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INVESTIGATING THE IMPACT OF SOCIAL AND PRODUCT OPINIONS ON ONLINE SHOPPING BEHAVIORS

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Abstract
The study investigates the role of eigenvalues, eigenvectors, and summarized social and product review data using advanced software technologies to understand their influence on consumers' purchase intents in social shopping contexts. It examines online shopping behavior based on various factors, including environmental consciousness, socio-economic status, product attributes and marketing tactics. The research highlights how technical expertise aids in evaluating product topographies and enhances credibility and trust in online shopping behavior. Data were collected through Google Forms surveys targeting youth, students and employees to gain insights into their online shopping perceptions. Analytical methods such as Principal Component Analysis, Partial Least Squares and Analysis of Variance were conducted using ORIGINPRO 2024 software. The proposed hypotheses were validated based on the analysis results. The study concludes that customer fulfilment – particularly among technically skilled students and employees – is the most influential and essential factor driving online shopping behavior.
Keywords: Online Shopping, Consumer Fulfilment, Principal Component Analysis, Analysis of Variance, Partial Least Square.

INTRODUCTION

Social commerce encompasses business activities that enhance consumer engagement in social shopping and foster active participation across diverse social media platforms (Jasrotia et al., 2025; Ngo et al., 2025). The social shopping experience and subsequent purchase decisions are influenced by information exchange and interactions among users via e-commerce technologies. In recent years, emerging business models have evolved around social interactions, integrating advanced digital technologies (Chong et al., 2025; Gensler & Rangaswamy, 2025). Both scholars and industry professionals have increasingly emphasized social commerce within the domains of retail, marketing and information systems (Thomas et al., 2025). Prior research indicates that social factors significantly shape consumer purchase decisions (France et al., 2024; Sharmin et al., 2025; Singh, 2024).

As e-commerce continues to evolve as a core component of customer relationship management and marketing strategy, the demand for innovative insights, models, and frameworks addressing online consumer behavior has grown substantially (Camps et al., 2025; Vafaei-Zadeh et al., 2025). Purchasing decisions are inherently individualistic and often complex. Personality traits can explain variations in consumer behavior even under similar circumstances (S. H.-Y. Hsu & Yen, 2016; Lv et al., 2024). During online shopping, consumers often face uncertainty when weighing potential risks and benefits. While e-commerce offers convenience and flexibility, it also entails greater perceived risks than traditional shopping. Despite access to textual descriptions and product images, consumers may still lack sufficient information to finalize a purchase decision. Therefore, an individual's confidence and trust propensity - the willingness to rely on others play a pivotal role in shaping online shopping behavior (El Hakioui & Louitri, 2017; McKnight & Chervany, 2001). Empirical studies underscore that online reviews have a considerable impact on business performance (Fadel, 2021). Companies must recognize that online shoppers heavily depend on reviews when making purchasing decisions(Fu et al., 2020). Since online consumers cannot physically assess products, they rely on reviews for guidance, unlike in-store shoppers who can directly examine items (Schneider & Zielke, 2020). A Google-led study analysing 57 million online customer reviews confirmed that these reviews exert a measurable influence on purchase outcomes (Morrison, 2015; Smieskol et al., 2025).

A 2020 study further revealed that younger consumers actively seek online reviews and view e-commerce as more convenient. They consider reviews and ratings essential sources of information when making purchase decisions (Shin & Darpy, 2020). These online reviews and opinions commonly referred to as electronic word-of-mouth (WOM) - offer consumers valuable insights that increase confidence in online purchasing. E-commerce platforms thus provide reviews as a substitute for physical product evaluation. Research also suggests that attributes of individual reviews - such as star ratings, tone, balance of feedback, recency, and writing style - may not independently serve as reliable indicators of satisfaction or quality. Hence, retailers must interpret these attributes collectively to make informed strategic decisions (Ahn & Park, 2024; Cutshall et al., 2022).

Globally, consumers are rapidly shifting toward online shopping, driving the accelerated growth of e-commerce. This digital transformation has compelled traditional retailers to adopt sustainable and eco-conscious practices, leading to the integration of green supply chain strategies and enhanced digital presence (Khan et al., 2023; C. Zhang & Gong, 2023). The global apparel market - valued at $1.5 trillion in 2021 - is projected to reach $2 trillion by 2026 (Patel et al., 2023; Smith, 2022; Statista, 2022). The expansion of online shopping is largely attributed to technological innovation (Botti, 2019; Farah & Ramadan, 2020; Yu et al., 2025). Moreover, the dissemination of preferences, opinions, and experiences through WOM and electronic WOM has played a vital role in influencing purchase behavior (Filieri et al., 2021).

Recent studies further affirm the positive impact of social media and EWOM on consumer decisions (Haq et al., 2024; Ismagilova et al., 2020; Ngo et al., 2025). Consumers now engage actively across platforms such as Facebook, Twitter, and LinkedIn, exchanging opinions. Eigenvalues, Eigenvectors, Factors and Social Information help in understanding young students' engagement in online shopping through social media platforms(Anik et al., 2020). It assesses their participation levels, ability to gather social information, technical proficiency, responsibility, adaptability and decision-making authority within the digital environment.

Young consumers, characterized by their rapid information-sharing behavior and technological fluency, actively generate positive word-of-mouth that promotes online shopping adoption. Their inclination toward early adoption and modernization serves as a driving force for e-commerce growth. The analytical framework employs Principal Component Analysis (PCA), Partial Least Squares (PLS), and one-way Analysis of Variance (ANOVA) using *OriginPro2024*. Eigenvalues and eigenvectors are extracted from a correlation matrix through PCA and eight latent factors are identified for further analysis. These are examined concerning predictor variable X and response variable Y using PLS, with fit statistics (R^2) confirming model consistency. Social components, product excellence and marketing tactics are further assessed through ANOVA, PCA, and PLS methods. The validated model supports the proposed hypotheses, concluding that customer fulfilment among young students - particularly those with technical proficiency - remains the most significant determinant of online shopping behavior. Moreover, instant information exchange and effective digital communication emerge as key drivers of e-commerce advancement.

LITERATURE REVIEW

Theoretical Background

Marketing continues to play a pivotal role in shaping consumer perceptions and influencing purchase decisions through strategic communication and positioning(Leenders & Wierenga, 2008; Mensah & Amenuvor, 2022; Nerkar & Roberts, 2004). In an increasingly competitive and digitalized marketplace, marketing strategies not only inform consumers but also shape their cognitive evaluations of brands and products. Branding, in particular, remains a crucial determinant of product performance and perceived quality, establishing a psychological connection that governs consumer attitudes and decision-making. Consumers frequently assess product quality through the lens of brand reputation, making perceived quality intrinsically tied to brand identity(Dwivedi et al., 2021; Huang et al., 2004; Pellegrino, 2024; Y. Zhang et al., 2025). This association reinforces the notion that well-recognized brands are often viewed as offering superior quality and reliable performance, thereby strengthening consumers' confidence in their purchase choices. Consequently, a robust brand identity enhances the perceived value and overall benefits derived from a purchase(Ismail, 2025; Rubio et al., 2014; Skare et al., 2026; Wang et al., 2024).

The social dimension of marketing, especially in the context of digital interaction, has transformed consumer behavior patterns. Research on social media friendships underscores the ambiguous and evolving nature of the term "friend"(Baym, 2012; Chacko et al., 2025; Z. Wu et al., 2026). On modern social platforms, the category of "friends" includes a wide spectrum of relationships - ranging from acquaintances and colleagues to close friends and family members (Bahraseman et al., 2025; Yang, 2020). This expanded notion of digital friendship carries significant implications for consumer psychology and marketing influence. As social media continues to dominate global communication, understanding how peer influence shapes attitude formation and purchase intentions has become increasingly relevant both theoretically and practically. Findings by (Elwalda et al., 2016) reveal that consumer trust and willingness to engage in online shopping are strongly driven by satisfaction with online customer reviews, highlighting the role of digital word-of-mouth in fostering purchasing confidence (Agarwal et al., 2024; Ghali et al., 2024).

In the digital era, the intersection between social interaction and marketing has become even more pronounced through electronic word-of-mouth (EWOM) communication. Prior research consistently demonstrates that social media platforms facilitate powerful consumer-to-consumer influence mechanisms that impact perceptions, attitudes, and behavioral outcomes (Ampornklinkaew, 2025; Babić Rosario et al., 2020). Information shared through EWOM serves as a key determinant in consumer decision-making, as users often rely on peer-generated content to mitigate uncertainty in online shopping contexts(Wanigapura et al., 2025). For instance, (An et al., 2025; Filieri, 2015) emphasized that the quality and credibility of online reviews play a crucial role in shaping purchase decisions, particularly when consumers evaluate unfamiliar brands or high-involvement products.

Furthermore, in industries such as online apparel retailing, perceived risk remains a critical factor influencing consumer intention and actual purchase behavior. Due to the intangible nature of digital shopping - where discrepancies may exist between product images, descriptions and real-world quality - consumers' perceptions of risk and trustworthiness significantly affect their willingness to buy. Understanding these psychological and perceptual variables is therefore essential for developing effective marketing strategies that build credibility, enhance satisfaction, and sustain consumer loyalty in digital commerce environments(An et al., 2025; Rahman et al., 2023; Tsai & Hsiao, 2025).

HYPOTHESIS

Demographic Characteristics

Domestic income plays a pivotal role in shaping purchasing power and influencing consumer behavior. Higher income levels generally enable consumers to make more frequent and higher-value purchases, thereby contributing to greater economic activity. In response, businesses strategically segment markets by targeting affluent consumers with premium offerings while simultaneously providing cost-effective alternatives for lower-income households. As income levels continue to rise in emerging markets, global consumer demand expands, fuelling the growth of both local and international markets. Consequently, understanding variations in household income allows companies to design more effective product portfolios and marketing strategies tailored to specific consumer segments(Kadigi et al., 2024; Talwar et al., 2024; Tsai & Hsiao, 2025).

Higher income is also positively associated with an increased inclination toward online shopping, driven by both enhanced purchasing power and the convenience of digital transactions. Consumers with greater financial resources tend to favour premium products and possess better access to technological infrastructure, further reinforcing their engagement in online shopping behavior (Han & Lai, 2025; Li & Lev, 2025; Sánchez et al., 2006). Moreover, purchasing decisions within households are often influenced by family members' opinions and recommendations, which strengthen trust, brand loyalty, and shared consumer experiences. Such collective shopping behaviors shape preferences and foster long-term consumption patterns. Larger families, in particular, frequently utilize online platforms to satisfy a wide range of needs, benefiting from convenience, variety, and cost savings(Ramtiyal et al., 2024; T. Wu et al., 2024). Based on this discussion, the following hypothesis is proposed.

H1: Demographic characteristics have a significant impact on online shopping behavior.

Product Characteristics

Product excellence serves as a critical determinant in online shopping, exerting a significant influence on customer accomplishment and overall purchase experience. Superior products that meet or exceed consumer expectations foster trust, reinforce credibility, and cultivate long-term brand loyalty. In digital marketplaces, product reviews and ratings function as key indicators of product excellence, providing social proof that enhances consumer confidence and satisfaction. Price consciousness represents another essential factor shaping sustainable purchasing decisions (Arranz-López et al., 2025; Califano et al., 2025; Lee et al., 2020). Consumers with lower price sensitivity tend to make purchasing decisions more readily, even at premium price levels (Hahnel et al., 2014; Pratiwi et al., 2025). Conversely, rising prices can act as a barrier to sustainable buying behavior, discouraging purchase intentions (Confente et al., 2021; Schiaroli et al., 2025).

Although digital platforms have enhanced accessibility and convenience in shopping, pricing continues to be a decisive factor - particularly within emerging markets where affordability plays a central role (Shi et al., 2022). Consumers often demonstrate strong cost awareness by engaging in extensive price comparisons prior to making online purchases (Bhutto et al., 2022). Moreover, price sensitivity reflects a consumer's willingness to pay a premium for environmentally sustainable or ethically produced goods (C.-L. Hsu et al., 2017; Ruggeri et al., 2024). The price–quality schema posits that higher prices are typically associated with perceptions of superior product quality, thereby influencing consumer purchasing behavior (Lichtenstein et al., 1993; Ryoo & Kim, 2023; Sinha & Batra, 1999; Yin et al., 2026). Based on this theoretical foundation, the following hypothesis is proposed.

H2: Product Characteristics positively augment online shopping behavior.

Social Characteristics

Environmental packaging plays a significant role in promoting sustainability and preserving environmental well-being for future generations(Nayak et al., 2026). Within the context of online shopping, family recommendations remain influential in shaping consumer decisions, fostering trust, and strengthening long-term brand loyalty(Fayyaz et al., 2025). Digital shopping platforms effectively cater to diverse household needs by offering convenience, cost efficiency, and extensive product variety at competitive prices. By minimizing the necessity for physical store visits, online shopping not only saves time but also contributes to the reduction of carbon emissions, thereby supporting environmentally sustainable consumer practices.

Encouraging online shopping behavior enhances overall efficiency, accessibility, and sustainability in modern consumption patterns. The adoption and promotion of biodegradable, recyclable, and reusable packaging materials resonate strongly with environmentally conscious consumers. Such initiatives reinforce sustainability goals when integrated into marketing strategies, loyalty programs, and brand positioning efforts. Consumers today are increasingly aware of and concerned about companies engaging in environmentally detrimental practices(Park et al., 2021). Consequently, the demand for organizations that uphold ethical standards and prioritize eco-friendly operations continues to rise (Hosseinifard et al., 2025; Quintana-García et al., 2022). Based on these insights, the following hypothesis is proposed:
H3: Social aspects motivate online shopping behavior.

Marketing Tactics

Online shopping offers unparalleled convenience, enabling consumers to browse, compare, and purchase products at any time and from any location(Abdelmeguid et al., 2024). The vast range of available products caters to diverse consumer preferences, while competitive pricing and exclusive promotional offers enhance affordability and encourage repeat purchases. Flexible delivery options, including doorstep delivery and express shipping, further streamline the online shopping experience, effectively eliminating geographical constraints and providing consumers with access to global markets and trends(Hasselwander & Weiss, 2025). Consumers actively evaluate both quality and affordability when making online purchases, balancing their preferences between branded and unbranded products while leveraging discounts and promotional offers to maximize value.

Detailed product descriptions, high-resolution images, and informative videos contribute to more informed purchase decisions. Clear product specifications and customer reviews play an essential role in establishing trust, enhancing transparency, and reducing product return rates. Additionally, interactive features such as zoom capabilities and 360-degree product views simulate in-store experiences, thereby improving satisfaction and fostering long-term brand loyalty. Consumer engagement deepens when individuals form meaningful and interactive relationships with brands (Hollebeek, 2011; Simoni et al., 2025). Furthermore, consumer awareness significantly shapes perceptions and exerts a direct influence on purchase intentions (Kara et al., 2009; Shehawy & Khan, 2024). Environmentally conscious behaviors also strengthen sustainable brand associations, reinforcing consumer commitment and loyalty toward responsible brands (Cheng & Huang, 2025; Gaspar Ferreira & Fernandes, 2022). Based on these insights, the following hypothesis is proposed:
H4: Marketing Tactics fascinates online shopping customers.

RESEARCH METHODOLOGY

Research Design

This study seeks to derive meaningful insights into the key factors influencing consumers' actual intentions toward online shopping. The research examines categorized factors and their corresponding indicators, optimizing them through both an extensive literature review and practical evaluation. Each factor is measured using its associated indicators - referred to as observed variables - which are operationalized based on responses obtained from participants(Almeida et al., 2025). The study incorporates four independent variables: male students (MS), female students (FS), male employees (ME), and female employees (FE). Each of these variables is linked to eight standardized observed variables, with every observed variable represented by three specific indicators. This structure forms an empirical framework based on a 4×3 relationship between respondents and indicators, as outlined by(Oikawa et al., 2025; Zikmund et al., 2000).

Explore the Factors and Indicators

Based on the observed trends and characteristics of questionnaire responses, suitable factors are identified and explored. Each factor is assessed using optimized indicators that accurately capture the underlying constructs. The relationship between respondents and indicators is utilized to analyze response patterns, which play a significant role in shaping the study's findings and interpretations (Sharifi and Shokouhyar, 2021; Zhang, Hassan, and Sheikh, 2024).

1 Respondent Household Member (RHM): [Hypothesis H1]
 (i) One - Two members. (ii) Three - Five members. (iii) Above Six members.
2 Respondent Annual Income (RAI): [Hypothesis H1]
 (i) Up to ₹ 7.00 Lakhs (ii) ₹ (7.00-10.00) Lakhs (iii) Above ₹ 10.00 Lakhs
3 Good Product Rating (GPR): [Hypothesis H2]
 (i) Excellent (ii) Good (iii) Not satisfied
4 Willing of Product Price (WPP): [Hypothesis H2]
 (i) More willing (ii) willing (iii) Less willing
5 Advocate Environmental Packing (AEP): [Hypothesis H3]
 (i) More Advocate (ii) Advocate (iii) Less Advocate
6 Guidance to Friends and Family for Online Shopping (GFFOS): [Hypothesis H3]
 (i) Strongly Guidance (ii) Guidance (iii) Neutral
7 Product Buying Reasons (PBR): [Hypothesis H4]
 (i) Design (ii) Price Access (iii) Delivery
8 Buying Key Focus (BKF): [Hypothesis H4]
 (i) Un-brand (ii) Brand-Cost (iii) Discount

H1 (RHM and RAI), H2 (GPR and WPP), H3 (AEP and GFFOS) and H4 (PBR and BKF)

Demographic Characteristics

Tiptur, in Karnataka, India, is a semi-urban city with a municipal council of 31 wards. It hosts small-scale industries and higher education institutions offering various courses. Popular as a copra market, it's vital to the economy, derived from the word 'Coconut' in the local language.

Data Measurement

A comprehensive literature review was undertaken using reputable academic databases such as Google Scholar, ScienceDirect, Scopus, IEEE Xplore, and Web of Science. Insights derived from the literature informed the development of both the questionnaire and the overall research design. The questionnaire was further refined through expert evaluation to ensure validity, and plagiarism screening was conducted to maintain originality. The data collection process involved both web-based and field survey methods. An online survey was administered via Google Forms, while field surveys were conducted in Tiptur city using structured questionnaires designed based on prior empirical studies.

A total of 29 questions related to users' perceptions and anticipations of online shopping were distributed through Google Forms and WhatsApp. The collected responses were compiled and processed in Microsoft Excel for data cleaning, which included the removal of incomplete or invalid entries to ensure data integrity. The final dataset comprised 773 valid responses, categorized into four groups: 270 MS, 308 FS, 111ME, and 84 FE. These cleaned and categorized responses formed the basis for subsequent statistical analysis. The study employed PCA, PLS, and ANOVA using OriginPro 2024 software. Table 1 presents the demographic characteristics of all respondents included in the analysis.

Table 1
Socio-Demographic Context of the Samples

Measure	Category		Response No's	%ge
Gender	Male		380	49.00
	Female		393	50.00
Age groups	≤ Twenty-five years		576	75.00
	≥ Twenty-five years		194	25.00
Marital Status	Married		161	20
	Unmarried		609	80
Family Size	< 3 members		53	7.00
	3 – 5 members		631	82.00
	> 6 members		90	12.00
Education	Under Graduate		586	76.00
	Post Graduate		130	17.00
	Above Post Graduate		54	7.00
Family Annual Income	≤ ₹ 5 Lakhs		646	84.00
	≤ ₹ 10 Lakhs		86	11.00
	₹10 to ≥ ₹ 20 Lakhs		37	5.00
Nature of Career	Student	Male	271	35.00
		Female	309	40.00
	profession	Male	110	14.00
		Female	85	11.00

Male and Female Student's Respondents

Understanding the online shopping behavior of students aged 20-25, commuting from rural areas to cities for undergraduate studies, is vital. This research highlights their technological proficiency, active communication, and responsible consumer habits, all shaped by parental influence. Despite geographical limitations, these semi-urban students show strong educational commitment and advanced tech skills compared to older generations. While parental guidance affects their decisions, they increasingly exercise autonomy in online purchases, seeking peer, teacher, and media input. Recognizing their demographics, technology use, and parental influence is key to designing effective engagement strategies that build meaningful connections with this empowered group (Habes et al., 2022; Javadi et al., 2012; Zendehdel et al., 2015).

Male and Female Employee Respondents

Understanding the online shopping behavior of male and female employees aged 30-50 in semi-urban areas is vital for developing tailored business strategies. This demographic, representing individuals in their career prime, blends urban and rural lifestyles that shape distinct consumption patterns. Gender influences preferences, habits, and decision-making, while both groups demonstrate strong technological and social media proficiency. Recognizing these demographics, gender-based, and technological factors is essential for effective online engagement with employee customers (Grewal et al., 2023; Rundel et al., 2024).

RESULTS AND DISCUSSIONS

Principal Component Analysis

A correlation matrix illustrates the correlation coefficients between pairs of variables, reflecting the strength and direction of their linear relationships. The eigenvalue equation is given as $d(\vec{A}) = \lambda(\vec{I})$, where 'd' denotes an operator acting on vector A, 'I' represents the eigenvector, and 'λ' is the eigenvalue. Eigenvalues indicate the proportion of variance accounted for by each principal component, while eigenvectors define the direction of variance in the data, establishing the principal components in PCA analysis (Abdi H, 2007). Table 2 presents an 8×8 correlation matrix in which all diagonal elements are +1, and the off-diagonal elements consist of both positive and negative values. Positive values close to +1 indicate a strong positive relationship between pairs of observed features, whereas negative values ranging from - 0.16 to - 0.31 suggest a moderate negative linear relationship between different feature pairs.

Table 2
Correlation Matrix

	RHM	RAI	GPR	WPP	PBR	BKF	AEP	GFFOS
RHM	1	-0.31	0.96	0.97	0.96	0.97	0.96	0.95
RAI	-0.31	1	-0.17	-0.27	-0.27	-0.31	-0.22	-0.16
GPR	0.97	-0.17	1	0.95	0.95	0.96	0.97	0.96
WPP	0.97	-0.26	0.96	1	0.97	0.97	0.97	0.97
PBR	0.96	-0.27	0.95	0.97	1	0.97	0.97	0.97
BKF	0.97	-0.31	0.96	0.97	0.97	1	0.97	0.96
AEP	0.9	-0.22	0.97	0.97	0.97	0.97	1	0.97
GFFOS	0.96	-0.17	0.96	0.97	0.96	0.96	0.97	1

Table 3(a) presents the eigenvalues obtained from the correlation matrix, where higher eigenvalues correspond to principal components (PC) that account for greater variance in the data. The first eigenvalue of 6.992 indicates that PC1 explains a substantial portion (87.4%) of the total variance. The second eigenvalue of 0.9471 shows that PC2 explains a smaller, yet meaningful, proportion of variance (11.84%) compared to PC1. Subsequent eigenvalues decrease progressively, signifying their reduced contribution to the overall variance. The variance percentage values show that PC1 is the dominant component, explaining 87.4% of the total variance, followed by PC2 with 11.84%, and so on. The cumulative percentage variance reflects the combined contribution of the PCs, indicating how many components are required to capture a specific amount of total variance. Collectively, PC1 captures 87.4% of the variance, and adding PC2 raises the cumulative explained variance to 99.24%, continuing until it reaches 100%.

Table 3
(a) Eigenvalues and (b). Eigenvectors of the Correlation Matrix

(a) Eigenvalue	Variance %	Cumulative %	(b)	PC1 Coefficients	PC2 Coefficients
6.98	87.40	87.40	RHM	0.377	-0.027
0.95	11.84	98.24	RAI	-0.112	0.978
0.041	0.53	98.97	GPR	0.370	0.18
0.012	0.15	99.53	WPP	0.378	0.016
0.002	0.03	99.56	PBR	0.374	0.015
0.002	0.03	99.59	BKF	0.376	-0.024
8.76E-4	0.01	100.00	AEP	0.376	0.069
2.06E-4	0.00	100.00	GFFOS	0.373	0.124

Table 3(b) presents the extracted eigenvectors, each corresponding to a PC. The coefficients within these eigenvectors represent the weights or contributions of the observed variables to each component. For instance, the coefficients for PC1 (0.377, –0.112, 0.37, etc.) indicate the extent to which each variable influences the direction of PC1. Positive coefficients show a positive correlation with PC1, while negative coefficients indicate a negative correlation. Larger coefficients reflect stronger contributions of the respective variables to PC1. Similarly, the coefficients for PC2 (–0.027, 0.9014, 0.11714, etc.) denote the contribution of observed variables to PC2, where the sign of each coefficient indicates the direction of the relationship, and its magnitude represents the strength of influence on PC2.

The scree plot, which graphs eigenvalues against their corresponding principal component numbers, reveals a steep initial drop in eigenvalues followed by a gradual decline. This steep drop indicates that PC1 explains a substantial portion of the total variance in the data. The first eigenvalue of 6.99201, associated with PC1, accounts for the largest share of variance, while the smaller subsequent eigenvalues (corresponding to PC2, PC3, etc.) reflect diminishing contributions. This graphical pattern aids in identifying significant components and determining how many PCs to retain for dimensionality reduction (Anderson, 1996; Bai, 2008).

Partial Least Squares

Partial Least Squares (PLS) analysis explores factor variables through linear combinations of predictor variables (X) and response variables (Y). In this approach, X represents the independent variables, while Y denotes the dependent variables. PLS emphasizes understanding and modelling the relationship between X and Y by generating latent factors that effectively capture the underlying structure within the data. These latent factors enable accurate prediction and modelling of dependent variables by maximizing the shared variance between X and Y. Cross-validation is used to determine the optimal number of latent factors, which in this study are represented as F1, F2, F3, F4, F5, F6, F7, and F8. Among these, F1 explains 87.40% of the variance in both X and Y, while F2 accounts for 11.84%, and F8 contributes the least, explaining only 0.0026% of the variance in X and Y.

The PLS results derived from the correlation matrix of both original and standardized data reveal that all principal diagonal elements are +1, while the off-diagonal elements are either positive or negative but very close to zero. The diagonal values of +1 indicate a perfect positive linear relationship among the same observed variables. Conversely, the near-zero values above and below the diagonal suggest that there is little to no correlation between different observed variables. This pattern demonstrates that PLS effectively captures the shared variance between X and Y through the extraction of latent variables. These constructs summarize the relationships between predictor and response variables, ensuring that the model focuses on maximizing the covariance between them.

The Variable Importance in Projection (VIP) values further indicate that all observed variables have equal importance in explaining the variation in the dependent variable. A VIP value of one for all predictor variables suggests that each contributes equally to the stability and balance of the PLS model. The cumulative percentage variance of X and Y across all eight latent factors confirms that these factors are systematically constructed to encapsulate the total information shared between X and Y. As the cumulative variance reaches 100%, it signifies that the model comprehensively captures all relevant variability in the data. Additionally, the variance percentages for X and Y are mirror images of each other, implying a symmetrical distribution of variability explained by the factors. In other words, the amount of variance captured in X corresponds precisely to that captured in Y, reinforcing the model's internal consistency.

The respective X loadings, Y loadings, and X weights for the observed variables concerning each latent factor (F1- F8) demonstrate identical and symmetrical patterns. Loadings represent the strength of the relationship between the observed variables and the latent factors - higher loadings indicate a stronger contribution of a variable to a given factor. Positive loadings suggest that as an observed variable increases, the associated latent factor also increases, whereas negative loadings reflect an inverse relationship. The symmetry between X and Y loadings confirms a perfect linear correspondence between the two sets of variables. Similarly, the X weights indicate the importance and direction of each observed variable's contribution to the latent factors - positive weights reflect a direct relationship, while negative weights represent an inverse relationship.

The X and Y scores derived from PLS are then utilized in the regression model to predict the relationship between the predictor and response variables. Positive and negative score values indicate the direction of influence or correlation. Finally, the X and Y residuals representing the differences between actual observed values and predicted values are found to be close to zero. This indicates an excellent model fit, where the predicted values align closely with the real observations, signifying the robustness and predictive accuracy of the PLS model(Joseph Jr, 2021; Teo et al., 2015; Wong, 2016).

Model Test

ANOVA is employed to compare the means of three optimized indicator groups to determine whether statistically significant differences exist among them. The test produces statistical values such as *t*, *F*, *q*, *p*, and significance (*sig*) to evaluate the hypothesis. It helps identify whether the differences observed between the groups are statistically meaningful (Gu & Gu, 2013; Santner et al., 2019).

Fit Statistics

ANOVA analysis provides supporting evidence that the proposed model fits the data appropriately and that there are statistically significant differences among the group means. Table 4 presents the observed values of R^2, variable coefficients, F-values, probability values, sum of squares, and mean squares. The four hypotheses, along with their corresponding eight features and R^2 values, are as follows: customers' family members (H1, R^2 = 66 %), customers' family income (H1, R^2 = 56 %), customer product satisfaction (H2, R^2 = 61 %), reliable product price (H2, R^2 = 63 %), eco-friendly packaging (H3, R^2 = 65%), shopping advice (H3, R^2 = 59 %), product features (H4, R^2 = 62 %), and marketing strategy (H4, R^2 = 65 %).

Table 4

Fit statistics One-Way ANOVA at 0.05 Level

Hypo-theses	Observed Factors	R^2	Coeff. Var.	Root MSE	Data Mean	F- Value	Prob. - p
H1	RHM	0.66	0.83	53.54	64.42	9.12	0.007
	RAI	0.56	1.14	73.23	64.42	5.90	0.023
H2	GPR	0.61	0.86	55.39	64.42	6.99	0.015
	WPP	0.63	0.76	48.87	64.42	7.81	0.011
H3	AEP	0.65	0.78	50.61	64.42	8.40	0.008
	GFFOS	0.59	0.76	49.05	64.42	6.58	0.017
H4	PBR	0.62	0.91	58.53	64.42	7.42	0.012
	BKF	0.65	0.90	58.045	64.42	8.58	0.008

These results demonstrate a strong fit between the proposed model and the observed data. The coefficients of variation in 83.1%, 86.0 %, 75.88%, 90.8%, 90.0%, 78.6%, and 76.0 % represent the ratio of the mean square between groups to the mean square within groups, indicating significant differences among the group means. The probability values of 0.0067, 0.023, 0.015, 0.011, 0.013, 0.0082, 0.01, and 0.0174 further confirm that, at the 0.05 significance level, there are statistically significant differences among the factor variable groups. These findings provide strong evidence supporting the acceptance of the proposed model. The sum of squares and mean square values serve as the basis for calculating the F-value.

Hypothesis Testing

Tables 5(a) and 5(b) present the ANOVA results conducted at a 0.05 significance level. Three sets of indicators were employed to evaluate the hypotheses using the Tukey and Fisher tests. The indicators corresponding to hypothesis are as follows: H1- [FM 1- 2, FM 3-5, FM 6 and above; 1- 7 Lakhs, 7-10 Lakhs, above 10 Lakhs]; H2 - [Excellent, Good, Not Satisfied; More-willing, Willing, Less-willing]; H3- [More-Advocate, Advocate, Less-Advocate; Strongly-Guidance, Guidance, Neutral]; and H4 - [Price-Access, Design, Delivery; Brand - Cost, Discount, Unbranded]. As shown in table, the *p*-values for two groups are less than 0.05, with values equal to 1, while one group has a *p*-value greater than 0.05 and a value of 0. This indicates that two groups exhibit statistically significant differences, whereas one group does not. Overall, these results support and validate all four hypotheses (H1 to H4). Levene's test of homogeneity of variances was performed for all variables.

The observed F-values between 30 and 40, the corresponding *p*-values were significantly lower than 0.05, signifying a violation of the homogeneity of variance assumption. In contrast, the Kruskal–Walli's test results showed the group ranks were nearly identical, with a *p*-value of 0.36, which exceeds 0.05. This suggests that there is no significant difference in the group medians, reflecting similarity in rank distributions. The inconsistency between the parametric ANOVA and the non-parametric Kruskal-Walli's results may stem from assumption violations, particularly related to normality or homogeneity of variances. Moreover, Kruskal-Walli's is inherently less affected by outliers and non-normal data compared to parametric. Therefore, the model is considered valid based on the testing outcomes and the model is accepted as reliable for interpretation and further analysis.

Table 5

Means Comparisons of One-Way ANOVA at 0.05 Levels: (**a**) H1-H2

5(a)	Obs. factor	Test	Indicator	q*/t*- Value	Prob	Sig
Hypothesis H1	RHM	Tukey Test q*	FM3-5 FM1-2	5.41	0.01	1
			FM6 Abov FM1-2	0.33	0.97	0
			FM6 Abov FM3-5	5.08	0.01	1
		Fisher Test t*	FM3-5 FM1-2	3.82	0.01	1
			FM6 Abov FM1-2	0.23	0.82	0
			FM6 Abov FM3-5	-3.59	0.006	1
	RAI	Tukey Test q*	(Ab7-10) L (1-7) L	4.17	0.039	1
			Ab 10 L(1-7) L	4.24	0.036	1
			Ab 10 L (Ab7-10) L	0.068	0.99	0
		Fisher Test t*	(Ab7-10) L (1-7) L	-2.95	0.016	1
			Ab 10 L (1-7) L	-3.001	0.015	1
			Ab 10 L (Ab7-10) L	-0.05	0.96	0
Hypothesis H2	GPR	Tukey Test q*	(Ab7-10) L (1-7) L	4.27	0.035	1
			Ab 10 L(1-7) L	0.57	0.92	0
			Ab 10 L (Ab8-10) L	4.84	0.019	1
		Fisher Test t*	Good Exce	3.02	0.014	1
			Not Satis Exce	-0.40	0.67	0
			Not Satis Good	-3.42	0.01	1
	WPP	Tukey Test q*	Willing Morewill	4.91	0.017	1
			Lesswill Morewill	0.14	0.99	0
			Less will Willing	4.77	0.02	1
		Fisher Test t*	Willing Morewill	3.47	0.01	1
			Lesswill Morewill	0.10	0.92	0
			Lesswill Willing	-3.37	0.008	1

Means Comparisons of One-Way ANOVA at 0.05 Levels: (**b**) H3-H4

5 (b)	Obs. factor	Test	Indicator	q*/t*- Value	Prob	Sig
Hypothesis H3	AEP	Tukey Test q*	Advocate MoreAdvo	4.86	0.018	1
			LessAdv MoreAdv	0.306	0.97	0
			LessAdv Advocate	5.16	0.013	1
		Fisher Test t*	Advocate MoreAdvo	3.44	0.007	1
			LessAdv MoreAdvo	-0.216	0.83	0
			LessAdv Advocate	-3.65	0.0053	1
	GFFOS	Tukey Test q*	Guide StrongGuide	4.189	0.038	1
			Neutral StrongGuide	0.47	0.94	0
			Neutral Guide	4.66	0.023	1
		Fisher Test t*	Guide StrongGuide	2.96	0.016	1
			Neutral StrongGuide	-0.332	0.748	0
			Neutral Guide	-3.294	0.009	1
Hypothesis H4	PBR	Tukey Test q*	Price-Access Design	4.69	0.022	1
			Del Design	0.06	0.99	0
			Del Price-Access	4.75	0.02	1
		Fisher Test t*	Price-Access Design	3.32	0.01	1
			Del Design	-0.043	0.97	0

BKF	Tukey Test q^*	Del Price-Access	-3.36	0.01	1
		Bra-Cost Un-brand	5.20	0.02	1
		Discount Un-brand	0.25	0.99	0
		Discount Bra-Cost	4.94	0.02	1
	Fisher Test t^*	Bra-Cost Un-brand	3.67	0.01	1
		Discount Un-brand	0.18	0.86	0
		Discount Bra-Cost	-3.50	0.01	1

Limitations and Future Studies

This study acknowledges few limitations. It primarily concentrates on a specific demographic - young students and employees - which may restrict the generalizability of the findings to other age groups or population segments. Furthermore, data collection through Google Forms and the use of self-reported responses may have introduced potential biases, including social desirability bias. Although the analyses were conducted using OriginPro2024 for PCA, PLS, and ANOVA, adopting longitudinal research methods in future studies could provide a deeper understanding of behavioral changes over time. Future research should consider expanding the sample to encompass a wider range of age groups, professional backgrounds, and geographic regions to improve the representativeness and applicability of the results. Additionally, investigating the influence of emerging technologies such as AI-driven recommendation systems and augmented reality could yield valuable insights into evolving online shopping behaviors. Exploring how cultural and psychological factors interact with technological proficiency would further contribute to a more comprehensive understanding of consumer behavior in the digital shopping environment.

CONCLUSIONS

This study investigates eight observed variables: RHM, RAI, GPR, WPP, BPR, BKF, AEP and GFFOS, which collectively show a positive influence on the four proposed hypotheses, highlighting their significant role in the online shopping environment. Younger students are found to be highly engaged in online shopping, motivated by factors such as social awareness, technological expertise, compatibility, adaptability, and relevance. The analysis, performed using OriginPro2024, applies Principal Component Analysis to examine eigenvalues and eigenvectors, while Partial Least Squares is used to identify and evaluate the eight latent constructs. The correlation coefficients indicate a strong model fit, validating the proposed conceptual context. As the results are consistent with the hypotheses, the model is considered statistically supported. Overall, customer fulfilment among younger consumers emerges as a key factor in shaping online shopping behavior, boosted by their technological competence, real-time information exchange, and interactive communication factors that collectively strengthen and enrich the online shopping experience.

Research ethics statement

This article is the authors' own original work, which has not been previously published elsewhere.

Author contribution statement

The corresponding author, Pushpalatha N, prepared the full version of the article, including the literature review, data collection, and the majority of the data analysis. She was responsible for ensuring that the manuscript description was accurate and approved by the co-author. P. Kanagaraju, the research supervisor, ensured the coherence of the research process from ideation to publication, particularly in refining the findings and conclusions.

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