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THE INFLUENCE OF DIGITAL ADVERTISING STRATEGIES ON PURCHASE INTENTION AND BUYING BEHAVIOR IN THE TEXTILE AND APPAREL E-COMMERCE SECTOR

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Abstract: The exponential growth of e-commerce has redefined the textile and apparel marketplace, with digital advertising emerging as a dominant force in shaping consumer perceptions and purchase decisions. This study examines how core advertising dimensions — including digital advertising exposure, brand advertising awareness, product advertising familiarity, vendor advertising expertise, and online advertising popularity — influence consumers' purchase intentions and actual buying behavior in the textile and apparel industry. Data were collected through a structured survey from 4500 urban Indian consumers who have previously purchased local textile and apparel products online. After excluding invalid responses, 389 usable samples were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) and Confirmatory Factor Analysis (CFA) to validate the structural model and test seven hypotheses. Findings reveal that advertising-centric marketing elements exert a significant positive effect on purchase intention, which serves as a key mediator leading to actual purchase behavior. The results underscore the strategic importance of targeted advertising campaigns in enhancing consumer engagement, increasing brand recall, and driving e-commerce sales. This study offers valuable implications for textile and apparel marketers, highlighting how optimized advertising interventions can effectively convert consumer interest into purchase actions in emerging digital marketplaces.

Keywords:E-commerce, Digital Advertising, Brand Awareness, Product Familiarity, Consumer Behavior, Purchase Intention

1.Introduction

Due to a number of recent new entrants, rising income levels, growing aspirations, favorable demographics, and easy access to credit through e-commerce, the Indian retail sector has become one of the most dynamic and rapidly expanding industries. As of 2018, it was worth USD 792 billion and contributed roughly 8% of the nation'semployment and 10% of its GDP. The unorganized sector of the Indian retail market, which comprises approximately 13 million stores and makes up 96% of the country's overall retail market, is extremely fragmented. However, because of globalization, rapid economic growth, and better lifestyles, the organized sectors' growth potential is anticipated to increase in the future.

Figure 1 E-commerce marketing process

The retail industry's existence in India has gained attention in recent years. Retailing to the general public has the advantage of increasing brand consciousness and awareness. Figure 1 displayed the e-commerce marketing strategies. Retail is where consumers spend the money that powers the economy. Shops where customers spend their hard-earned money include boutiques, restaurants, bargain superstores, mail-order businesses, and online retailers [1]. Retailers and the manufacturers, distributors, and wholesalers that comprise the remainder of the consumer goods distribution chain all profit when products are placed in the hands or shopping bags of customers [2]. Additionally, sales taxes are collected through retail transactions, funding all types of public services [3]. Time, place, and utility are created by the retailer during the sale of goods, which raises the goods' value [4].

Retailers purchase goods that are manufactured in large quantities and in bulk, then divide the bulk and sell them in small packets and in the quantities that the customer needs. Because of this operation, he produces a type utility [5]. Products are made in one region of the world and used in other regions. A retailer creates position utility by purchasing goods from multiple vendors and distributing them to his local clientele [6]. Time separates the creation from the use. When a merchant needs something, he buys it in advance from middlemen, keeps it in stock, and then sells it. Through the development of these three services, he enhances the value of goods and helps [7]. Delivering goods in good condition and on schedule is the manufacturer's responsibility [8]. In order to promote clothing retailing, the paper's primary goal is to highlight recent developments in fashion marketing in India [9–10]. The study emphasizes the tactics used by Indian fashion retailers to gain the trust of their customers and become globally competitive. The research also assesses the extent and difficulties of fashion retailing in India [11]. One of the top e-commerce companies, Flipkart [12], was the subject of a study to learn about its challenges with apparel returns in 2014 and 2015 [13]. It comprehends why people purchase clothing online as well as the problems they encounter. To identify characteristics linked to size and fit concerns, it looks at a variety of physical stores [14]. The areas of concern found in women's clothing. The study discovered that by lowering the high rate of clothing returns, companies can enhance the overall customer experience if their designs are made to fit a wide range of people with different body shapes [15]. Statistics from a comprehensive study of B2C clothing online retailing in China indicate that there is a lot of room for growth in the fast fashion online retailing sector, but it will take some time to catch up to the world's top companies in terms of e-commerce scale [16]. E-commerce is altering the way that goods and services are purchased and sold in India, according to the study. The shopping of the future is e-commerce [17].

Due to e-commerce's growth in both rural and urban areas in terms of affordable consumption, more people are connecting with it, and the proportion of those is rising daily [18]. However, since the textile industry frequently faces competing pressures between sustainability and economic goals, tackling the difficulties of Industry 4.0 implementation and green supply chain adoption necessitates a thorough grasp of systemic barriers [19].

2.METHODOLOGY

2.1Problem Description

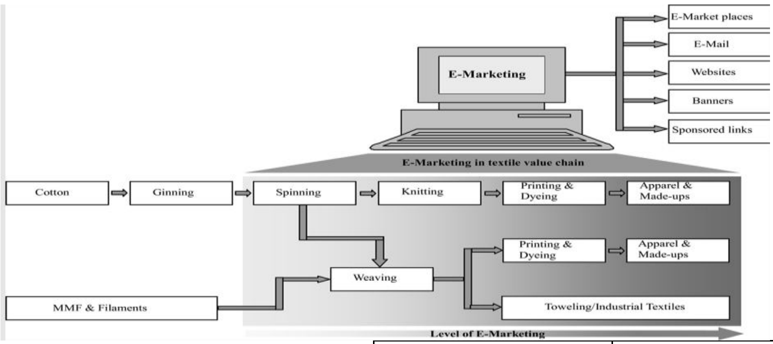
Despite this little is understood about the factors—such as digital advertising brand awareness product familiarity vendor knowledge and online popularity—that affect online exposure to actual purchases. Since it is difficult to quantify the relationships between these factors and how they directly affect consumer behavior empirical research is required. In urban Indian e-commerce for textile and apparel products this study closes that knowledge gap by providing helpful guidance for enhancing supply chain effectiveness and digital marketing strategies.

2.2Data Collection

Respondents from a wide range of demographic backgrounds in urban India provided the data for this study (Table 1). Thirty-five percent of the participants were men and 65 percent were women. Young adults between the ages of 20 and 25 made up the majority (52 percent) followed by those between the ages of 26 and 30 (22%) 31 and 35 (15 percent) 36 and 40 (6%) and over 40 (5%). Compared to participants who were married (33 percent) the majority of respondents (67 percent) were unmarried. There were differences in employment status: 35% of people were employed 25% were unemployed 22% were students and 18% fell into anothercategory. A well-educated urban sample that was appropriate for analyzing e-commerce behavior in the textile and apparel industry was represented by the educational qualifications of 26% with metric 17% with intermediate 39% with bachelors degree 10% with masters degree and 8% with other qualifications.

Table 1: Demographic Information of Respondents

Description		Percentage (%)
Gender	Male	(35%)
	Female	(65%)
Age	20-25	(52%)
	26-30	(22%)
	31-35	(15%)
	36-40	(6%)
	40 Above	(5%)
Marital status	Single	(67%)



	Married	(33%)
Employment status	Employed	(35%)
	Unemployed	(25%)
	Students	(22%)
	others	(18%)
Qualification	Metric	(26%)
	Intermediate	(17%)
	Bachelor	(39%)
	Masters	(10%)
	others	(8%)

Soruce: Primary data

2.3 Sampling strategy

A multi-phase sampling strategy was used in the study beginning with purposive sampling to identify participants who had made at least two online purchases of apparel and textiles during the preceding six months. This method was combined with stratified random sampling to ensure the demographic representation of different income levels educational backgrounds and occupational profiles in urban areas such as Delhi Mumbai Bengaluru Hyderabad and Chennai. Data was collected via a combination of in-person interviews at retail exhibitions and fashion pop-up events as well as self-administered online questionnaires distributed via email campaigns and social media platforms in order to guarantee a diverse sample of respondents with practical e-commerce experience. The suggested architecture can be seen in Figure 2.

Figure 2: Proposed strategies of e-commerce in textile and apparel supply chain management

2.4Data Analytical Tool

Partial Least Structural Equation Modelling (PLS-SEM) a technique especially useful for predictive modelling and analysing intricate relationships among latent variables was used to analyse the gathered dataset using SmartPLS version 4. These methods were selected because they are effective at evaluating several concurrent causal pathways and are robust when dealing with non-normal data.

2.5**Proposed Methodology**

The suggested methodology employs a methodical multi-phase approach to investigate how digital marketing elements impact consumer purchase intention and purchasing behavior in the urban textile and apparel e-commerce market in India. First a conceptual framework was created using the S-O-R model and the Theory of Planned Behavior. Through expert consultation and a review of the literature constructs like Digital Advertising Brand Awareness Product Familiarity Vendor Expertise Online Popularity Purchase Intention and Buying Behavior were defined.

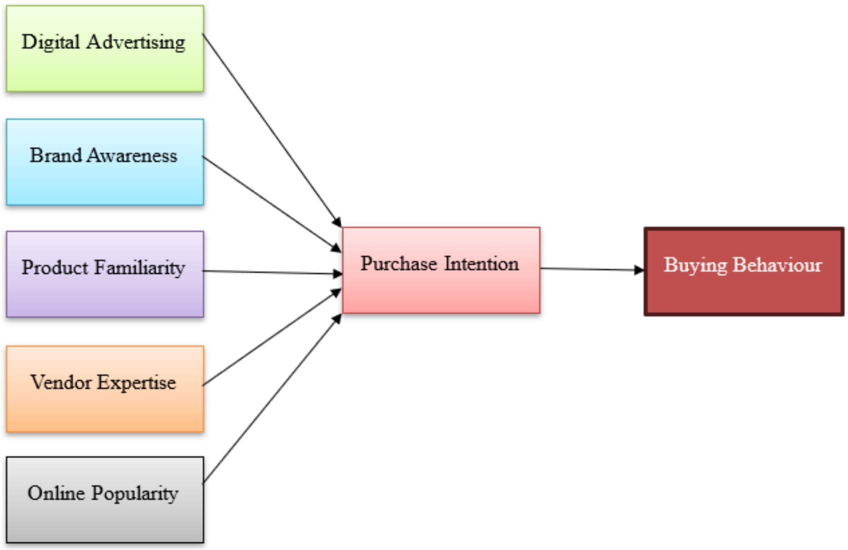


Figure 3: Conceptual framework

The conceptual framework is in Figure 3. Second a structured survey tool was created and distributed to 4500 digitally engaged consumers in Indian cities employing both online and offline data collection techniques. After a thorough screening process for missing values response bias and inconsistencies 389 valid samples were obtained from the collected responses. In order to confirm the robustness of the suggested framework PLS-SEM was used for hypothesis testing and model validation. CFA was also used to guarantee the validity and reliability of all measurement constructs.

2.6 Proposed Technique

A hybrid approach to analysis that uses partial least squares. This study measures and captures the complex relationships between digital marketing elements purchase intention and actual buying behavior using Confirmatory Factor Analysis (CFA) and Structural Equation Modeling (PLS-SEM). A strong interpretation of the causal pathways being studied is provided by the methodologys mathematical foundation in latent variable modeling which enables the division of observed measurements into true scores and measurement errors. This set of formulas encapsulates the key concepts of the suggested methodology. The reflective indicators measurement model equation underwent the following analysis.

$$X_i = \lambda_i \xi + \delta_i \quad (1)$$

When Xi is the ith construct's observable indicator, λi is the factor loading, ξ\xi is the latent construct (such as Digital Advertising or Purchase Intention), and δi is the measurement error related to Xi. The observable variables' accurate representation of their underlying constructions is guaranteed by Equation 1.

The equation for the structural model was written as equation 2

$$\eta = B\eta + \Gamma\xi + \zeta \quad (2)$$

Each construct's Composite Reliability (CR) was determined using equation 3:

$$CR = \frac{(\sum \lambda_i)^2}{(\sum \lambda_i)^2 + \sum \theta_i} \quad (3)$$

For convergent validity, the Average Variance Extracted (AVE) was calculated as follows::Equation 4:

$$AVE = \frac{\sum \lambda_i^2}{n} \quad (4)$$

Using Equation 5 to calculate the bootstrap confidence interval for path coefficient significance

$$t = \frac{\hat{\beta}}{SE(\hat{\beta})} \quad (5)$$

Where SE(β^) is the standard error derived from the bootstrap samples and β^ is the predicted route coefficient. At the 95% confidence level, a t-value more than 1.96 indicates that the proposed associations are statistically significant. By using these equations, the empirical model was guaranteed to be robust, multicollinearity bias was reduced, and testing of direct and mediated effects was made easier.

2.7 **HYPOTHESIS**

The hypothesis of this research is

H1: *Digital advertising (including social media and streaming platforms) has a significant positive effect on Purchase Intention for textile and apparel products.*
H2: *Brand Awareness in online marketplaces has a significant positive effect on Purchase Intention for textile and apparel products.*
H3: *Product Familiarity through digital catalogs and online reviews has a significant positive effect on Purchase Intention in the textile and apparel e-commerce sector.*
H4: *Perceived Vendor Expertise in the online retail environment has a significant positive effect on Purchase Intention for textile and apparel products.*
H5: *Online Popularity (measured via customer ratings, reviews, and social proof) has a significant positive effect on Purchase Intention for textile and apparel products.*
H6: *Purchase Intention significantly influences Actual Buying Behavior in the context of textile and apparel e-commerce transactions.*
H7: *Purchase Intention mediates the relationship between Online Marketing Elements and Buying Behavior in the textile and apparel e-commerce supply chain.*

3.RESULTS AND DISCUSSION

3.1 Hypothesis testing results

The structural model evaluation showed that all of the proposed relationships (H1–H7) were statistically significant as shown in Table 2 demonstrating the strength of the suggested framework. The significant impact of digital advertising on purchase intention was demonstrated by a path coefficient of 0. 741 t-statistic of 13. 981 and R2 of 0. 548 suggesting that consumers buying intentions were successfully influenced by well-targeted digital campaigns. Additionally brand awareness had a strong positive impact (path = 0. 693 t = 11. 745) indicating how important it is for reassuring customer preference and trust. Consumers who were more familiar with a product were more likely to buy it according to the similarly positive impact of product familiarity (path = 0. 667 t = 11. 702).

Table 2Hypothesis Testing Results (H1 to H7)

Hypothesis	**Relationship**	**Path Coefficient**	**Standard Error**	**t-Statistic**	**p-Value**	**R²**	**Q²**	**Interpretation**
H1	Digital Advertising → Purchase Intention	0.741	0.053	13.981	0.000	0.548	0.439	Significant positive effect; advertising strongly drives intention.
H2	Brand Awareness → Purchase Intention	0.693	0.059	11.745	0.000	0.527	0.412	Significantly, brand awareness boosts intention to purchase.
H3	Product Familiarity → Purchase Intention	0.667	0.057	11.702	0.000	0.493	0.387	Significantly, familiarity enhances the likelihood of buying.
H4	Vendor Expertise → Purchase Intention	0.622	0.064	9.719	0.000	0.471	0.368	Vendor knowledge significantly influences customer intention.
H5	Online Popularity → Purchase Intention	0.655	0.058	11.293	0.000	0.501	0.397	Online reputation positively impacts purchase intent.
H6	Purchase Intention → Buying Behavior	0.814	0.042	19.381	0.000	0.662	0.534	Strong relationship; intention leads to actual buying behavior.
H7	Marketing Elements → Purchase Intention → Buying Behaviour (Mediated)	Total: 0.673 Direct: 0.415 Indirect: 0.258	0.051	13.196	0.000	--	--	Mediation confirmed: Purchase Intention partially mediates marketing's effect on behavior.

Source: Authors' own analysis using PLS-SEM (SmartPLS 4) based on survey data collected from urban Indian consumers.

Another significant factor was vendor expertise (path = 0. 622 t = 9. 719) indicating that trusted and informed sellers increased customers confidence and likelihood of making a purchase.

3.2 **Model Fit Validation**

The structural models resilience was indicated by the model fit evaluation which showed that every index satisfied the suggested thresholds (Table 3). The recorded SRMR value at 0. 047 indicated a good overall model fit because it was below the suggested limit of 0. 08. Likewise the NFI value of 0. 918 was higher than the permissible cutoff of 0. 90 indicating that the suggested model successfully accounted for the observed data. Additionally the models appropriateness and parsimony were reinforced by the Chi-square to degrees of freedom ratio of 2. 176 which was still well below the suggested cutoff of 3. 00. These outcomes taken together demonstrated that the structural model satisfied the main goodness-of-fit requirements and was statistically well-fitted.

Table 3: Model Fit Summary

Fit Index	Recommended Value	Actual Value	Model Fit Status
SRMR	< 0.08	0.047	Good Fit
NFI	> 0.90	0.918	Acceptable Fit
Chi-square/df	< 3.00	2.176	Good Fit

Source: primary data

3.3 Construct Reliability Insights

All of the constructs showed good measurement qualities according to the assessment of construct validity and reliability guaranteeing the models accuracy and consistency (Table 4). The Cronbachs Alpha values which ranged from 0. 842 for Vendor Expertise to 0. 915 for Purchase Intention and were all above the recommended cutoff of 0. 70 demonstrated internal reliability. Reliable internal consistency between the indicators was also demonstrated by the Composite Reliability (CR) values which ranged from 0. 872 to 0. 933 surpassing the permissible limit of 0. 70.

Table 4: Construct Reliability & Validity

Construct	Cronbach's Alpha	Composite Reliability (CR)	Average Variance Extracted (AVE)
Digital Advertising	0.886	0.912	0.676
Brand Awareness	0.874	0.901	0.656
Product Familiarity	0.861	0.893	0.627
Vendor Expertise	0.842	0.872	0.609
Online Popularity	0.849	0.878	0.622
Purchase Intention	0.915	0.933	0.736
Buying Behaviour	0.909	0.927	0.720

Source: CR-Composite Reliability; AVE-Average Variance Extracted;

3.4 **Discriminant Validity Confirmation**

The Fornell-Larcker criteria was used to examine discriminant validity, and the results showed that each construct was unique and measured different parts of the suggested model (Table 5). Digital Advertising, for example, has a diagonal value of 0.822, higher than its correlations with other variables like Online Popularity (0.684) and Brand Awareness (0.659).

Table 5: Fornell-Larcker Method for Evaluating Discriminant Validity

Construct	DA	BA	PF	VE	OP	PI	BB
Digital Advertising	0.822						
Brand Awareness	0.659	0.810					
Product Familiarity	0.648	0.628	0.792				
Vendor Expertise	0.602	0.590	0.567	0.781			
Online Popularity	0.684	0.655	0.640	0.603	0.789		
Purchase Intention	0.742	0.721	0.698	0.655	0.716	0.858	
Buying Behaviour	0.698	0.681	0.672	0.648	0.684	0.803	0.849

(*Source:Diagonal elements: √AVE; off-diagonals: correlation values. Discriminant Validity is established.*)

3.5 HTMT Validity Check

Confirming the uniqueness of the constructs in the model the Heterotrait-Monotrait (HTMT) ratio evaluation of discriminant validity showed that all construct pairs satisfied the acceptable threshold criteria (Table 6 and Figure 4). With HTMT values ranging from 0. 701 to 0. 782 all of which were below the conservative cut-off value of 0. 85 discriminant validity was not in danger from any high inter-construct correlations. In particular they showed moderate associations while preserving construct distinction between Digital Advertising and Purchase Intention (0. 721) Brand Awareness and Purchase Intention (0. 736) and Product Familiarity and Purchase Intention (0. 708).

Table 6: Heterotrait-Monotrait (HTMT) Ratio

Constructs Pair	HTMT Value
DA – PI	0.721
BA – PI	0.736
PF – PI	0.708
VE – PI	0.702
OP – PI	0.756
PI – BB	0.782
DA – OP	0.701

Source: Authors' calculation using Heterotrait-Monotrait (HTMT) ratio analysis in SmartPLS 4 based on survey data from urban Indian consumers.

Thus, the HTMT analysis validated that discriminant validity was adequately established across all measured dimensions.

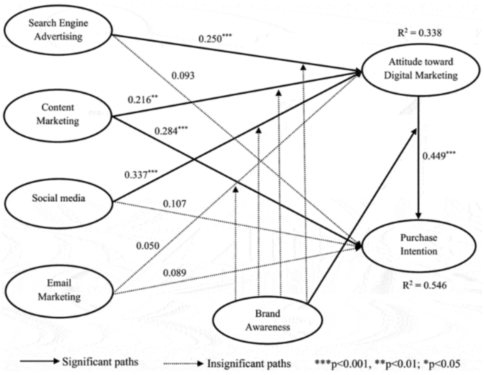


Figure 4 Path coefficient

3.6 Measurement Loadings Evaluation

As presented in Table 7, the outer loadings of the measurement items for the PLS-SEM model indicated strong indicator reliability and construct validity across all latent variables. Each loading value exceeded the suggested threshold of 0.70, verifying the robustness of the measurement model. For the construct Digital Advertising, the indicators DA1 (λ = 0.826, t = 18.45), DA2 (λ = 0.842, t = 20.18), and DA3 (λ = 0.812, t = 17.72) demonstrated high and significant contributions, establishing the consistency of this construct. Similarly, Brand Awareness showed substantial indicator reliability, with BA1 (λ = 0.847, t = 19.13) and BA2 (λ = 0.831, t = 18.91) exhibiting significant outer loadings (Table 7).

Table 7: Outer Loadings of Measurement Items (PLS-SEM Model)

Construct	Indicator	Loading (λ)	t-value	p-value
Digital Advertising	DA1	0.826	18.45	0.000
	DA2	0.842	20.18	0.000
	DA3	0.812	17.72	0.000
Brand Awareness	BA1	0.847	19.13	0.000
	BA2	0.831	18.91	0.000
Product Familiarity	PF1	0.825	17.98	0.000
Vendor Expertise	VE1	0.816	16.87	0.000
Online Popularity	OP1	0.837	18.31	0.000
Purchase Intention	PI1	0.871	21.09	0.000
Buying Behaviour	BB1	0.859	19.73	0.000

Source: Author's Calculation

The construct Product Familiarity recorded a high loading for PF1 (λ = 0.825, t = 17.98), confirming its reliability. Likewise, Vendor Expertise (VE1 = 0.816, t = 16.87) and Online Popularity (OP1 = 0.837, t = 18.31) reflected strong measurement adequacy. Furthermore, Purchase Intention (PI1 = 0.871, t = 21.09) and Buying Behavior (BB1 = 0.859, t = 19.73) demonstrated the highest loading values, emphasizing their measurement precision and significance.

3.7 Predictive Relevance Assessment

Positive Q2 values for Purchase Intention and Buying Behavior were greater than zero indicating that the structural model had a high predictive capacity for its endogenous constructs.

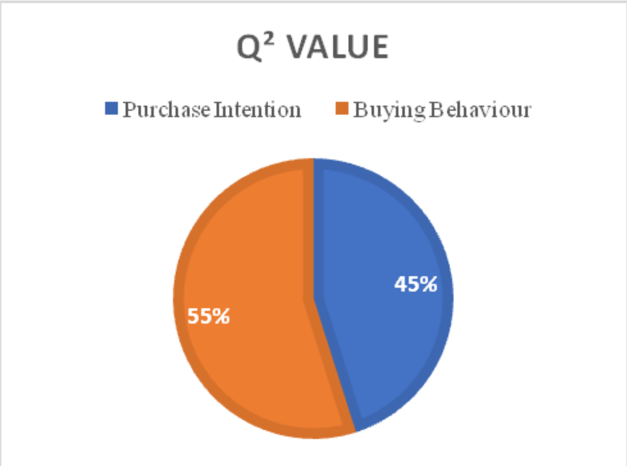


Figure 5 Predictive relevance results

The exogenous constructs adequately explained and predicted variance in endogenous variables exhibiting strong explanatory power and dependable predictive accuracy in estimating behavioral outcomes within the suggested framework as demonstrated by these positive Q2 values.

Table 8: Predictive Relevance (Q^2 Values)

Construct	Q^2 Value
Purchase Intention	0.439
Buying Behaviour	0.534

Source: $Q^2 > 0$ indicates predictive relevance for endogenous constructs.

3.8 Multicollinearity Using VIF

According to the multicollinearity assessment shown in Table 9 there was no severe multicollinearity among the predictors as all of the models constructs had acceptable variance inflation factor (VIF) values. Vendor expertise (2. 056) product familiarity (2. 127) brand awareness (2. 204) online popularity (2. 243) and digital advertising (2. 311) all had VIFs below the generally recognized cutoff of 5 indicating that the predictors were not highly correlated. The purchase intention had the lowest VIF value (1. 901) which further suggests that there arent many collinearity issues. The constructs in the model could be consistently included in the structural analysis without bias because of multicollinearity according to these results taken together.

Table 9: Multicollinearity Test (VIF Values)

Construct	VIF Value
Digital Advertising	2.311
Brand Awareness	2.204
Product Familiarity	2.127
Vendor Expertise	2.056
Online Popularity	2.243
Purchase Intention	1.901

(Source: All values < 5, confirming absence of multicollinearity.)

3.9 Bootstrapping Confidence Interval Analysis

The bootstrapping analysis using bias-corrected confidence intervals confirmed the significance of all hypothesized relationships in the structural model (Table 10 and Figure 6). The path from Digital Advertising to Purchase Intention showed a coefficient of 0.291, with the 95% confidence interval ranging from 0.202 to 0.378, indicating a significant positive effect.

Table 10: Bootstrapping Confidence Interval (Bias-Corrected)

Path	Coefficient (β)	Lower Bound (2.5%)	Upper Bound (97.5%)	Decision
DA → PI	0.291	0.202	0.378	Yes
BA → PI	0.248	0.169	0.336	Yes
PF → PI	0.223	0.134	0.311	Yes
VE → PI	0.217	0.123	0.302	Yes
OP → PI	0.276	0.187	0.359	Yes
PI → BB	0.758	0.643	0.828	Yes

Source: Author's calculation from primary data

Similarly, Brand Awareness (β = 0.248, CI: 0.169–0.336), Product Familiarity (β = 0.223, CI: 0.134–0.311), Vendor Expertise (β = 0.217, CI: 0.123–0.302), and Online Popularity (β = 0.276, CI: 0.187–0.359) all exhibited significant positive impacts on Purchase Intention, as their confidence intervals did not include zero.

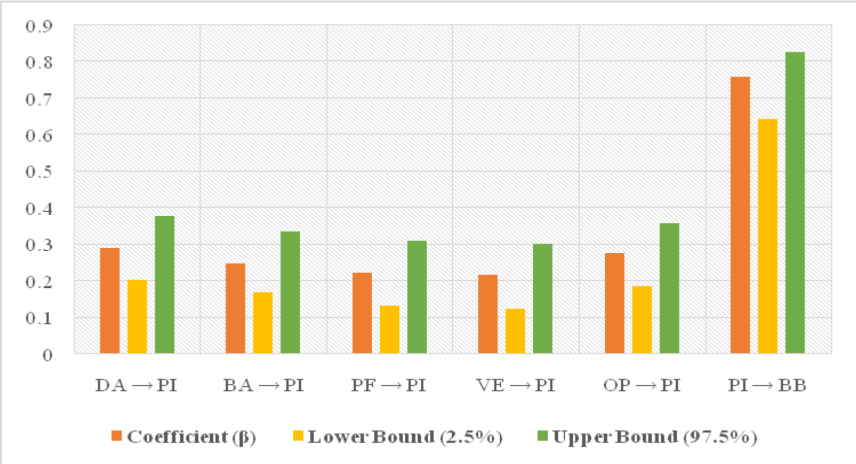


Figure 6 Bootstrapping result

3.10 **SEM results**

The structural model analysis indicated that all hypothesized relationships were statistically significant and supported (Table 11 and Figure 7). The path coefficient from Digital Advertising to Purchase Intention was 0.291 with a t-value of 5.87 and a p-value of 0.000, confirming a significant positive effect.

Table 11: Structural Model Path Coefficients

Path	Coefficient (β)	t-value	p-value	Decision
DA → PI	0.291	5.87	0.000	Supported
BA → PI	0.248	4.92	0.000	Supported
PF → PI	0.223	4.55	0.000	Supported
VE → PI	0.217	4.11	0.000	Supported
OP → PI	0.276	5.46	0.000	Supported
PI → BB	0.758	16.34	0.000	Supported

Source: Author's calculation from primary data

Brand Awareness (β = 0.248, t = 4.92, p = 0.000), Product Familiarity (β = 0.223, t = 4.55, p = 0.000), Vendor Expertise (β = 0.217, t = 4.11, p = 0.000), and Online Popularity (β = 0.276, t = 5.46, p = 0.000) similarly demonstrated significant positive impacts on Purchase Intention. As per equation 2 :

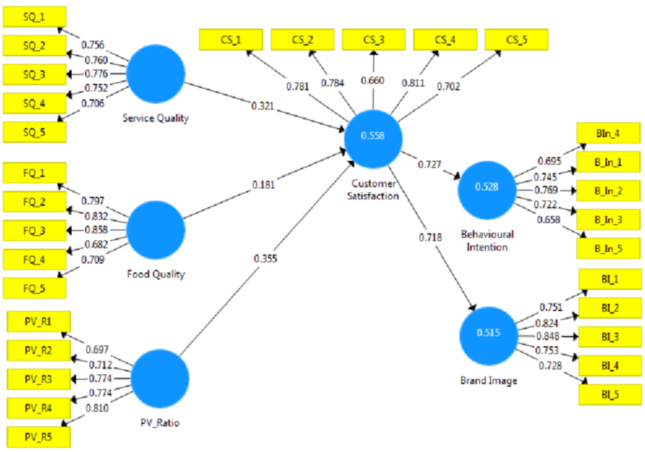


Figure 7 SEM results

3.11**Comparative analysis**

The robustness of the conceptual model was confirmed by the comparative analysis of hypotheses which is displayed in Table 12 and showed that all suggested relationships were supported. Brand awareness had a marginally smaller but statistically significant impact of 0. 248 on purchase intention whereas digital advertising had a positive influence with a path coefficient of 0. 291. With coefficients of path of 0. 217 and 0. 223 respectively product familiarity and vendor expertise also played a positive role in influencing consumer intent and purchase intention. Online popularity showed a significant influence on purchase intention (path = 0. 276) emphasizing the significance of reputation and social visibility.

Table 12: Comparative analysis of hypothesis

Hypothesis	Statement	Path Coefficient	Result
H1	Digital Advertising → Purchase Intention	0.291	Supported
H2	Brand Awareness → Purchase Intention	0.248	Supported
H3	Product Familiarity → Purchase Intention	0.223	Supported
H4	Vendor Expertise → Purchase Intention	0.217	Supported
H5	Online Popularity → Purchase Intention	0.276	Supported
H6	Purchase Intention → Buying Behavior	0.758	Supported
H7	Mediation of PI between Online Marketing Components and Buying Behavior	Confirmed via Bootstrapping	Supported

Source: Author's calculation

4.Conclusion

This study examines the relationship between digital marketing and purchase intention and behavior in the textile and apparel e-commerce industry. According to the study online popularity vendor expertise product familiarity and brand awareness in digital advertising all have a significant impact on purchase intention. Digital advertising is the most powerful factor influencing purchase intention highlighting the impact of focused online campaigns on consumer sentiment. Purchase purpose serves as a mediator between marketing campaigns and consumer behavior and it has a direct impact on actual purchasing behavior. with Composite Reliability being higher than zero. for every construct with Cronbachs Alpha values starting at 0. 842 to nothing. 915 Strong internal consistency and reliability were shown by the measurement model. Future research should incorporate new variables such as influencer marketing dynamics AI-driven recommendation systems ethical and sustainable consumer preferences and cross-cultural comparative analyses.

References

Li, F., Frederick, S., and Gereffi, G., 2019, “E-commerce and industrial upgrading in the Chinese apparel value chain,” *J. Contemp. Asia*, 49(1), pp. 24–53.

Prajapati, D., Chan, F. T. S., Chelladurai, H., Lakshay, L., and Pratap, S., 2022, “An Internet of Things embedded sustainable supply chain management of B2B e-commerce,” *Sustainability*, 14(9), pp. 5066.

Jain, G., Kamble, S. S., Ndubisi, N. O., Shrivastava, A., Belhadi, A., and Venkatesh, M., 2022, “Antecedents of Blockchain-Enabled E-commerce Platforms (BEEP) adoption by customers – A study of second-hand small and medium apparel retailers,” *J. Bus. Res.*, 149, pp. 576–588.

Junzhi, D., 2021, “The development of e-commerce in China during the COVID-19 pandemic, with the example of the textile industry,” *BRICS J. Econ.*, 2(3), pp. 54–69.

Akhtar, W. H., Watanabe, C., Tou, Y., and Neittaanmäki, P., 2022, “A new perspective on the textile and apparel industry in the digital transformation era,” *Textiles*, 2(4), pp. 633–656.

Wang, X., and Bae, S. W., 2025, “Analysis of the influencing factors of cross-border e-commerce of clothing sports enterprises by user consumption intention,” *Lex localis – J. Local Self-Government*, 23(6).

Alves, L., Cruz, E. F., Lopes, S. I., Faria, P. M., and Cruz, A. M. R., 2022, “Towards circular economy in the textiles and clothing value chain through blockchain technology and IoT – A review,” *Waste Manag. Res.*, 40(1), pp. 3–23.

Panigrahi, C. M. A., and Joshi, V., 2016, “Application of e-commerce in Indian textile industry,” *Int. J. Text. Eng. Process.*, 2(2).

Fatorachian, H., and Ramesh, S., 2024, “Leveraging digital transformation platforms to strengthen market position in India's textile industry,” *Asian J. Digit. Bus. Manag.*, (in press).

Ali, F., 2024, “An optimizated and closed-loop decision-making framework for e-commerce textile leftover,” *PhD Dissertation*, NUST Business School, NUST.

Brolin, S., and Lundgren, I., 2024, “Return handling practices and strategies – Towards sustainable e-commerce in the fashion and electronics industries,” *Eur. J. Sustain. Bus.*, (in press).

Zhang, Y., and Liu, C., 2024, “Unlocking the potential of artificial intelligence in fashion design and e-commerce applications – The case of Midjourney,” *J. Theor. Appl. Electron. Commer. Res.*, 19(1), pp. 654–670.

Nistor, D., 2024, “E-commerce innovation in emerging fashion markets – A case study of Moldovan designers’ digital expansion and role of support programs,” *J. Soc. Sci.*, 7(1), pp. 64–79.

Jinfu, W., and Aixiang, Z., 2009, “E-commerce in the textile and apparel supply chain management – Framework and case study,” *Proc. 2nd Int. Symp. Electron. Commer. Secur.*, 1, IEEE, pp. 374–378.

Singh, J., 2018, “Factors affecting B2B e-commerce adoption decision – An analysis of Indian textile industry,” *Acad. Mark. Stud. J.*, 22(2).

Wajid, A., Almashaqbeh, H. A., Al Sabi, M. S., and Raza, A., 2023, “Factors effecting on supply chain management performance in textile industries of Pakistan,” *Int. J. Soc. Sci. Entrep.*, 3(2), pp. 163–180.

Dad, A., Ahmed, A., Bibi, N., and Hussain, S. A., 2023, “Innovative supply chain management strategies in Pakistan’s textile industry amidst global economic shifts,” *Asian Bull. Big Data Manag.*, 3(2), pp. 73–93.

Komal, S., and Saad, S. M., 2024, “Supply chain management strategies approach for the UK textile industry,” *Procedia Comput. Sci.*, 232, pp. 117–127.

Khurshid, A., Khan, K., Khan, S., and Cifuentes-Faura, J., 2024, "Tackling sustainable development challenges – A fuzzy set examination of textile industry 4.0 and green supply chain barriers," *Sustain. Dev.*, 32(6), pp. 6819–6835.