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A Comprehensive Analysis of Online Product Reviews

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Abstract

Purpose: The rise of e-commerce to prominence can be attributed to the advancement of technology and the internet, which has revolutionised the way businesses are conducted around the globe. In an era of information overload and limitless product options, online product reviews (OPRs) have become a vital source of information. In online shopping, prospective online buyers typically do not have the product experience available to reviewers. Online prospective consumers make their decisions based on the opinions and experiences shared by the buyers cum reviewers in the reviews. The current study aims to investigate the determinants of online product reviews (OPRs) and examine the intricate interplay of online product review determinants in the Indian e-commerce context, which helps consumers navigate through the overwhelming choices available to them.

Methodology: As the market leader in Indian e-commerce, Amazon provides a reliable, fair, and transparent review system. Its standardised, multi-dimensional review format, which covers text, ratings, reviewer attributes, and helpful votes, applies across all categories, making it the most appropriate choice for this study. A multistage sampling technique and exclusion of outliers yielded a comprehensive dataset of 4,900 reviews from 49 best-selling products across three top-selling product categories: beauty, fashion and electronics on Amazon. in. The dataset was analysed using Exploratory Factor Analysis (EFA) in SPSS 22. The extant literature has reported different dimensions of OPRs and analysed single or a limited number of review determinants. Based on prior literature, this study examines seven determinants of OPRs: *volume, valence, visual cues, helpful vote count, reviewer expertise, reviewer trustworthiness, and reviewer identity disclosure.*

Findings: Exploratory factor analysis identified three latent determinants of OPR: ***Credibility*** (reviewer expertise, reviewer trustworthiness, and the presence of visual cues in the reviews), ***Salience*** (volume, valence, and reviewer identity disclosure), and ***Usefulness*** (helpful vote count). Notably, *the Credibility* reflects the perceived believability and trustworthiness of the review source and content presentation, which is associated with a higher perceived credibility of the review. An interesting finding was the negative loading of visual cues, suggesting an inverse relationship with other determinants, indicating that highly credible reviews tend to rely less on images or videos to establish credibility. The *salience* captures the visibility, prominence and relatability of the reviews. The *usefulness* reflects peer endorsement and social validation, which enhances the functional value of the reviews. Interestingly, *Usefulness* appears to be an *outcome* of other review determinants, with helpful votes aggregating peer judgments of content and source-based reviews. Collectively, these findings provide robust empirical evidence for the complex nature of how consumers evaluate and process online information.

Implications: These findings significantly contribute to the theoretical understanding of online consumer behaviour and electronic word-of-mouth (eWOM) communication. This study empirically validates the multidimensional nature of online product reviews in the Indian e-commerce context. It clarifies how credibility, salience, and peer endorsement or helpfulness interact to shape consumer judgment. Notably, the negative loading of visual cues suggests that images/videos are negatively associated with perceived credibility, aligning with recent studies reporting similar effects. Platforms can better support consumer decision-making by prioritising cues of reviewer expertise and trustworthiness, optimising review prominence and elevating peer-endorsed reviews. Theoretically, the findings extend source credibility, information processing and social proof theories by showing that helpful vote counts aggregate peer judgements across content and source-based cues. Future research should evaluate effects on key outcomes: purchase intentions, sales, and brand image, examine moderating roles of other marketing variables and product categories, and probe the counterintuitive influence of visual cues.

Keywords: eWOM, Online product reviews, e-commerce, online consumer behaviour, amazon.in, credibility, helpfulness, salience, India**.**

1. Introduction

Technological advancements have brought about a paradigm shift in the way businesses are conducted. Organisations worldwide are harnessing the potential of the internet. It has transformed access to quick, comprehensive, and up-to-date information by removing time and geographical barriers. One of the most significant advancements in this digital age is the rise of e-commerce. As of 2023, approximately 2.64 billion people purchased goods and services online, highlighting the growing prominence of e-commerce (Oberlo, 2023). The global e-commerce industry has experienced accelerated growth since the COVID-19 pandemic, as consumers have increasingly turned to online platforms to meet needs previously fulfilled by physical stores. Amazon.com, for example, recorded nearly 5.22 billion visits in June 2020, followed by eBay.com with 1.52 billion visits (Statista, 2022). As of December 1, 2020, online marketplaces such as Amazon, eBay, and Alibaba accounted for half of global online shopping orders (Statista Research Department, 2020). In 2022, global e-commerce sales surpassed 5.7 trillion US dollars (Statista Research Department, 2020).

This growth is accompanied by a shift in how consumers make their decisions. The proliferation of online product reviews (OPRs) has been a defining element of this transformation. OPRs, as peer-generated evaluations in text, image, or video form, provide insights into product quality, performance, and usage experience. Extensive literature has demonstrated that online reviews have a significant influence on consumer attitudes and purchasing decisions. Unlike marketer-driven product descriptions, these reviews are user-generated and often perceived as more credible and relatable. The reliance on these personal experiences shared by the reviewers highlights the unique credibility and relatability of the reviews. This helps to reduce prospective customers' uncertainty by building trust in a way that traditional marketplaces lack. Online consumers often go through various steps (e.g., information search, alternatives evaluation) to reach a final purchase decision. Studies reveal that nearly 90% of online shoppers consult reviews before purchase. As of August 25, 2023, a survey conducted in October 2018reported that approximately 19% consumers trust reviews and find that they improve decision accuracy and confidence as much as personal recommendations by friends or family (Statista, 2018). This prevalence of review usage emphasises the need to understand what aspects of online reviews drive their impact on consumers.

The potential in the Indian digital economy is a striking example of this revolutionary growth. With the exponential growth in India's internet and online infrastructure, it was no surprise that the e-commerce market experienced a similar boost. With over 1.2 billion internet users as of 2023, the Indian digital economy is among the fastest growing in the world and is projected to exceed 1.6 billion users by 2050 (Statista, 2020a). The e-commerce retail industry in India was valued at USD 103 billion in 2023 and is expected to grow at a CAGR of 15% through 2027 (Statista, 2020b). This growth has been facilitated by increasing internet penetration, structural shifts in the retail sector, and supportive government policies, including full foreign direct investment in B2B e-commerce.

Within this ecosystem, Amazon India has established itself as a dominant player, recording more than 3.2 billion monthly visits in 2022 (Statista, 2022a). Categories such as beauty, fashion, and electronics, which often involve varying degrees of perceived consumer risk, are particularly influenced by OPRs that act as a form of “free sales assistance.”

Against this backdrop, the present study seeks to examine the determinants of OPRs and their interplay on Amazon India. Online reviews are inherently multidimensional, encompassing both content-related factors such as volume, valence, and helpful votes, and source-related factors such as reviewer expertise, trustworthiness, and identity disclosure. This multidimensionality makes reviews a complex yet powerful driver of consumer behaviour. Understanding their structure requires comprehensive analytical approaches capable of capturing how credibility, salience, and usefulness interact in shaping purchase decisions.

The significance of this research extends beyond academic inquiry. On a theoretical level, it contributes to the understanding of electronic word-of-mouth (eWOM) in emerging marketplaces such as India. On a practical level, it offers actionable insights for e-commerce platforms and marketers, for improving the design review systems that reinforce consumer trust, improve visibility and credibility, and thereby facilitate more confident decision-making. The findings have direct implications for platform design, marketing strategies, and consumer protection, while also contributing to a more trustworthy and efficient digital marketplace.

2. Review of Literature

Online consumers often go through various steps (e.g., information search, alternatives evaluation) to reach a final purchase decision. It has been observed that customers refer to interpersonal communication using multiple online platforms while going through various phases of the buying process, especially during the evaluation of available alternatives (Ghasemaghaei et al.,2018; Mudambi and Schuff, 2010). To address the inherent uncertainties of online buying, scholars have increasingly turned to the concept of consumer behaviour. The rapid convergence of physical and virtual environments has bestowed an opportunity to the online marketer to reach out to the potential customer at an altogether different level, enabling engagement across the entire decision journey. Notably, eWOM operates during every stage of decision-making, and consumers may develop a differential attitude towards eWOM within and across the stages (Ngarmwongnoi et al., 2020; Hall et al., 2017).

Within this context, online product reviews (OPRs) serve as arguably the most influential information sources for digital consumers. On e-commerce platforms, OPRs enable potential buyers to compare products and reduce information asymmetry—filling gaps forged by the lack of physical product inspection—by offering access to experiences from previous purchasers (Lackermair et al., 2013; Bae & Lee, 2011; Salehan& Kim, 2016). Notably, review activity correlates positively with sales metrics (Hu et al., 2008). Different review features influence differently, leading to different outcomes. The presence of reviews and ratings has been shown to enhance consumers' confidence in their decisions (Mudambi & Schuff, 2010). Review valence tells whether feedback is predominantly positive or negative—relates strongly to attitudes and purchase intentions; positive clusters tend to raise intention, while negative reviews draw disproportionate attention due to negativity bias (Ahluwalia, 2002; Chen et al., 2022). Review features likewise influence trust, which in turn relates to purchase decisions in online marketplaces. Therefore, the impact of online reviews cannot be undermined in facilitating consumer decision-making. Since reviews on the internet are so effective in influencing consumer confidence and purchasing intent, it is then worthwhile considering how such reviews coexist with another prominent variable—perceived risk. In fact, perceived risk offers a valuable insight to understand consumer reliance on review features, particularly in contexts where uncertainty is high and product trial is not possible.

Perceived risk, a central concept in consumer behaviour, is defined as the customer's overall sense of uncertainty and anticipated adverse consequences in purchasing (Mitchell, 1999). In the online retail space, this risk is not just present but is amplified due to the intrinsic limitations of digital shopping environments (Verhagen et al., 2006; Xu et al., 2010; Hajli, 2015). Among various mitigators, the return and replacement policy emerges as a pivotal consideration, signalling both retailer fairness and risk-reduction (Yan, 2009). Consumers consider the return or replacement policy as one of the criteria while evaluating functional, financial or psychological risks associated with online buying (Erden &Swait, 1998). Building on signalling theory, favourable return policies—such as full refunds—have a marked positive effect on purchase intentions, surpassing less comprehensive options (Pei et al., 2014; Ahsan & Rahman, 2022).

eWOM and Online Product Reviews: The stupendous increase in the availability of competing products and overloaded information creates a dilemma for customers when making purchase decisions. With the convergence of physical and virtual marketplaces, eWOM communication has evolved in many forms, such as reviews or opinions on e-commerce sites (Amazon), review sites (TripAdvisor), blogs (bloggers.com), videos (YouTube) or likes and comments on social networking sites (Facebook, Twitter) (Cheung and Thadani, 2012). A large body of literature demonstrated that customer reviews are among the most influential factors affecting consumer online shopping decisions (Chen et al., 2008; Duan et al., 2008; Engler et al., 2015). The e-commerce sites like Amazon.com offer consumer platforms to post reviews, opinions and experiences with the purchased goods, which in turn attract more customers (Cao et al., 2011). The significant influence of OPRs over the performance of the retailers is reported by several studies (Chen et al., 2008; Chevalier and Mayzlin, 2006; Clemons et al., 2006; Ghose and Ipeirotis, 2006), which contradicts the negligible effect reported by some studies (Chen, Wu, and Yoon, 2004; Duan, Gu, and Whinston, 2008), or uncertain (Eliashberg and Shugan, 1997), or depends on context (Chatterjee, 2001; Li and Hitt, 2008). Important features include the number of reviews (the total reviews accumulated by a product; Lu et al., 2013; Cheung and Thadani, 2012), sentiment or valence (the overall positive or negative tone), star ratings, extremity of reviews (the degree of positivity or negativity), recency and sequence (Kaushik et al., 2018), reviewer credibility, identity disclosure, trustworthiness, and homophily between readers and reviewers. Many studies focus on how one or a few of these features influence consumer outcomes, such as how review valence and volume affect sales or purchase intentions (Chen et al., 2022), or how reviewer expertise and disclosed identity impact perceived review helpfulness. Volume, for example, refers to the quantity of reviews a product has received (Lu et al., 2013) and serves as a potential proxy for sales where actual data is unavailable (Chen et al., 2004) and provides social proof of a product's popularity (Park & Lee, 2007) and reliability. It influences satisfaction, and product selection acts moderator (Anastasiei and Dospinescu, 2019). Nonetheless, quantity remains significant; it boosts consumer confidence and correlates positively with sales (Babic Rosario et al., 2016; Berger et al., 2010). *Valence:* The sentiment tone (positive, negative, or neutral) steers consumer attitudes directly. Predominantly positive reviews strengthen positive perceptions and purchase intentions, while negative ones, particularly in volume or extremity, can sharply deter sales (Chen et al., 2022; Li et al., 2020; Chua & Banerjee, 2014). Importantly, valence interacts with volume: high positive sentiment gains more influence when backed by a substantial number of reviews.

Amazon and similar platforms embed a "helpful" voting mechanism to foster trust and credibility. Helpfulness votes are treated as a community consensus on review quality, acting as both a marker for other users and a predictor of product sales (Kaushik et al., 2018; Park & Lee, 2009). Characteristics that boost helpfulness include review depth, clarity, and moderate (not extreme) sentiment, as well as reviewer identity and credibility (Mudambi & Schuff, 2010; Korfiatis et al., 2012; Yin et al., 2016; Fan et al., 2019; Deng et al., 2020; Tseng et al., 2023). In general, the helpful vote count is considered an outcome of various review features, as it is the culmination of how content and source factors are perceived by the community.

Review Timing and Sequence

Review timing, measured by the number of days since the review was posted(Hu et al., 2008), exerts a complex influence: older reviews may accrue more helpful votes, but recency can also increase perceived relevance (Salehan& Kim, 2016; Cao et al., 2011).

The sequence of display: According to the belief adjustment model (Hogarth and Einhorn, 1992), the sequence of reviews may also play a vital role in the user's decision-making process. It is about understanding whether most helpful versus most recent—can meaningfully impact purchase decisions, especially when displaying a mix of positive and negative feedback (Hu et al., 2014; Kaushik et al., 2018; Hogarth & Einhorn, 1992).

Review balance, defined by the ratio of positive to negative reviews, shapes interpretative context and is increasingly recognised as pivotal (Purnawirawan et al., 2012; Kaushik et al., 2018). The identity of the reviewer—signalled through profile details or images—serves as a vital source credibility cue. In the context of amazon.in, a profile image of the reviewer (if present) serves as an identity cue. Identity disclosure is positively associated with trust and perceived utility of the review (Forman et al., 2008; Karimi & Wang, 2017; Liu & Park, 2015).

Reviewer Expertise and Trustworthiness

Reviewer expertise, measured by activity metrics or platform badges (e.g., "Top 50 Reviewer", presently non-existent on Amazon India). Whereas reviewer trustworthiness, signalled by community validation, both amplify review credibility (Xu, 2014). In Amazon's case, some profiles display a "helpful reviewer" rank or heart icons received for their reviews, indicating that the prospective consumers find the reviewer's contributions valuable. The reviews offered by credible, identifiable sources or established "helpful" reviewers tend to be especially persuasive, reinforcing the classic dual dimensions of source credibility in communication theory.

Research Gap

Although there is a rich literature available on online product reviews, some important gaps remain unaddressed, especially in the context of emerging markets like India. Most of the existing studies have analysed single review characteristics or a limited set of variables. It has been observed that most prior studies were focused on Western countries, and limited attention has been given to emerging markets such as India, where e-commerce is booming. The adoption patterns, cultural factors, and consumer behaviour may differ significantly from those observed in other geographical locations; thus, an understanding of the review system in emerging countries is required. Additionally, it has been observed that most prior studies focused on experimental or specific or limited review characteristics rather than a comprehensive analysis of a larger range of factors. The current study intends to address these gaps by employing a comprehensive factor analysis to analyse the underlying dimensions of online product reviews using a dataset of 4900 reviews from 49 products from the Indian e-commerce market, and provide a more holistic view of the online product review construct, and contribute a novel perspective to the literature on online consumer reviews. By addressing this gap, the current study aims to offer deeper insights into the determinants of online reviews and their collective influence on consumer behaviour.

3 Research Methodology

The current study aimed to investigate the determinants of online product reviews. It examined the intricate interplay of OPR determinants, influencing consumer perception and information mechanisms concerning online reviews. The study is focused on one e-commerce platform, *Amazon. in*, to control for platform-specific effects, which maintains the validity of the research. Additionally, the study examines three different best-selling product categories to enhance the generalizability of the findings across diverse product types.

Data Collection and Sampling

Platform Selection:amazon.inhas been selected as the data source for this study due to its dominant position in the Indian e-commerce market and the richness of its review system. Amazon India emerges as a market leader with more than 3.2 million online shoppers holding 35% market share in 2022 and over 345 million shoppers in 2023 (Statista, 2022a, 2022b, 2023a). These reports attest to the promising potential of the Indian e-commerce market. The review system of the platform is widely recognised as fair and transparent due to its complex algorithms, offering multidimensional information such as textual content, ratings, reviewer characteristics, and helpful votes. Its standardised review format across categories ensures consistency in data collection and facilitates comparative analysis. Its significance in shaping Indian consumer behaviour and bridging global and local market practices further supports its suitability for online review research. research.

Product Category Selection: A multistage sampling technique was employed to ensure a robust and representative dataset. The study focused on best-selling products within categories selected for their role in mitigating perceived consumer risk and classified according to return policies. Following Shiprocket (2020), three categories were identified: Beauty (high risk, non-returnable), Electronics (medium risk, replaceable), and Fashion (low risk, returnable). From each category, the top 100 products were extracted using Amazon Best Seller Rank (BSR) along with their Amazon Standard Identification Numbers (ASINs), resulting in an initial pool of 300 products. Subcategories were refined to include skin and hair care in Beauty, all electronic goods in Electronics, and clothing and accessories in Fashion. Products were further classified by lifecycle stage (new or mature) and price segment (low or high). The final sample comprised 59 best-selling products, yielding 5,900 consumer reviews for analysis.

Data Assessment and Cleaning:

The data was assessed and cleaned to ensure data quality and suitability for the factor analysis. Firstly, reviews were screened for completeness, where incomplete or corrupted entries were removed from the data. No missing values were observed in the data set. Secondly, the data was analysed for outliers, resulting in a final dataset of 4900 reviews extracted from 49 products after excluding 10 outliers.

Understanding of the Data Metrics: The study analysed seven different dimensions of the OPRs.*Volume:* Review volume, commonly researched as *Volume* by various studies, is determined by the total number of reviews. *Helpful vote count*: A helpful vote count has been considered an important indicator of helpfulness or usefulness of the review,measured by the

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number of "*helpful thumbs up*" received at the end of the review message.*Visual cue*: A visual cue is represented by images or videos embedded in reviews, which can enhance the credibility and persuasiveness of the reviewer's feedback. *Valence:*Valence reflects the sentiment of the reviews, measured by the number of star ratings on a scale of 1 to 5.Reviewer trustworthiness: Reviewer trustworthiness can be inferred from the number of positive endorsements in the form of "hearts" a reviewer has received on their profile. *Reviewer Identity disclosure*: The presence of a reviewer's profile picture enhances their credibility by fostering a sense of personal connection and accountability.*Reviewer expertise:* The number of reviews written by a reviewer serves as a tangible indicator of their experience and knowledge in a particular product or service category.

Understanding of Tools and Methods Used: For the sampling purpose, the study used ***Keepa price tracker*** to extract the 180-day average price for the products on Amazon India. Further, products were chosen based on brand age to compile a comprehensive list of 59 products. To extract 5900 online product review determinants, web scraping was done *using* ***Python*** as the programming language to scrape the review data from Amazon. For the analysis, Exploratory factor analysis was performed using IBM SPSS 22 (Statistical Package for the Social Sciences).

4. Data Analysis and Findings

The study aims to examine the determinants of online product reviews and their complex interplay in influencing customers' buying decisions. *Primarily*, the descriptive statistics were computed. Further, to uncover the determinants of online products, the study employed EFA using IBM SPSS 22 (Statistical Package for the Social Sciences). EFA was found to be appropriate as the study seeks to *explore* the latent structure of the online product reviews.

Descriptive Analysis:

Descriptive statistical analysis was employed on the final dataset of 4,900 reviews from 49 products (excluding 10 outliers) sourced from the top three best-selling categories from Amazon. in.

Table 1 Descriptive Statistics

	Mean	Std. Deviation	Analysis N
Volume	17410.1224	17265.34075	49
Reviewer_ID	.1827	.07091	49
Reviewer_expertise	8.0394	1.76942	49
Reviewer_trust	10.7898	11.28500	49
Helpful_vote	.8794	.94356	49
Visual_cues	.1659	.09390	49
Valence	4.0449	.26146	49

The descriptive statistics presented in Table 1 confirm the absence of missing values, indicating the completeness and ensuring unbiased factor solutions (Little & Rubin, 2019). The analysis revealed several important characteristics of online product reviews on Amazon. in.The volume varied considerably (M = 17,410.12; SD = 17,265.34), consistent with products at different life-cycle stages and levels of market adoption. The mean value of 0.18 indicated that only 18% of reviewers disclosed their identity. On average, reviewers contributed 8.04 reviews, suggesting a reasonably consistentcontributor base. *Reviewer Trustworthiness*, measured through peer endorsement, showed high variability (M = 10.79; SD = 11.29), highlighting significant differences across products and categories.Reviews received an average of 0.88 helpful votes, signalling modest peer acknowledgement. Approximately 17% of reviews contained images or videos (M = 0.17), pointing to the presence of multimodal content in consumer feedback. Valence (star rating) reflected a generally positive orientation with low dispersion (SD = 0.26), typical of best-selling products that have achieved market acceptance (Hu et al., 2017).

Communalities Analysis

Table 2 Communalities for Factor Extraction

	Initial	Extraction
Volume	1.000	**.639**
Reviewer_ID	1.000	**.628**
Reviewer_expertise	1.000	**.865**
Reviewer_trust	1.000	**.559**
Helpful_vote	1.000	**.869**
Visual_cues	1.000	**.535**
Valence	1.000	**.518**

Extraction Method: Principal Component Analysis.

Table2 shows the communalities before and after extraction, using Principal Component Analysis. The extracted communalities are above 0.50, which makes it fit for further analysis (Hair and Black, 2013). The *helpful vote count* displayed the highest communality (**.869),** followed by reviewer **expertise (0.865)**, thus suggesting that helpful vote count and quantity of reviews written by the reviewer are important variables having a strong relation to the underlying structure of OPRs. The communalities of all the other dimensions vary from 0.639 to 0.518, which exceeds the commonly accepted threshold of 0.50 for inclusion in the factor analysis. These findings suggest a meaningful contribution to the underlying structure of OPRs.

Factor Extraction and Eigenvalue Analysis

Table 3 Total variance explained: EFA

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2.332	33.308	33.308	2.332	**33.308**	33.308	1.890	**26.997**	26.997
2	1.187	16.956	50.265	1.187	**16.956**	50.265	1.611	**23.017**	50.015
3	1.094	15.634	65.899	1.094	**15.634**	65.899	1.112	**15.884**	**65.899**
4	.927	13.237	79.135						
5	.726	10.368	89.503						
6	.525	7.506	97.009						
7	.209	2.991	100.00						

Extraction Method: Principal Component Analysis.

The eigenvalue analysis (Table 3) used Principal Component Analysis (PCA), which reduced seven review variables to three factors with eigenvalues above 1 (Kaiser criterion) The first factor with the highest eigenvalue (1.89) accounted for 26.99% of the total variance explained after rotation. The substantial eigenvalue indicated that the first factor denotes the core dimension of OPRs, which is crucial for understanding consumer buying behaviour.Factor 2 (eigenvalue 1.18) with 23.01% and Factor 3(eigenvalue 1.09) with 15.88%. Collectively, these three factors explained 65.90% of the total variance, exceeding the minimum acceptable threshold of 60% in social science research (Field, 2013; Hair et al., 2010; Malhotra & Dash, 2016), confirming factor adequacy and validity. The remaining four factors, with eigenvalues below 1, were excluded.

Factor Rotation and Interpretation

Table 4 Rotated Component Matrix[a]

	Component		
	1	2	3
Reviewer_expertise	**0.898**	0.187	-0.151

Visual_cues	**-0.731**	0.025	0.009
Reviewer_trust	**0.639**	0.217	0.322
Volume	-0.061	**0.789**	0.116
Valence	0.151	**0.699**	0.086
Reviewer_ID	0.336	**0.645**	-0.314
Helpful _vote	0.026	0.049	**0.931**

Extraction Method: Principal Component Analysis.

Rotation Method: Varimax with Kaiser Normalization.[a]

a. Rotation converged in 4 iterations.

Orthogonal rotation using the *Varimax* method was employed to refine the initial factor loadings, making them more coherent.Table 4 represents the components clustered into three groupings defined by the highest loading on each variable. The rotated factors showed better interpretability, with variables showing stronger loadings on one factor and reduced cross-loadings on other factors. Factor 1 is characterised by a high positive loading for 'reviewer expertise' (.898), 'reviewer trustworthiness'(.639), and an intriguing finding of substantial negative loading for 'visual cues' (-.731). Factor 2 shows strong loadings on *Review Volume* (0.789), *Review Valence* (0.699), and *Reviewer Identity* (0.645). Factor 3 is dominated by a single variable: helpful vote count with a very high loading of 0.931 on the corresponding factor. Additionally, a visual scree plot method was also employed.

Figure 1Component plot of the OPR factors in rotated space

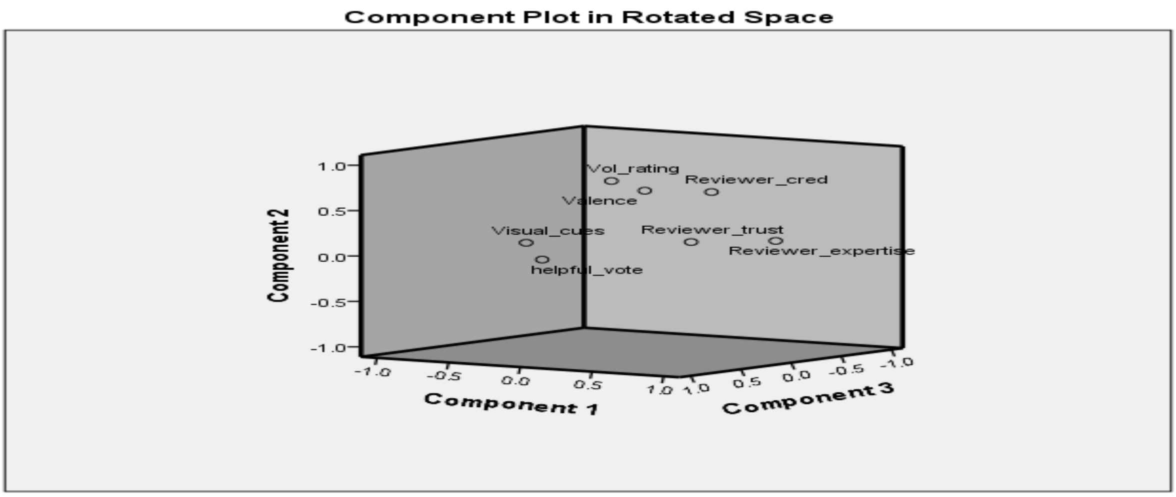

Figure 1 shows the visualised scree plot for rotated factor analysis, which confirms the findings of the rotated component matrix (Table 4).

***Factor scoring and naming**:* For this analysis, the Anderson-Rubin method has been used to save the factor scores (due to orthogonal factor scores). Further, each factor was assigned a label to capture the essence of the constituent determinants aptly, guided by previous literature and researchers' logic (Table 5).

TABLE 5 Labelling the factors		
Factor	**Components with loadings**	**Label/ Name**
FACTOR1	Reviewer Expertise (.898) Reviewer Trustworthiness (.639) Visual Cues (-731)	*Credibility*
FACTOR 2	Volume (.789) Valence (.699) Reviewer identity (.645)	*Salience*
FACTOR3	Helpful Vote Count (.931)	*Usefulness*

5. Discussion and Conclusion:

The current study provides comprehensive insights into the underlying dimensional structure of online product reviews. The exploratory factor analysis of 4,900 reviews from 49 bestselling products on Amazon. in resulted in three distinct factors of OPRs: *Review Credibility (Factor 1), Review Salience (Factor 2), and Review Usefulness (Factor 3)*. The descriptive statistical analysis reports data completeness, ensuring unbiased and reliable factor solution and highlighting key patterns in review characteristics (Little & Rubin, 2019). The large variation in review volume reflects heterogeneity in product maturity and adoption, while the low value of identity disclosures (18%) emphasises the consumer privacy concerns and platform norms that facilitate anonymity (Tadelis, 2016). At the same time, the presence of a consistent reviewer expertise (M = 8.04 reviews per contributor) provides stability in review credibility, even as peer-endorsed trustworthiness varies considerably across products and categories. Furthermore, the substantially high helpful vote counts and the limited use of visual cues (17%) indicate opportunities for platforms to promote peer endorsements and consumer-generated images (CGIs) (Purnawirawan et al., 2012). The overall positive sentiment orientation, with minimal variance, reflects consumer satisfaction with market-accepted best-selling products (Hu et al., 2017). Collectively, these patterns emphasise the multidimensionality of reviewer behaviour (identity disclosure, expertise, trustworthiness), along with review content variables (valence, volume, helpful vote count, and visual cues) which shape perceptions of review effectiveness and provide a strong empirical basis for subsequent factor analysis.

These three factors explain 66% of the total variance in online review characteristics, which substantiates a robust representation of the latent construct and affirms the adequacy of factor retention. The findings reflect that Factor 1 captures a core dimension of OPRs (27% of total variance explained), which is crucial to understanding consumer perception and buying behaviour. The other two factors collectively account for 39% of total variance explained, indicating that the reviewer and prospective buyers do not judge the OPR based on a single dimension. These findings validate that online buyers form an opinion based on the core dimensions of OPRs before making a purchase decision. The study suggests that online buyers do not judge OPRs based on a single dimension but instead pay attention to various aspects of OPRs. Within the Indian e-commerce landscape, the growing trust of consumers and the increasing acceptance of platforms such as Amazon have accentuated the importance of OPRs as a crucial determinant of buying decisions.

Factor 1: *Credibility*: The analysis displayed a high positive loading for 'reviewer expertise' (.898), 'reviewer trustworthiness' (.639), and an intriguing finding of substantial negative loading for 'visual cues' (-.731). 'Credibility' projecting a dimension related to the believability and trustworthiness of the review source and content presentation format, capturing the idea that reviews written by more expert, trusted reviewers tend not to rely on images.

The high loading of Reviewer expertise indicates that it is the primary indicator of the factor. It suggests that consumers are influenced by the experience or knowledge demonstrated by reviewers while making a purchase decision. Reviewer expertise can be observed through different cues on the reviewer's profile (Lo & Yao, 2019). Cues, such as the number of reviews written by the reviewer (Cheung et al., 2008; Cox et al., 2009; Gretzel et al., 2007; Lee et al., 2011). Some studies have signified the importance of the level of *badges gained by the reviewer* (*Baek* et al., 2012), such as the *Top Reviewer badge*, *the Hall of Fame* (amazon.uk) platform-generated review ranking system, to acknowledge the expert reviewers. The importance of the reviewer ranking system has been highlighted by certain studies, where it affects the conditioning of the prospective customer's opinion and consequently their buying decisions (Huang et al, 2015; Wang et al, 2019; Wu, 2019). Such tags enhance the credibility of the reviewer's profile, but this system is absent on amazon.in. Apart from these heuristic cues, reviewer expertise is defined as a reviewer's ability to understand product attributes and to process & display product information. In his study, O' Connor (2008) had pointed out that the number of reviews written by an individual is the most important factor to evaluate the credibility of online reviews.

Additionally, '*reviewer trustworthiness'* displays moderate to high loading (.639) on Factor 1, reinforcing the credibility dimension of the reviews by suggesting that peer endorsements trust indicators (hearts on the reviewer's profile) significantly contribute to making the review impactful.*Reviewer trustworthiness is described as "the extent to which the review-writer can be trusted"(*Mayer, 1995; Dong et al., 2019). In the absence of prior interactions and familiarity with the source, it makes it difficult for consumers to assess the trustworthiness of the message. Certain indicators may be helpful to minimise uncertainty. This may build a bond between the source and prospective buyer, which may further facilitate the latter in his decision-making by building trust. Park et al. (2014) suggested that such indicators on the profile characteristics of the reviewer may reinforce trust in the reviewer. Hence, reviewer-trustworthiness is an antecedent of trust under consumer review (Colquitt et al., 2007). Even in their study (Banerjee et al.,2017) suggested that prospective consumer trusts the reviewer before they accept the content of OPR.

Collectively, '*reviewer trustworthiness'* and '*reviewer expertise'* highlight the relevance and importance of source credibility, which aligns with the Information Adoption Model (IAM; Sussman &Siegal, 2003) and prior studies(Forman et al.,2008; Cheung & Thadani, 2012; Chakraborty & Bhat, 2017; Chih et al., 2013; Mumuni et al., 2019; Mumuni et al., 2020; Reyes et al., 2019; Shan, 2016; Pooja &Upadhya, 2022; Racherla et al., 2012; Baek et al., 2012). Interestingly, the substantial negative loading of *visual cues* suggests an inverse relationship within the factor. This finding aligns with recent studies (Guan et al, 2023; Guan, 2019; Nazlan et al., 2018; An, Ma, Du, Xiang, & Fan, 2020), indicating a negative relationship between visual cues and review effectiveness. These studies have indicated that under certain circumstances, the presence of visual cues may exert a negative influence on the consumer's decision-making process. These findings contradict the intuitive and conventional understanding ofprior studies have shown that the presence of Visual cues enhances the perceived credibility and richness of online reviews by serving as a cue for strong engagement on behalf of reviewers (King et al., 2014; Davis &Khazanchi, 2008) for sceptical customers who do not trust product images created by the marketer due to the fixed format of presentation(Goh et al., 2013) in contrast to customer generated images(CGIs). Whereas the combination of CGIs and user-generated content makes them more impactful than the review content alone (Wang et al., 2016). These studies suggest that the presence of images enhances the significance of experience sharing and increases the persuasive power of reviews, thereby reinforcing the credibility of the information source (Herr, Kardes, & Kim, 1991). These counterintuitive findings of the current study can be attributed to the information processing perspective, subjectivity and selection bias. Firstly, visual cues may contribute to information overload and distract customers' cognitive information processingand thereby be detrimental to decision quality. Guided by the ELM model, Guan (2019) indicated that the presence of videos or images may enhance the expectation of the consumers, which may lead to post-purchase dissonance. Instead of aiding understanding, the presence of visual cues may divert attention and distract potential customers from more critical textual details in the reviews (Guan et al, 2019).*Secondly,*the presence of visual cues may lead to an inaccurate interpretation of reviews due to inherent subjectivity and potential bias embedded in visual cues. Unlike objective textual content, images or videos are more prone to personalised interpretation. It has been observed that reviewers with a positive experience are more likely to post images or videos (An et al., 2020). This supports the reason for subjectivity in reviews, contributing to selection bias. Satisfied customers are more likely to post images or videos; however, this tendency may not accurately represent overall reviews due to the subjectivity of the reviewer (An et al., 2020; Nazlan et al., 2018; Guan et al., 2023; Sun & Yang, 2023). Furthermore, the prospective customers may perceive the inclusion of visual cues as unnecessary, ambiguous or even misleading. According to prior studies, eWOM is considered credible if the reviews or the content are believed to be factual, accurate, believable and persuasive (Fogg et al., 2001; Tseng & Fogg, 1999; Cheung et al., 2009; Dong et al., 2019), perceived as authentic rather than its objective veracity (Erkan & Evans, 2016).

Based on the findings, the Information Adoption Model(IAM) given by Sussman & Siegal(2003), prior literature suggests that the most common operationalisation of review credibility is conceptualised by taking into consideration two source characteristics: reviewer expertise (Anastasiei et al. 2021; Fang 2014; Fang and Li 2016; Jha and Shah 2021) and reviewer trustworthiness (Chakraborty & Bhat, 2018; Cheung et al., 2012; Chih et al., 2013; Mumuni et al., 2019; Reyes-Menendez et al., 2019; Shan, 2016). Cheung and Thadani (2012) defined source credibility as perceived knowledge or competence of the message source, which is one of the primary determinants of consumers' perception of response to online reviews.

These findings get support from the most popular theories in review credibility literature, such as The Elaboration Likelihood Model (ELM), social influence theory, accessibility- diagnosticity theory, attribution theory and theory of reasoned action. (Pooja &Upadhya 2022).

Collectively, these theories signify that review credibility is a multifaceted construct, deeply intertwined with both source attributes and consumer cognitive evaluation processes. These insights provide a conceptual foundation for examining how consumers interpret reviews and how certain review features (such as visual content and reviewer trust signals) may serve as proxies for credibility in online marketplaces like Amazon India. Review credibility plays a crucial role in determining the effect of reviews in the decision-making process, as consumers often rely on the credibility cues to assess the value of the reviews (Cheung et al., 2012; Hsieh & Li, 2020). Consumers consider reviewer expertise, reputation and embedding visual cues contribute toward the perception of consumers for reviewers' authenticity and usefulness (Pooja& Upadhyaya, 2022). It has been observed that credible reviews have a greater impact on customers' perceptions and purchase intention towards the product (Mackiewicz, 2010). Thus, the credibility of reviews is a crucial dimension of OPRs, which is paramount in consumer decision-making.

Factor 2: Salience: Salience shows strong loadings on *Review Volume* (0.789), *Review Valence* (0.699), and *Reviewer Identity* (0.645). This factor represents a group of features implying the *prominence or visibility* of the product reviews. The accessibility and diagnostic theory emphasise the importance of readily available informative inputs (Pooja and Upadhya, 2022). These determinants of Review salience make reviews more noticeable and captivating (Purnawirawan et al., 2012; Lynch Jr &Srull, 1982).

High loading of volume reflects the importance of quantity, which is an indicator of product popularity and market acceptance. This observation aligns with the foundations of Social Proofing Theory, which suggests that consumers are inclined to conform to the actions of others, particularly in uncertain conditions (Cialdini, 2007).Valence indicates the prevailing opinion (positive or negative sentiment) in the form of aggregated star ratings. Very often, consumers quickly scan the star ratings to form an initial impression, thereby augmenting the salience of their associated reviews.Identity disclosure implies that reviewers are not anonymous. Together, they project *high visibility and resonance* for products that have quantifiable reviews, clear sentiment, and identifiable reviewers, potentially making the feedback more trustworthy at first glance. These three determinants collate a comprehensive measure of review prominence and visibility that influences consumer attention and thus accentuates trust in the product (Zaman et al., 2023), which aligns with the theory of information salience (Hamilton & Fallot, 1974). Thereby, factor 2 is labelled as 's*alience*'. The current study reinforces the importance of salience documented by previous literature (Huang et al, 2018). Thus, the study reports that salience draws the attention of potential customers and affects the evaluation of review effectiveness.

Factor 3: Usefulness is interpreted as a single measure of perceived usefulness or utility to the reader. It is worth noting that helpful votes could be considered an outcome of other variables. The number of *Helpful votes* provides social cues and peer endorsement, suggesting that a particular review has been useful to the prospect user before making a decision. It measures the collective peer endorsement of review utility by other prospective users and accentuates the role of social validation to enhance the functional value of OPR. The findings emphasise the complex and multidimensional nature of online review systems while providing a clear and actionable framework for future research and practical applications. The high vote count warrants the review to be useful, informative and practical. It mitigates the limitation of information overload and facilitates quick and informative decisions for prospective buyers.

Theoretical Contributions: ***Advancement in eWOM Literature***

The study resulted in the identification of three distinct factors providing empirical support for the multidimensional nature of OPRs, which challenge the approaches with a focus on single review characteristics. The independence of the three factors suggests that consumers employ different cognitive and social processes.

'Credibility' strengthens the source credibility theory, showing that source expertise and trustworthiness collectively shape review effectiveness. The negative association between visual cues and 'credibility' challenges the existing multimodal benefits, aligning with the contradicting findings of recent studies. These findings contribute to the review credibility literature by highlighting the complex interplay of content and source-based review dimensions. The findings of '*salience'* reinforce Information-Processing, Information Overload theories and literature by highlighting the paramount importance of prominence, visibility and resonance influential in consumers' decision-making processes. The emergence of *'Usefulness'* as a single dimension in the factor analysis distinguishes it as a clear measure of perceived review utility, supporting social proofing theory and cognitive bases by exemplifying the social validation system that arises from peer recommendations and endorsements. These findings contribute to the **Accessibility and Diagnosticity Theory**(Feldman & Lynch, 1988; Herr et al., 1991; Pooja & Upadhya,

2022),which emphasises the significance of readily available and informative inputs in shaping consumer attitude and purchase intentions (Cheung et al., 2009; Filieri, 2015; Erkan & Evans, 2016).It measured the collective peer endorsement of review utility by other prospective users and accentuates the role of social validation to enhance the functional value of OPR.

Collectively, these findings extend the theories of online consumer behaviour. Methodologically, the utility and validation of Exploratory factor analysis for uncovering the latent structure in OPRs is recommended.

Practical Contribution:

e-commerce platform: The findings emphasise the need to design algorithms that integrate multiple review dimensions reflecting credibility, salience, and usefulness, to enhance the effectiveness.

The study recommends a *reviewer ranking system,* as highlighted on Amazon UK, which distinguishes the top reviewer via the Hall of Fame or top reviewer rank, can reinforce trust by recognising expertise and rewarding valuable contributions.

The findings of the current study are interpreted within the specific socio-cultural and digital environment of Amazon India and thus contribute to the broader Indian e-commerce landscape also. In collectivist cultures like India, cues like peer endorsements, reviewer identity disclosure are particularly salient (Chakraborty & Bhat, 2018; Hofstede, 2001). The '*Brandwagon effect*' of high review volume, helpful vote count, and positive valence illustrates the stronger role of social validation in such markets.

Future Research Recommendations:

Future studies should examine the impact of OPRs on sales performance and explore the role of other market determinants. Longitudinal research can assess the stability of identified factors over time, while cross-platform studies may provide deeper insights. Emerging technologies, such as artificial intelligence (AI) and machine learning, can enhance online reviews analysis through advanced sentiment analysis, topic modelling and content. The three factors proposed in the study offer a direction for ongoing research to understand the evolving role of the OPRs in shaping online consumer behaviour.

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