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INDUCING FACTORS IMPACT ON CUSTOMER SATISFACTION IN THE REALM OF ONLINE SHOPPING

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ABSTRACT

The empirical study explores encapsulates the eigenvalues, eigenvectors, factors, social and product opinion information using software technology. It influences on consumers intention to make purchase decisions via social shopping. The consumer's behavior in shopping platform depends on various features influencing online shopping. Features: socioeconomic status, product characteristics and product marketing strategies. Technical proficiency helps in evaluation of product features in online reviews affecting the credibility and trust impacting online shopping behavior. Information technology-based Google Forms streamlines questionnaire surveys to gather insights from students and employees on online shopping habits. ORIGINPRO2024 software is implemented for the analysis of Principal Component Analysis, Partial Least Squares and Analysis of Variance. Proposed hypotheses are accepted on the merit of results. We resolve that the students and employees with technical proficiency customers satisfaction is the most powerful and essential component in online shopping.

KEYWORDS: Online shopping; Consumer satisfaction; Principal component analysis; Eigenvalue; Eigenvector; Analysis of Variance; Partial least square.

1. INTRODUCTION

Social commerce denotes business activities that promote consumer engagement in social shopping and encourage active involvement across various social media channels (Liang and Turban, 2011;

Zhang et al., 2014; Chen and Shen, 2015). Social shopping experience via social media and the purchase decision depends on the information exchange and interaction with the friends through e-commerce technology. Now a day's new business models are exposed that the models are designed based on social interactions with the incorporation of new technology (Zhu et al., 2019). Academics and practitioners are widely adopting the social commerce in the areas of retail, marketing and information systems (Yadav et al., 2013; Zhu et al., 2019). Social commerce studies finding reflects that social factors have major role on purchase decision of consumer behavior (Yadav et al., 2013; Park et al., 2014; Bai et al., 2015; Wang and Yu, 2017).

As electronic commerce develops into an essential element of customer relations and marketing strategy, there is an increasing demand for fresh insights, concepts and models regarding internet consumer behavior (Close and Kukar-Kinney, 2010). Consumers' purchasing choices are individual and frequently difficult activities. Personality could be a factor explaining the variations in procurement choices among individuals challenged with a comparable scenario (Kassarjian, 1971; Hoyer and Ridgway, 1984). During the process of online purchase decisions, consumers frequently experience uncertainty for assessing potential risks and benefits. Although online shopping provides consumers with increased convenience and flexibility, it also presents greater risks compared to traditional brick-and-mortar shopping experiences. Even though acquiring product information as a textual bulletins or images, there are insufficient to realizing many purchases merely based on online information. Thus, an individual's level of confidence rightly

pointed impacts their behavior during online shopping. Trust Propensity denotes the degree of an individual is inclined to rely on others (McKnight and Chervany, 2001).
A realistic statistic of research revealed that every business impact on online reviews(Fadel, 2021). Business firms are required to knowing the reviews information as online shoppers' purchase decisions based on online reviews (Fu et al., 2020). Customers rely on online reviews as they cannot physically touch and feel the product like offline customers can (Schneider and Zielke, 2020). A study led by Google, evaluating 57 million online customer reviews, revealed that these reviews significantly impacted consumers' decisions during purchases (Morrison, 2015).

In 2020 research study proposed that younger consumers keenly pursued online reviews and found online shopping to be more convenient. They considered reviews and ratings as two crucial sources of information during purchase decisions (Shin and Darpy, 2020). These reviews and opinions establish on the internet and e-commerce platforms are frequently referred as electronic word-of-mouth (WOM). Online reviews serve as a valuable resource for consumers, providing them with product related information that enhances their confidence when making online purchases. E-commerce companies offer these reviews as substitutes for physical or visual interactions with the product. Research study indicates that individual factors such as star ratings, review tone, mix of positive and negative feedback, recent reviews and writing style are not reliable indicators of customers' perceived satisfaction and product quality. Instead, retailers face a macro-level challenge of analyzing these attributes collectively to inform purchase decisions effectively (Cutshall, Changchit and Pham, 2022) Consumers globally are increasingly choosing online shopping over in-person retail experiences. This shift towards digital purchasing behavior has fueled the growth of e-commerce like never before. Traditional retail businesses are now under pressure from customers to embrace sustainable practices, leading to the implementation of eco-

friendly supply chain efforts, such as enhancing their online presence (Khan, Tabish and Zhang, 2023; Zhang and Gong, 2023). The worldwide apparel market, priced at $1.5 trillion in 2021, is projected to create $2 trillion by 2026 (Statista, 2022). This amazing flow in online shopping can be credited to technological advancements (Kautish and Sharma, 2018; Botti, 2019). Primarily, the sharing of interests, preferences and opinions about apparel among people through WOM and EWOM has been crucial in transmitting information (Filieri et al., 2021). Present studies affirm the beneficial impact of electronic WOM and social media on consumer behavior (Filieri, 2016; Gautam and Sharma, 2017; Ismagilova et al., 2020). Consumers engage on online platforms like Facebook, Twitter and LinkedIn, where they exchange opinions about products and services with fellow users.

The uniqueness of this study explores the features of Eigenvalues, Eigenvectors, Factors and Social-information using software technology for focusing on how younger generation students engage in online shopping through social media platforms. It analyzes their active participation, gathering social information, technical skills, responsibility, suitability, adaptability and authoritatively in this scenario. Youngsters are swift in sharing the information to larger extent using technology and this leads to positive word of mouth dynamically and it promotes online shopping. The inherent tendency of younger generation sections is that they are modernizers and early adapters. This provides online shopping a better scope and promotes online shopping in digital market extensively. The study is analyzed through Principal Component Analysis (PCA), Partial Least Squares (PLS) and one-way Analysis of Variance (ANOVA) using ‘OriginPro2024.’ Eigenvalues and eigenvectors are grown by Correlation matrix using PCA. Eight latent factor variables are grown and analyzed with predictor variable X and response variable Y using PLS. Fit statistics R2 are well consistent to the model, social components, product qualities, product sales marketing strategies; are analyzed using ANOVA, PCA and PLS. The designed model is validated and accepted in the scope of this study analysis and the results are favorable to the hypotheses. Eventually, youthful customer student’s satisfaction is the most powerful and indispensable components in online shopping. User friendly technical proficiency, immediate information sharing and familiar communication promotes online shopping.

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2. Literature review and hypotheses development

2.1 Theoretical background

Marketing has the power to shape consumer perceptions regarding product in thoughtful ways (Nerkar and Roberts, 2004) and to determine their possibility to purchase (Leenders and Wierenga, 2008). Product performance and quality are linked with branding, forming an essential relation in shaping consumer perceptions. The perceived quality of a product is integrally tied to its brand, as consumers judge product quality based on its brand name (Huang et al., 2004). For many consumers, this establishes a direct connection: a familiar brand typically indicates a product of high quality and effective performance. Therefore, a strong brand enhances the perceived advantages anticipated from a potential purchase (Rubio et al., 2014). Studies on friendship and social media highlight the uncertain definition of the term 'friend' (Baym, 2012). On social media, individuals referred to as 'friends' encompass a spectrum, ranging from strangers and acquaintances to family members, friends and various other connections (Baym, 2012). As social media becomes increasingly widespread, understanding of how friends' social influence boosts attitude accessibility and intention holds substantial theoretical and practical significance. (Elwalda, Lü and Ali, 2016) suggested that Customer trust and their inclination to engage in digital purchases are greatly shaped by the satisfaction derived from online customer reviews. In present-day digital era, prior studies have affirmed the influence of social media on consumer behavior via EWOM (Hennig-Thurau et al., 2004; Lee and Koo, 2012; López and Sicilia, 2014; Babić Rosario, De Valck and Sotgiu, 2020). For example, (Filieri, 2015) documented that the ability of information provided in online reviews regarding product quality, disseminated through Electronic EWOM, significantly impacts consumer purchasing decisions. Furthermore, the risk associated with online apparel purchases, where discrepancies between advertised and actual product quality may occur, it is crucial to investigate the influence of perceived risk on purchase intention and actual buying behavior.

2.2 Hypothesis

2.2.1 Demographic features

Family income significantly impacts purchasing power and customer habits. Higher income enables frequent, high-value purchases, boosting economic activity. Businesses target affluent demographics while providing affordable options for lower-income families. Rising incomes in emerging markets expand global consumer markets. Understanding income levels aids in tailoring products and marketing efforts. Higher incomes are linked to frequent online shopping, driven by purchasing power and convenience. Affluent individuals prioritize premium products and access technology easily, enhancing online shopping behaviour (Sánchez et al., 2006). Family members influence shopping behaviour through recommendations, fostering trust and brand loyalty. Shared experiences shape preferences and habits. Larger families rely on online platforms for diverse needs, benefiting from convenience and savings. Hence, the hypothesis is: H1 - Demographic features strongly influence online shopping.

2.2.2 Product Features

Product quality is a key component in online shopping, contributing significantly to customer satisfaction. High-quality products meet expectations, build trust, and foster brand loyalty. Reviews and ratings validate product excellence, enhancing the shopping experience. Price consciousness is another crucial factor influencing sustainable purchase decisions (Lee, Lalwani and Wang, 2020). Lower price sensitivity increases purchase likelihood, even at higher prices (Hahnel et al., 2014). Conversely, rising prices constrain sustainable purchasing (Confente et al., 2021). Digital platforms have made shopping more accessible, though price remains critical, especially in emerging markets (Shi, Huang and Sarigöllü, 2022). Consumers frequently compare prices, reflecting cost awareness (Bhutto et al., 2022). Price sensitivity also reflects a willingness to pay more for eco-friendly products (Hsu, Chang and Yansritakul, 2017). The price-quality schema links higher prices to perceived excellence, shaping purchase decisions (Zeithaml, 1988; Lichtenstein, Ridgway and Netemeyer, 1993). Hence, the hypothesis H2 is: 'Product features enhance online shopping.'

2.2.3 Social Features

Eco-friendly packaging supports sustainability, fostering a healthier planet for future generations. Family recommendations influence shopping choices, building trust and brand loyalty. Online shopping meets diverse household needs, offering convenience, cost-effectiveness, and a vast array of choices at competitive prices. It eliminates unnecessary trips to stores, saving time and reducing carbon emissions. Recommending online shopping promotes efficiency, accessibility, and sustainability in shopping habits. Promoting biodegradable, recyclable, or reusable materials attracts environmentally conscious consumers, encouraging sustainability through marketing and rewards. Consumers are increasingly concerned about organizations engaging in environmentally harmful practices (Park et al., 2021). The preference for environmentally friendly and ethical companies continue to grow (Quintana-García, Marchante-Lara and Benavides-Chicón, 2022). Hence, the hypothesis H3 is: "Social factors stimulate online shopping."

2.2.4 Marketing Strategy

Online shopping offers unmatched convenience, enabling consumers to browse and purchase anytime, anywhere. A wide array of products caters to diverse preferences, with competitive pricing and exclusive discounts enhancing affordability. Delivery options, such as doorstep and express shipping, accelerate the experience while overcoming geographical barriers to access global trends. Consumers strategically balance quality and affordability by choosing between branded and unbranded products, leveraging discounts and promotions for added savings. Detailed product descriptions, images, and videos empower decision-making, while precise specifications and reviews build trust and minimize

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returns. Interactive features like zoom and 360-degree views mimic in-store experiences, enhancing satisfaction and loyalty. Engagement increases when individuals interact meaningfully with brands (Hollebeek, 2011). Awareness shapes consumer perceptions, impacting purchase intentions (Kara et al., 2009). Environmentally conscious behaviour fosters sustainable brand associations, strengthening loyalty (Gaspar Ferreira and Fernandes, 2022). Hence, the hypothesis H4 is: "Marketing strategy magnetizes online shopping customers."

3. RESEARCH METHODOLOGY

3.1 Research design

This study is focus to extract the information of consumers' realistic intention factors in the realm of online shopping. The research work is to investigate the categorized factors with their indicators and these are optimized through literature and realistically. The factors are measurable quantities through their indicators called observed variables. The factors and indicators are operational by the respondents. The respondents' male students (MS), female students FS), male employees (ME) and female employees (FE) are the independent variables with eight standardized observed variables and each drive three indicators. This empirical evaluation is performed with the relation of 4×3 between respondents and indicators (Zikmund et al., 2000). Figure 1 represents the designed model; eight observed variables are measured as correlations coefficients (R2 values) and it relates with the hypothesis (H1- H4).

3.2 Explore the factors and Indicators

On the basis of trend and characteristic of responses on questionnaires suitable factors is explored. Each factor is measured through optimized indicators. The respondents and indicators are applied to analyze the responses as a significant role in this study (Sharifi and Shokouhyar, 2021; Zhang, Hassan and Sheikh, 2024)

1 Respondent Family Member (RFM): [Hypothesis H1]
(i) 1 to 2 members. (ii) 3 to 5 members. (iii) Above 6 members.

2 Respondent Annual Income (RAI): [Hypothesis H1]
(i) Up to ₹ 8.00 Lakhs (ii) ₹ (8-10.00) Lakhs (iii) Above ₹ 10.00 Lakhs

3 Satisfactory Opinion of Product Quality (SOPQ): [Hypothesis H2]
(i) Excellent (ii) Good (iii) Not satisfied

4 Satisfactory Opinion of Product price (SOPP): [Hypothesis H2]
(i) More satisfaction (ii) Satisfaction (iii) Less satisfaction

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5 Encourage Eco-friendly Packing (EEFP): [Hypothesis H3]

(i) More encourage (ii) Encourage (iii) Less encourage

6 Advice to Friends and Family for Online Shopping (AFFOS): [Hypothesis H3]

(i) Strongly Advice (ii) Advice (iii) Neutral

7 Product purchase Reasons (PPR): [Hypothesis H4]

(i) Design (ii) Price Access (iii) Delivery

8 Main Purchase Focus (MPF): [Hypothesis H4]

(i) Un-brand (ii) Brand-Cost (iii) Discount

H1 (RFM and RAI), H2 (SOPQ and SOPP), H3 (EEFP and AFFOS) and H4 (PPR and MPF)

3.3 Data measurement

A comprehensive literature review using Google Scholar, Science Direct, Scopus, IEEE Xplore, and Web of Science. Questionnaire and research design were informed by this literature. The questionnaire underwent expert evaluation and plagiarism testing. Google Forms facilitated the web-based survey administration. Field surveys gathered primary data from 'Tiptur' city using structured questionnaires based on prior research. Twenty-nine questions on 'Users anticipation on online purchase' were circulated via Google Forms and WhatsApp. Responses were incorporated to excel sheet for data cleaning, removing improper responses. The valid respondents comprise 270 male students (MS), 308 female students (FS), 111 male employees (ME), 84 female employees and totally 773 respondents. The respective responses are used for analyses in the present research work. The demographic information of all the respondents is shown in the table 1. In this work we analyze the, PCA, PLS, and ANOVA using OriginPro2024(Kyle et al., 2003; Gross and Brown, 2008; Chikweche and Fletcher, 2010).

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Table 1 Socio-demographic outline of the samples

Measure	Category		Response No's	%ge
Gender	Male		381	49.28
	Female		392	50.72
Age groups	≤ Twenty-five years		575	74.67
	≥ Twenty-five years		195	25.33
Marital Status	Married		162	21
	Unmarried		608	79
Family Size	< 3 members		52	6.75
	3 – 5 members		630	81.81
	> 6 members		88	11.42
Education	Under Graduate		587	76.23
	Post Graduate		129	16.76
	Above Post Graduate		54	7.01
Family Annual Income	≤ ₹ 5 Lakhs		647	84.02
	≤ ₹ 10 Lakhs		87	11.29
	₹10 to ≥ ₹ 20 Lakhs		36	4.69
Nature of Career	Student	Male	270	34.92
		Female	308	39.84
	profession	Male	111	14.35
		Female	84	10.86

3.4 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.

3.5 Male and female student's respondents

Understanding the online shopping behavior of student customers aged 20-25, commuting from rural villages to cities for undergraduate studies, is crucial. This research explores their unique characteristics, technological proficiency, frequent engagement in communication, and consumer responsibility, significantly influenced by parental guidance. Pursue their undergraduate programs in semi-urban areas, reflecting dedication to education despite geographical limitations, crucial for understanding lifestyle and preferences. Students in this demographic exhibit advanced technological skills surpassing older generations. College students are influenced by parental guidance in decision-making processes. They assert autonomy in online shopping decisions consulting parents. They engage with peers, teachers, media for information exchange and demonstrate responsible online shopping habits, prioritizing quality and ethics. Drawing upon these strategic points, this concept suggests that understanding student customer demographics, technology use and parental influence is crucial for effective online engagement. Tailoring strategies accordingly enhances relationships and resonates with this empowered group (Javadi et al., 2012; Zendehdel, Paim and Osman, 2015; Habes et al., 2022).

3.6 Male and Female Employee respondents

Understanding online shopping behaviors of male and female employees aged 30-50 in semi-urban areas is crucial for tailored business strategies. The demographic of male and female employees, active in semi-urban areas, reflects individuals in their career prime. Their lifestyle blends urban and rural elements, influencing consumption patterns. Gender shapes consumer behaviors, including preferences and shopping habits, essential for tailored marketing. Both genders show technological proficiency, enhancing online shopping capabilities. In view of the components, successful engagement both genders employee customers in online shopping to understand demographic profiles, gendered behaviors, technology use, and social media habits is essential for effective online engagement with employee customers (Grewal et al., 2023).

4. RESULTS AND DISCUSSIONS

4.1 Principal Component Analysis

A correlation matrix reveals the correlation coefficients between pairs of variables. Coefficients measure the strength and direction of the linear relationship between two observed variables. Eigenvalue equation is: $d(\vec{A}) = \lambda(\vec{I})$, where ‘d’ is an operator operating the vector A, I am eigenvector and λ is eigenvalue. Eigenvalue represent the amount of variance by each principal component, eigenvector represent the direction of variance in the data to define the principal component in PCA analysis (Abdi H, 2007). Table 2 represents the correlation matrix of order 8×8 with all the diagonal elements is +1 and on either side of the diagonal elements are positive and negative values. The positive values are very close to +1 indicates the good positive relation between the pairs of two observed features.

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Table 2 Correlation matrix

	RFM	RAI	SOPQ	SOPP	PPR	MPF	EEF	AFFOS
RFM	1	-0.32095	0.97956	0.99319	0.98268	0.99232	0.99172	0.98253
RAI	-0.32095	1	-0.18244	-0.27878	-0.27842	-0.31822	-0.22729	-0.17591
SOPQ	0.97956	-0.18244	1	0.97015	0.96123	0.96986	0.98109	0.97733
SOPP	0.99319	-0.27878	0.97015	1	0.99033	0.99302	0.99589	0.99269
PPR	0.98268	-0.27842	0.96123	0.99033	1	0.9957	0.99246	0.98915
MPF	0.99232	-0.31822	0.96986	0.99302	0.9957	1	0.99239	0.98636
EEF	0.99172	-0.22729	0.98109	0.99589	0.99246	0.99239	1	0.99649
AFFOS	0.98253	-0.17591	0.97733	0.99269	0.98915	0.98636	0.99649	1

Negative values in the range of (-0.1759 to -0.3185) indicates the negative moderate linear relation between the pairs of different features. Table 3 (a) represent the eigenvalues derived from the correlation matrix and higher eigenvalue relate to principal components (PC) that capture more variance in the data. The first eigenvalue is 6.992 indicating the PC1 explains a significant (87.4%) amount of variance in the data. The second eigenvalue is 0.9471 indicating the PC2 explains less variance (11.84%) than PC1 but is still relevant. The subsequent eigenvalues decrease further, indicating diminishing importance in explaining variance. The values of Varian's percentage represent the PC1 explain 87.4% of the total variance in the data, making it a dominant factor.

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

(a) Eigenvalue	Variance %	Cumulative %	**(b)**	PC1 Coefficients	PC2 Coefficients
6.99201	87.40	87.40	RFM	0.37697	-0.02787
0.94718	11.84	99.24	RAI	-0.11181	0.98149
0.04277	0.53	99.77	SOPQ	0.37028	0.11714
0.01223	0.15	99.93	SOPP	0.37702	0.01676
0.0027	0.03	99.96	PPR	0.37574	0.01552
0.00203	0.03	99.99	MPF	0.37735	-0.02545
8.75E-4	0.01	100.00	EEF	0.37698	0.0723
2.07E-4	0.00	100.00	AFFOS	0.37478	0.1256

The PC2 explains 11.84% of the variance, and so on. The cumulative percentage variance represents add more PC. It gives the number of PC are needed to capture a certain amount of total variance. Cumulatively, PC1 87.4 % of the total variance is captured, adding PC2 99.24%, and so on adding to become 100%. Table 3 (b) represent the extracted eigenvectors. Each eigenvector links to PC and the coefficients within the eigenvectors indicate the weights or contributions of the observed variables to that component. Coefficients for PC1 are 0.3769, -0.1118, 0.3702 etc. represents the contributions of each variable to the PC1. These coefficients indicate how much each variable influences the direction of PC1. Positive coefficients suggest that these variables are positively correlated with PC1 and negative coefficient is negatively correlated with PC1. Higher coefficients indicate stronger contributions of the corresponding variables to PC1. The coefficients for PC2 are -0.02787, 0.9014, 0.11714, etc. represents the contributions of the observed variables to the PC2. Positive or negative coefficients indicates the direction of the relationship between each variable and PC2. Positive coefficients mean a positive correlation, while negative coefficients mean a negative correlation. The magnitude of the PC2 coefficients reflects the

strength of each variable's influence on PC2. The graphical representation of scree plot, plotted eigenvalue versus Principal component (PC) numbers. It is observed that a steep drop in eigenvalues at the beginning and tailing with more gradual decrease. The steep drop indicates the PC1 explain a significant amount of variance in the data. The first eigenvalue of 6.99201 with the relevant PC1 explains the substantial amount of variance, the remaining lower eigenvalues with the related (PC2, PC3, etc.) indicate decreasing contributions to the variance. This plot involves identifying patterns in the eigenvalues and using them decisions about the number of PC to keep in dimensionality reduction techniques (Anderson, 1996; Bai, 2008).

4.2 Partial Least Squares

PLS explore factor variables with the linear combinations of predictor variable (X) and response variable (Y). X is the input variable called independent variable; the response variable Y called the dependent variable. PLS influence the relationships between X and Y to create latent factors that facilitates accurate prediction and modeling of the dependent variables. Cross validation is selecting the suitable eight latent factors such F1, F2, F3, F4, F5, F6, F7 and F8. F1 explains the 87.40 % of X and 87.40 % of Y, F2 is 11.83971% of X and 11.83971% of Y and last F8 is 0.00258% of X and 0.00258% of Y. Observed PLS result of correlation matrix of original and standardized data, principal diagonal elements are +1 and the elements on either side of the principal diagonal are positive and negative with very close to zero in both of original and standardized data matrix. Principal diagonal elements are 1 indicates positively strong linear relation among the same observed variable. Above and below the diagonal are close to zero indicates that there is no relation among the different observed variables. It substantially describes that PLS focuses to evaluate latent variables through maximizing the variables X and Y. Hence, the latent variables are capturing shared information among the variables X and Y. Variables Important in Projection (VIP) it is seen that the values are one for all the observed variables, it indicates that all predictor variables are equally important and contribute equally

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to explaining the variation in the response variable for balance and stable model. The respective cumulative percentage variance of X and Y for all the eight latent factor variables relative to all the observed variables. These variables are constructed to capture the information among X and Y; the captured information is in cumulative percentage to becomes 100%. The percentage variance for X and Y is exactly the mirror image, it implies that the variability explained by the factors in the model is symmetrically distributed between X and Y or in other words variability captured by the factors mirrors each other. The respective X loadings, Y loadings and X weights, for the respective observed variables in relates with the F1, F2, F3, F4, F5, F6, F7 and F8. It is seen that the loading values of X and Y is exactly identical and some are positive and negative values. Loadings represent the strength of the relation between the observed variables with the latent factors. Higher loading F indicates explains more variance than the other F; Positive values indicate the increase in observed value correspondingly latent factor also increases, whereas the negative value indicates the converse relation among them. X loading and Y loading values are exactly the symmetry; it is the perfect relationship between observed variables and factors. The X-weights represent the importance of each observed variable in contributing to the factors. Positive and negative weights indicate the direction and strength of the relationship between each variable and the factors. Positive weights mean that as the variable increases, so does the corresponding factor. Negative weights mean the variable and factor move in opposite directions. The respective X and Y scores used in regression model and predict the relationship between X and Y. Scores with positive and negative values indicates the respective positive and negative influence or correlation. X and Y residuals refer to the differences between the actual observed values and the predicted values for the predictor and response variables respectively. The fact that all the residual values for both X and Y are very close to zero indicate a well-fitted regression model, where the model's predictions align closely with the actual observed values in the dataset (Teo et al., 2015; Wong, 2016; Hair Jr et al., 2021).

4.3 Model test

ANOVA is used to compare the means of optimized three indicator groups. To determine they are statistically significant differences between them. ANOVA tests are conducted to generate the values of t, F, q, p and significance (sig) to test the hypothesis. It assesses that the difference between two groups is statistically significant different (Gu and Gu, 2013; Santner et al., 2018).

4.4 Fit statistics

ANOVA studies provide evidential information that relates proposed model suitable to the data and there is a substantial significant difference between the group means. Table 4 shows the observed values of R^2, coefficient of variables, F value, prob. value, sum square and mean square.

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Table 4 Fit statistics One-way ANOVA at 0.05 level

Hypo-theses	Observed Factors	R-Square	Coeff. Var.	Root MSE	Data Mean	F- Value	Prob. - p
H1	RFM	0.67131	0.83122	53.54411	64.41667	9.19091	0.00669
	RAI	0.56755	1.13788	73.29867	64.41667	5.90585	0.023
H2	SOPQ	0.60851	0.85984	55.38828	64.41667	6.99448	0.0147
	SOPP	0.63443	0.75876	48.87655	64.41667	7.80954	0.0108
H3	EEFP	0.6512	0.78574	50.61483	64.41667	8.40135	0.00874
	AFFOS	0.5938	0.7615	49.05298	64.41667	6.57826	0.01735
H4	PPR	0.62266	0.90866	58.53275	64.41667	7.4257	0.01245
	MPF	0.65597	0.90116	58.04955	64.41667	8.58033	0.00822

The designed model in figure 1 depicts four hypothesis, eight features and its R^2 values are: Customers family members (H1, R^2=67.131%), Customers family income (H1, R^2= 56.155%), customers product satisfaction (H2, R^2=60.851%), reliable product price (H^2, R^2=63.443%), ecofriendly package (H3, R2= 65.12%), shopping advice (H3, R^2= 59.38%), product features (H4, R^2=62.266%) and marketing strategy (H4, R^2=65.597%).

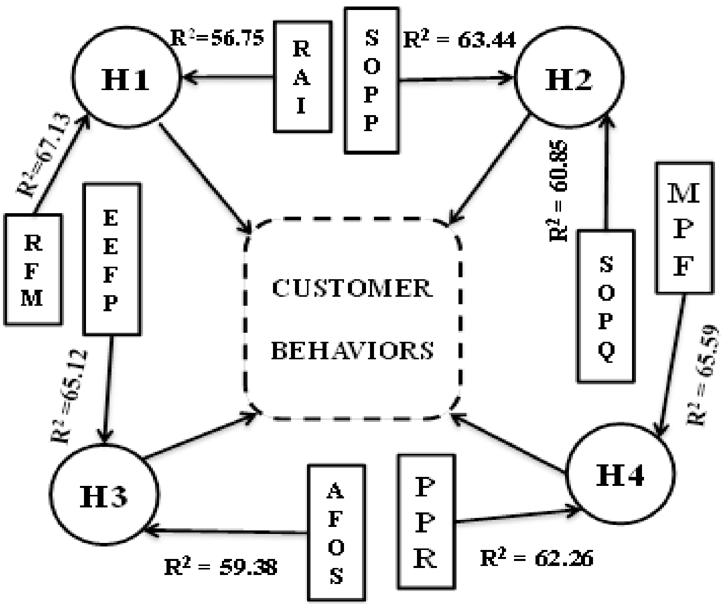

Figure 1 Designed model

These values indicate is better fit to the proposed designed model. Coefficient of variation values are found to be 83.122%, 85.985%, 75.876%, 90.8%, 90.11%, 78.57% and 76.15%; the ratio of the mean

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square between groups to the mean square within groups and these values indicating a significant difference between the group means. The probability values are found to be .00669, 0.023, 0.0147, 0.0108, 0.01247, 0.00822, 0.00874 and 0.01735; indicates at the 0.05 level there is a significant difference between the groups of factor variables and evidence to accepting the hypothesis in favoring the proposed model. Sum square and mean square are components to calculate F value.

4.5 Hypothesis testing

Figure 1 shows the designed model of four hypotheses with their eight features and R2 values are represented. Table 5 (a) and (b) represents ANOVA tests measurements are at 0.05 levels results. Three sets of indicators are used to test the hypothesis with the tests Tukey and Fisher. The indicators for the respective hypothesis are - H1 is [FM 1-2, FM 3-5, FM 6 above'; 1-8 Lakhs, 8- 10 Lakhs, above 10 Lakhs]; H2 is [Excellent, Good, Not Satisfied'; 'More Satisfy, Satisfy, Less Satisfy]; H3 is [More Encourage, Encourage, Less Encourage'; 'Strongly Advice, Advice, Neutral] and H4 is [Price-Access, Design, Delivery'; 'Brand-Cost, Discount, Un-brand].

Table 5 Means comparisons tests results of one-way ANOVA at 0.05 levels
(a) H1-H2 and (b) H3-H4

5(a)	Obs. factor	Test	Indicator	q^*/t^*- Value	Prob	Sig
Hypothesis H1	RFM	Tukey Test q^*	FM3-5 FM1-2	5.40676	0.01023	1
			FM6 Abov FM1-2	0.32683	0.97108	0
			FM6 Abov FM3-5	5.07992	0.0145	1
		Fisher Test t^*	FM3-5 FM1-2	3.82315	0.00407	1
			FM6 Abov FM1-2	0.23111	0.8224	0
			FM6 Abov FM3-5	-3.59205	0.00582	1
	RAI	Tukey Test q^*	(Ab8-10) L (1-8) L	4.1747	0.03896	1
			Ab 10 L(1-8) L	4.24291	0.03614	1
			Ab 10 L (Ab8-10) L	0.06821	0.99872	0
		Fisher Test t^*	(Ab8-10) L (1-8) L	-2.95196	0.01617	1
			Ab 10 L (1-8) L	-3.00019	0.01495	1
			Ab 10 L (Ab8-10) L	-0.04823	0.96258	0
Hypothesis H2	SOPQ	Tukey Test q^*	(Ab8-10) L (1-8) L	4.26986	0.03508	1
			Ab 10 L(1-8) L	0.56871	0.91553	0
			Ab 10 L (Ab8-10) L	4.83857	0.01882	1
		Fisher Test t^*	Good Exce	3.01924	0.0145	1
			Not Satis Exce	-0.40214	0.69696	0
			Not Satis Good	-3.42139	0.00761	1
	SOPP	Tukey Test q^*	Satisfy More Satisfy	4.91033	0.01741	1
			LessSatisfy More Satisfy	0.14322	0.99437	0
			LessSatisfy Satisfy	4.76711	0.02034	1
		Fisher Test t^*	Satisfy More Satisfy	3.47213	0.00703	1
			LessSatisfy More Satisfy	0.10127	0.92156	0
			Less Satisfy Satisfy	-3.37086	0.00825	1

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5 (b)	Obs. factor	Test	Indicator	q^*/t^*- Value	Prob	Sig
Hypothesis H3	EEFP	Tukey Test q^*	Encourage More Encour	4.86024	0.01838	1
			Less Encour More Encour	0.30623	0.97455	0
			Less Encour Encourage	5.16647	0.01321	1
		Fisher Test t^*	Encourage More Encour	3.43671	0.00743	1
			Less Encour More Encour	-0.21654	0.8334	0
			Less Encour Encourage	-3.65325	0.00529	1
	AFOS	Tukey Test q^*	Advice Strongly Advice	4.18935	0.03833	1
			Neutral Strongly Advice	0.46888	0.94159	0
			Neutral Advice	4.65823	0.0229	1
		Fisher Test t^*	Advice Strongly Advice	2.96232	0.0159	1
			Neutral Strongly Advice	-0.33155	0.74782	0
			Neutral Advice	-3.29387	0.00932	1
Hypothesis H4	PPR	Tukey Test q^*	Price-Access Design	4.68968	0.02213	1
			Del Design	0.0598	0.99901	0
			Del Price-Access	4.74948	0.02073	1
		Fisher Test t^*	Price-Access Design	3.31611	0.009	1
			Del Design	-0.04228	0.9672	0
			Del Price-Access	-3.35839	0.00841	1
	MPF	Tukey Test q^*	Bra-Cost Un-brand	5.19384	0.01283	1
			Discount Un-brand	0.24979	0.98298	0
			Discount Bra-Cost	4.94405	0.01679	1
		Fisher Test t^*	Bra-Cost Un-brand	3.6726	0.00513	1
			Discount Un-brand	0.17663	0.86371	0
			Discount Bra-Cost	-3.49597	0.00677	1

It is observed in table 8 for all the tests p value of the two groups is less than 0.05 and the sig value is 1 and one group p value is greater than 0.05 and sig value is zero. It indicates that the two groups are statistically significant different and one group is not significantly different. Hence, the result is favorable for the entire hypothesis H1 to H4.

Levene's test of homogeneity of variance has been conducted for all the variables. The observed results of F value are 30-40 and p value is very less compared to 0.05. It indicates the violation of the assumption of homogeneity of variances. Further, Kruskal-Wallis tests results indicate the ranks are almost same in groups and p value 0.36 is more than 0.05. It indicates that there is no significant difference in the medians of the groups, as of similarity in ranks. The discrepancy between the parametric ANOVA and non-parametric Kruskal-Wallis tests may be due to violations of assumptions such as normality or homogeneity of variance. Additionally, the Kruskal-Wallis test is less sensitive to outliers or non-normality compared to parametric tests. The means comparison tests results are favorable to hypotheses. Hence, the designed model is validated on the grounds of the hypothesis and the model has been accepted.

4.6 Limitations and Future Studies

This study is limited by its reliance on a specific demographic, focusing predominantly on younger students and employees, which may restrict the generalizability of the findings to other age groups or populations. Additionally, the data collection through Google Forms and reliance on self- reported responses could introduce biases, such as social desirability bias. The analysis, while robust using OriginPro2024 for PCA, PLS, and ANOVA, could benefit from incorporating longitudinal methods to capture behavioural changes over time.

Future research could explore a more diverse sample, including different age groups, professions, and geographic locations, to enhance the generalizability of the findings. Expanding the scope to include emerging technologies, such as AI-driven recommendation systems and augmented reality, could provide deeper insights into online shopping behaviour. Moreover,

investigating the interplay of cultural and psychological factors with technical proficiency could further enrich the understanding of consumer behaviour in online shopping.

5. CONCLUSIONS

The study explores the eight observed variables as RFM, RAI, SOPQ, SOPP, PPR, MPF, EEF and AFFOS. These observed factors is positively favorable to the four hypotheses and satisfying impact in the realm of online shopping. The younger generation students enthusiastically engage in online shopping activities leveraging social insights, technical expertise, consciousness, compatibility, flexibility and significance. Study is analyzed using originpro2024. Eigenvalues, eigenvectors are explored using the PCA. Eight latent factors are explored and analyzed using PLS. Correlation coefficient R2 values fit the proposed model. The proposed model is accepted as the tests results are positively favorable to the hypotheses. Ultimately the satisfaction of younger customers is the important component of online shopping facilitated by technical expertise, real- time information sharing and oral communication that fosters and promotes the online shopping experience.

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Conflict of Interest

The authors declared that they have no conflict of interest

Data availability

Data will be made available on request

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