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Research Article

A Meta-Analysis on the Determinants of Online Product Reviews with Moderating Effect of Product Type

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Abstract

The technological advances in digital space have provided a renewed impetus for business to expand their footprint across digital modes. The growth of the internet and the ease of its access to the masses has encouraged many businesses to go online. Online e-commerce platforms make it easy to search, locate and place orders. Technology-assisted supply chains and fast delivery mechanisms ensure that users don't have to go elsewhere to fulfill their needs. To earn loyalty and customer satisfaction, e-commerce platforms have evolved into a sophisticated recommender system. It has evolved from just an informational source to a participative mode where users can share their experiences about their purchases. Customer values other user experiences more than the information provided by the seller. The presence of many conflicting and contradicting reviews can make the task of making rational decisions difficult for many users. Many studies were performed to understand what constitutes a review helpful and came up with different or mixed outcomes. The present study reviews the factors that influence online customer reviews helpful. Meta-analysis was performed to reconcile the mixed findings of different factors of online review helpfulness. The meta-analysis found that with the moderating effect of product type, factors like review length, readability, rating, reputation, and expertise positively correlate with helpfulness. Further, the customer finds moderate reviews more helpful in terms of polarity. Meta-analysis has a mix of findings for the selected data points in the study. The mixed findings include product type (search, experience, or other) and helpfulness measurement criteria.

Keywords: *Meta-analysis, e-commerce, online reviews, decision-making, helpfulness*

1. Introduction

The conventional way of marketing and shopping for products and services has undergone tremendous changes with the advent and reach of the digital ecosystem. Shoppers increasingly find it convenient and user-friendly to shop online at any time or place. Compared to traditional shopping, modern online shopping ensures that the physical interaction between buyers and sellers is reduced to almost naught. There are many significant advantages of this virtual shopping mode. Still, there are a couple of disadvantages as well, which, if not taken care of, could ultimately lead to a loss of

credibility of this virtual shopping mode in the minds of customers and businesses. The most significant disadvantage is the uncertainty in evaluating the product before purchase. Listing many similar product offerings on the portal without a proper evaluation mechanism for end users could impair the end user's decision-making thoughts. These uncertainties and impairment of decisions could increase the chances of delayed purchases or unsatisfied users. Unsatisfied users may have the bad word of mouth among their social circles. It is well known that users believe other fellow users' experiences as more trustworthy than business advertisements or clarifications. In the current era of online social networking, bad word of mouth, supported by evidence, could become viral in no time. If timely corrective measures were not taken, these could impact the credibility of the e-commerce business in the minds of other potential customers.

To reduce the uncertainty, various factors affecting purchase decisions were researched by many researchers. As per the research by researchers, online reviews (a form of user-generated content) have become more critical and prominent for purchase-related decisions (Li & Hitt, 2010); (Zhu & Zhang, 2010).

Major popular e-commerce portals allow end users to share their experiences of their recent purchases in the form of reviews or comments directly on their portal. Users are also allowed to rate reviews shared by other users. Online reviews constitute the feedback mechanism shared by users on any interactive web platform. In the case of e-commerce portals, the feedback is given for goods and services purchased from the portal or commented or rated on the others' feedback. It chiefly consists of two parts- rating on a scale of 1-5 stars and content (text) posted by consumers (Mudambi & Schuff, 2010). But, with the information load, it is an important task to present helpful reviews in front of customers, which helps reduce the uncertainty in the customers' minds. Hence, it led to the attention of academicians and practitioners (Li & Hitt, 2008).

According to Lackermair, Kailer, and Kanmaz,(2013), users search for a product's overall performance. Users also compare the positive and negative feedback for the product. Organizations view online reviews as a good indicator of product quality in customers' eyes (Xiang, Schwartz, Gerdes, & Uysal, 2015).

Kats (2018), concluded that most online customers refer to reviews before making any purchase. According to a report by (BrightLocal, 2019), 82% of customers read the available reviews before making any purchase decision (Lin, 2021).

Nowadays, most online trading companies allow users to write their experiences with their recent purchases. These reviews are available for future prospective customers. The overwhelming numbers and the associated quality of online reviews affected the effective use of online reviews. Thus, understanding the characteristics of helpful reviews is an important task (Hao, Ye, & Li, 2010).

Online reviews have found profound interest among researchers from diverse areas of expertise. Many researchers shared their respective work and findings, and others continue to explore and expand the scope of their research based on existing outcomes. Several studies have examined the relationship between different factors of online reviews and their helpfulness. The studies have mixed findings in terms of the relationship (strong/weak) between the factors of online reviews and online review helpfulness. Accordingly, this paper attempts to answer the following research question:

> ➢ What is the relation between different factors of online reviews and the helpfulness of online reviews?

Based on the research question, the primary objective of the study is:

> ➢ Analyze the relationship between different factors of online reviews and the helpfulness of online reviews.

Meta-analysis is an appropriate research method to infer the prior studies and deal with the mixed research findings problem. As a statistical analysis technique, meta-analysis offers a wide range of methods that can be used to quantify inconsistencies among studies. Research in information systems has benefited from meta-analysis techniques (Ismagilova , Slade, Rana, & Dwivedi, 2020); (Tamilmani , Rana , & Dwivedi , 2020); (Trang & Brendel, 2019).

To better understand online review helpfulness, the study aims to fill the research gap by

performing a meta-analysis on research done in the respective areas and reconciling the mixed results concerning review length, readability, polarity, rating, reputation, and expertise. (Hong, Xu, Xu, Wang, & Fan, 2017) performed a meta-analysis on a few studies in context to the online review helpfulness and found inconsistent results for those studies.

The reasons for inconsistent results were the variations in the background, research designs, data sources, and research methods applied in those studies. Thus, if the business wants to take a competitive advantage from the information in the form of online reviews, it must consider a deep analysis of various factors that influence the helpfulness of online reviews. To fill this gap, the present paper has taken some more factors that influence the helpfulness of online reviews by applying a meta-analysis.

The remaining paper is organized as follows. Section 2 confers a review of the literature on factors shaping online reviews and the relationship with review helpfulness. Section 3 describes the research methodology used in the study. Section 4 presents the results of the meta-analysis. Section 5 provides the study's conclusion, limitations, and implications and proposes directions for future research.

2. Literature Review

The theory of informational influence gives the elaboration likelihood model (ELM) (Petty & Cacioppo, 1986). The ELM model provides a theoretical framework to understand how people undertake messages that are expected to be impressive. As per ELM, there are two major routes by which a message can be undertaken - the central and peripheral routes. The central route includes a high level of elaboration, whereas the peripheral route includes a low level of elaboration.

When a message is taken through the central route, the receiver of a message thoughtfully picks up the issue presented and assesses the merits of the message. With these conditions, the receiver will undergo additional cognitive processing and apply more effort to evaluate a message. Conversely, the less cognitive effort is required in the peripheral route. In this route, people use plain heuristic clues like source credibility, one of the critical indicators of information, to assess the credibility of a message. Conceptually, people either process a message via the central or the peripheral route.

2.1 Determinants Based on Central Cues

Review length is the most common and essential measure of online reviews. Studies have found that review length has a significant relation with review helpfulness (Mudambi & Schuff, 2010); (Pan & Zhang, 2011); (Yin, Bond, & Zhang, 2014). Review readability is the cognitive efforts and educational levels expected to peruse and understand the reviews. A simple review will be more beneficial than a complex review (Ghose & Ipeirotis, 2011); (Yin, Bond, & Zhang, 2014). The sentiment of the review text (the extent to which the emotions are expressed in the review) can influence any user's thoughts and actions (Baumeister, Vohs, DeWall, & Zhang, 2007); (Lench, Flores, & Bench, 2011).

2.2 Determinants Based on Peripheral Cues

The overall assessment of products or services can be represented through star ratings (Pan & Zhang, 2011). Customers provide their negative or positive attitude toward a product or service by providing their response in the reviews as a star rating.

Reputation and the expertise level are the two essential attributes of a reviewer that influences review helpfulness (Forman, Ghose, & Wiesenfeld, 2008); (Ghose & Ipeirotis, 2011); (Pan & Zhang, 2011). These two attributes of a reviewer depict the capability and credentials of writing quality reviews which helps to provide helpful information and are perceived by the social media community (Zhu, Yin, & He, 2014).

Table 1 summarizes the determinants of review helpfulness from twenty-six available literature.

Based on ELM theory, determinants of review helpfulness are divided into central and peripheral cues. Central cues require more effort to evaluate the message (or review), whereas peripheral cues require less effort to evaluate the review. Table 1 shows different studies with mixed findings. All the factors are weak or strong, positively/negatively influencing helpfulness. Meta-analysis is necessary to understand and reconcile the mixed findings on review-related factors.

Table 1: Factors and Their Relationship with Review Helpfulness

Dimension based on ELM	Factors	Explanation	Reference
Central Cues	Review Length	Total Words in the review	(Mudambi & Schuff, 2010); (Gan, Cao, & Jones, 2012); (Korfiatis, Barriocanal-Garcia, & Sanchez, 2012); (Zhiming, Li, & Lu, 2014); (Yin, Zhang, & Li, 2014); (Ullah, Zeb, & Kim, 2015) (Baek, Ahn, & Choi, 2012); (Willemsen, Neijens, Bronner, & Ridder, 2011); (Yin, Wei, Xu, & Chen, 2014); (Zhu, Yin, & He, 2014); (Wu, Heijden, & Korfiatis, 2011); (Chua & Banerjee, 2015); (Siering & Muntermann, 2013); (Kuan, Prasarnphanich, Hui, & Lai, 2015); (Yin, Mitra, & Zhang, 2016); (Mengmeng, Zhihong, & Ming, 2015); (Salehan & Kim, 2014); (Chen, Sheng, Wang, & Deng, 2016); (Kang & Zhou, 2016); (Yin, Bond, & Zhang, 2014); (Liu & Park, 2015); (Aghakhani, Oh, & Gregg, 2017); (Aghakhani N. , Oh, Gregg, & Karimi, 2020)
	Review Readability	Number of spelling errors	(Gan, Cao, & Jones, 2012); (Yin, Zhang, & Li, 2014); (Ghose & Ipeirotis, 2011); (Korfiatis, Barriocanal-Garcia, & Sanchez, 2012); (Yin, Wei, Xu, & Chen, 2014); (Zhu, Yin, & He, 2014); (Wu, Heijden, & Korfiatis, 2011); (Kuan, Prasarnphanich, Hui, & Lai, 2015); (Kang & Zhou, 2016); (Yin, Bond, & Zhang, 2014); (Liu & Park, 2015); (Li, Hou, Guan, Chong, & Pu, 2017)
	Review Polarity	Text represents whether the expressed opinion in that text is positive, negative, or neutral.	(Siering & Muntermann, 2013); (Zhiming, Li, & Lu, 2014); (Salehan & Kim, 2014); (Willemsen, Neijens, Bronner, & Ridder, 2011); (Yin, Mitra, & Zhang, 2016)
Peripheral Cues	Review Rating	The star rating of the product	(Mudambi & Schuff, 2010); (Ghose & Ipeirotis, 2011); (Korfiatis, Barriocanal-Garcia, & Sanchez, 2012); (Zhiming, Li, & Lu, 2014); (Gan, Cao, & Jones, 2012); (Yin, Zhang, & Li, 2014); (Ullah, Zeb, & Kim, 2015); (Willemsen, Neijens, Bronner, & Ridder, 2011); (Ghose & Ipeirotis, 2007); (Yin, Wei, Xu, & Chen, 2014); (Zhu, Yin, & He, 2014); (Wu, Heijden, & Korfiatis, 2011); (Chua & Banerjee, 2015); (Kuan, Prasarnphanich, Hui, & Lai, 2015); (Yin, Mitra, & Zhang, 2016); (Salehan & Kim, 2014); (Kang & Zhou, 2016); (Yin, Bond, & Zhang, 2014); (Liu & Park, 2015); (Aghakhani, Oh, & Gregg, 2017)
	Reviewer Reputation	Rank of the reviewer	(Chua & Banerjee, 2015); (Kuan, Prasarnphanich, Hui, & Lai, 2015); (Mengmeng, Zhihong, & Ming, 2015); (Chen, Sheng, Wang, & Deng, 2016); (Zhiming, Li, & Lu, 2014)
	Reviewer Expertise	Average helpfulness of all reviews written by the given reviewer	(Willemsen, Neijens, Bronner, & Ridder, 2011); (Zhu, Yin, & He, 2014); (Liu & Park, 2015)

3. Research Methodology

A meta-analysis is a statistical technique from which results of multiple studies for a common research question will be integrated. A common problem in different studies has mixed research findings due to different factors (Hunter, Schmidt, & Jackson, 1986). The meta-analysis found to be an appropriate research methodology to resolve the issue of mixed research findings (King & He, 2005). Meta-analysis helps to systematically review the accumulated existing studies on a particular area, provide quantitative summaries, integrate and validate the research findings found in the studies, and provide an overall interpretation of the studies (King & He, 2005).

3.1 Meta-Analysis Protocol

PRISMA protocol (PRISMA-P) has been adopted in the present study. PRISMA protocol guidelines (Shamseer, et al., 2015), recommend certain details such as; study rationale, criterial for study selection, strategy for study search, moderator variables if any, publication bias, and statistical approach; for conducting meta-analysis.

3.2 Data Collection

A crucial step in the meta-analysis is data collection. Keyword search for a broad range of publications is done to assure the multidisciplinary approach. Search string used in systematic review included keywords- "Determinants of online review helpfulness AND Analysing online review helpfulness". The papers must meet the following criteria for inclusion in the study -

➢ Papers that included data as online customer product review.
➢ Papers must have reported mean and standard deviation of the factors.
➢ Papers must have reported the sample size.
➢ Papers published from 2010-2021.

There are number of databases to find the relevant studies/articles in each area. It is up to the researcher to select the most relevant sources for the research. Google scholar platform is used to cover a wide range of publications in present study. The initial search returned a big volume of studies. Based on the inclusion criteria, the studies which are not eligible for the meta-analysis were discarded.

The present study included eighty-six datapoints from twenty-six research papers. Fig 1 shows the flow of inclusion and exclusion of the searched records (articles).
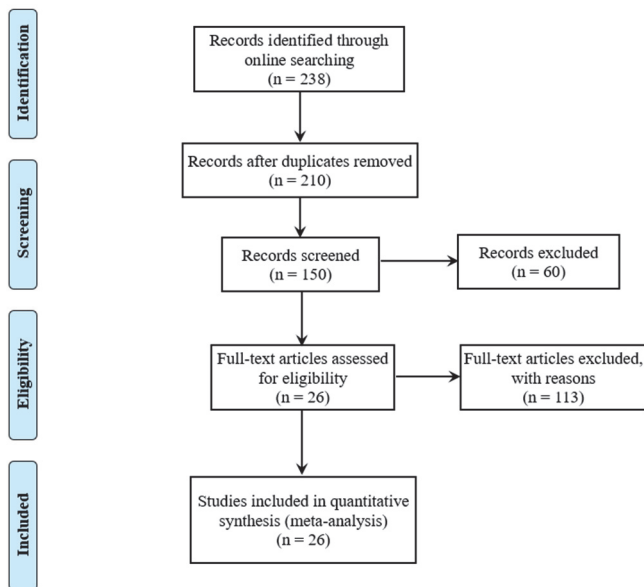

Figure 1: PRISMA Flow Diagram

The initial search returns a big volume of studies (238).

In the initial collection, few studies were found to have duplicate records; few had the abstract and research title not concurrence with each other. After filtering out these studies, 150 articles remained.

The present paper considers the studies which are full or complete for closer inspection.

After analysis of 150 remaining articles, 113 articles did not fall into present study requirement and filtered out. The remaining 26 articles became the final dataset considered for the present study. From the last set of 26 articles, 86 data points were identified and used for the final meta-analysis.

4. Results and Discussion

The study employed Comprehensive Meta-analysis (CMA) 2.0 software for data analysis. The first step is to enter the data from the collected literatures as database into the tool. Fixed-effect model or a random-effect model is generated by CMA 2.0. To conduct the meta-analysis, effect sizes from the included studies are extracted. In the present study, mean, standard deviation and sample size are used to extract the effect size.

4.1 Study Heterogeneity

For meta-analysis, identification of true heterogeneity in effect size is a crucial step.
Q-statistics (ratio of observed variation to within-study variance) can help in identification of heterogeneity. Q statistics reveals the overall true heterogeneity between studies variations. A statistically significant Q-statistic shows that the included studies do not share a common effect size, thus indicates no heterogeneity. Also, I^2 percentage, which represents the proportion of observed variation which is the actual difference between studies. Higher the I^2 value higher is the heterogeneity.

Table 2: Study Heterogeneity

	Q - Value	df (Q)	p-value	I - Squared
Review Length	37403.019	28	0.000	99.925
Readability	241873.118	15	0.000	99.994
Rating	650436.328	23	0.000	99.996
Polarity	124537.077	5	0.000	99.996
Reputation	34462.787	7	0.000	99.980
Expertise	49175.697	2	0.000	99.996

Table 2 shows that all factors included in the study have statistically significant Q values and high I^2 values. This concludes that all the studies for the relevant factors have very high inter study variance and heterogeneity. Thus, the study chose random-effects model.

4.2 Effect Size

Effect size is a statistical technique that is used to measure the relationship strength of two variables measured on a numeric scale. In meta-analysis, the effect size of all the included studies is considered and combined into single analysis. Three ways to measure effect sizes are standardized mean difference, odd ration, and correlation coefficient. The present study has taken mean and standard deviation, and the effect size is measured by the method of standardized mean difference**.**

Table 3: Effect Size

Independent Variable	Studies included	Sample Size	Combined Effect Size
Review Length	29	415702	0.975
Readability	16	228929	2.414
Rating	24	414509	1.795
Polarity	6	148540	-1.459
Reputation	8	115874	-0.602
Expertise	3	63873	-1.114

For review length, the study reported twenty-nine datapoints. All the datapoints have reported to have a positive influence on review helpfulness. All the datapoints did not find a similar or constant

effect size.

For readability, the study reported sixteen datapoints. Two of the datapoint showed a negative influence while remaining fourteen datapoints have positive influence on review helpfulness. We arrive at the conclusion that more the review is readable, the more it leads to helpfulness.

For rating, the study reported twenty-four datapoints. Altogether it has positive influence on review helpfulness. Eleven datapoints have reported negative influence and remaining thirteen datapoints have positive influence. We arrive at the conclusion that higher scale ratings influence the review helpfulness.

For polarity, the study reported six datapoints. Two datapoints have positive influence while remaining have a negative influence and thus leads to overall negative influence on review helpfulness. We arrive at the conclusion that customers find moderate reviews more helpful than the extreme positive or negative reviews.

For reputation, the study reported eight datapoints. Out of eight datapoints, three reported negative influence and remaining five datapoints have reported positive effect on review helpfulness. Ecommerce portal assign reputation rank to each reviewer. The reputation rank is in numerical format. The numeric value of reputation rank is inversely proportional to helpful review. Lower the rank score, higher the reputation of reviewer. We arrive at the conclusion that a reputed user leads to higher helpful reviews.

For expertise, the study reported three datapoints. Two datapoints have negative effect and remaining one reported positive effect. Expertise of the reviewer has been operationalized differently in different study. Lesser the numerical value of the expertise measure, more the reviewer is expert. We arrive at the conclusion that an expert reviewer leads to more helpful reviews.

4.2.1 Publication Bias

Publication bias is a phenomenon in academic research wherein researcher circumvents the outcome having statistically insignificant results and reports only the significant outcomes and results (Kraemer & Andrews, 1982). There is a presumption that studies having stronger significant effects have higher probability for publication and included in meta-analysis.

There is a need to detect the presence of publication bias in meta-analysis. Recent times have seen development of various methods that can detect publication bias in meta-analysis. The current study evaluates the publication bias with fail-safe N.

Table 4: Publication Bias

Independent Variable	N	5*N+10	Fail-safe N
Review Length	29	155	962679
Readability	16	90	946125
Rating	24	130	299440
Polarity	6	40	27376
Reputation	8	50	80928
Expertise	3	25	27066

As per Table 4, all fail-safe N (relationships) are greater than the corresponding "5*N + 10" (N is the number of studies/datapoints). This indicates no evidence of publication bias (Rosenthal, 1979).

4.3 Moderator Analysis

A moderator analysis helps to find the reason of heterogeneity. Researcher can make use of moderator analysis to assess the existing intervention's effectiveness. The assessment could help in designing a new potentially effective intervention. The present study conducted moderator analysis

to assess the influence of product type (search and Experience) on the relationship of factors used in the study.

The evaluated Z-score was used to validate the significant difference among the two subgroups (Cohen & Cohen, 1985). Also, Q statistics, from moderator analysis using meta-regression apprise the influence of moderator variable on the dataset.

Table 5: Moderator Analysis

Group	Point Estimate	Standard Error	Variance	Lower Limit	Upper Limit	Z-value	p-value
Search	0.846	0.120	0.014	0.611	1.082	7.052	0.000
Experience	1.050	0.114	0.013	0.827	1.272	9.248	0.000

Table 5 shows that Z value for both the groups, i.e.., search and experience under product type have a significant difference, hence confirms the moderating effect of product type in the relationship of all the factors and review helpfulness.

Q-statistics re-validated the results and found that the product type has a moderating effect with Q = 14.10, p = 0.0009. The significant Q value suggest that the product type, as a set can explain the substantial amount of the variance, or mean effect size varies by group.

5. Conclusion, Implications, Limitations and Future Research

The study analysed the determinants of online review helpfulness. Based on the ELM theory, two key factors - central and peripheral, influences perceived helpfulness. Meta-analysis helped to reconcile the findings on the factors included in the study. Results of the present paper on meta-analysis confirmed that review length, readability, rating, reputation, and expertise are positively related to helpfulness, while moderate reviews are helpful in terms of polarity. Few of the studies have contractive with the meta-analysis results. Product type, data type and research methods are the main reasons of the mixed finding in the available literatures for online reviews helpfulness.

5.1 Theoretical Implications

The study contributes in both theoretical and practical ways. The study adds on to the literatures of online review helpfulness. The study has utilized ELM theory to re-conceptualize the review helpfulness. Second, based on the mixed results in the included studies helps to investigate the reasons of the inconsistencies. Third, the study had utilized different sample datapoints which have different focuses on different product features. This adds to the marketing literature by uncovers heterogeneity of individual preference and choice.

5.2 Practical Implications

The study outcome helps identify helpful reviews from a large set of reviews. This will help both sellers and buyers to filter out helpful reviews and improves their decision-making ability.

Second, the positive influence of various determinants of reviews on review helpfulness, could help online retailers to produce new and improved research model of review helpfulness. The review helpfulness redrawn upon the improved model could improve the overall crowdedness and health of online review communities.

Third, the moderating effect of product type helps marketers to align separate marketing strategies to promote the product.

Fourth, based on the conclusion of the moderating effect, there could be some other subgroups for the dataset, marketers can identify those subgroups and accordingly design their strategies to

satisfy the need and wants of the customers.

Lastly, the methods, technique, and model discussed in this study can be applied for improvement of the design and development of ecommerce portals.

5.3 Limitations and Future Research

There are certain limitations of the study. Although the study did not find any publication bias, but still not all previous studies on online review helpfulness are included in the study. The selected literatures are limited to mentioned time frame of 10 years. Future research can include more study to get more fine results. Second, the study had examined the influence of review length, readability, polarity, rating, reputation and expertise on review helpfulness, future research can include more variables to improve the efficiency of the model. Third, the present study had examined the moderating effect of product type, still other variables like dataset type, location and many others are not considered. Some more complex models will be considered in future research with multi moderating variables. Fourth, the present study has utilized variables with quantitative data. Future research could consider the variables with qualitative data as well. Finally, researchers can employ different techniques and in-depth meta-analysis for better results.

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