ISSN No: 2349-512X
Peer Reviewed & Refereed Journal (IF: 6.95)
Journal Website www.nrjsmm.in

# UNDERSTANDING THE MOTIVATIONAL DRIVERS FOR READING ONLINE REVIEWS AMONG GEN Z: A FACTOR ANALYTIC APPROACH

**Yashu**

Research Scholar, Mittal School of Business, Lovely Professional University, Punjab, India

**Krishan Gopal**

Associate Professor, Mittal School of Business, Lovely Professional University, Punjab, India

## ABSTRACT

In today's digital marketplace, online reviews play a pivotal role in shaping consumer decision-making. This study investigates the motivational drivers behind Gen Z consumers' engagement with online reviews**,** focusing on individuals born between 1995 and 2012. Despite the growing relevance of this consumer segment, limited research has examined their review-reading motivations through structured statistical methods. This study addresses that gap by employing Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA) to identify and validate key motivational constructs. A total of 350 valid responses were collected from Gen Z consumers across three populous districts in Punjab using purposive sampling. Data were analyzed using SPSS and Smart PLS (CB-SEM). The findings reveal multiple underlying motivational factors such as risk reduction, Product information and right product choice which significantly influence Gen Z's engagement with online reviews. The results provide valuable insights for marketers and e-commerce platforms to better align their digital review strategies with the preferences and expectations of Gen Z consumers.

**Keywords:** Gen Z, Online Reviews, Exploratory Factor Analysis, Confirmatory Factor Analysis, Motivation, Digital natives

## 1. INTRODUCTION

In the digital age, online reviews have become a critical component of the consumer decision-making process. From product quality to service satisfaction, reviews offer firsthand experiences and insights that significantly influence purchase intentions (Chen et al., 2022). Among the various consumer segments, Generation Z (Gen Z) individuals born between the mid-1990s and early 2010s—stands out due to its high digital literacy and reliance on peer-generated content. As digital natives, Gen Z consumers frequently consult online reviews before making buying decisions, making it essential to understand the underlying motivations driving this behavior (Jayatissa et al., 2023). Despite the abundance of literature on online consumer behavior, there is a notable gap in research that specifically explores why Gen Z reads online reviews (Perez et al., 2024)**.** While some studies have addressed general motivations such as information-seeking, trust-building, and risk reduction, few have examined these factors through a structured and empirical lens tailored to Gen Z's unique behavioral patterns (Harahap et al., 2023). To bridge this gap, the present study employs a factor analytic approach**,** utilizing both Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA) to identify and validate the key motivational dimensions that drive Gen Z consumers to engage with online reviews. This methodological framework allows for the identification of latent constructs and provides robust validation, offering deeper insights into the psychological and behavioral tendencies of this influential consumer segment. By

ISSN No: 2349-512X
Peer Reviewed & Refereed Journal (IF: 6.95)
Journal Website www.nrjsmm.in

uncovering these motivational drivers, the study aims to contribute to the fields of consumer behavior, digital marketing, and e-commerce strategy, helping brands and marketers better align their review systems and content strategies with Gen Z's preferences and expectations.

## 2. REVIEW OF LITERATURE

The motives that drive individuals to engage with online communication are closely tied to their behaviors, indicating that these motivations are strong predictors of how they respond to online feedback (Buchanan & Tullock, 1977). Typically, when consumers seek information about a product, they start by drawing from internal sources, such as their own past experiences or recollections. After utilizing these internal resources, they turn to external information like advertisements, catalogs, or media articles (Bell et al., 2019; Olshavsky, 1979). Research suggests that services are often viewed as more risky than tangible products due to their intangible characteristics (Davis et al., 1979; Sparks & Browning, 2010). The ease of use of the internet makes it simple for consumers to search for and compare products, as they can conveniently access this information from home, work, or other locations (Bell et al., 2019). Additionally, advertisements on television can motivate consumers to seek further information online. According to (Hennig-Thurau et al., 2007) Hennig-Thurau and Walsh, the motives behind reading online reviews plays a key role in shaping consumer behavior. Study found that many consumers turn to online reviews primarily to save time and make more informed purchasing choices (Hennig-Thurau et al., 2007; G. Walsh et al., 2010). To assess how virtual opinion platforms influence consumer choices, it is important to understand the motivations behind why consumers seek information from these resources. Motives are the "general drivers that direct a consumer's behavior toward attaining his or her needs". “Motives are needs or desires that cause a person to act and are a significant determinant of consumer behavior” (Ziegele & Weber, 2015). From an academic perspective, it is essential to address the questions: “Who writes online reviews?” and “What drives individuals to write, seek out, and share online reviews?” “Why consumers read others comments on virtual opinion platforms?” The study’s (Schuckert et al., 2015) findings suggest that when consumers experience superior product performance—such as high-quality, reliable, and durable items—and receive satisfying interactions with company employees, they are more likely to engage in positive word-of-mouth. Conversely, unresolved issues tend to drive consumers to spread negative word of mouth. Consumers frequently post online comments about their experiences and may ask for advice from others to resolve their problems (Ziegele & Weber, 2015). In summary, (Hennig-Thurau et al., 2003; Sparks & Browning, 2010) studies found that consumers primarily read electronic word-of-mouth (eWOM) to save time and improve their purchasing decisions. (Oguta & Cezara, 2012) discovered that higher ratings and lower prices encourage customers to write reviews, and complaints about poor experiences also motivate customers to leave, typically negative, reviews. The first motive stems from theories related to risk, where consumers seek reassurance from the experiences of others to make informed purchasing decisions (Wiedmann et al., 2001). This risk-reduction motive suggests that consumers look to the experiences of others to feel confident in their choices regarding a product or service. The second motive revolves around reducing the time spent obtaining a product, driven by the consumer's perception of limited time availability (G. Walsh et al., 2010). The dissonance-reduction motive involves consumers seeking validation of their purchase by reviewing others' experiences with the same product or service after making a purchase. Another key motive, called the determination-of-social-position motive, refers to the desire to compare one’s evaluation of a product or service with the opinions of others. (Schiffman et al., 1951) also identify a set of ‘product-involvement motivations’, where consumers seek to learn how to use a product and discover new products

ISSN No: 2349-512X
Peer Reviewed & Refereed Journal (IF: 6.95)
Journal Website www.nrjsmm.in

on the market. (Goldsmith & Horowitz, 2006) found that 20% of the customer comments in a news group were dedicated to discussing product usage, showing the significance of this motive in online articulations. (Hennig-Thurau et al., 2007) further classified the motivations behind reading and contributing to user-generated reviews into four key categories: (a) risk reduction, (b) reduction of search time, (c) dissonance reduction, and (d) group influence. The risk-reduction motive emphasizes that consumers look to others' experiences to minimize uncertainty in their purchasing decisions (Engelbertink & Van Hullebusch, 2013). The reduction of search time reflects the desire to quickly gather information to make more efficient buying decisions. Dissonance reduction occurs when consumers seek reassurance by reading reviews after making a purchase, helping them feel more confident about their choices (Ziegele & Weber, 2015; G. Walsh et al., 2010). Lastly, group influence highlights the role of social interactions and shared experiences in shaping consumer behavior on these platforms. Together, these four categories provide a comprehensive framework for understanding why user-generated reviews are so widely utilized and valued by consumers (Burton & Khammash, 2010). This framework demonstrates how user-generated content, such as online reviews, has become an essential tool for consumers navigating an increasingly complex and information-saturated marketplace (Ziegele & Weber, 2015; Bell et al., 2019).

## 3. RESEARCH METHODOLOGY

This study utilizes a descriptive approach and a quantitative methodology to collect data from respondents, specifically targeting Gen Z individuals born from 1995 to 2012 who are engaged in online shopping of apparel. Data were collected among three districts of Punjab: Amritsar, Jalandhar and Ludhiana, selected based on their high population density as reported in the Statistical Abstract of Punjab. Purposive sampling was used in data collection. Questionnaires were distributed both in hard copy and via Google Forms through various channels such as WhatsApp, Gmail and LinkedIn. All items were measured by using a five-point Likert scale ranging from ‘strongly disagree’ to ‘strongly agree’. Individuals were allocated five points if they strongly agreed with the statement, four points for agreement, three points for neutrality, two points for disagreement and one point if they strongly disagreed with the statement. Out of a total of 372 responses, 22 questionnaires were excluded due to incomplete data, resulting in 350 responses being valid, which were used in this research article. Data were analysed through SPSS and Smart PLS (CB-SEM). The EFA was conducted using the SPSS software suite, utilizing the principal component analysis as the extraction method and the varimax rotation method was employed. The confirmatory factor analysis was conducted by using the Smart PLS (CB-SEM) software, utilizing the model fit indices, chi-square, degree of freedom, probability value.

## 4. DATA ANALYSIS AND RESULTS

EFA is a statistical method designed to examine the underlying structure of datasets. Developed in the early 20th century to explore whether intelligence is composed of multiple dimensions or a single entity, EFA has since evolved into a widely used method for reducing the dimensionality in diverse fields (M. D. Cooper & Phillips, 2004). EFA is a statistical technique used to analyze correlations among measured data variables. It helps summarize data by extracting essential information using a smaller number of factors to represent the original data, thereby clarifying complex relationships between variables. The primary goal of EFA is to identify potential latent factors or unobserved variables that depend on the measured variables. It ensures sample size adequacy and validates the content of questionnaire items. EFA is particularly valuable because it aims to identify groups of items

ISSN No: 2349-512X
Peer Reviewed & Refereed Journal (IF: 6.95)
Journal Website www.nrjsmm.in

that, when combined, explain the maximum amount of observed covariance. These groups of observed variables are referred to as factors or latent factors (Thompson, 2004).

**4.1 Exploratory Factor Extraction**

Exploratory factor analysis (EFA) consolidates variables that have high factor loadings into distinct latent factors. Factor loadings represent the correlation coefficient between individual variables and their corresponding common factors (Thompson, 2004). The analysis was performed using the principal component factor analysis extraction method. Table 4.1 presents the total variance derived from the factor analysis, including the components, initial eigenvalues, extraction suns of squared loadings, and rotated sums of squared loadings. The percentage of variance column indicates the proportion of the total variance explained by each component expressed as a percentage. The Cumulative% column shows the cumulative percentage of variance explained by the first n components (Polit & Beck, 2008). For instance, the cumulative percentage for the second component is the sum of the percentages of variance accounted for by both the first and second components (M. D. Cooper & Phillips, 2004). In table 4.1 three latent factors was extracted, which showed a total variance of 69.025%. The latent factors with eigen value greater than 1 were extracted through EFA.

The rotated component matrix was utilized to categorize the items. From this matrix, a total of three factors were identified. Only factor loadings with a minimum value of 0.50 or higher were considered (Polit & Beck, 2008). Based on the factor analysis results, the variables were grouped into three dimensions. The table 4.2 presents the three extracted latent factors along with their respective factor loadings after the rotation of the correlation matrix. Each extracted common factor was labeled to reflect its shared and potential characteristics for easier comprehension. Here one very important item M16 (online reviews protect myself from fraudulent schemes) was omitted by EFA as its factor loading was less than 0.50.

**4.2 Confirmatory Factor Analysis**

Confirmatory Factor Analysis was utilized in this study for construct validation to investigate the relationships between variables associated with the motives for reading online reviews. In this section confirmatory factor analysis performed with the CB-SEM. It is often considered more user-friendly compared to other programs like AMOS, LISREL and Mplus. Confirmatory Factor Analysis (CFA) offers straightforward, step-by-step guidance The 'p' value is significant at the 1% level. Seven items load onto the factor of right product choice, five items onto the factor of product information, and three items onto the factor of risk reduction. CFA model is evaluated using various model fit indices, including Chi-square, Goodness of Fit Index, Adjusted Goodness of Fit Index, Normal Fit Index, Tucker Lewis Index, Comparative Fit Index, Root Mean Square Residual, and Root Mean Square Error of Approximation. According to (L.-T. Hu & Bentler, 1995), a satisfactory model fit is indicated by Comparative Fit Index (CFI), Tucker Lewis Index (TLI), and (Normal Fit Index) NFI values of 0.90 or higher, with values near 1 representing an excellent fit. For the Root Mean Square Error of Approximation (RMSEA), a value below 0.08 suggests a reasonable fit, while a value below 0.05 indicates a good fit considering the degrees of freedom. The results of the Confirmatory Factor Analysis, as shown in the table 4.3, indicate the following values: chi-square = 258.228, degrees of freedom = 87, p-value = 0.055, chi-square/DF = 2.967, GFI = 0.927, AGFI = 0.962, NFI = 0.928, TLI = 0.941, CFI = 0.951, RMR = 0.066, and RMSEA = 0.068. All these values fall within acceptable limits, suggesting that the model fits the data well.

ISSN No: 2349-512X
Peer Reviewed & Refereed Journal (IF: 6.95)
Journal Website www.nrjsmm.in

## 5. CONCLUSION

According to the exploratory factor analysis results, three distinct factors were identified, highlighting the motivations for Gen Z consumers to read online reviews. the confirmatory factor analysis results indicate that the proposed model fits the data exceptionally well. Results of new findings on the motives to read online reviews by Gen Z consumers reflect the earlier research outcomes, while incorporating the novel insights through detailed analysis. In their earlier studies, authors utilized readers' stories and interviews to identify themes related to reading other consumers' reviews. Author revealed that the motivations behind customers' online interactions are significant predictors of behavioral responses in online communities. Consequently, opinion portal providers should thoroughly examine the motive structures of their communities to effectively manage key interaction elements. This research adopts a qualitative narrative approach to gain a deeper understanding of consumer motivations for reading on online opinion portals (M. Khammash, 2005). Understanding these motivations is crucial for marketers, as it enables them to better manage how eWOM influences consumers' purchasing decisions (Shah & Unnithan, 2020). In the age of technological advancement and the booming of e-commerce industry, online shopping is on the rise, consequently elevating the significance of online reviews. Consumers now prefer to read online reviews over seeking opinions from peers and relatives while making the purchasing decisions. Managers also value online reviews as they provide insights into consumer preferences and sentiments towards the products.

## 6. REFERENCES

1. Bell, C., Clark, V., & Mack, E. (2019). Influential Article Review-Using an Online Approach to Help End-users to Overcome Information Surplus. Journal of Marketing Development and Competitiveness, 13(6).
2. Buchanan, J. M., & Tullock, G. (1977). The expanding public sector: Wagner squared. Public Choice, 147–150.
3. Burton, J., & Khammash, M. (2010). Why do people read reviews posted on consumer-opinion portals? Journal of Marketing Management, 26(3–4), 230–255. https://doi.org/10.1080/02672570903566268
4. Chen, T., Samaranayake, P., Cen, X., Qi, M., & Lan, Y. C. (2022). The impact of online reviews on consumers' purchasing decisions: Evidence from an eye-tracking study. Frontiers in Psychology, 13, 865702
5. Cooper, M. D., & Phillips, R. A. (2004). Exploratory analysis of the safety climate and safety behavior relationship. Journal of Safety Research, 35(5), 497–512.
6. Davis, D. L., Guiltinan, J. P., & Jones, W. H. (1979). Service characteristics, consumer search, and the classification of retail services. Journal of Retailing, 55(3), 3.
7. Engelbertink, A., & Van Hullebusch, S. (2013). The effects of education and income on consumers' motivation to read online hotel reviews. Research in Hospitality Management, 2(1–2), 57–61. https://doi.org/10.1080/22243534.2013.11828292
8. Goldsmith, R. E., & Horowitz, D. (2006). Measuring Motivations for Online Opinion Seeking. Journal of Interactive Advertising, 6(2), 2–14. https://doi.org/10.1080/15252019.2006.10722114
9. Harahap, R. H., Marpaung, N. Z., & Asengbaramae, R. (2023). Consumptive Behaviour of Gen-Z and Identity in the Digital Era. Jurnal Sosiologi Andalas, 9(2), 183-192.

ISSN No: 2349-512X
Peer Reviewed & Refereed Journal (IF: 6.95)
Journal Website www.nrjsmm.in

10. Hennig-Thurau, T., Houston, M. B., & Walsh, G. (2007). Determinants of motion picture box office and profitability: An interrelationship approach. Review of Managerial Science, 1(1), 65–92. https://doi.org/10.1007/s11846-007-0003-9

11. Hu, L.-T., & Bentler, P. M. (1995). Evaluating model fit

12. Jayatissa, K. A. D. U. (2023). Generation Z–A new lifeline: A systematic literature review. Sri Lanka Journal of Social Sciences and Humanities, 3(2).

13. Khammash, M. (2005). Electronic Word-of-Mouth: Motives for reading customer opinions online: Research plan for the UK market.

14. Oguta, H., & Cezara, A. (2012). The factors affecting writing reviews in hotel websites. Procedia-Social and Behavioral Sciences, 58, 980–986.

15. Olshavsky, R. W. (1979). Task complexity and contingent processing in decision making: A replication and extension. Organizational Behavior and Human Performance, 24(3), 300–316.

16. Polit, D. F., & Beck, C. T. (2008). Nursing research: Generating and assessing evidence for nursing practice. Lippincott Williams & Wilkins.

17. Schiffman, L. G., Kanuk, L. L., & Kumar, S. R. (1951). Consumer. Marketing.

18. Schuckert, M., Liu, X., & Law, R. (2015). Hospitality and Tourism Online Reviews: Recent Trends and Future Directions. Journal of Travel & Tourism Marketing, 32(5), 608–621. https://doi.org/10.1080/10548408.2014.933154

19. Shah, C. S., & Unnithan, A. B. (2020). Why People Read Online Reviews: Scale Development to Measure Motivations.

20. Sparks, B. A., & Browning, V. (2010). Complaining in Cyberspace: The Motives and Forms of Hotel Guests' Complaints Online. Journal of Hospitality Marketing & Management, 19(7), 797–818. https://doi.org/10.1080/19368623.2010.508010

21. Thompson, B. (2004). Exploratory and confirmatory factor analysis: Understanding concepts and applications. Washington, DC, 10694(000), 3.

22. Walsh, G., Hennig-Thurau, T., Sassenberg, K., & Bornemann, D. (2010). Does relationship quality matter in e-services? A comparison of online and offline retailing. Journal of Retailing and Consumer Services, 17(2), 130–142.

23. Walsh, V. (2003). A theory of magnitude: Common cortical metrics of time, space and quantity. Trends in Cognitive Sciences, 7(11), 483–488.

24. Wiedmann, K.-P., Walsh, G., & Mitchell, V.-W. (2001). The Mannmaven: An agent for diffusing market information. Journal of Marketing Communications, 7(4), 195–212. https://doi.org/10.1080/13527260127413

25. Ziegele, M., & Weber, M. (2015). Example, please! Comparing the effects of single customer reviews and aggregate review scores on online shoppers' product evaluations. Journal of Consumer Behaviour, 14(2), 103–114. https://doi.org/10.1002/cb.1503

## 7. Tables

### Table 4.1: Total Variance Explained

| Total Variance Explained | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| 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 | 4.468 | 27.924 | 27.924 | 4.468 | 27.924 | 27.924 | 4.335 | 27.093 | 27.093 |
| 2 | 3.812 | 23.827 | 51.751 | 3.812 | 23.827 | 51.751 | 3.874 | 24.211 | 51.304 |
| 3 | 2.764 | 17.274 | 69.025 | 2.764 | 17.274 | 69.025 | 2.835 | 17.720 | 69.025 |
| 4 | .960 | 5.997 | 75.022 | | | | | | |
| 5 | .669 | 4.183 | 79.205 | | | | | | |
| 6 | .511 | 3.196 | 82.401 | | | | | | |
| 7 | .473 | 2.957 | 85.358 | | | | | | |
| 8 | .434 | 2.714 | 88.072 | | | | | | |
| 9 | .375 | 2.343 | 90.415 | | | | | | |
| 10 | .305 | 1.908 | 92.323 | | | | | | |
| 11 | .300 | 1.878 | 94.201 | | | | | | |
| 12 | .252 | 1.575 | 95.775 | | | | | | |
| 13 | .217 | 1.358 | 97.133 | | | | | | |
| 14 | .189 | 1.181 | 98.314 | | | | | | |
| 15 | .164 | 1.025 | 99.339 | | | | | | |
| 16 | .106 | .661 | 100.000 | | | | | | |
| Extraction Method: Principal Component Analysis. | | | | | | | | | |

*Source: SPSS Software*

### Table 4.2: Rotated Component Matrix

| Component Matrix | | | |
|---|---|---|---|
| | Component | | |
| | 1 | 2 | 3 |
| M1 | .796 | | |
| M2 | .812 | | |
| M3 | .713 | | |
| M4 | .839 | | |
| M5 | | .903 | |
| M6 | .852 | | |

ISSN No: 2349-512X
Peer Reviewed & Refereed Journal (IF: 6.95)
Journal Website www.nrjsmm.in

| | | | |
|---|---|---|---|
| **M7** | | .803 | |
| **M8** | .865 | | |
| **M9** | | | .832 |
| **M10** | | | .789 |
| **M11** | | | .838 |
| **M12** | | .903 | |
| **M13** | | .768 | |
| **M14** | .865 | | |
| **M15** | | .837 | |
| **M16** | | | |
| **Extraction Method: Principal Component Analysis.**<br>**Rotated Method: Varimax with Kaiser Normalization.** | | | |
| **a. 3 components extracted.** | | | |

**Table 4.3: Threshold Limits**

| **Indicators** | **Value** | **Recommended Value** |
|---|---|---|
| Chi-Square Value | 258.228 | - |
| DF | 87 | - |
| P Value | 0.055 | >0.05 (Hair et al, 1998) |
| Chi-square value/DF | 2.967 | <5.00 (Hair et al, 1998) |
| GFI | 0.927 | >0.90 (L.-T. Hu & Bentler, 1995) |
| AGFI | 0.962 | >0.90 (Hair et al, 1998) |
| NFI | 0.928 | >0.90 (L.-T. Hu & Bentler, 1995) |
| TLI | 0.941 | >0.90 (L.-T. Hu & Bentler, 1995) |
| CFI | 0.951 | >0.90 (Daire et al., 2008) |
| RMR | 0.066 | <0.08 (Daire et al., 2008) |
| RMSEA | 0.068 | <0.08 (Hair et al. 2006) |