed

Table 4
Descriptive Statistics of Review Sentiments.

Measures	*Negative*	*Neutral*	*Positive*	*Compound*
Mean	0.083	0.614	0.303	0.685
Standard Error	0.002	0.004	0.004	0.013
Median	0.066	0.624	0.285	0.893
Mode	0	0.651	0	0.992
Standard Deviation	0.083	0.130	0.140	0.473
Sample Variance	0.007	0.017	0.020	0.224
Kurtosis	1.548	0.528	0.756	3.448
Skewness	1.186	−0.226	0.623	−2.072
Range	0.459	1	1	1.981
Minimum	0	0	0	−0.982
Maximum	0.459	1	1	0.999
Sum	113.25	837.21	413.55	934.13
Count	1364	1364	1364	1364

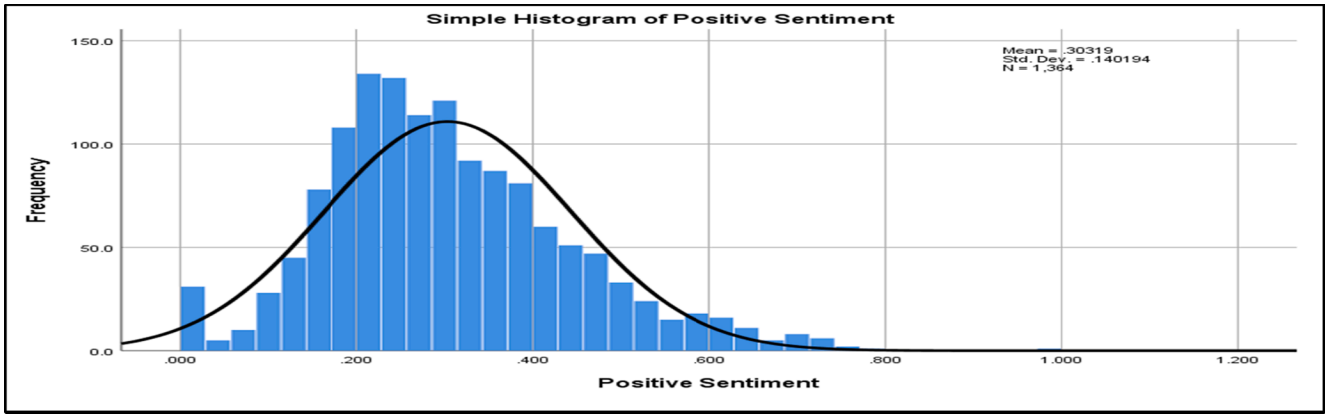


Fig. 2. Positive Sentiment Distribution.

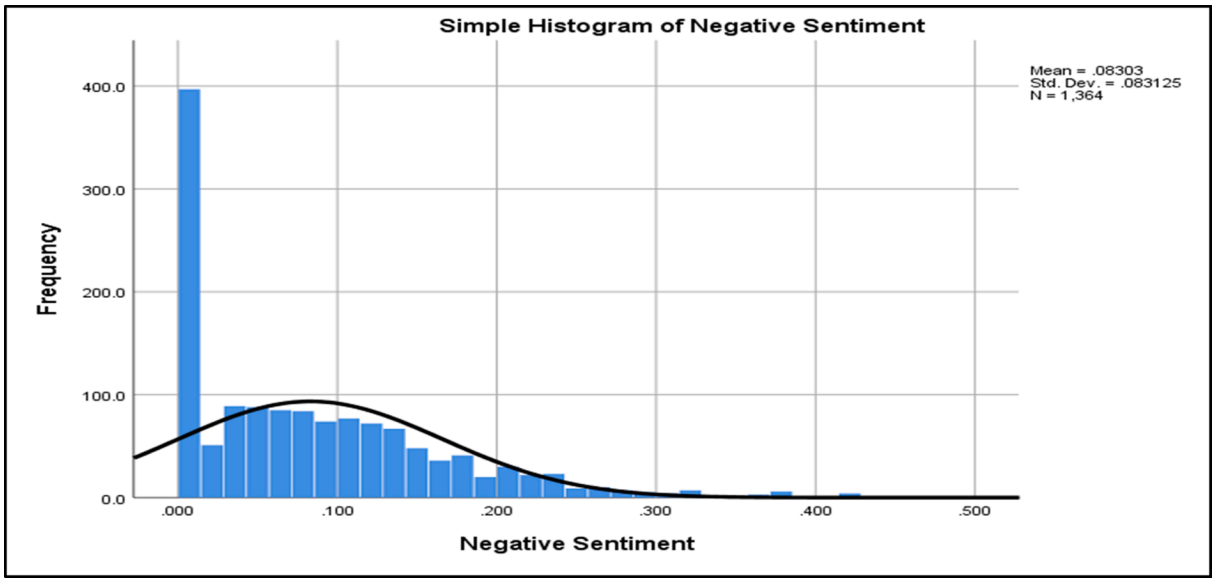


Fig. 3. Negative Sentiment Distribution.

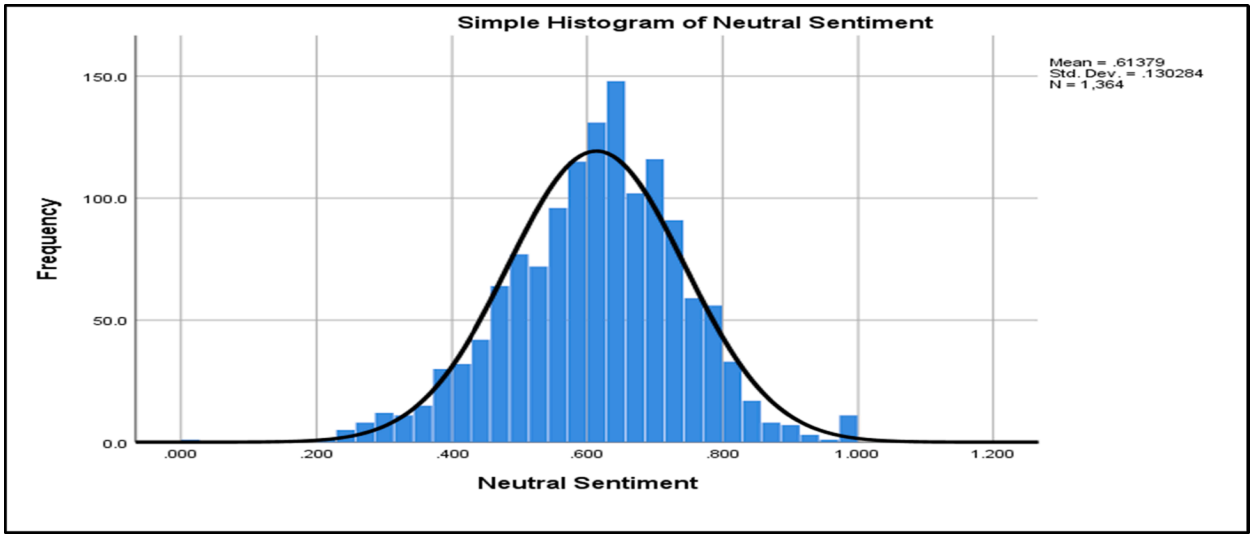


Fig. 4. Neutral Sentiment Distribution.

distribution (Skewness = 1.186) whereas, positive (Skewness = 0.623) and neutral (Skewness = -0.226) sentiments are almost symmetric in nature. Further, we examined whether positive and negative distributions are similar across the three products, namely digital music, grocery item, and videogame, understudy. We derived the Population Pyramid Histogram for all the three products on the same scale to observe that there is no difference in the distribution patterns of sentiments across the three products (as depicted in Figs. 5 and 6).

Even though the visualizations affirm that there is hardly any difference in the distribution of sentiment patterns across products, the study wanted conclusive statistical evidence. The present study formulated three hypotheses (6–8), based on the data visualizations, to examine whether the proportion of positive, negative & neutral sentiments in reviews are different across various products. It deployed a one-way ANOVA to test the following hypotheses.

Hypothesis 6. *The proportion of negative sentiment in reviews varies across products*.

Hypothesis 7. *The proportion of positive sentiment in reviews varies across products*.

Hypothesis 8. *The proportion of neutral sentiment in reviews varies across products*.

Table 5 provides the descriptive statistics highlighting the fact that the average proportion of sentiments is not the same across products. This is also confirmed in the output of the ANOVA test (Table 6), which shows that the proportion of negative sentiments is not same across product type ($F = 35.763$ (2, 1361); $p < 0.01$). The proportion of neutral sentiment is also not the same ($F = 23.556$ (2,1361); $p < 0.01$); however, there is no difference in the proportion of positive sentiment across products ($F = 0.974$ (2, 1361); $p > 0.05$).

Thus, the hypotheses 6 and 8 are supported while hypothesis 7 is not supported.

5.3. Customer reviews: a comparative analysis across overall star ratings

We wanted to examine the correlation between the star ratings and the positivity and negativity embodied in their reviews to assess the consistency of customer feedback using five-point exploratory data analysis tools.

The box plot in Fig. 7 shows that the average positive sentiment is higher against the star ratings 4 and 5 than that at the star ratings 1 and 2. The findings from Fig. 8 with respect to negative sentiment are complementary to those about positive sentiments. Average negativity is higher on the ratings 1 and 2 in comparison with the ratings 4 and 5. These comparative studies indicate that there is consistency between reviews and star ratings. This is further evidenced in the distribution of neutral feedback (Fig. 9), which shows a similar pattern from 1 through 5-star ratings.

5.4. Knowledge discovery

5.4.1. Polarity analysis

Polarity Analysis determines the extent of positive and negative terms in a document. The text mining algorithm extracted 9381 positive *terms* and 4804 negative *terms* from the entire corpus under 8 positive and negative concepts including positive (negative), positive (negative) feeling, positive (negative) functioning, positive (negative) recommendations, positive (negative) competence, positive (negative) budget, positive (negative) attitude, and positive (negative) emotion. Table 7 shows the frequency distribution of all positive and negative sentiments from the entire corpus as well as the number of reviews that carry these sentiments.

The results indicate that, overall, customers possess mostly positive sentiments for the products they buy, except in the case of attitude and functioning. When customers are not happy with the functioning of the products purchased, they may develop negative attitude towards them. However, their overall comments appear to be positive. Further, product-wise polarity was analyzed, based on positive and negative *concepts*. We observed (Fig. 10) that digital music and videogame reviews carry less positive *concepts* as against the grocery item. A videogame is an experience product, as is digital music to a large extent, reviews may carry mostly subjective opinions and that probably causes less positivity in the reviews. On the contrary, the grocery item is a search product; reviews are based on the characteristics of the products and therefore, objective in nature. Customers are sure about expressing

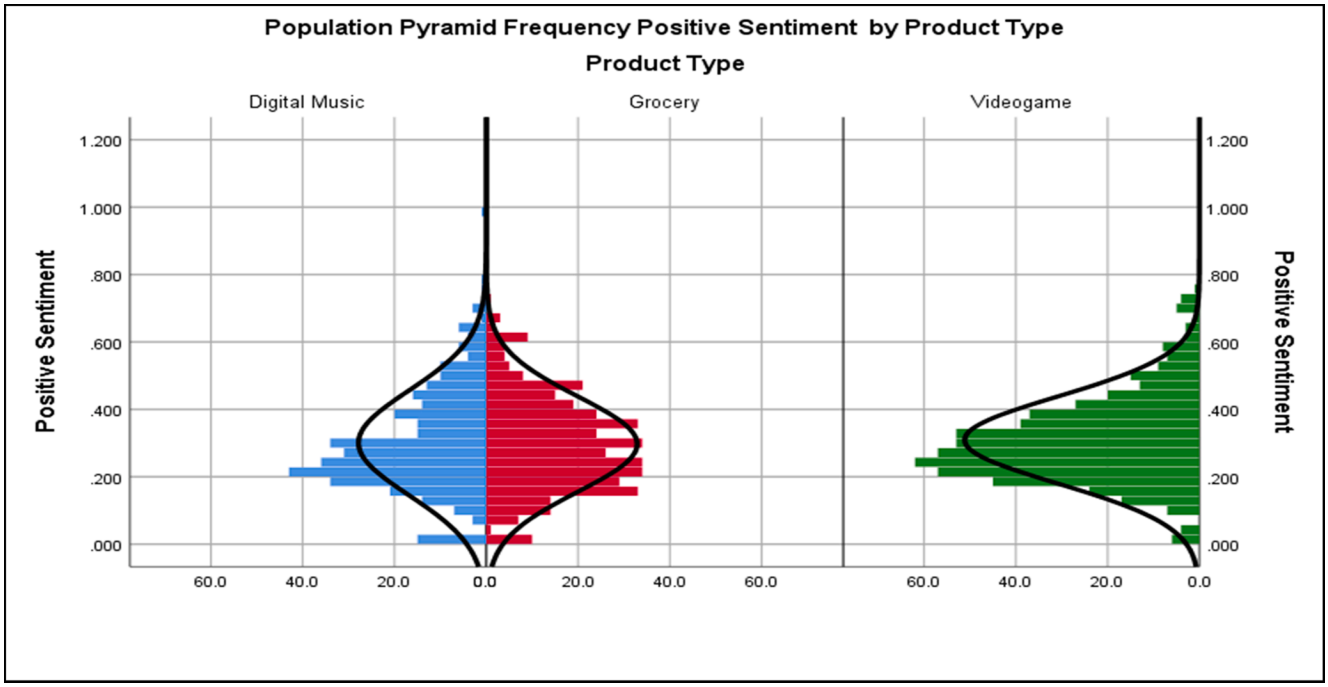


Fig. 5. Histogram of Positive Sentiment by Product Type.

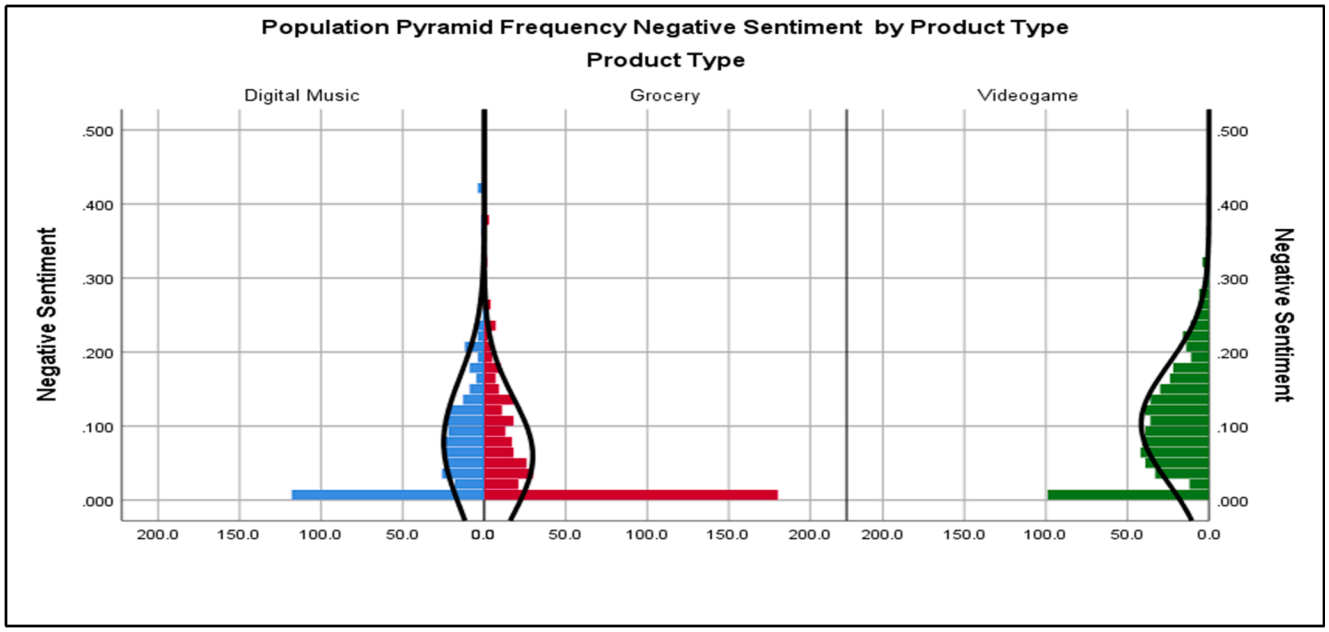


Fig. 6. Histogram of Negative Sentiment by Product Type.

Table 5
Descriptive statistics: product-wise proportions of sentiments.

Sentiment	Products	N	Mean	Std. Deviation
Negative	Digital Music	379	0.0781	0.08697
	Grocery	408	0.0593	0.07813
	Videogame	577	0.1031	0.07910
Positive	Digital Music	379	0.3007	0.15511
	Grocery	408	0.2970	0.14144
	Videogame	577	0.3092	0.12852
Neutral	Digital Music	379	0.6212	0.14620
	Grocery	408	0.6437	0.13571
	Videogame	577	0.5878	0.10854

Table 6
ANOVA.

Sentiment Type	F	Sig.
Negative	35.763	0.000
Positive	0.974	0.378
Neutral	23.566	0.000

their opinions about the products.

5.4.2. Sentiment pattern

The study demonstrates the process of sentiment extraction from the reviews of the videogame, since it is an experience product,. First, we derived the *terms* from the reviews as explained in section 3.3. The top 20 terms extracted are presented in Table 8 (see Tables 9 and 10).

We further extracted the pattern of use of these terms by visualizing web maps. Two such maps pertaining to the terms 'excellent' and 'entertaining' are presented in Figs. 11 and 12 respectively for readers' understanding. It is clear how positive attitudes, such as '*excellent*' or '*entertaining*' are connected to certain features of the product (see Figs. 13 and 14).

To identify the pattern of the two concepts which finally led to the formation of the categories of sentiments, we derived a web-cloud on these concepts. We have demonstrated only two such web clouds to illustrate customers' opinions about the videogame.

5.5. Model Estimation

We performed a multiple regression analysis by taking perceived usefulness as the dependent variable and the factors, review content, review length, star rating, and the total number of votes received as independent variables. The study performed two regression models. The first model estimated the following relationship:

[1] Perceived Usefulness $= \beta_0 + \beta_1$ Review Content $+ \beta_2$ Review Length $+ \beta_3$ Star Rating $+ \beta_4$ Total Votes Received $+ \varepsilon_1$.

It is evident from the results that all four factors significantly and positively affect the perceived usefulness of reviews. This in line with the concept of normative social influence developed by Deutsch and Gerard (1955) using the dual process theory. Latane (1981) mentioned that one of the ways to explain normative social influence is through the number of sources. In our study, we find that the total votes received, which can be considered as the number of sources has a significant influence on perceived usefulness**.** Further, as the study wanted to examine the moderating effect of product type on review content, a second regression analysis was performed incorporating two interaction variables, namely, Digital Music*Depth and Videogame*Depth along with the independent variables from the first model. The interaction variables were incorporated to examine the moderation effect of Product Type on Perceived Usefulness. The second model with moderation effect is presented below:

[2] Perceived Usefulness $= \beta_0 + \beta_1$ Review Content $+ \beta_2$ Review Length $+ \beta_3$ Star Rating $+ \beta_4$ Total Votes Received $+ \beta_5$ Digital Music $+ \beta_6$ Videogame $+ \beta_7$ Review Content*Digital Music $+ \beta_8$ Review Content*Videogame $+ \varepsilon_2$.

As the moderating effects were found to be significant, we built the following estimation models of perceived usefulness for the three chosen products:

[3] Perceived Usefulness (*Grocery*) = -1.382 + 0.251 (Total Votes) + 0.546 (Star Rating) + 0.004 (Review Length).

[4] Perceived Usefulness (*Digital Music*) = -1.382 + 0.251 (Total Votes) + 0.546 (Star Rating) + 0.004 (Review Length) + **1.072** (Review Content).

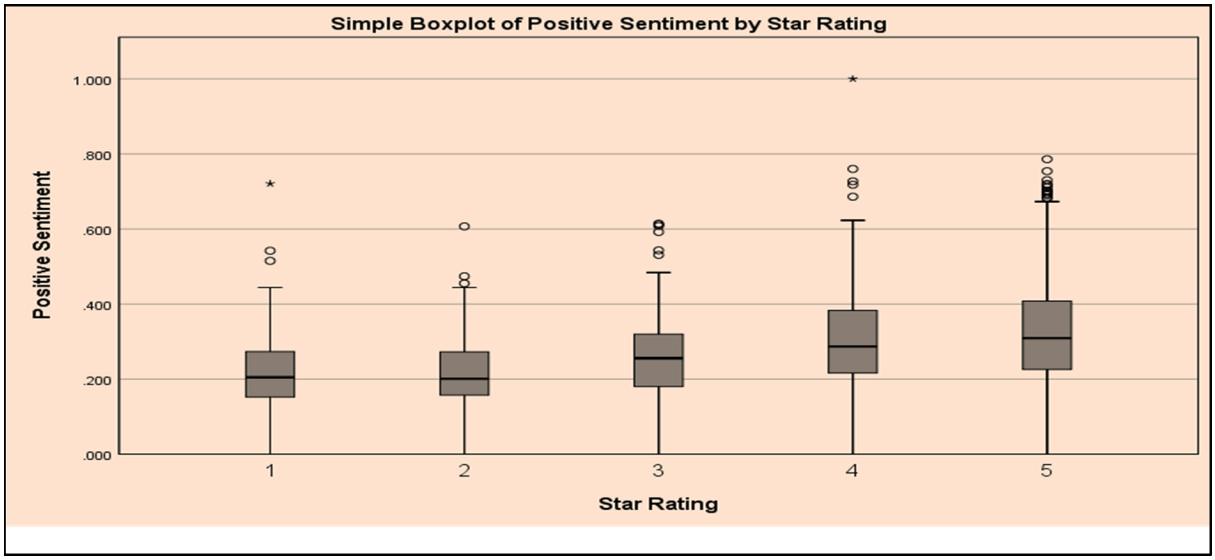


Fig. 7. Comparison of Positive Sentiment across Star Ratings.

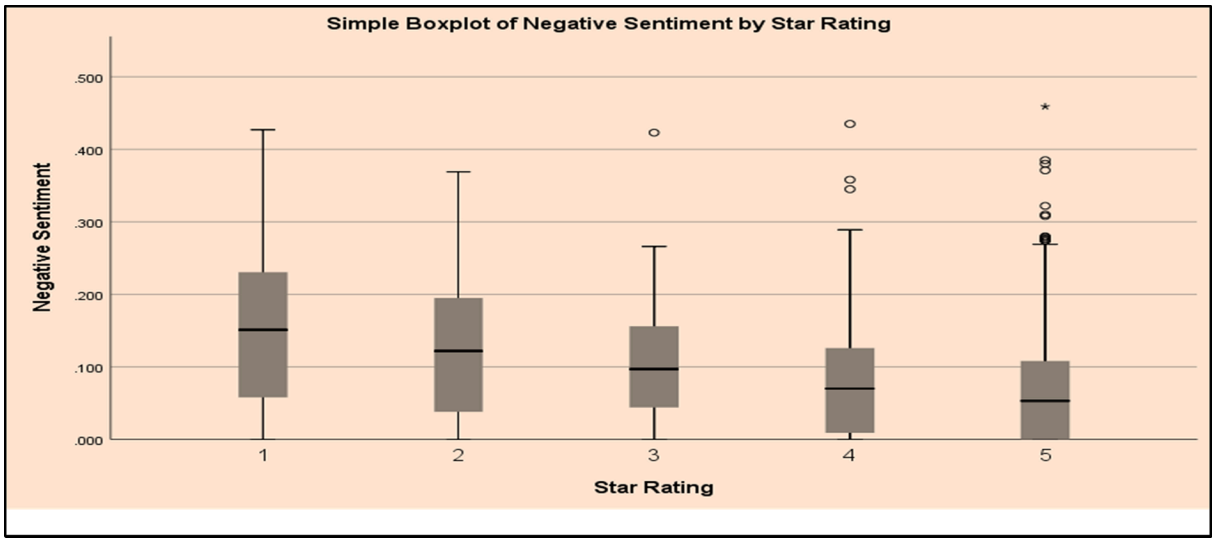


Fig. 8. Comparison of Negative Sentiment across Star Rating.

[5] Perceived Usefulness (*Videogame*) = - (1.382 + 0.834) + 0.251 (Total Votes) + 0.546 (Star Rating) + 0.004 (Review Length) + 1.**512** (Review Content).

It is clear from equation [3] that customers do not rely on review content in the case of grocery products, rather they depend more on the star rating as well as on the popularity of reviews indicated by the total number of votes; review length also has a positive effect on perceived usefulness, as every additional word in review is expected to increase usefulness by 0.004 units. This could be because customers' purchase decisions for '*search*' products do not depend much on the subjective evaluation of the product. However, the scenario is different in the case of the videogame and digital music. In addition to the star rating, the popularity of the review, and the review length, customers depend on the user comments about the products. It is further evidenced from the study that review content has a greater impact (1.512, $p < 0.01$) on videogame customers compared to that of digital music (1.072, $p < 0.1$). It is apparent that future customers for '*experience*' products rely mostly on subjective evaluations of current users in addition to other parameters of reviews. Further, as digital music lies in the middle of the *search-experience* continuum scale, the degree of impact of subjective content is lesser than that of videogame, which falls under the pure experience category. Online reviews are moderated by the product type (Xia & Bechawati, 2008). Search products can be evaluated accurately before purchase because of their attributes. So, review content is not significant for search goods. These are based on objective criteria (Sen & Lerman, 2007). Consumers suffer from uncertainties before buying experience goods. They are based on subjective criteria (Park & Park, 2013; Sen & Lerman, 2007; Purnawirawan et al, 2015). Therefore, review content is significant for experience goods. It is in fact stronger in the case of pure experience goods. Therefore, after evaluating both models, we conclude that all the five hypotheses (H_1 through H_5) are supported by the study. Finally, we present the results of the hypothesis testing in Table 11.

6. Implications and directions for future research

6.1. Implications of the study

The findings from the present study have important practical implications that can be useful for managers and researchers. Our study helps in explaining the importance of the central and peripheral routes

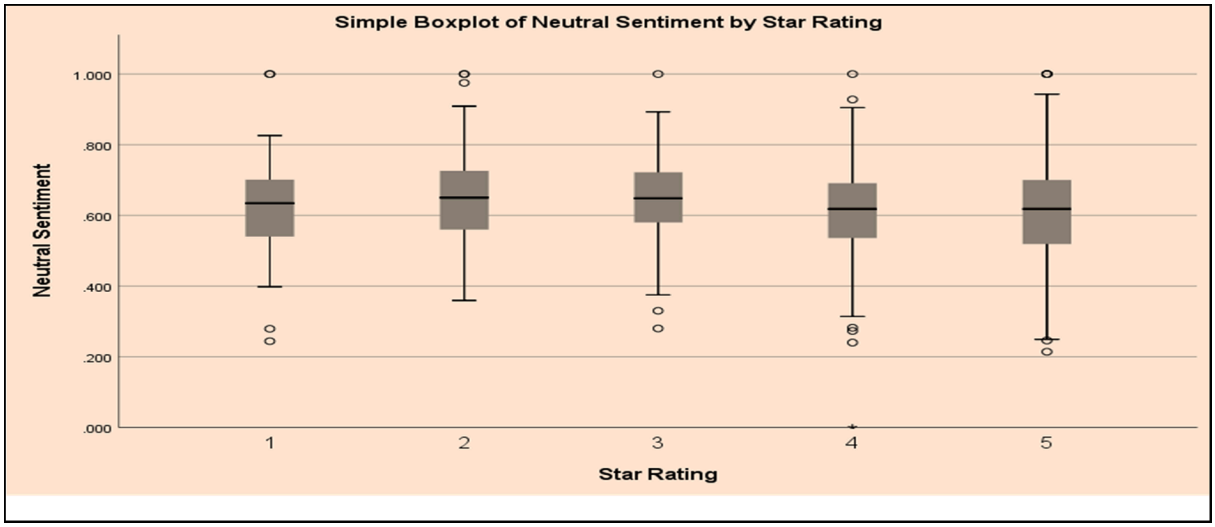


Fig. 9. Comparison of Neutral Sentiment across Star Rating.

Table 7
Positive and negative terms.

Positive Sentiment	Sentiment Frequency	Review Frequency	Negative Sentiment	Sentiment Frequency	Review Frequency
Positive	7942	1266	Negative	3383	921
Positive Feeling	761	411	Negative Feeling	265	191
Positive Functioning	175	149	Negative Functioning	818	386
Positive Recommendation	116	113	Negative Recommendation	60	57
Positive Competence	122	105	Negative Competence	9	9
Positive Budget	111	94	Negative Budget	67	55
Positive Attitude	115	88	Negative Attitude	191	133
Positive Emoticon	39	32	Negative Emoticon	11	11
Total	9381		Total	4804	

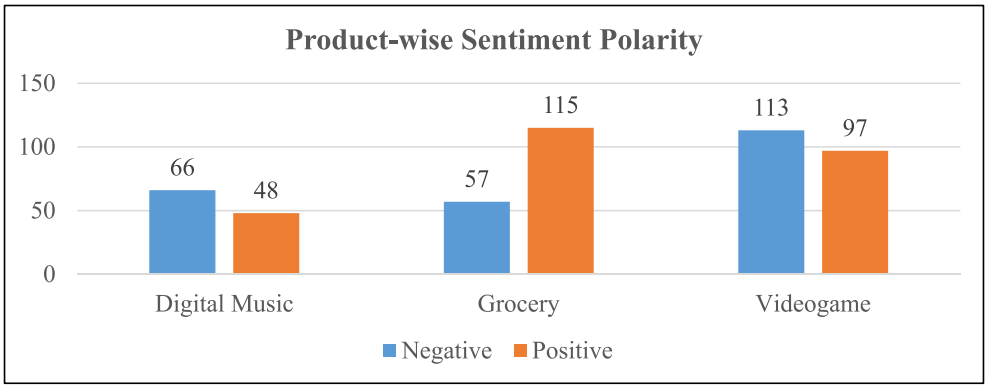


Fig. 10. Comparison of sentiments between the products.

to persuasion for experience and search goods and the relative importance of the peripheral route for experience goods. It provides insights to online retailers about the types of online reviews which would be useful for a particular type of product. The findings from the study will help them focus on the types of reviews depending on the product. The peripheral route can be given more importance for search goods. Experience goods have intangible attributes. Consumers do not know much about a product until they have sensory experience (Nelson, 1970), therefore, reviews by experienced customers adds more value.

The analysis of sentiment polarity offers that reviews on search products carry more positive sentiments whereas reviews of experience products are burdened with negative sentiments. However, online retailers should not be excited with the positivity of search products as review content is not important for consumers of search products (Hypothesis 5).

The polarity analysis (section 5.4.1) reveals that customers are not happy with the functioning of the products considered in this study. Practitioners, therefore, need to revisit the product design to customize it according to customer preferences. This would also enhance the attitude towards the product.

The study shows that on an average, 61.4% comments are neutral, which does not help either the future customers or the online retailers. Online review platforms need to consider how to articulate review questions to trigger effective comments.

The study contributes to research methodology as it adopts a hybrid method of combining exploratory as well as hypothesis-driven deductive

Table 8
Top *terms* extracted from the reviews for the videogame.

Term	Term Frequency	Document Frequency
Excellent	1115	392
Game	1076	436
Good	467	265
Like	345	208
Well	292	184
Entertaining	287	183
Bad	232	140
Difficult	223	137
Play	181	141
Graphic	153	125
Large	151	96
Easy	128	90
Time	126	93
Creative	126	89
Problem	124	83
Level	116	77
not working	107	79
Old	100	79
Classic	99	69
Crashed	99	28

study. The exploratory study results in the development of three hypotheses which have been derived from data visualization in section 5.2. This is one of the unique contributions of this study.

The study contributes to theory also. Hong et al (2017) pointed out that mainstream studies have produced mixed results as far as the determinants of perceived usefulness is concerned. The study contributes to the existing literature by adopting a comprehensive ELM framework to evaluate the impact on perceived usefulness using the central and peripheral routes.

The study contributes to literature in consumer knowledge sharing (CSK) because perceived usefulness of online reviews positively impacts customer knowledge sharing. They are willing to share knowledge about products and services through social media (Baima et al., 2022).

The study also adds to the literature on International Marketing. Companies can use social media platforms and the information to gain competitive advantage globally (Berthen et al., 2012).

6.2. Limitations and directions for future research

The study is subject to some limitations. Only three products were considered including two experience and one search product. However,

Table 9
Model 1 - regression output.

Independent Variables	*Coefficients*	*Standard Error*	*t Stat*	*p-value*	R^2	*F Test*	*p-value*
Intercept	−1.869***	0.373	−5.016	0.000	0.359	190.25	0.000
Total Votes	0.249***	0.010	25.134	0.000			
Star Rating	0.529***	0.088	5.989	0.000			
Review Content	0.380*	0.229	1.661	0.097			
Review Length	0.004***	0.000	7.840	0.000			

Note: '*' – Significant at 10% level; '***' – Significant at 1% level.

Table 10
Model 2 - regression output with moderation effect.

Independent Variables	*Coefficients*	*Standard Error*	*t Stat*	*P-value*	R^2	*F Test*	*P-value*
Intercept	−1.382***	0.472	−2.930	0.003	0.363	96.72	0.000
Digital Music	−0.395	0.494	−0.800	0.424			
Videogame	−0.834*	0.443	−1.883	0.060			
Total Votes	0.251***	0.010	24.983	0.000			
Star Rating	0.546***	0.089	6.164	0.000			
Digital Music*Content	1.072*	0.611	1.754	0.080			
Videogame*Content	1.512***	0.536	2.818	0.005			
Review Content	−0.702	0.460	−1.528	0.127			
Review Length	0.004***	0.000	7.582	0.000			

Note: '*' – Significant at 10% level; '***' – Significant at 1% level.

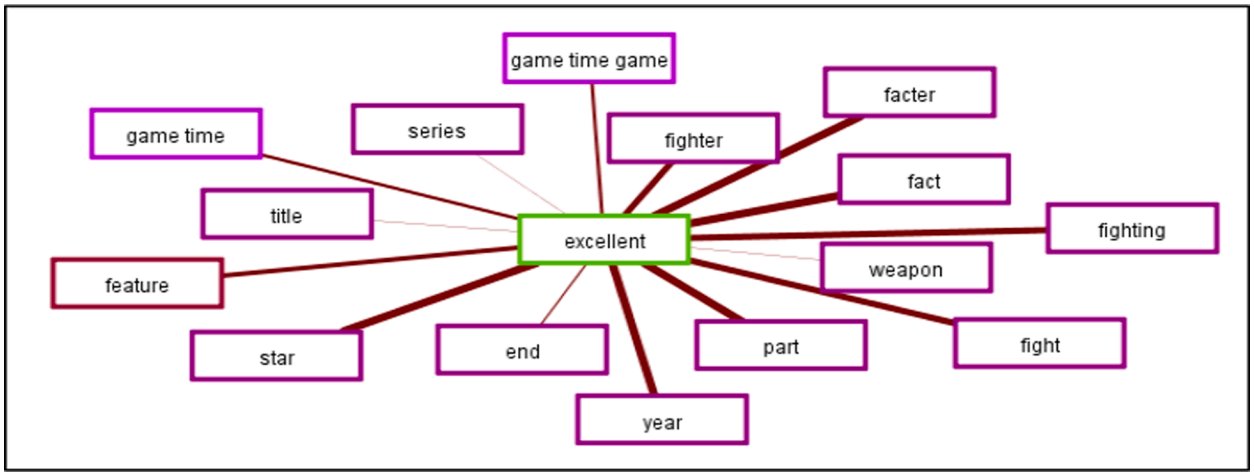


Fig. 11. A Web-map of *Excellent* in Videogame.

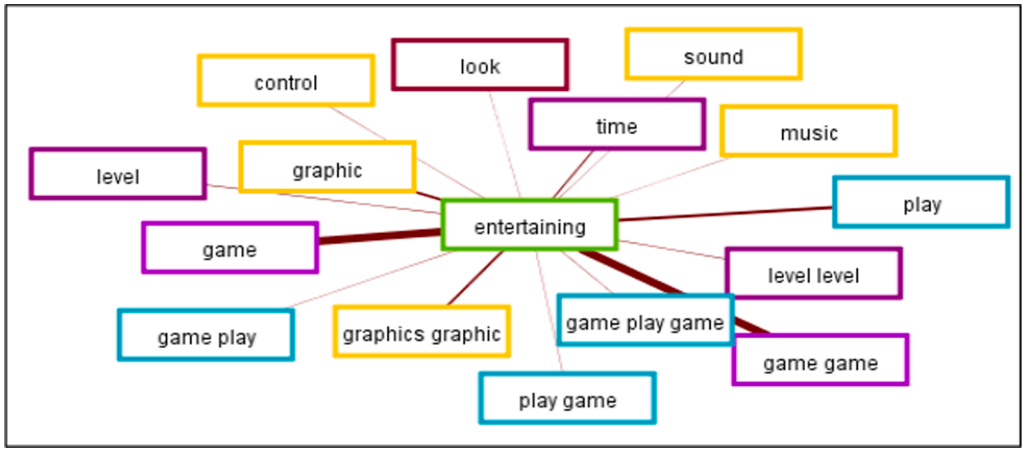


Fig. 12. A Web-map of *Entertaining* in Videogame.

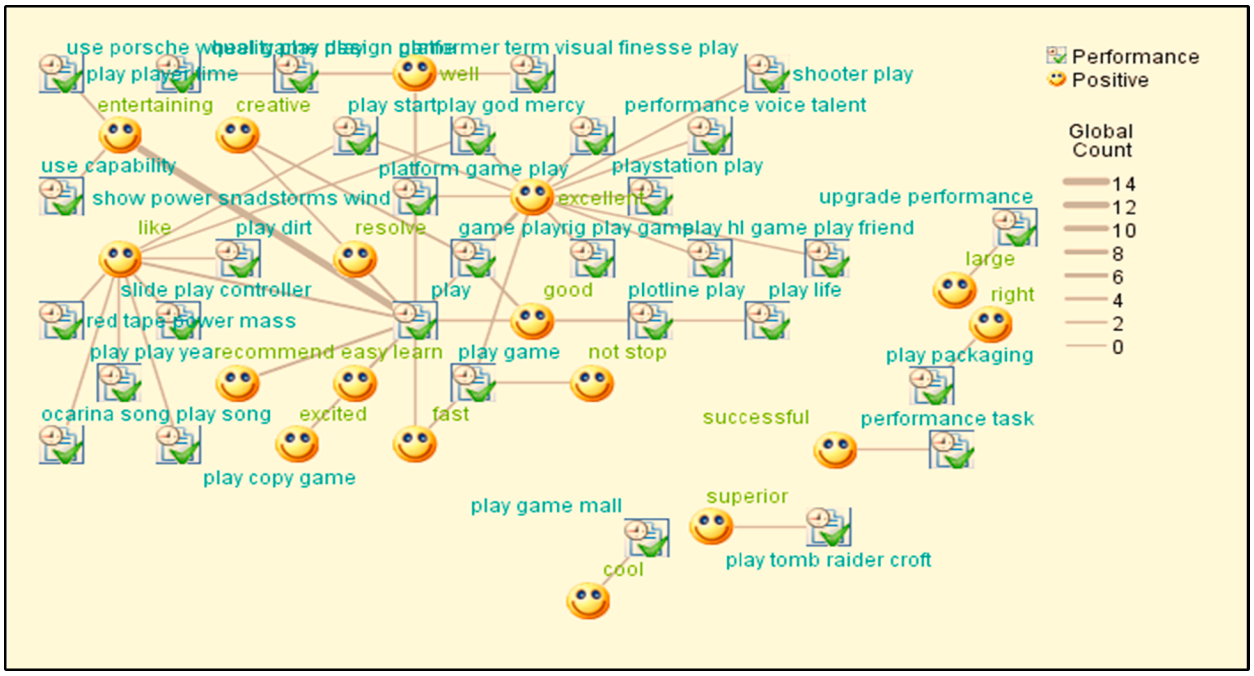


Fig. 13. Videogame Web-Cloud on *Positive Performance.*

if we would have considered a wider range of products, the results could have been generalised for other categories as well. Further, the Amazon platform has been taken as the single source of data, whereas multiple review platforms would have extracted reviews in multiple formats. The study did not include the metadata of the reviewers. Future studies can include metadata and examine the impact of the demographics of reviewers on the usefulness of reviews. Further, future studies can examine the reviews of the same product on multiple platforms and also of multiple products on the same platform. Future research can delve into cross-cultural aspects. Different cross-cultural and contextual settings can influence purchase intentions (Ferraris et al., 2019). So, the research question that can be on the impact of cross-cultural settings on purchase decisions. Vaidyanathan et al. (2013) pointed out that consumer behavior can be impacted by cultural differences. So, researchers can check whether cultural differences have any impact on perceived usefulness of online reviews. Based on this, companies can seek to target international markets. Consumer cosmopolitanism can be a powerful segmentation base (Makrides et al. 2021) for online retailers. Perceived usefulness of online reviews positively influences customer knowledge sharing (CKS). Researchers can also study the impact of cross-cultural differences on customer knowledge sharing.

COVID 19 has resulted in structural changes in consumer behavior (Gordon-Wilson, 2021; Yap et al., 2021; Rayburn et al., 2021; Kursan Milakovic, 2021; Nayal et al., 2021; Sharma, Thomas & Paul, 2021; Chopdar, Paul & Prodanova, 2022). For example, online transactions have become part of people's life in many sectors including healthcare, financial services, hotel booking, food delivery etc (Siddiqui, Akhter & Islam, 2022; Chakraborty & Paul, 2022; Purohit, Arora & Paul, 2022; Chopdar, Paul, Korfiatis, & Lytras, 2022). As an outcome, we need new theories, scales, methods and paradigms to carry research studies in the post-pandemic era to analyze the new processes, patterns and problems. We concur with the prior calls (Paul & Bhukya, 2021), for developing new frameworks and models as platforms to carry out future studies in the area of online reviews and consumer.

7. Conclusion

Online reviews, considered as electronic word-of-mouth, have

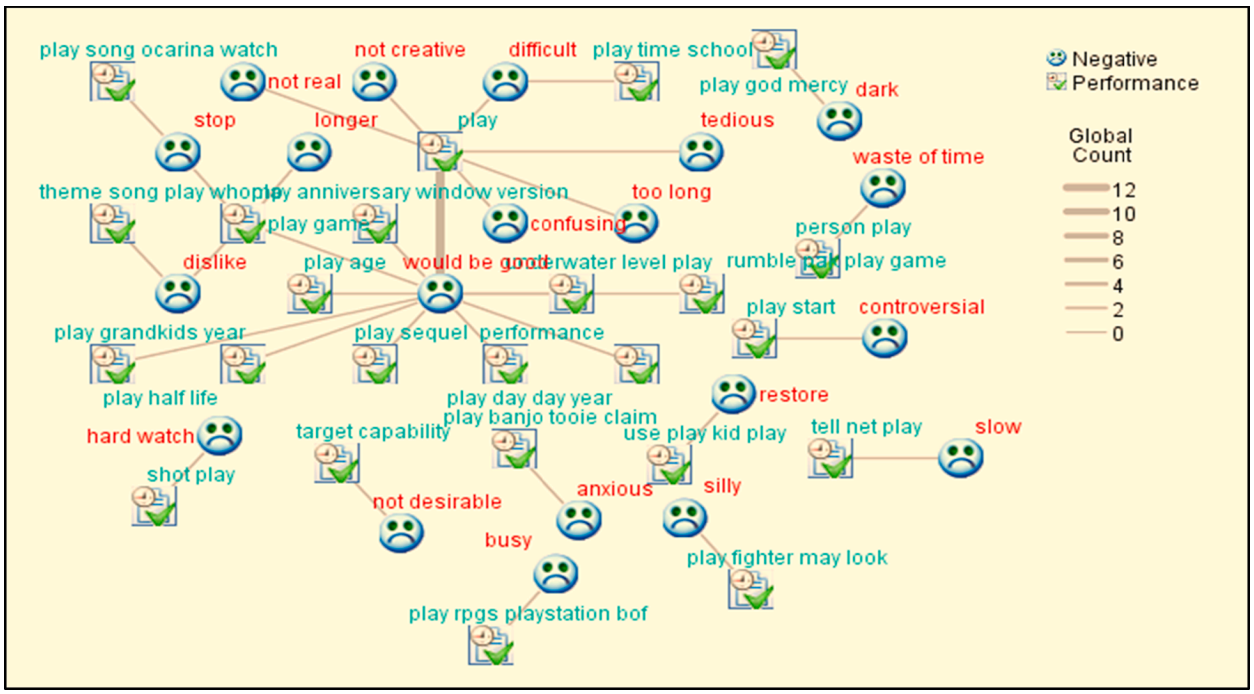


Fig. 14. Videogame Web-Cloud on *Negative Performance.*

Table 11
Results of hypotheses testing.

No	Hypothesis	Supported/Not Supported
H1	*Content of the review has a positive effect on the perceived usefulness* of the review.	Supported
H2	*The star rating has a significant impact on the perceived usefulness of a review.*	Supported
H3	*Review length significantly influences the perceived usefulness of a review.*	Supported
H4	*Total number of votes has a positive impact on the perceived usefulness of reviews.*	Supported
H5	*Product type moderates the effect of review content on the perceived usefulness of reviews.*	Supported
H6	Proportions of *negative* sentiment in reviews vary across the products.	Supported
H7	Proportions of *positive* sentiment in reviews vary across the products.	Not Supported
H8	Proportions of *neutral* sentiment in reviews vary across the products.	Supported

become very critical in the era of e-commerce (Verma & Yadav, 2021) as they facilitate the purchase decisions of future customers and also help online retailers to understand the acceptability of their product. Hence, the present study focuses on discovering knowledge from such reviews. Even though a few studies have concentrated on understanding the helpfulness of customers' reviews (Chiou et al., 2018), the present study contributes to analyzing customer reviews from three perspectives: understanding sentiment polarity, identification of sentiment pattern, and finally, analyzing the impact of various factors on the perceived usefulness of reviews under the moderation effect of *search* and *experience* products.

The main insight which can be drawn from the study is that the peripheral route of persuasion has a more significant impact than the central route on the perceived usefulness of online reviews. The impact is also dependent on the product category. In fact, the central route captured through review content loses its significance in the case of 'search' products as potential customers rely more on the star rating and other parameters, whereas the content is quite important in the case of '*experience*' products. Even within experience goods, the impact is less for digital music which lies in the middle of the *search-experience* continuum scale. The impact of review content is the greatest in the case of the videogame which is a pure experience product. Since experience products have intangible characteristics, customers like sensory evaluation, therefore, review content assumes greater importance as potential users seek more information from the experiences of customers who have already used them.

A few additional insights were also drawn from the study. i) Even though there is no significant difference in positive comments, customers' negative comments depend on the product category. ii) There exists a consistency between reviewers' comments and their star rating. iii) Polarity analysis reveals that customers usually opine in a positive manner; however, they are more positive while reviewing '*search*' products rather than '*experience*' products. iv) Various factors including star rating, review length, number of votes, and review content have a positive impact on the perceived usefulness of reviews.

CRediT authorship contribution statement

Madhumita Guha Majumder: Writing – review & editing, Writing – original draft, Validation, Methodology, Formal analysis, Data curation, Conceptualization. **Sangita Dutta Gupta:** Writing – review & editing, Visualization, Validation, Supervision, Project administration, Conceptualization. **Justin Paul:** Writing – review & editing, Visualization, Validation, Supervision, Project administration, Conceptualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Dr. Madhumita Guha Majumder is an accomplished professional who has acquired more than 25 years of teaching & training experience at national and international arenas. Currently, she is working as a Professor & Head at Welingkar Institute of Management Development and Research, Bangalore, India. Her core competencies lie in the areas of *Statistical Model Building, Data Visualization, Descriptive Analytics, Machine Learning, Predictive Modeling, Optimization Analytics, Pattern Identification, Marketing Analytics, Financial Modeling & Risk Analytics. Supply Chain Analytics, HR Analytics and Text Mining (Natural Language Processing)*. She conceptualizes analytics in effective business transformation using various analytical tools. She has trained more than 1000 corporates to enhance their career opportunities which also facilitates the brand building of the parent organization. She constantly trains the trainers to build a strong platform of faculty in the area of Analytics and research. Her current research is based on diversified areas including knowledge management, financial management, employee engagement & consumer analytics. She has bagged many publications in referred journals where the applications of analytics in business decision making as well as policy related research have been examined. She serves as an Editorial Board member in a few journals including International Journal of Banking, Risk and Insurance, Amity Journal of Economics and in Journal of Learning in Business Management, Economics & Finance. She offers outstanding organizational & cross functional leadership with a strong track record of creating business models for the organization.

Dr. Sangita Dutta Gupta is an educator and researcher with more than 20 years of teaching experience at the undergraduate and postgraduate levels. She is currently associated with BML Munjal University as Associate Professor of Economics. She has published research papers in well-known peer-reviewed journals like Technological Forecasting and Social Change, Management Decision, Benchmarking: An International Journal, South Asia Economic Journal, Gender in Management, International Journal of Emerging Markets, etc. She has presented her research papers in well-known national and international conferences including GWO Conference in Sydney, CIS Conference in Boston, and India Finance Conference at IIM C. Dr. Dutta Gupta is on the editorial review board of the International Journal of Emerging Markets, She is a reviewer of top journals

Dr. Justin Paul Dr Justin Paul, serves as Editor-in-chief of A ranked International Journal of Consumer studies (IF 3.9), and as an Associate Editor of Journal of Business Research. A former faculty member with the University of Washington, he serves as Full Professor of PhD & MBA programs, University of Puerto Rico, USA (AACSB). He holds three honorary titles as 'Distinguished Professor' with three reputed universities including- Indian Institute of Management (IIM-K), and SIBM, Pune. He is known as an author/co-author of books such as Business Environment (4th ed), International Marketing, Services Marketing, Export-Import Management (2nd edition), Management of Banking & Financial Services by McGraw-Hill, Oxford University Press & Pearson respectively. He is also an Associate Editor with European Management Journal, & Journal of Strategic Marketing. Dr. Paul introduced the Masstige model and measure for brand management, CPP Model for internationalization, SCOPE framework for Small firms and 7-P Framework for International Marketing. His articles have been downloaded over 800,000 times during the last six years. He is ranked among the world's top 1% highly cited researchers based on Web of Science statistics with citations increasing at 375 per month in 2021. An author of over 130 research papers in SSCI journals, Justin has over 70 papers are in A or A star journals. He has also served as an associate professor at Nagoya University, Japan and as Department

Chair at IIM. In addition, he has taught full courses at Aarhus University- Denmark, Grenoble Eco le de Management-& University of Versailles -France, University-Lithuania, Warsaw -Poland and has been a visiting professor at University of Chicago, Vienna University- Austria, Fudan & UIBE-China, UAB- Barcelona and Madrid and has published three best selling case studies with Ivey & Harvard. He has visited over 60 countries as a visiting professor / speaker.