What are the significant determinants of helpfulness of online review?
An exploration across product-types

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Abstract

This paper proposes a novel empirical framework based on *Source Credibility Theory* and *Cognitive Theory of Multimedia Learning* to identify the effect of features (such as review text, review title and reviewer attributes) on the perceived helpfulness of an online review in the presence of product type (*tangible vs. intangible*) as a moderator. In addition, we employed *quantile regression* as a robustness check. We investigated two sets of hypotheses – first, the direct relationships within each variable and the helpfulness, and second, the moderating effect of product type (*tangible vs. intangible*) on each relationship. The results show that a more readable review can help the user process information faster. The arousal, star ratings received, and multimedia content positively affect review helpfulness. The practical implications of the paper are as follows. First, it highlights the importance of using multimedia content, such as videos and images that reviewers submit, in addition to regular textual reviews. Second, we propose a customised sorting mechanism based on product type to highlight the significant reviews for a specific product. The theoretical implications of the paper are as follows. The textual and multimedia information represents the fundamental essence of a review. This is part of the essential processing outlined by the *Cognitive Theory of Multimedia Learning* because the essential processing helps comprehend the message more easily. However, review length had an inverse U-shaped (concave) relationship because a long review increases extraneous processing.

***Keywords*:** Online review helpfulness, Tangible-Intangible products, Cognitive Theory of Multimedia Learning (CTML), Source Credibility Theory (SCT).

1. Introduction and Motivation

Web 2.0 has enabled the availability of a plethora of information about online product reviews on e-commerce platforms, followed by the mutual exchange of relevant product-related information. It may comprise sellers' descriptions, online reviews posted by consumers who had purchased and used the products, and comments from both parties (Mudambi and Schuff, 2010; Ghose and Ipeirotis, 2010; Ismagilova et al., 2020a). Surveys confirm that almost 93 per cent of consumers decided to purchase a product via online platforms after reading online reviews[1]. The available reviews increase trustworthiness among other potential consumers within the online community (Ismagilova et al., 2020a; Siering et al., 2018). Moreover, like other forms of electronic word-of-mouth, users may find Online Customer Reviews (OCR) helpful for decision-making, often leading to successful sales (Floyd et al., 2014; Ismagilova et al., 2020b; Li et al., 2020; Park et al., 2023).

Ismagilova et al. (2020a; 2020b) noted that many customers develop trust in reviews based on the number of helpful votes they receive. Thus, it is imperative to determine the factors contributing to review helpfulness. In this context, Fernando and Aw (2023) pointed out that consumers evaluate several product alternatives before purchasing, and the judgment reflects their opinion regarding the alternatives. When there is a plethora of available information, many of which are contradictory to each other, then there is information overloading, and it is not easy to pick one from the list. Therefore, the effect of the reviewer's credibility may influence the consumer's decision, and it may vary across different products. To address this gap, we re-examine the antecedents of online review helpfulness in the presence of reviewer credentials using the Source Credibility Theory (SCT). For instance, a reviewer's credibility may be enhanced when a user finds many reviews posted by him/her, but this may

[1] Qualtrics: Online reviews statistics to know in 2021

not extend to all product types. The user's involvement in decision-making varies across products, and thus, the SCT needs to be re-examined for different product categories.

Literature suggests several scholars have referred to popular theories such as the ELM and HSM in this context. Although these theories are widely acknowledged in the related literature, there are two major shortcomings. First, they do not speak on the trustworthiness of the reviewer, i.e., how a person decides that a review from a particular reviewer is useful and trustworthy and second, these theories directly do not state the role of media (e.g., the presence of photo, multimedia) in determining whether a central cue or a peripheral cue will be used in decision-making. To address these gaps, we re-examined the antecedents of online review helpfulness in the presence of multimedia files using the Cognitive Theory of Multimedia Learning (CTML). We compared the effects of pure textual reviews vs multimedia reviews.

Further, we observed that most reviews had no helpful vote associated with them. Almost all the existing scholars have addressed this issue by ignoring such reviews. However, this process does not explain why these reviews did not get any helpfulness votes. Thus, it is a case of an inflated number of reviews. We addressed this case in the methodology using negative binomial regression.

Besides, scholars have found that the customers' perception of these OCRs and their helpfulness towards purchasing decisions may vary significantly across different categories of products (Li et al., 2020; Ren and Nickerson, 2019). However, to date, none of the scholars have used the tangible-intangible dimension in this context and investigated the effect of this dimension on OCR helpfulness. In the context of online purchasing, scholars such as Vijaysarathy (2002) noted that shopping intention across electronic media is affected by product tangibility. There is also a salient belief that intangible products can be examined more easily than tangible ones. Peterson et al. (1997) argued that intangible products are more suitable for examination in electronic media than tangible products. In tangibility, we realise that an intangible product can be assessed better by reading its description, whereas this might not be true for a tangible product. However, if the source of the review is credible, then the description generates trust about the product. Moreover, with our current internet technologies permitting more use of multimedia files, it may be possible to provide a more detailed description of tangible products. Thus, the determinants of helpfulness of OCRs may vary across product categories defined by the dimensions of tangible-intangible.

From the discussions above, we conclude that product helpfulness will depend on the reviewer's credibility, the review's characteristics, and the product type defined in the tangible-intangible dimensions. Therefore, in this study, we explore the broad research objectives:

1. Identify and examine the effects of the significant (review-based) and (reviewer-based credibility) determinants of online review helpfulness based on SCT and CTML, respectively.
2. Explore the differential effect of product type (i.e., tangibility-intangibility) on the relationships between the significant determinants (review-based/reviewer-based) of online review helpfulness.

The remaining structure of the paper is as follows. In Section 2, we review the extant literature on various attributes of perceived helpfulness and develop the theoretical foundations of this study. In Section 3, we develop the hypotheses for our proposed model. Section 4 describes the data for our study. In Section 4, we present the methodology and empirical model used in the research. In Section 5, we present the results and discuss the findings. Section 7 presents our study's major implications. Finally, Section 8 concludes the study with limitations and directions for future research.

2. Literature review and theoretical frameworks

We highlight our literature review regarding the determinant of online helpfulness, the product types considered in the models and the theories used by the scholars. Our review of extant literature, presented in Table A1 of the Appendix, suggests that most scholars focused on two theories, namely the Elaborative Likelihood Model (ELM) or the Dual Process Theory and Heuristic Systematic Model (HSM). In the section above, we have briefly discussed the shortcomings of these theories and built our model using the SCT and CTML.

Online reviews help customers make better decisions while purchasing products. Mudambi and Schuff (2010) defined the helpfulness of a review as the perceived value of a given entry to inform purchase decisions. However, since every product receives a wide range of reviews, it is difficult for customers to judge the helpful ones. Our review of extant literature (see Table A1 in the Appendix) suggests that most scholars focused on two theories, namely the Elaborative Likelihood Model (ELM) and Heuristic Systematic Model (HSM), to develop their frameworks. The ELM throws light into how people process stimuli and posits that two paths are used to process information, i.e., central and peripheral (Kitchen et al., 2014). Central cues are used when extensive information processing is needed, and peripheral cues are used when less processing is required. On the other hand, the HSM Theory talks of systematic processing and heuristic processing, where the former is used to scrutinise the merits of the message, and the latter uses a subset of information in the message to accept or reject it. Although these theories are widely acknowledged in the related literature, there are two major shortcomings. First, they do not directly address how multimedia can influence the helpfulness of online reviews. For instance, ELM and HSM do not directly state the role of media (e.g., photo, multimedia) in determining whether a central or peripheral cue will be used in decision-making. Secondly, neither ELM nor HSM explain how the reviewer's trustworthiness might affect the online helpfulness of OCRs. Subsequently, to address these gaps, we proposed an empirical framework, primarily based on the Source Credibility Theory (SCT) and the Cognitive Theory of Multimedia Learning (CTML), to segregate the determinants into review-title, review text and reviewer characteristics. After that, we studied the impact of product type on the relationship between the count of helpful votes with each of them.

2.1 Trustworthiness of reviewer and Source Credibility Theory

Figure 1 depicts a typical review and some of its features. The figure shows two reviews containing some salient features such as the names of the reviewers; reviewer 1 has his picture, both reviews display the number of stars received, and the title of the review. Other features, such as the presence of multimedia content, review length, arousal of review, and valence, must be extracted from the review. Across e-commerce platforms, source credibility helps build trust between the buyer and the seller and, therefore, plays an important role in purchasing decisions. With Web 2.0 and online reviews being available within e-commerce platforms, users trust messages from highly credible sources because such messages are deemed more valid (Ismagilova et al., 2020b; Raoofpanah et al., 2023). Further, the proliferation of fake reviews on e-commerce platforms raises suspicion among users and leads to a loss of trust. Therefore, the credibility of online reviewers emerges as an important factor, particularly across intangible products such as gift cards and Kindle e-books sold on Amazon (see Figure 1). While some literature examines online reviews through the lenses of reviewer's credibility on travel and tourism-related platforms, such as TripAdvisor (Chan et al., 2017; Filieri et al., 2018a), airport travellers (Filieri et al., 2018b), there is scant literature that examines products sold on commonplace e-commerce platforms such as Amazon with the lenses of source credibility. Here, we found that tourism services and airline bookings were mostly intangible products (i.e., services) sold on specialised e-commerce platforms. At the same time, literature has not cross-examined tangible vs intangible products from the same platform, i.e., Amazon, a traditional e-commerce platform.

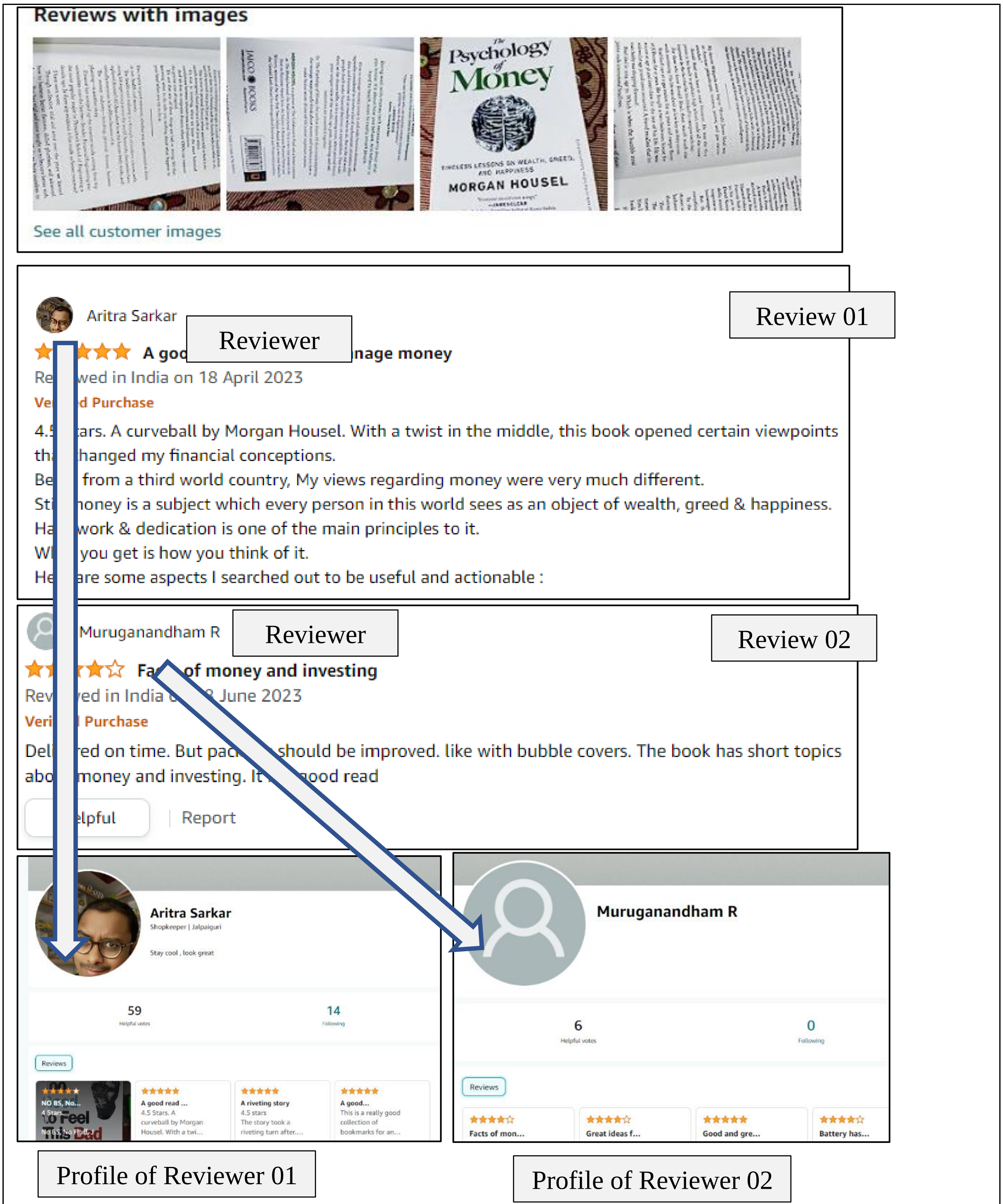

Figure 1 – Reviews for an intangible product such as a Kindle e-book and profiles of two comparable reviewers who posted reviews

The Source Credibility Theory was proposed by Hovland et al. (1953), which states that "people are more likely to be persuaded when the source presents itself as credible." Source credibility implies how the positive characteristics of a message communicator affect its acceptance among the receivers. While examining the cogency of a message, scholars have found strong support for source credibility (Hovland and Weiss, 1951; Wilson and Sherrell, 1993). Across e-commerce platforms, source credibility helps build trust among the buyer and the seller and, therefore, plays an important role in purchasing decisions. With the advent of Web 2.0 and online reviews being available within e-commerce platforms, users trust messages from highly credible sources because such messages are deemed more valid (Banerjee et al., 2017; Ismagilova et al., 2020b; Raoofpanah et al., 2023). Furthermore, the trust-building mechanism between the two transacting parties in face-to-face communication may develop over time. In contrast, in an electronic platform, users must depend on the reviewer's profile and related characteristics, which will be pillars of source credibility (Xu, 2014). In this manner, the perceived credibility of reviewers can positively impact the reliability of reviews on an online platform (Luo et al., 2015; Li et al., 2020; Park et al., 2023) and lead to successful sales (Floyd et al., 2014; Ismagilova et al., 2020b; Li et al., 2020; Park et al., 2023).

Next, we look at the extant literature using the lenses of Source Credibility Theory on e-commerce, which has examined various antecedents of online reviews from the reviewers' perspective. Ayeh et al. (2013) examined the perceptions of online travellers on TripAdvisor using the Source Credibility Theory and how these perceptions affected their intentions toward reading online reviews for planning travel in the future. The author combined the Technology Acceptance Model (TAM) and the Source Credibility Theory to identify the variations in perceived usefulness and attitudes unaccounted for by TAM. Filieri et al. (2018a) examined the effects of identifiable reviewer information (such as real name and location). They found that they could improve the perceived trustworthiness of online hotel reviews. However, too much personal information could adversely affect the booking intentions. Banerjee et al. (2017) examined review data from Yelp to identify the factors contributing to the trustworthiness of reviewers, such as the number of followers, average review rating per user, and the number of reviews written. Fernandes et al. (2022) built a measurement scale to identify the influence of online reviews on consumer purchase decisions, resulting in four dimensions, including source credibility.

2.2 Cognitive Theory of Multimedia Learning, multimedia reviews and their effect on review helpfulness

The second gap we explore in this study stems from applying the Cognitive Theory of Multimedia Learning (CTML) in examining online reviews. CTML theorises that “multiple-channel communications appear superior to single-channel communications when relevant cues are summated across channels” (Severin, 1967). To elaborate further, a successful understanding of the review content happens in the reader's mind when more signals are available (Moore et al., 2004; Severin, 1967). Therefore, an online review with additional images or videos can be more helpful (see Figure 1). Further, a more readable review or one with more relevant keywords related to the product can help the reader process information faster. It can be a part of essential processing in line with CTML theory.

In addition, the arousal generated from reading the review content and star ratings received also positively affect review helpfulness. Sometimes, the presentation format of the reviews may also play a part in the review processing (Vali et al., 2021). Apart from applying CTML in this study, we find that although ELM and HSM theories are widely acknowledged in the related literature (see Table A1 in Appendix), they do not directly address how multimedia can influence the helpfulness of online reviews. ELM and HSM do not directly state the role of media (e.g., presence of photo, multimedia) in determining whether a central cue or a peripheral cue will be used in decision-making. To address this gap, we re-examined the antecedents of online review helpfulness in the presence of multimedia files using the Cognitive Theory of Multimedia Learning (CTML). We compared the effects of pure textual reviews vs multimedia reviews.

The Cognitive Theory of Multimedia Learning (CTML) was first proposed by Mayer (2005), and it helps to explain why multimedia messages are more likely to be accepted than ordinary ones. According to Mayer (2005), "CTML states that there are five cognitive processes in multimedia learning. First, the selection of relevant words from the presented text or review in the context of this study. The second is selecting relevant images from the graphics (e.g., multimedia reviews submitted by the reviewer). Third, organising the words to form a coherent verbal representation. Fourth, the selected images are organised into a coherent pictorial representation. Fifth and finally, integrating the pictorial and verbal representations and with prior knowledge." Thus, our study applies the CTML theory to examine the OCRs, which have both textual and multimedia content, and examine their effect on the review's helpfulness.

Next, we look at the limited extant literature using the lenses of CTML within e-commerce, which has examined various antecedents of online reviews. For instance, Wang and Tong (2022) have studied online product reviews and have shown from their results that along with characteristics of the review text, the perceived product quality and product-unrelated information from review images would also influence product sales. In another study, Vali et al. (2021) propose and evaluate the effect of mixed comparative reviews on review value. The authors compare the results with separate comparative and regular reviews. The results from the study indicate that mixed comparative reviews in text format and images are perceived as less valuable than separate comparative reviews in text format. However, mixed comparative reviews in tabular format are more valuable than text format reviews. They are perceived as more valuable than regular reviews of one product in either format.

2.3: Differential effects of antecedents across different product types (tangible vs intangible)

Our review of extant literature (see Table A1 in Appendix) on OCRs suggests that scholars have mostly focused on the search-experience dimension of product classification (Mudambi and Schuff, 2010; Lee and Shin, 2014; Krishnamoorthy, 2015; Weathers et al., 2015; Lee and Choeh, 2016; Sun et al., 2019; Mousavizadeh et al., 2022; Li et al., 2020). While classifying products helps determine how consumers search and evaluate products, it can help uncover the decision-making process and related factors (Li et al., 2020). The tangibility of the product is an attribute that is difficult to evaluate in electronic media (Kim, 2023) and might affect customer involvement in the decision-making process. The customer's involvement in the decision-making process can be conceptualised regarding product and purchase involvement (Kim and Sung, 2009). Based on the customer’s involvement in decision-making, the process can be classified into three categories: habitual or routinised, limited, and extended decision-making. In habitual decision-making, the customer has the least involvement, as the decision-making is a routinised affair. This is true for products that are purchased very frequently and are relatively inexpensive (Kim and Sung, 2009). In limited decision-making, the customer seeks information about the product before the purchase, as the product is slightly more expensive, the purchase frequency is less, and some risk is involved. In extended decision-making, the customer's involvement in gathering product information is the highest as more risk is associated with the product. The customer gathers information through reviews only when the product is either more expensive, riskier or something that she/he may not purchase very often. Thus, this would be a part of extended decision-making. In the context of electronic commerce, it is most difficult to evaluate tangible product attributes as there is no scope for the “touch and feel” of the product. A detailed review, along with the use of multimedia files, might help in this regard. Similarly, for an intangible product, an extensively detailed review of the product that gives the reader a higher psychological arousal by providing the details of a hotel room and its features can make the review more helpful. These gaps motivate us to classify products available on e-commerce platforms as tangible vs intangible and investigate their influence on online helpfulness.

3. Hypothesis development

3.1 Effects of review-title characteristics on the perceived helpfulness

Online reviews are typically composed and delivered in textual format. In this study, we focus on the emotional content of the title as it can generate arousal in the reader's mind and the ease with which one can read the title (Kaushik et al., 2018; Ismagilova et al., 2020a). The helpfulness perceived by customers can widely fluctuate with the length of the title, often measured by the number of words (Salehan and Kim, 2016). Therefore, it can significantly influence the perceived helpfulness of a review to the reader (Yin et al., 2014). Next, we look at readability, which is the ease with which one can comprehend a piece of textual information (Raoofpanah et al., 2023). For instance, a title stating, "very bad laptop performance with poor functionality," might have a weaker effect on helpfulness than one saying, "The laptop I purchased gets heated up very quickly," as it is more precise and easily comprehensible due to the presence of relevant keywords leading to higher readability and arousal. Further, according to the CTML Theory, the composure of any message adds to its credibility and is measured using more formal and structured content of the message. Therefore, selecting relevant words from the presented review and organising them to form a coherent verbal representation will help improve its helpfulness. Therefore, we hypothesise the following.

> H1a: The arousal and readability of the review title will positively influence the helpfulness of online reviews.

3.1.1. Influence of product type on the review-title characteristics

In the case of a tangible product, a complete assessment of its important features is unknown without personal encounters such as touch and feel (Fernandes et al., 2021; Kim, 2023). Consequently, merely reading an OCR title might not be as useful for tangible and intangible products. To comprehend the psychological arousal of the review title, we refer to the Uncertainty Reduction Theory, which argues that more uncertainty encourages individuals to seek additional information about the product (Berger and Calabrese, 1974). The intangibility of a product increases the uncertainty component involved in a purchase decision, thus making it riskier (Fernandes et al., 2021; Kim, 2023). Thus, in the second part of the hypothesis (H1b), we examine how the tangible-intangible nature of the product would affect the relationship between the title and the helpfulness of an OCR.

> H1b: The relationship between arousal and readability within the review title and the helpfulness will be influenced by the product category and higher for intangible products than tangible products.

3.2 Effect of review-text characteristics on the perceived helpfulness

Our review of extant literature has shown that the review content is an integral measure of the perceived helpfulness of an OCR (Ismagilova et al., 2020a; Kaushik et al., 2018; Kim, 2023; Mousavizadeh et al., 2022). Online product reviews comprise textual comments, star ratings, and multimedia files, which can signal the reviewers' positive or negative sentiments about the product and finally affect the purchase decision of the potential buyer who reads the review (Ismagilova et al., 2020a; Kaushik et al., 2018; Kim, 2023; Mousavizadeh et al., 2022). As per CTML theory, essential processing is required to process textual and multimedia information and mentally represent this fundamental essence of the review. This also influences a reader's psychological arousal, making them more aware of the product. Besides the number of stars a review receives, the ease with which a user comprehends the review also increases its credibility (Kim, 2023; Krishnamoorthy, 2015). Thus, we expect that reviews with higher arousal, higher ease of readability, and higher number of stars received will positively influence the helpfulness of the review.

Regarding review length, longer reviews can convey messages more accurately and, per CTML theory (Mayer, 2005), can be used for essential processing. However, if the review is too long, it may contain irrelevant information that needs to be filtered out by the reader. This might require processing extraneous information and could be detrimental to the overall helpfulness. Thus, we conceptualise that the helpfulness of the review will initially increase with word count. However, after reaching an optimal word count level, it will decrease, leading to an inverted U-shape.

> H2a: The arousal, star ratings received, review readability, and use of multimedia will positively influence online review helpfulness.
>
> H3a: The review length will have an inverted U-shaped (concave) relationship with online review helpfulness.

3.2.1 Influence of product-type on the review-text characteristics

Siering et al. (2018) examined online reviews for airlines (i.e., an intangible product) and reported that review sentiments were an important determinant for recommending an airline service. Park (2018) found that online reviews possessed varying linguistic characteristics for different product types. They also found that other features have varying impacts on their perceived helpfulness. We argue that the reader would require more psychological arousal from the review before procuring an intangible product, such as hotel booking, which requires more information sharing from the service users. Besides, the star ratings received by the review would increase the credibility, which is more about experience sharing about the service (Fernandes et al., 2021; Kim, 2023). Besides, when the readers read such experiences, they would like to emphasise the review readability and use of multimedia in the review as these features make the review experience more realistic. Again, the user will be more engaged in reading the OCRs due to insufficient representation of physical attributes of intangible products when expressed via online reviews (Fernandes et al., 2021; Kim, 2023). Thus, readers will find longer reviews more helpful for intangible products than tangible ones. Thus, in the second part of the hypothesis (i.e., H2b and H3b), we examine how the product type (i.e., tangible vs. intangible) will affect the main effects. Hence, we hypothesise:

H2b: The effect of arousal, star ratings received, review readability, and use of multimedia in an OCR on review helpfulness will be influenced by the product category and will be higher for intangible products than for tangible products.

H3b: The effect of review length on review helpfulness will be influenced by the product category and higher for intangible products than tangible products.

3.3 Effects of reviewer characteristics on the perceived helpfulness

In addition to the review-title and text-based features, the reviewer’s characteristics also significantly influence the perceived helpfulness of an OCR. According to the Source Credibility Theory, the credibility of the review source, i.e., the reviewer, implies how the positive characteristics of a message communicator affect its acceptance among the receivers. A reviewer’s expertise can be defined by their credentials and capability to write useful reviews (Ghose and Ipeirotis, 2010; Raoofpanah et al., 2023; Siering et al., 2023). While reading online reviews for a product, the reviewers who have generated more reviews and belong to the top reviewer status are deemed to possess expert knowledge about the product (Banerjee et al., 2017; Chan et al., 2017; Raoofpanah et al., 2023). In addition, the reviewer's credibility can be measured by the number of helpful votes they have received in the past, how long they have been reviewing and whether they have been actively reviewing online products (Chua and Banerjee, 2015). Besides, the presence of a photograph (Hu et al., 2022; Lee and Shin, 2014; Mousavizadeh et al., 2022; Xu, 2014) and personal information such as the full name and detailed location of the reviewer (Xie et al., 2011) generate more credibility as this inspires more trust among readers. Thus, we hypothesise the following.

H4a: The total number of helpful votes received, total reviews posted, personal information, top reviewer status, and the presence of a profile photo will positively influence online review helpfulness.

3.3.1 Influence of product-type on the reviewer’s characteristics

According to the Uncertainty Reduction Theory (Berger and Calabrese, 1974), the ambiguity involved while users browse ecommerce platforms will be higher for intangible products. However, this uncertainty can be reduced by learning about the product’s attributes from an experienced reviewer (e.g., a reviewer with higher helpful votes or a reviewer with more reviews). Therefore, consumers are increasingly required to assess the trustworthiness of reviewers and the quality of products without the option of physical verification of the product features as opposed to more traditional commercial interactions (Flanagin et al., 2014). Also, according to our discussion on the source credibility theory, the presence of the reviewer’s profile photo adds to the reviewer's credibility (Hu et al., 2022; Lee and Shin, 2014; Mousavizadeh et al., 2022; Xu, 2014). Since the risk associated with purchasing intangible products in the online channels is higher, additional credibility from the reviewer’s background details will increase the helpfulness of OCRs. Thus, in the second part of the hypothesis (H4b), we examine how the product type (tangible vs intangible) will affect the main effects. Thus, we hypothesise:

> H4b: The effect of total helpful votes, total reviews posted, and the presence of the profile photo of a reviewer will be influenced by the product category defined by the dimensions of tangible-intangible and shall be stronger for intangible products than tangible ones.

We present the summary of recent literature on the influence of product types on the perceived helpfulness of OCRs in Table A1 (see Appendix). We also present the theoretical support for our framework in Table A2. Additionally, we present the proposed framework to study the determinants of the count of helpful votes with the help of its determinants; see Figure 2 below.

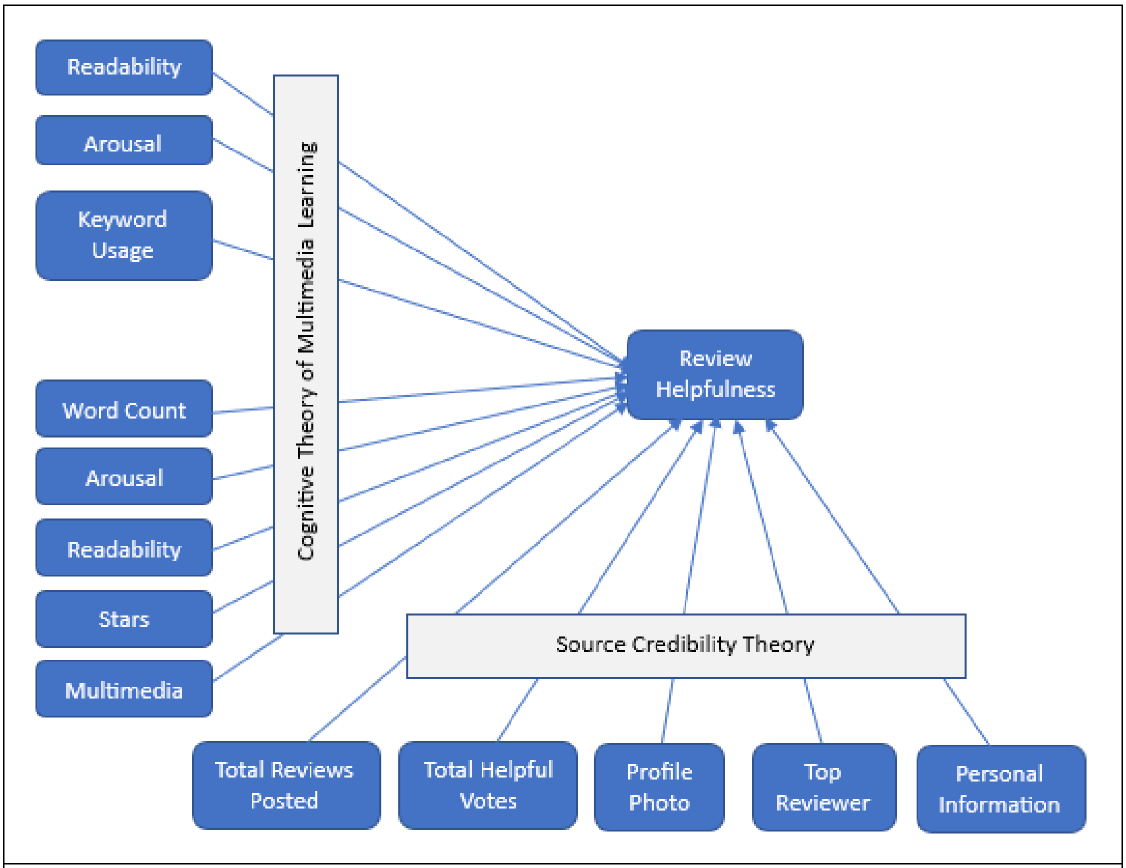

Figure 2- Our proposed framework

4. Data description

In this study, we analysed online customer reviews across various products collected from Amazon India (www.amazon.in): We classified products across the broad dimensions of *tangible* and *intangible* depending upon the presence of physically available and perceptible features for the user. For instance, groceries and books could be perceived physically and possessed distinguishable physical features and, therefore, deemed tangible products (Kim and Sung, 2009). In contrast, e-books and insurance plans did not possess physical attributes and were deemed intangible products. Therefore, our choice of products is as follows: (i) tangible: books (4,565), electronics-mouse (1,306), groceries (2,953); electronics - fitness band and printer cartridge (3,737), apparel (4,659), travel accessories (1,771); (ii) intangible: e-gift cards (2,468), insurance plans for mobiles (853), Kindle e-books (3,244); anti-virus software (2,718), operating systems software (952), video games (1,197). The number in parentheses represents the count of reviews extracted for each product.

Next, we retrieved recent reviews from Amazon India (30,423 reviews) up to June 2021. The scraped reviews included various data types, such as numeric, textual, and multimedia files. The number of helpful votes received is the dependent variable for our analysis. Next, based on the framework proposed in this study (see Figure 2), we retrieved the relevant features of each review using text mining (Fernando and Aw, 2023; Ghose and Ipeirotis, 2010; Park et al., 2023; Salehan and Kim, 2016; Yi and Oh, 2022). We classified those features into two groups: (i) review-title readability and arousal; (ii) review-content: word count, readability, arousal, and star ratings; and (iii) reviewer-attributes: the presence of profile-photo, total reviews posted by the reviewer, and total helpful votes received.

Next, we calculated the pairwise correlations and variance inflation factor (VIF) values for the predictors. We have presented the pairwise correlation from the tangible subgroup in Table A5 and the intangible subgroup in Table A6. We found that the pairwise correlations for the two variables were relatively higher than 0.5. Firstly, review word count and readability were -0.69 (tangible products) and -0.68 (intangible products). Secondly, the total helpful votes received and total reviews posted were 0.61 (tangible products) and 0.50 (intangible products). Similarly, the VIF values were closer to 2 for these abovementioned variables. However, the VIF values were much lower than the prescribed limit of 3.

5. Empirical models

5.1 Negative binomial regression

The response variable (i.e., helpful votes received) is count data, so our usual choice for predictive modelling is Poisson regression (Salehan and Kim, 2016). However, there is a drawback to this method of modelling. Poisson assumes equality of mean and variance, an assumption which is violated in most real-life data. Especially here, we talk about the inflated frequency for zero counts. This type of inflation traditionally leads to over-dispersion (Lambert, 1992; Yi and Oh, 2022), and for modelling over-dispersed count data, a more suitable option is using the Negative Binomial regression.

Let y_i be the count of upvotes given by users for the i^{th} review, and y_i follows a Negative Binomial distribution with mean μ. The response (count of helpful votes) y_i ~ Negative Binomial (r, p), where r is the number of successes (or helpful votes) and p is the probability of success. Moreover, r * p = μ is the mean rate of count of upvotes given by users.

Thus, the linear component in the regression model helps in parametrising the mean rate of the count of upvotes given by users μ and is expressed in the following functional form:

$$y_i = \log \mu = \beta_0 + \beta_1 x_1 + \cdot \cdot \cdot + \beta_k x_k \tag{1}$$

The Negative Binomial regression model is used for fitting the expected number of counts of upvotes given by users, as follows:

$$\begin{aligned} \log\mu = \beta_0 + \beta_1(\text{Title readability}) + \beta_2(\text{Title Arousal}) + \beta_3(\text{Review word count}) + \\ \beta_4\ (\text{Review word count})^2 + \beta_5(\text{Review readability}) + \beta_6(\text{Review arousal}) + \\ \beta_7(\text{Multimedia review}) + \beta_8(\text{Stars}) + \beta_9(\text{Profile photo}) + \beta_{10}(\text{Total helpful votes received}) + \\ \beta_{11}(\text{Total reviews posted}) \end{aligned} \tag{2}$$

where the link function g(μ) = log(μ) is the (natural) logarithm. In Equation (2), β_0 is the intercept, and the regression coefficients $\beta_1, \beta_2, \beta_3, . . ., \beta_k$ are unknown parameters which are to be estimated from the available data on reviews of products from an e-commerce platform. The final estimates of these coefficients are labelled as $b_1, b_2, b_3, . . ., b_k$.

5.2 Robustness checks using quantile regression

In addition to the above count-data model, extensions of Negative Binomial regression are sometimes applied to over-dispersed count-data to check the robustness of the Negative Binomial (NB) model. In the NB model, we regressed the mean rate of helpfulness votes received by online reviews. However, fitting a quantile regression helps model the quantiles from the count distribution. A comparison of the coefficients across the quantiles with the

Negative Binomial regression ascertains the robustness of the coefficient estimates and their significance across the range of quantiles for the entire distribution. Further, the conditional mean-based regression models are more sensitive to outliers in the response variable. Therefore, we considered a quantile regression approach to model this over-dispersed count data. Extant studies have extensively applied zero-inflated quantile regression techniques to model counts of motor insurance claims (Fuzi et al., 2016), motor vehicle accidents (Washington et al., 2014), freight-train derailments (Liu et al., 2013), and adjust for similar overdispersion problems with inflated count-data (Ling, 2019). Such a model focuses on fitting the conditional mean of the response data using the explanatory variables in each specified quantile separately.

6. Results and discussion

6.1 Main results

This section discusses the results generated from the Negative Binomial regression analysis (Table A7). First, looking at the review title characteristics, we focus on the readability (measured here by the Flesch index) of the review title. The Flesch index taking low values (in the range of 0-40) indicates that the text is difficult to comprehend, whereas it is much easier for the high Flesch index (in the range of 70-100). From our results, we can see that in the case of tangible products, there is a negative impact of readability ($\beta = -0.0011$), and it is statistically insignificant (Table A7). The negative relation indicates that the increasing simplicity of the title decreases the helpfulness. This is expected because when a user reads the review title and finds a more general overview, finds it less helpful. However, more comprehensive, complex text in the review title may give users greater insight into the product. In the intangible products, the relation is negative ($\beta = -0.0029$) and statistically insignificant (Table A7). The insignificance could be because the conjectural nature of the products creates an uncertainty in the users' minds that cannot be alleviated with only the review title. Users probably expect to learn more about the product from the review text.

Next, we see that the effect of arousal (-4: calm, 4: excited) on review helpfulness is negative for tangible and intangible products. However, they are significant for tangible products and insignificant for intangible types. This implies that the more aroused the review text, the lower the review helpfulness. This can be explained by the fact that words high on arousal are often linked with more subjective opinions and might seem more like an outlier than the regular review (Ren and Nickerson, 2018).

Second, looking at the characteristics of the review text, we find that review length (tangible: $\beta = 0.0149$, intangible: $\beta = 0.0267$) has a statistically significant positive effect across both product types (Table A7). Therefore, a user perceives a longer OCR to be more helpful. This is especially true for intangible products (with a higher coefficient value) where the product cannot be physically perceived, so users may depend on an elaborate review from someone who has already used the product. Next, for the review readability score (calculated by the Flesch readability index) (tangible: $\beta = -0.00053$, intangible: $\beta = 0.0028$) (Table A7), users find its impact on the perceived helpfulness of the OCR not statistically significant and positive for intangible and negative for tangible products. With increasing ease with which a user can understand the review, we can conclude that the OCR is more helpful for intangible products, but for tangible products, the effect is the opposite. This can be attributed to the fact that the intangible nature of the product adds to the difficulty in perceiving its attributes, so more comprehensible review content helps the user. Next, we look at the effect of emotional arousal in the review text on the helpfulness of OCRs (tangible: $\beta = 0.0994$, intangible: $\beta = -0.3495$) (Table A7); we find from the results that for tangible products higher the expressed emotion higher will be the impact on helpfulness but for intangible products, there is a negative impact of arousal on review helpfulness. However, it is statistically significant for intangible products only.

We investigate the effects of star rating (tangible: β = -0.0541, intangible: β = -0.0515) (Table A7) on the perceived helpfulness of an OCR. Generally, if the review has received higher star ratings for any product type, a user might not perceive it helpful for further purchase decisions. It is also true that Star rating is not the only parameter on which a user's purchase decision depends. However, it can be considered one of the explicit cues that act as a surrogate for product quality.

Next, we investigate the effect of the presence of the profile photo of the reviewer on the perceived helpfulness of the review. For tangible and intangible products, the presence of a profile photo is negative for tangible products and positive for intangible (tangible: β = -0.0541, intangible: β = 0.2491) (Table A7). This can be attributed to the fact that the presence of a profile photo gives the reviewer a sense of reliability. Especially for intangible products with no visible physical qualities, relying on the OCR written by a more reliable reviewer is more logical.

Next, in the case of total helpful votes received, many users prefer to write reviews for tangible products (β = 0.4752), which is easier, given its tangible nature. In contrast, it is lower for intangible products (β = 0.00091) (Table A7). Thus, existing reviews on tangible products can attract more helpful votes than intangible products. The coefficients for both tangible and intangible products are statistically significant. The effect of total reviews posted by a reviewer (tangible: = -0.0015, intangible: β = -0.0011) is statistically significant for tangible products only but is inversely related to the perceived helpfulness for both product types. Therefore, merely writing a huge volume of reviews may not benefit users.

Finally, as hypothesised in the present study, the review word count follows a concave relationship with review helpfulness. From Table A7, we can see a significant and positive impact of review word count on review helpfulness, whereas in the case of ReviewWordcount^2, extremely lengthy reviews exhibited a quadratic effect on review helpfulness for both tangible and intangible product types(tangible: β = -0.00002, intangible: β = -0.00004) (Table A7), supporting a significant concave relationship between review word count and review helpfulness. Therefore, consumers draw reduced utility from OCRs after a certain word length.

6.1.1 Robustness results from quantile regression

Results from quantile regression gave us deeper insights into the effects of the explanatory variables for each quantile (Tables A9 and A10) and across the entire spectrum of helpful votes. We found that the positive impact of total helpful votes received by the reviewer was significant for almost all levels of helpful reviews ($p<0.001$ for Q1, Q2, Q4; Q5, Q6; Q8; Q9), especially across tangible products. In the case of intangible products, relatively stronger effects were observed for higher levels of the count of helpful votes ($p<0.001$ for Q3, Q5; Q6, Q7, and Q9). The reviewer's characteristics, such as the number of reviews posted by the reviewer, seemed to negatively impact helpfulness for tangible products and were consistently insignificant. This is consistent with the Negative Binomial regression (Table A7) baseline results, where the relationship is negative but insignificant. However, in the case of intangible products, it is consistently positive. In addition, the relation is statistically significant at the second, third, and eighth quantiles (Q2; Q3; Q8). The positive association is not in tandem with the baseline results from the Negative Binomial regression. This finding indicates the relatively stronger effect of the reviewer's characteristics upon helpfulness due to the intangibility of the products.

Third, the most significant reviewer characteristic that influences the helpfulness of OCR is the profile photo of the reviewer. The presence of the reviewer's profile photo has a significant positive effect on the helpfulness of OCR consistently for all the quartiles.

Among the review text characteristics, word count has a statistically significant and positive effect on helpfulness across the higher quartiles (Q7, Q8, Q9). Therefore, longer reviews have a stronger positive impact on helpfulness. This is congruent with our baseline results from the

Negative Binomial regression. Again, multimedia reviews have a positive and mostly significant effect on helpfulness votes. In the case of tangible products, all quantiles of helpfulness votes have a statistically significant and positive effect. We also found an interesting phenomenon that the size of the effect (in terms of the regression coefficients) increased with higher quantiles. A similar pattern is also found in the case of intangible products. However, the statistical significance is inconsistent for the higher quantiles, and statistical significance was noted mostly for the lower quantiles.

Next, the impact of arousal of the review title is also congruous to the baseline results from the Negative Binomial regression. It negatively impacts the helpfulness and is statistically significant for the higher quartiles (Q6; Q7; Q8). Finally, the square of review word count demonstrates a concave relationship with helpfulness and is statistically insignificant across most quantiles.

7. Implications of the study

7.1 Theoretical implications

Our study has two primary theoretical contributions to the relevant literature examining the helpfulness of online reviews. First, it uses the theoretical lenses of CTML theory to identify the determinants of helpfulness, such as readability and arousal generated by the review title, which positively affected the helpfulness of the review. Keeping in line with CTML theory, a more readable review can help the reader process information faster and be a part of essential processing. Next, according to the CTML theory, essential processing helps to understand a review faster. Therefore, a product’s textual and multimedia information represents a review’s core parts and constitutes the essential processing of a review. Next, the review length was hypothesised to have an inverse U-shaped (concave) non-linear relationship with the helpfulness. This seemed logical because more information in a review can be helpful. However, an unnecessarily long and tedious review might dissuade the reader as it increases extraneous processing, according to the CTML Theory. To the best of our knowledge, CTML Theory has not been previously used in the context of OCRs on e-commerce platforms for examining tangible and intangible products.

Second, this study uses the theoretical lenses of Source Credibility Theory to support the effect of predictors such as the total number of helpful votes received by a reviewer, total reviews posted by a reviewer, and the presence of a profile photo on helpfulness. Using the Source Credibility Theory, we argued that these predictors would increase the reviewer's credibility and generate more helpfulness among users. For instance, a reviewer's credibility may be enhanced when a user finds many reviews posted by him/her, but this may not extend to all product types. Especially for intangible products with no visible physical qualities, relying on the reviews written by a more reliable reviewer is more sensible. Therefore, the user's involvement in decision-making varies across products, and thus, we re-examined the effects using the lens of SCT for different product categories.

7.2 Managerial implications

Our study is also useful to practitioners due to the following reasons. First, our study highlights the importance of using multimedia content such as videos and images that reviewers submit and regular textual reviews. In the past, scholars such as Fulk et al. (1987) and Short et al. (1976) argued that media could be differentiated based on communication richness, the level of interactivity that it provides, and social presence. We argued that the company of multimedia strongly drives the perceived helpfulness of the associated reviews for all product categories. In this context, the impact of product type, defined in the dimension of tangible-intangible, on the influence of total reviews posted by the reviewer and the presence of profile photos on review helpfulness. Such findings will benefit the sellers of corresponding categories of products on e-commerce platforms.

Second, based on our findings, we can propose an ordering of online reviews as displayed on e-commerce platforms (such as Amazon). Currently, Amazon allows sorting reviews based on their newness or importance, i.e., top and most recent reviews. Currently, the sorting is the same for all types of products on the platform. However, a customised sorting mechanism based on product type might help highlight the most significant reviews for the specific product. Also, categorising reviews as top reviews is debatable as it is not disclosed to the user. More transparency can be brought into the process by specifying more filters that help sort reviews.

7.3 Policy implications

Our study offers two insights to policymakers. First, we argued and empirically found the review helpfulness to be positively affected by the helpful votes received by a reviewer, total reviews posted by a reviewer, and the presence of a profile photo of the user, as this feature increases the reviewer's credibility. In the current era, many reviews are termed paid reviews, where the company pays the reviewers to write positive words about the product. Such reviewers have low credibility, and the relevant authorities can assign scores to the reviewer's credibility by using these reviewer attributes. This would help the customers in making more informed decisions. Second, we found review readability and the use of multimedia to influence online review helpfulness positively. This effect was more for intangible products. Taking a cue from this finding, we believe that the relevant authorities can assign readability scores to reviews and allow only those reviews to be posted that have crossed a minimum threshold, more so for intangible products such as a service where the description of the “intangibility” is very important as it gives the potential customer an idea about the service. Besides, for intangible products such as hotel bookings, multimedia can be made mandatory as it gives a detailed picture of the service.

8. Conclusion

Some of the interesting findings from this study and future directions from the study can be summarised as follows. Firstly, we inferred that the antecedent factors for generating online review helpfulness vary across product categories defined as tangible vs intangible. This categorisation has never been used before in the context of OCRs. This is useful in two ways. First, all products can be classified using our proposed dimensions. Second, relevant literature has shown that online platforms are more suitable for selling intangible products and services. In addition, we showed that the review and reviewer features that generate helpfulness varied significantly according to this categorisation.

Despite some insightful contributions, our study has a few limitations. First, there are many diverse aspects of perceived helpfulness. While we examined ten features in this study, future research could extend them according to distinct product types. Second, we identified a limited set of determinants of online review helpfulness using the Cognitive Theory of Multimedia Learning and Source Credibility Theory. Future studies could extract alternative determinants of review helpfulness by exploring other theories from psychology and marketing. Third, sequential bias within the helpfulness voting mechanism can contaminate empirical results. Therefore, future studies could incorporate novel empirical frameworks by aggregating many helpfulness votes for a few reviews. Lastly, our literature review on OCRs shows that most scholars have used the search-experience dimension to categorise products. We used a novel dimension of tangible-intangible in this work. However, we believe there may be other dimensions to categorise products than the one we used. Future scholars can review such dimensions and test how they might affect the helpfulness of online reviews.

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Supplementary to: What are the significant determinants of the helpfulness of online reviews? An exploration across product-types

Table A1: Summary of relevant literature on the influence of product type on OCRs

Sl. No.	Academic Source(s)	Major Determinants	Context: Product attributes/types	Focus: Dependent variable(s)	Theory(ies) Used	Methodology / Data	Main Findings
1	Mudambi and Schuff (2010) MISQ	Depth and extremity of OCRs	Search - Experience	Review helpfulness	Social Comparison Theory, Information Economics Theory	Tobit regression with the percentage of helpfulness, data from Amazon.com	Product type is important to understand what makes a review helpful
2	Lee and Shin (2014) CHB	Quality of OCRs, profile photo of the reviewer	Search - Experience	Purchase intention, Reviewer evaluation	Elaboration Likelihood Model	Web-based experiment	The quality of online reviews strongly affects purchase intention
3	Weathers et al. (2015) DSS	Uncertainty and equivocality of OCRs, trust and expertise of reviewers	Search - Experience	Review helpfulness	-	Multi-dimensional scaling, Logistic regression with data from Amazon.com	Helpfulness is affected by credibility and product type
4	Lee and Choeh (2016) BIT	Identity and reputation of reviewers, depth, and extremity of OCRs	Search - Experience	Review helpfulness	Social Learning Theory	Linear Regression with data from Amazon.com	The reputation and identity of a reviewer positively affect the helpfulness while the product type moderates them
5	Kaushik et al. (2018) JRCS	Ratings, valence, information richness, source credibility and review sequence	-	Sale of products	Message Persuasion Theory, Source Credibility Theory	Linear Regression with data from Amazon.com	Helpful reviews and their sequences impact product sales
6	Li et al. (2020) JRCS	Meta-analysis with review and reviewer-related factors	Effect of product-type	Sale of products	-	Meta-analysis of 28 studies in the marketing domain	Product category moderates the effect of determinants on sales

7	Ismagilova et al. (2020b) JRCS	Meta analysis with expertise, trustworthiness and homophily	-	Perceived usefulness	Source Credibility Theory	Meta-analysis of 20 studies in the marketing domain	Expertise and trustworthiness influence the usefulness and credibility
8	Mousavizadeh et al. (2020) ISF	Popularity, extremity, sentiments, and readability of OCRs	Search - Experience	Review helpfulness, Review popularity	Elaboration Likelihood Model	9257 reviews of 17 different products were collected from Amazon.com	The product-type moderates the effect of utilitarian and hedonic cues on helpfulness
9	Kim (2023) JRCS	Content and valence	Search - Experience	Sales Ratio, Search Rank	-	Customer reviews on artwork as experience goods	Impact of content and valence on the market performance of experience goods
10	***This Study***	***Readability, word count, arousal of OCRs, Star ratings of OCRs. Profile photo, total helpful votes, total reviews posted by reviewers***	***Tangible - Intangible***	***Review helpfulness***	***Cognitive Theory of Multimedia Learning, Source Credibility Theory***	***Negative binomial regression with review data from Amazon India***	***Product type (tangible-intangible) moderates the effect of the determinants on helpfulness***

Table A2: Theoretical support for our framework

Antecedent Group	Antecedent Variable	Nature of Relationship	Theoretical Support
Review Title Based	Title Arousal	Linear and positive	CTML
	Readability of title	Linear and positive	CTML
Review Based	Review Length	Inverted U shaped	CTML
	Review Arousal	Linear and positive	CTML
	Star Rating	Linear and positive	CTML
	Use of Multimedia files	Linear and positive	CTML
Reviewer Based Characteristics	Total helpfulness votes received by reviewer	Linear and positive	SCT
	Total reviews posted	Linear and positive	SCT
	Photo of reviewer	Linear and positive	SCT

CTML= Cognitive Theory of Multimedia Learning; SCT = Source Credibility Theory

Table A3: Descriptive Statistics of the variables (Tangibles)

Statistic	N	Mean	Std. Dev.	Min	Max
Title Readability	9926	74.41	44.24	0.00	100.00
Title Arousal	9926	-0.894	0.743	-4.00	4.00
Review word count	9926	8.53	18.45	0.00	534.00
Review Readability	9926	71.95	41.94	0.00	100.00
Review Arousal	9926	-0.93	0.69	-4.00	4.00
Multimedia Review*	9926	-	-	0.00	1.00
Stars	9926	4.15	1.22	1.00	5.00
Profile photo*	9926	-	-	0.00	1.00
Total helpful votes received	9926	33.39	232.43	1.00	10245.00
Total reviews posted	9926	25.09	63.65	1.00	2903.00
Helpfulness	9926	5.33	18.88	1.00	277.000

***** Binary variable, therefore no mean and std. deviation.

Table A4: Descriptive Statistics of the variables (Intangibles)

Statistic	N	Mean	Std. Dev.	Min	Max
Title Readability	6600	77.43	49.37	0.00	100.00
Title Arousal	6600	-0.81	0.69	-4.00	4.00
Review word count	6600	9.44	12.63	0.00	510.00
Review Readability	6600	64.53	38.05	0.00	100.00
Review Arousal	6600	-0.96	0.55	-4.00	4.00
Multimedia Review*	6600	-	-	0.00	1.00
Stars	6600	4.45	1.05	1.00	5.00
Profile photo*	6600	-	-	0.00	1.00
Total helpful votes received	6600	39.05	312.35	1.00	12523.00
Total reviews posted	6600	25.79	63.54	1.00	2920.000
Helpfulness	6600	7.69	32.66	1.00	472.000

***** Binary variable, therefore no mean and std. deviation.

Table A5: Pairwise correlation and VIF among the variables (Tangible)

	VIF	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]
Title Readability [1]	1.086	1								
Title Arousal [2]	1.054	-0.15	1							
Review word count [3]	2.009	-0.03	0.04	1						
Review Readability [4]	1.998	0.12	-0.07	-0.69	1					
Review Arousal [5]	1.022	-0.01	0.12	-0.04	0.04	1				
Stars [6]	1.110	0.08	-0.04	0.07	-0.08	-0.06	1			
Total helpful votes received [7]	1.695	-0.16	-0.01	0.25	-0.26	-0.05	0.14	1		
Total reviews posted [8]	1.711	-0.02	-0.07	0.26	-0.22	-0.08	0.21	0.61	1	
Helpfulness [9]	1.137	-0.13	-0.05	0.35	-0.27	-0.02	0.02	0.24	0.15	1

N=9926*;* $^{*}p<0.1$*;* $^{**}p<0.05$*;* $^{***}p<0.01$*;* VIF = Variance Inflation Factor

Multimedia Review and *Profile photo* are Binary variables; therefore, no pairwise correlations were calculated.

Table A6: Pairwise correlation and VIF among the variables (Intangible)

	VIF	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]
Title Readability [1]	1.124	1								
Title Arousal [2]	1.072	-0.14	1							
Review word count [3]	1.965	-0.14	0.02	1						
Review Readability [4]	2.075	0.28	-0.002	-0.68	1					
Review Arousal [5]	1.043	-0.05	0.14	-0.01	-0.07	1				
Stars [6]	1.092	-0.07	-0.13	0.11	-0.03	0.05	1			
Total helpful votes received [7]	1.378	-0.05	0.04	0.11	-0.03	0.05	0.12	1		
Total reviews posted [8]	1.365	-0.05	-0.01	0.13	-0.12	0.01	0.13	0.50	1	
Helpfulness [9]	1.040	-0.08	-0.01	0.10	-0.06	-0.06	0.03	0.11	0.03	1

N=6600*;* $^{*}p<0.1$*;* $^{**}p<0.05$*;* $^{***}p<0.01$*;* VIF = Variance Inflation Factor

Multimedia Review and *Profile photo* are Binary variables; therefore, no pairwise correlations were calculated.

Table A7: Coefficient estimates using Negative Binomial Regression

	Dependent variable: *Count of Helpful Votes*	
	Model 1 (Tangible)	**Model 2 (Intangible)**
Title Readability	-0.001	-0.003
	(0.001)	(0.002)
Title Arousal	-0.220***	-0.180
	(0.065)	(0.109)
Review word count	0.0149***	0.0267***
	(0.0024)	(0.005)
(Review Word count) ^2	-0.00002***	-0.00004***
	(0.000006)	(0.00001)
Review Readability	-0.0005	0.003
	(0.001)	(0.003)
Review Arousal	0.099	-0.349*
	(0.092)	(0.167)
Multimedia Review	0.717***	1.228***
	(0.118)	(0.242)
Stars	-0.054	-0.051
	(0.032)	(0.045)
Profile Photo	0.422***	-0.401*
	(0.101)	(0.187)
Total helpful votes received	0.475***	0.0009***
	(0.098)	(0.0001)
Total reviews posted	-0.002*	-0.001
	(0.0006)	(0.0008)
Intercept	0.861***	0.838**
	(0.1827)	(0.316)
Observations	9926	6600
AIC	3042.3	1850.5

*Note: * p<0.1; **p<0.05; ***p<0.01 ****p<0.001;*
Standard errors in parenthesis;

Table A8: A summary of hypotheses testing for primary results

Hyp.	Statement	Expected	Model Estimates		Product Type		Outcome
			Effect	Sig.	Effect in "T"	Effect in "IT"	
H1a	The review title defined in terms of arousal and readability will positively influence online review helpfulness.	[+/+]	[-/-]	[N/N]	-	-	NS
H1b	The relationship between arousal and readability of the review title and the review helpfulness will be influenced by the product category and higher for intangible products than tangible products.	-	-	-	[-/-]	[-/-]	NS
H2a	The arousal, star ratings received, review readability and multimedia will positively influence online review helpfulness.	[+/+/+/+]	[+/-/+/+]	[Y/N/Y/Y]	-	-	PS
H2b	The relationship between arousal and readability of the review title and the review helpfulness will be influenced by the product category and higher for intangible products than tangible products.	-	-	-	[+/-/+/-]	[-/-/+/+]	S
H3a	The review length will have an inverse U-shaped (concave) relationship with online review helpfulness.	Inverted U	Inverted U	Y	-	-	S
H3b	The effect of review length on review helpfulness will be influenced by the product category and higher for intangible products than tangible products.	-	-	-	[-]	[-]	S
H4a	The total number of helpful votes received by a reviewer, total reviews posted by a reviewer, and the presence of profile photo will positively influence online review helpfulness.	[+/+/+]	[+/+/-]	[Y/Y/N]	-	-	PS
H4b	The effect of total helpful votes received by the reviewer, total reviews posted by the reviewer, and presence of profile photo will be influenced by the product category defined by the dimensions of tangible-intangible and shall be higher for intangible products than tangible products.	-	-	-	[-/+/-]	[+/+/-]	PS

Eff = Effects; Sig. = Significance; S = Hypothesis Supported; PS = Hypothesis Partially Supported; NS = Hypothesis Not Supported; T=Tangible; IT=Intangible

Based on the quantile regression approach, the final model is of the following form:

$$Q_\theta(y|X) = \exp(\beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \cdots + \beta_k x_{ki}) \quad \text{(A1)}$$

where Q_θ (y|X) is the θ^{th} quantile of perceived helpfulness, which is conditioned on the covariates $x_{1i}, x_{2i}, \ldots, x_{ki}$, and θ (0; 1). Thus, in this study, equations 2 and 4 describe the models used in the parametrisation of μ_i, π_i and Q_θ (y|X) in terms of our choice of explanatory variables, which is written as:

$$\begin{aligned} Y = \exp\{&\beta_0 + \beta_1(\text{Title readability}) + \beta_2(\text{Title Arousal}) + \beta_3(\text{Review word count}) + \\ &\beta_4\,(\text{Review word count})^2 + \beta_5(\text{Review readability}) + \beta_6(\text{Review arousal}) + \\ &\beta_7(\text{Multimedia review}) + \beta_8(\text{Stars}) + \beta_9(\text{Profile photo}) + \beta_{10}(\text{Total helpful votes received}) + \\ &\beta_{11}(\text{Total reviews posted})\} \end{aligned} \quad \text{(A2)}$$

where Y is the count of helpful votes received by the review.

Table A9: Coefficient estimates using Quantile Regression for Tangible products

	Dependent variable: Count of Helpful Votes								
	Q1	**Q2**	**Q3**	**Q4**	**Q5**	**Q6**	**Q7**	**Q8**	**Q9**
Title readability	-0.0003	-0.0006	-0.0008	-0.0009	-0.0014	-0.0014	-0.0017	-0.0015	-0.0007
	(0.0002)	(0.0003)	(0.0006)	(0.0008)	(0.0009)	(0.0010)	(0.0016)	(0.0022)	(0.0017)
Title arousal	-0.0201	-0.0366	-0.0469	-0.0538	-0.0623	-0.1034*	-0.1334*	-0.2136***	-0.2861
	(0.0136)	(0.0223)	(0.0339)	(0.0428)	(0.0524)	(0.0576)	(0.0705)	(0.0645)	(0.1702)
Review word count	0.0005	0.0011	0.0007	0.0016	0.0052	0.0068	0.0076***	0.0083***	0.0079*
	(0.0007)	(0.0013)	(0.0016)	(0.028)	(0.0053)	(0.0064)	(0.0012)	(0.0004)	(0.0039)
(Review Word count)^2	0.000003	0.000007	0.000008	0.000009*	0.000003	-0.000004	-0.000009	-0.00002	-0.00003*
	(0.000006)	(0.000004)	(0.00004)	(0.000004)	(0.000007)	(0.000007)	(0.000015)	(0.00001)	(0.000015)
Review readability	-0.0002	0.0001	-0.0003	0.0002	0.0002	-0.0011	-0.0021	-0.0049	-0.0083*
	(0.0004)	(0.0008)	(0.0011)	(0.0014)	(0.0013)	(0.0019)	(0.0025)	(0.0034)	(0.0034)
Review arousal	0.0092	0.0019	0.0091	0.0066	0.0089	0.0234	0.0325	0.0981	0.0093
	(0.0149)	(0.0229)	(0.0308)	(0.0388)	(0.0459)	(0.0549)	(0.1086)	(0.0835)	(0.2072)
Multimedia Review	0.1226**	0.2132*	0.2823*	0.3992***	0.5120**	0.6324**	0.7731***	0.7901***	0.6385*
	(0.0427)	(0.0682)	(0.1152)	(0.1197)	(0.1589)	(0.1869)	(0.1541)	(0.1483)	(0.3042)
Stars	-0.0019	-0.0074	-0.0147	-0.0128	-0.0178	-0.0108	-0.0054	-0.0105	-0.0822
	(0.0067)	(0.0111)	(0.0153)	(0.0189)	(0.0241)	(0.0278)	(0.0442)	(0.0452)	(0.0523)
Profile Photo visible	0.0727***	0.1523***	0.1847***	0.2538***	0.3977***	0.4873***	0.5267***	0.5015***	0.5861**
	(0.0247)	(0.0406)	(0.0595)	(0.0721)	(0.0875)	(0.0842)	(0.1605)	(0.1556)	(0.2268)
Total helpful votes received	0.0001***	0.0001***	0.0009	0.0008***	0.0008***	0.0007***	0.0009	0.0009***	0.0011***
	(0.00003)	(0.00004)	(0.0008)	(0.00006)	(0.0001)	(0.0001)	(0.0021)	(0.0002)	(0.0002)
Total reviews posted	-0.0002	-0.0001	-0.0008	-0.0006	-0.00009	0.0002	-0.0007	-0.0007	-0.0011
	(0.0002)	(0.0004)	(0.0007)	(0.0004)	(0.0015)	(0.0012)	(0.0018)	(0.0015)	(0.0026)
Intercept	0.0932**	0.1146	0.2320*	0.2254**	0.2398*	0.3265	0.5518*	1.0548***	1.7400***
	(0.0408)	(0.0704)	(0.146)	(0.1193)	(0.1403)	(0.2466)	(0.2489)	(0.2415)	(0.4657)

*N=9926 observations; Note: * p<0.1; **p<0.05; ***p<0.01 ****p<0.001; Standard errors in parenthesis*

Table A10: Coefficient estimates using Quantile Regression for Intangible products

	Dependent variable: Count of Helpful Votes								
	Q1	**Q2**	**Q3**	**Q4**	**Q5**	**Q6**	**Q7**	**Q8**	**Q9**
Title readability	0.0004	0.0010	0.0015*	0.0016	0.0011	-0.0004	-0.0017	-0.0036	-0.0061
	(0.0004)	(0.0006)	(0.0007)	(0.0009)	(0.0012)	(0.0016)	(0.0015)	(0.0031)	(0.0049)
Title arousal	-0.0184	-0.0075	-0.0193	-0.0491	-0.0859	-0.1199	-0.1205	-0.1313	-0.2011
	(0.0307)	(0.0452)	(0.0515)	(0.0677)	(0.0774)	(0.0963)	(0.1348)	(0.1714)	(0.2303)
Review Word count	0.0027	0.0058	0.0072***	0.0071***	0.0083	0.0089*	0.0112	0.0180	0.0377*
	(0.0026)	(0.0047)	(0.0007)	(0.0008)	(0.0051)	(0.0047)	(0.0114)	(0.0176)	(0.0155)
(Review Word count)^2	0.000012*	0.00001	-0.000001	-0.000006	-0.000009	-0.00002	-0.00003**	-0.00005	-0.00008***
	(0.000004)	(0.000007)	(0.000007)	(0.000005)	(0.000008)	(0.000013)	(0.000009)	(0.000021)*	(0.000012)
Review readability	0.0009	0.0014	0.0021	0.0020	0.0025	0.0034	0.0033	0.0039	0.0159**
	(0.0008)	(0.0012)	(0.0014)	(0.0015)	(0.0017)	(0.0018)	(0.0026)	(0.0049)	(0.0056)
Review arousal	0.0473	0.0511	0.0566	0.0703	0.0814	0.0551	0.0077	0.1298	0.1443
	(0.0452)	(0.0661)	(0.0826)	(0.0921)	(0.0848)	(0.1119)	(0.1458)	(0.3087)	(0.3681)
Multimedia Review	0.1959	0.3114*	0.4042*	0.4453**	0.4353	0.6176	0.7347**	0.8901	1.3836
	(0.1540)	(0.1245)	(0.1585)	(0.1695)	(0.2229)	(0.4115)	(0.2689)	(0.6373)	(2.4198)
Stars	-0.0059	-0.0119	-0.0165	-0.0344	-0.0555	-0.0626	-0.0601	-0.0514	-0.1028
	(0.0113)	(0.0176)	(0.0235)	(0.0306)	(0.0315)	(0.0334)	(0.0594)	(0.0774)	(0.2404)
Profile photo visible	0.0171	0.0937	0.1783*	0.2362**	0.2342*	0.2484*	0.1410	0.2173	0.3257
	(0.0526)	(0.0868)	(0.0971)	(0.1190)	(0.1132)	(0.1248)	(0.1808)	(0.4812)	(0.6511)
Total helpful votes received	0.00008	0.0002	0.0002*	0.0002	0.0004**	0.0005***	0.0006***	0.0006	0.0011*
	(0.0001)	(0.0001)	(0.00007)	(0.0007)	(0.0002)	(0.0001)	(0.00009)	(0.00006)	(0.0004)
Total reviews posted	0.0013	0.0011**	0.0011*	0.0009	0.0009	0.0012	0.0024	0.0014***	-0.0005
	(0.0010)	(0.0004)	(0.0006)	(0.0017)	(0.0013)	(0.0023)	(0.0056)	(0.0029)	(0.0046)
Intercept	0.0411	0.0368	0.0409	0.1764	0.3229	0.4527*	0.6215	1.0249	1.1843
	(0.0925)	(0.1395)	(0.1372)	(0.1591)	(0.1751)	(0.2073)	(0.2907)	(0.6441)	(1.0960)

*N=6600 observations; Note: * $p<0.1$; **$p<0.05$; ***$p<0.01$ ****$p<0.001$; Standard errors in parenthesis*

Table A11: Robustness checks using Negative Binomial Regression (response truncated at 2, 5 and 10)

	Dependent variable: *Count of Helpful Votes*					
	M1a	**M1b**	**M2a**	**M2b**	**M3a**	**M3b**
Title Readability	-0.0002	0.001	-0.001	-0.0001	-0.001	0.00004
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Title Arousal	0.015	-0.054	-0.066	0.017	-0.065	-0.046*
	(0.062)	(0.090)	(0.049)	(0.067)	(0.048)	(0.065)
Review word count	0.0004	0.0002	0.00008	0.003	0.001	0.006***
	(0.002)	(0.004)	(0.001)	(0.003)	(0.001)	(0.002)
(Review Word count) ^2	-0.000007	-0.00004	-0.000005	-0.00005	-0.00002	-0.000002***
	(0.000009)	(0.0001)	(0.000007)	(0.00007)	(0.000006)	(0.00002)
Review Readability	0.00002	0.001	-0.001	0.0002	-0.002*	0.003
	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)
Review Arousal	-0.005	0.056	0.036	0.008	0.012	0.117*
	(0.085)	(0.121)	(0.064)	(0.098)	(0.067)	(0.094)
Multimedia Review	0.135	0.088	0.250***	0.254	0.467	0.257****
	(0.127)	(0.218)	(0.091)	(0.157)	(0.083)	(0.147)
Stars	-0.020	-0.022	0.013	-0.019	-0.006	-0.013*
	(0.031)	(0.036)	(0.023)	(0.029)	(0.023)	(0.028)
Profile Photo	0.150	0.027	0.261****	0.025	0.226***	0.097
	(0.096)	(0.140)	(0.072)	(0.105)	(0.072)	(0.098)
Total helpful votes received	0.00008	0.00005	0.00008	0.00003	0.00003	0.00004
	(0.001)	(0.0001)	(0.00006)	(0.00009)	(0.00003)	(0.00008)
Total reviews posted	0.00003	0.001	-0.00005	0.002**	0.0003	0.002***
	(0.001)	(0.001)	(0.0004)	(0.0006)	(0.0004)	(0.001)
Intercept	0.242	0.199	0.457****	0.560***	0.777***	0.546***
	(0.172)	(0.233)	(0.133)	(0.184)	(0.133)	(0.183)
Observations	452	213	552	272	602	291
AIC	939.822	517.726	1409.399	789.310	1907.931	1010.568

*Note: * p<0.1; ** p<0.05; *** p<0.01 **** p<0.001; Standard errors in parenthesis;*
***M1**: Response truncated at 2; **M2**: Response truncated at 5; **M3**: Response truncated at 10;*
***a**: tangible products; **b**: intangible products*