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# Investing Webrooming Behavior Among Consumers: A Theory of Planned Behavior Approach

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## Abstract

The current research explores factors determining webrooming behavior of consumers in Haryana by employing the theory of planned behavior. In particular, attitude, subjective norms, and perceived behavioral control were assessed as independent variables predicting webrooming behavior among consumers. The research data were obtained from 309 participants using structured questionnaires. PLS-SEM (version 4.1.1.8) analysis revealed that all three independent variables have a significant and positive impact on webrooming behavior. Subjective norms turned out to be the strongest predictor among the three independent variables considered in this study. Also, it was noted that educational qualification was the only significant demographic control variable in this research. This means that consumers who have higher levels of education were more engaged in webrooming behavior. The conclusions drawn from this research are of great importance for various stakeholders such as retailers, marketers, and consumers.

**Key Words:** Webrooming behavior, Theory of Planned Behavior, Consumer Behavior, Online Information Search, Offline Purchasing.

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## Introduction

The retail businesses and consumers' shopping habits have experienced a large number of changes because of two factors, which are digitalization and increased internet accessibility. The increasing use of mobile phones, online platforms, and digital technology has changed the traditional buying process with a more complex multichannel shopping experience (Azim et al., 2026; Hossain et al., 2026). Today, consumers actively use different channels to gather information, compare prices, read online reviews, and make more informed purchase decisions (Aw et al., 2020). The emergence of hybrid shopping behaviors through showrooming and webrooming has developed because of this transformation. Webrooming refers to the consumer behavior of searching for product-related information online before purchasing the product from a physical store (Flavian et al., 2020). The increasing popularity of webrooming shows that online shopping and offline shopping methods work together as a complementary system instead of competing against each other (Wu et al., 2023).

Retailers in India have started to recognize webrooming as an important consumer trend, which has emerged because people in Haryana now have better access to the internet and businesses use multiple sales channels (Rani & Sharma, 2025). Consumers mainly engage in webrooming to get product information, compare alternatives, reduce perceived risk, and improve confidence in purchase decisions (Lavuri & Thaichon, 2025). Despite the convenience and extensive product information that online shopping offers, consumers still value physical stores because they want to examine products directly and experience their tactile qualities (Lavuri & Thaichon, 2025). Online channels provide users with informational advantages together with convenience, while customers at offline stores can experience products through sensory evaluation and direct product testing (Rathore & Sharma, 2026). Consumers visit physical stores because they want to reduce uncertainty, which comes with online shopping and its associated post-purchase risks (Yadav et al., 2024). The online shopping process involves both inconveniences and risk factors, which make consumers shift from searching online to purchasing items from physical retail stores (Kim & Han, 2023). Retailers who operate a multichannel retail system need to study webrooming behavior because it has become essential for their commercial operations (Guo et al., 2026).

Webrooming has become more popular, yet existing research fails to explain why consumers decide to switch from online searching to buying products in physical stores (Rani & Sharma, 2025). Previous research has mainly investigated three areas: technological factors, channel-related elements, and utilitarian design features that help users save time and achieve their goals (Azim et al., 2026). The research has focused on how consumers make webrooming decisions because the psychological factors and behavioral patterns that drive these decisions remain unexplored (Rathore & Sharma, 2026). Most of the prior research on webrooming is concerned with technology and channel-based aspects. Nevertheless, few studies have looked into the consumer's decision-making process in relation to webrooming activity. In other words, a more holistic behavior model is required to explain why consumers seek information from online sources before buying goods from physical stores. These activities can be explained by means of three main determinants, namely attitudes, social influence, and behavioral control.

To fill this gap, the present study applies the theory of planned behavior (TPB) to explain the webrooming behaviors of consumers. The TPB framework serves as a suitable model that researchers can apply to study complex consumer decision-making processes (Arora & Sahney, 2018). The theory explains behavior using three main elements: attitude, subjective norms, and perceived behavior control, which together shape what people do. Jain and Shankar (2022), found that consumers who search online and use different channels display specific patterns that affect their webrooming behavior. The study stated that subjective norms function as a critical factor that directs purchase decisions for consumers who want to buy high-involvement products in emerging markets. According to Ajzen (1991), consumers' perceptions of their resources, knowledge, and capacity to carry out a specific behavior are known as perceived behavioral control. In the context of webrooming, consumers with proficiency in using online platforms and channel switching exhibit higher rates of

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webrooming (Arora et al., 2022). The integrated behavioral frameworks display higher accuracy when they predict consumer webrooming behavior compared to other prediction methods (Jain & Shankar, 2022).

The main purpose of this research study is to analyze how different components of the TPB model affect consumers' webrooming practices in Haryana, India. The demographic variables were used as control variables in order to compare the differences in webrooming among different customers. This research is mainly concentrating on the psychological and behavioral variables that affect webrooming in emerging retail markets. This paper can provide relevant suggestions for marketers and retailers about webrooming behaviors.

## Theoretical Background and Hypotheses Development

### Theory of Planned Behavior (TPB)

The Theory of Planned Behavior, a concept in social psychology, was created as an expansion of the Theory of Reasoned Action (TRA) by Icek Ajzen in 1985 and was further detailed in 1991. TRA maintains that an individual's behavior is entirely governed by behavioral intent, while TPB enlarges this perspective by adding an extra construct to accept those behaviors in which the person has only partial volitional control. TPB indicates that behavioral intention is the direct cause of actual behavior (Ajzen, 1991; Arora & Sahney, 2018). An attitude is defined as an individual's overall positive or negative assessment of doing a certain behavior (Ajzen, 1991; 2020). On the other hand, subjective norms represent social pressure that the individual perceives from others, as well as the impact of influencing people on the individual's decision-making. Fishbein and Ajzen (1977), point out that these crucial referents are usually family members, friends, and colleagues whose opinions and expectations can strongly influence a consumer's intentions for buying. Perceived behavior control is, however, mostly an individual's evaluation of what kind of efforts are needed to carry out a specific behavior, under those given circumstances (Ajzen, 1991). The Theory of Planned Behavior is kind of one of the most common, effective theoretical frameworks for figuring out and predicting human social behavior (Ajzen, 2011). These relationships have also been validated in the context of webrooming behavior, where consumers' online search and offline purchase intentions are significantly influenced by the TPB construct (Arora & Sahney, 2018; 2019; Shankar & Jain, 2021).

**Attitude and Webrooming Behavior**

Attitude is sort of that whole thing where an individual makes a general positive or negative judgment about doing a specific behavior. In terms of the Theory of Planned Behavior, attitude is pretty important for predicting behavioral results, because people tend to take part in an action when they see it as beneficial and also desirable (Ajzen, 1991). In particular, attitude is a measure of how positively or negatively a consumer assesses the anticipated results of a behavior. Ajzen and Fishbein (1975), emphasized the complexity of attitude by conceptualizing it as a complex structure with cognitive, emotional, and conative (behavioral) components. In this sense, attitude is a person's overall evaluation of participating in a certain activity, which directly affects their intention and subsequent actions. Using this information in the context of webrooming, valuable research indicates that consumers who have a favorable attitude toward online information search are more likely to participate in webrooming behavior (Flavian et al., 2020; Gopi et al., 2024). This opinion is further supported by empirical data from Arora & Sahney (2019), who show that customers have a more favorable attitude toward internet searches before and during in-store purchases. Thus, it can be concluded that attitude significantly influences webrooming behavior in a positive manner (Sahu et al., 2020; Shankar & Jain, 2021). Therefore, the subsequent hypothesis was proposed:

H1: Attitude has a significantly positive impact on webrooming behavior.

**Subjective Norms and Webrooming Behavior**

Subjective norms are the perceived social pressure that influences an individual's decision to take a specific action (Ajzen & Madden, 1986). Subjective norms demonstrate how significant reference groups, such as friends, family, and peers, influence an individual's decision-making process in the Theory of Planned Behavior (Ajzen, 1991). Earlier studies

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also suggested that subjective standards have a strong influence on how consumers act, especially when they switch channels and when cross-channel free riding happens (Arora and Sahney, 2017). Furthermore, webrooming intention has been found to positively correlate with subjective norms, suggesting that social influence plays a significant role in encouraging consumers to conduct online research before making an offline purchase (Arora & Sahney, 2019; Shankar & Jain, 2021; Rani & Sharma, 2025). Moreover, it has been argued that consumers' channel choices are shaped by the need to gain acceptance from important others or to avoid their dissatisfaction (Chou et al., 2016). Similarly, social influence has been found to predict consumers' intention to engage in webrooming (Han & Ryu, 2012; Sahu et al., 2020). From this, it can be concluded that subjective norms have a strong positive impact on webrooming behavior. Therefore, the following hypothesis is formulated:

H2: Subjective Norms have a significantly positive impact on webrooming behavior.

**Perceived Behavioral Control and Webrooming Behavior**

Perceived Behavioral Control (PBC) is about how a person sees their capability and the kind of control over doing a particular behavior (Ajzen, 1991; 2020). In the middle of the whole webrooming process, PBC basically captures how people think they can use multiple channels efficiently within one buying process (Arora and Sahney, 2018). More specifically, it covers whether the opportunities, the information, and the resources are there and whether they can really be leveraged to do what they have in mind. In the case of webrooming, this idea is closely related to how consumers can access and then integrate online and offline channels during the purchasing process. Prior studies also indicate that webrooming is tied to consumers' readiness for multi-channel buying (Chiu et al., 2011; Verhoef et al., 2015; Arora and Sahney, 2018). Also, this behavior doesn't just occur by itself; it needs the right skills and supporting means. Therefore, an individual's perception of how easy or difficult it is to follow a particular behavior is reflected in perceived behavioral control (PBC). If people believe that the necessary conditions, like available opportunities and the right resources, are present, then their readiness to take part in webrooming is expected to increase (Perugini and Bagozzi, 2001; Arora et al., 2022). So, webrooming behavior is expected to be positively and

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directly influenced by perceived behavioral control. Hence, the next hypothesis was put forward:

H3: Perceived behavior control has a significantly positive impact on webrooming behavior.

## Methodology

### Target Respondents and Sampling Method

The current study is based on a survey that was made using an adapted questionnaire to look at consumers' intentions toward webrooming behavior, like how they act when they combine online browsing with in-store purchase, to estimate how far and why webrooming is actually taking place. A cross-sectional research approach was chosen instead of the longitudinal design, because it is used widely in management studies and other domains, and also because the respondents had hectic schedules (Spector & Pindek, 2016). This method is particularly useful when researchers aim to examine relationships between variables at a specific point in time without the need for long-term observation (Beyman, 2016).

In the present study, we used a non-probability convenience sample strategy, kind of to pull together information from customers in Haryana, who were actively engaged in webrooming. This method was chosen because it is, in a way, practical for getting to respondents who are actively looking for products on the internet and buying them through physical stores. Convenience sampling is considered a kind of fit for research that deals with big and varied consumer groups, particularly when time and resources are limited, even though it has some downsides that come from the fact that it is not random. Moreover, due to the convenience sampling, it was easy to reach out to people who actually engaged in webrooming behavior at shopping malls or retail shops, as they were easily accessible for participation in the research study. The respondents were pulled from a range of demographic categories, like variations in age, gender, income, and education levels, across Haryana, so that the sample would feel more representative and maybe reduce possible bias.

### Measurement Instrument

Measurement scales that came from earlier validated studies got tweaked slightly to make a more structured questionnaire for gathering primary data. The study's main constructs- attitude (ATT), subjective norm (SN), perceived behavioral control (PBC), and webrooming behavior (WB)- were addressed in the first section using multiple items. The items of attitude are adapted from Gopi et al. (2024) and Arora and Sahney (2019), while Arora and Sahney (2019) are referred to for the perceived behavioral control items. For webrooming behavior, the items were pulled from Goraya et al., (2022), and the subjective norm items were modified based on Shankar and Jain (2023). These adjustments supported content validity and also helped keep things in line with earlier research, which is sort of the whole idea.

In the second section, the questionnaire noted the respondents' sociodemographic details like age, gender, occupation, residential area, education, and income level. A 5-point Likert scale was used to collect the answers, 1-point in the scale means "strongly disagree" and 5 means "strongly agree". Every construct was operationalized as a reflective measure, so they could be treated in that way. Since the 5-point Likert scale is straightforward and relatively easy to grasp, it was picked to improve the response quality and reduce respondent fatigue (Babakus & Mangold, 1992; Sachdev & Verma, 2004). Furthermore, previous studies indicate that a 5-point scale is better suited for multiple- item questionnaire since it enhances response consistency in comparison to longer scales (Sauro, 2010; Newson,2021).

**Sample Size**

G*power, a widely used tool for statistical power analysis, was used to figure out the minimal sample size needed for the investigation. In social and behavioral research, a threshold of 0.80 is often recommended; a statistical power level of 0.95 was chosen (Faul et al., 2007; 2009). By estimating a suitable size using the effect size, the significance level, and the desired statistical power, researchers can run G*power to lower the chance of a Type I and Type II error (Cohen, 1988).

The method makes sure the study is adequately powered by maximizing these parameters, which improves the reliability and validity of the findings. In this analysis, it was shown that

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a minimum sample size of 119 respondents was needed in order to reach the statistical power goal, but the final dataset ended up with 309 genuine responses. That is, it is above the minimum criteria, and it also confirms the stability of the empirical findings. Figure 1 shows the approximate sample size required.

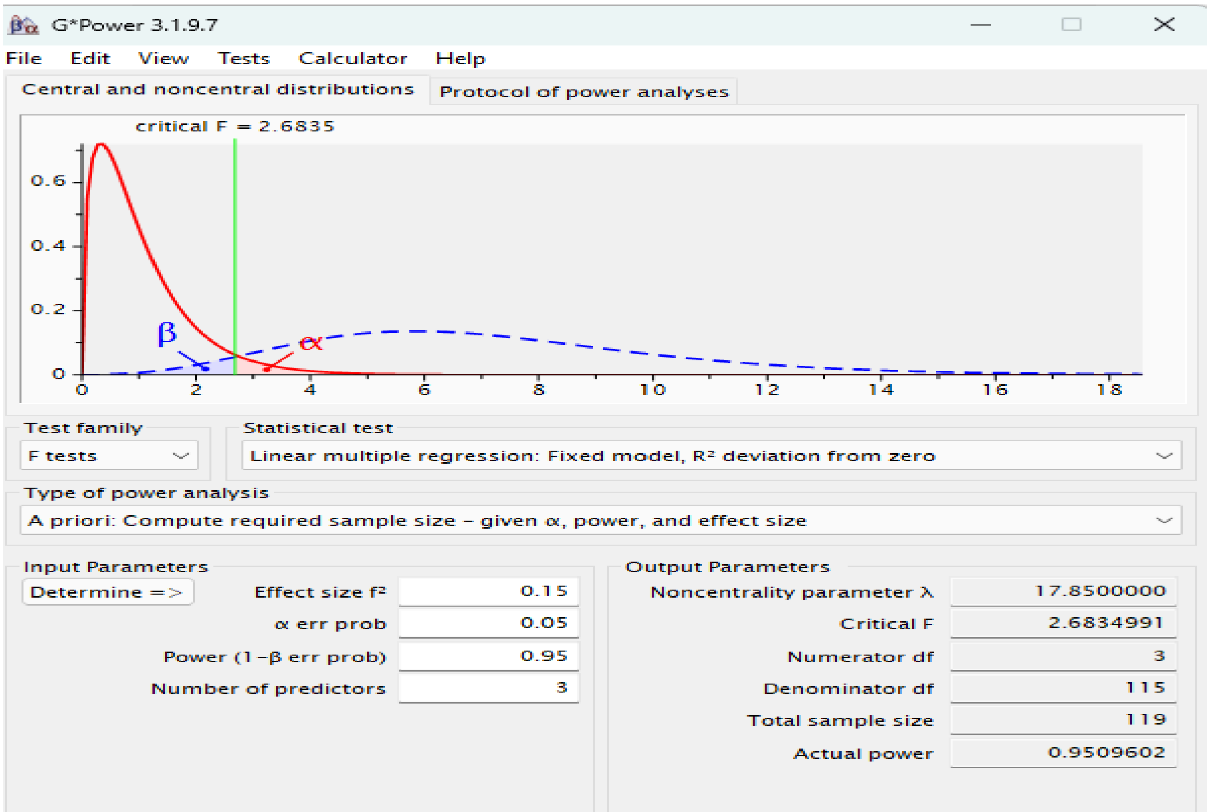


Figure 1. G*Power 3.1.9.7 Analysis.

Source: Faul et al. (2007, 2009).

**Pilot Testing, Data Collection, and Data Cleaning**

A pilot test was carried out with 50 respondents before researchers moved on to the main survey, basically so researchers could see and fix any potential problems that might mess up the data collection process. The pilot study's outcomes seemed to confirm that the questionnaire had good clarity, decent organization, and it was easy to understand, so it looked fit for broad use. After that, 500 customers in Haryana were asked to fill out the

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questionnaire for the final data gathering, using both offline and online survey methods (Google Forms), so participation would rise. Altogether, 350 responses were received, but 41 of those were eliminated because the answers were not consistent or some sections were incomplete. Therefore, finally, 309 valid responses were retained for further analysis, and this gave a response rate of 61.8%, which is typically seen as acceptable in empirical research.

**Data Analysis**

Partial Least Squares Structural Equation Modeling (PLS-SEM) was used to analyze the data with the help of SmartPLS (version 4.1.1.8). Researchers chose this approach since it can work with data even when normal distribution assumptions are not really that strict, and it also fits studies where the sample size can be more flexible. Moreover, PLS_SEM seems quite fitting for mapping connected relationships among constructs in behavioral research (Hair et al., 2019; Henseler et al., 2009).

**Biasness Check**

First, the dataset was assessed just to confirm it was suitable for statistical analysis. After that, the Variance Inflation Factor (VIF) values were applied to take a look at multicollinearity among the independent variables. Based on the findings, multicollinearity doesn't seem to be a concern in this work since every VIF value sat under the recommended cutoff of 3.3 (Diamantopoulos & Siguaw, 2006).

After that, we also thought about Common Method Bias, since the whole set of data was gathered using a single self-administered questionnaire. The concept behind the usual technique variance is checked through Harman's single-factor approach. The first factor described 39.206%, which is under 50% of the overall variation, according to the unrotated exploratory factor analysis results, so it kind of looks like common method bias isn't really that much of an issue (Podsakoff et al., 2003; Bishnoi & Ubba, 2025). These results suggest the dataset is enough and, in other words, confirm that common technique variance doesn't meaningfully affect the study's conclusions.

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## Results

### Socio-demographic Profile of Participants

Table 1 presents the demographic details of the 309 participants, including gender, age, educational level, residence, yearly family income, and occupation. It was observed that 37.9% were males while the rest 62.1% were females. The group of people aged between 20-30 years made up the highest proportion of the sample size, which contributed 54.7%. The results showed that about 68% of participants were students or research scholars. The study found that 61.2% of participants came from rural areas, while 38.8% originated from urban areas. The sample appears to be well educated, as 36.6% of respondents had a postgraduate degree. About 62.5% respondents belonged to families having an income up to ₹300,000.

**Table 1: Demographic Distribution.**

| Variables | Response Category | Frequency (n=309) | Percent |
|---|---|---|---|
| Gender | Female | 192 | **62.1** |
| | Male | 117 | 37.9 |
| Age | Below 20 | 109 | 35.3 |
| | 20-30 | 169 | **54.7** |
| | 30-40 | 26 | 8.4 |
| | Above 40 | 5 | 1.6 |
| Education status | Up to 12 | 100 | 32.4 |
| | Graduation | 81 | 26.2 |
| | Post graduation | 113 | **36.6** |
| | Professional | 15 | 4.9 |
| Occupation | Student/Research Scholar | 210 | **68** |
| | Business owner | 13 | 4.2 |
| | Employee | 50 | 16.2 |
| | Homemaker | 21 | 6.8 |
| | Other | 15 | 4.9 |

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| | | | |
|---|---|---|---|
| Residential | Urban | 120 | 38.8 |
| | Rural | 189 | **61.2** |
| Family Income | Up to 300000 | 193 | **62.5** |
| | 300000-600000 | 72 | 23.3 |
| | 600000-1200000 | 31 | 10 |
| | Above 1200000 | 13 | 4.2 |

**Source:** Authors' depiction based on primary data by using SPSS v. 26.

**Note:** For easier comparison, bolded values show the greatest value within each group.

**Table 2: Reliability and Validity Analysis.**

| Constructs | Items | Factor Loadings | AVE | Cronbach's Alpha | CR (rho_a) | CR (rho_c) |
|---|---|---|---|---|---|---|
| Attitude | ATT1 | 0.797 | 0.604 | 0.868 | 0.873 | 0.901 |
| | ATT2 | 0.789 | | | | |
| | ATT3 | 0.760 | | | | |
| | ATT4 | 0.790 | | | | |
| | ATT5 | 0.819 | | | | |
| | ATT6 | 0.703 | | | | |
| Perceived Behavioral Control | PBC1 | 0.821 | 0.608 | 0.919 | 0.922 | 0.933 |
| | PBC2 | 0.759 | | | | |
| | PBC3 | 0.784 | | | | |
| | PBC4 | 0.770 | | | | |
| | PBC5 | 0.781 | | | | |
| | PBC6 | 0.744 | | | | |
| | PBC7 | 0.767 | | | | |
| | PBC8 | 0.838 | | | | |
| | PBC9 | 0.750 | | | | |

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| | | | | | | |
|---|---|---|---|---|---|---|
| Subjective Norms | SN1 | 0.728 | 0.570 | 0.811 | 0.817 | 0.869 |
| | SN2 | 0.717 | | | | |
| | SN3 | 0.729 | | | | |
| | SN4 | 0.824 | | | | |
| | SN5 | 0.773 | | | | |
| Webrooming Behavior | WB1 | 0.712 | 0.618 | 0.911 | 0.913 | 0.928 |
| | WB2 | 0.751 | | | | |
| | WB3 | 0.828 | | | | |
| | WB4 | 0.794 | | | | |
| | WB5 | 0.778 | | | | |
| | WB6 | 0.860 | | | | |
| | WB7 | 0.788 | | | | |
| | WB8 | 0.769 | | | | |

**Source**: Compiled by authors based on results extracted from Smart PLS.

**Note**: AVE: Average variance extracted; CR: Composite reliability; SN: Subjective Norms; ATT: Attitude; PBC: Perceived Behavioral Control; WB: Webrooming Behavior.

***Measurement Model***

Validity and reliability checks for the variables were conducted first, before the assessment of the measurement model. Among the many tests applied to determine the validity and reliability of the measurement model were convergent validity, composite reliability, discriminant validity, and Cronbach's alpha (Table 2). Notably, all the items had a factor loading higher than the threshold value of 0.70 (Hair et al., 2019). Internal consistency of the measurement model is measured by composite reliability (CR-rho_a), and it seems the internal consistency remains within the acceptable range of 0.7-0.95 (Hair et al., 2019). It is also important to note that here, Cronbach's alpha is within the range of 0.817-0.922, which means it fits into the acceptable cutoff. Further, the values of composite reliability obtained using CR (rho_c) are well within the range of 0.7-0.95, meaning that the constructs can be considered reliable. For all structures, CR values exceeded 0.70 (Table 2), which means that

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internal consistency is appropriate. Furthermore, convergent validity was established using the average variance extracted (AVE) test score, which was beyond the cut-off of 0.50 for all the constructs, higher-order, and lower-order constructs (Hair et al., 2019).

Discriminant validity was tested through the use of the HTMT ratio test. Discriminant validity was also established using the heterotrait-monotrait (HTMT) ratio (Henseler et al., 2015). The results indicated that discriminant validity had been achieved since the HTMT ratios were below the threshold of 0.90 (Table 3). Mean, standard deviation, skewness, kurtosis, and inter-construct correlation values are presented in Table 4. The level of significance for correlations between constructs is 0.01.

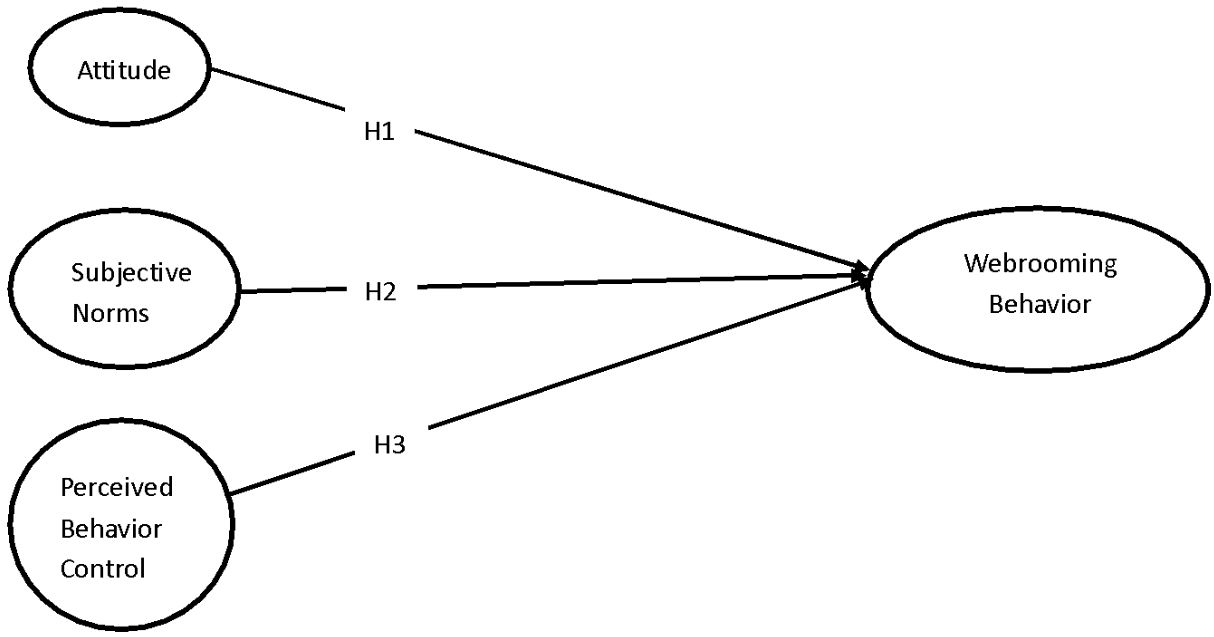


**Figure 2**. Proposed Research Model

**Table 3** Heterotrait- Monotrait (HTMT) Ratio Matrix.

| Variables | ATT | PBC | SN | WB |
|---|---|---|---|---|
| ATT | | | | |
| PBC | 0.448 | | | |

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| | | | |
|---|---|---|---|
| SN | 0.711 | 0.576 | |
| WB | 0.643 | 0.541 | 0.751 |

**Source:** Extracted from Smart PLS.

**Note:** PBC: Perceived Behavioral Control; ATT: Attitude; SN: Subjective Norms; WB: Webrooming Behavior.

**Table 4:** Descriptive Statistics and Correlation.

| | Mean | SD | Skewness | Kurtosis | ATT | SN | PBC | WB |
|---|---|---|---|---|---|---|---|---|
| ATT | 35.2492 | 6.22725 | -1.701 | 3.667 | 1.000 | - | - | - |
| PBC | 24.1036 | 3.70095 | -1.636 | 4.109 | 0.400 | 1.000 | - | - |
| SN | 18.5825 | 3.40127 | -0.460 | 0.611 | 0.497 | 0.597 | 1.000 | - |
| WB | 30.8188 | 6.01725 | -0.626 | 0.654 | 0.495 | 0.570 | 0.644 | 1.000 |

**Source:** Compiled by authors based on results extracted from SPSS.

**Note:** PBC: Perceived Behavioral Control; ATT: Attitude; SN: Subjective Norms; WB: Webrooming Behavior.

**Structural Model**

The structural model approach is employed in testing the hypothesis, and also to evaluate the model's explanatory and predictive power in accordance with the criteria set out by Sarstedt et al. (2021). The p-values necessary at a 5% significance level, and also the computation of the t-value necessary for evaluation of the relevance of the paths under consideration in the hypotheses, were obtained through conducting bootstrapping analysis employing 10,000 samples in Smart PLS. In this approach, R-squared, goodness of fit model, and the path hypothesis testing are considered critical for the evaluation. Before analyzing the relationships between variables in the structural model, the issue of multicollinearity was established through the VIF test. The Variance Inflation Factor (VIF) values were all below the recommended cutoff of 3.3, indicating that multicollinearity was not a significant concern in the analysis (Diamantopoulos & Siguaw, 2006). The "Standardized Root Mean Square

Residual (SRMR) global fit index" was used to check the goodness of fit indicator, because in the current era of PLS-SEM model research, a global model fit index, like SRMR, is considered essential for evaluating how well the model fits (Hair et al., 2020). An SRMR value under 0.08, in the context of an estimated model, is often seen as evidence of a good fit (Henseler et al., 2015). So, the SRMR for our estimated model comes out to 0.056, which indicates a good model fit. The proposed framework, see Figure 2, which incorporates respondents' age, gender, occupation, education, and annual family income as control variables, was adopted to conduct the empirical study. Subsequently, to measure the predictive accuracy of the model, the coefficient of determination ($R^2$) was computed. The coefficient of determination for webrooming behavior was 0.503, meaning that 50.3% of the variance in the dependent variable could be predicted from the model.

To examine the effect size of each of the independent variables, an analysis was carried out by $F^2$. Cohen (1988), and Hair et al., (2014), suggest that effect sizes of at least ≥0.02, ≥0.15, and ≥0.35 are considered to be weak, moderate, and strong, respectively. From the findings, it is evident that subjective norm ($F^2 = 0.170$) has a greater effect, although still considered moderate, compared to the other variables used. On the other hand, attitude ($F^2 = 0.101$) has a weaker effect than subjective norm, while perceived behavioral control ($F^2 = 0.046$) has the weakest effect on webrooming behavior.

Hypothesized relationships were determined to be significant based on path coefficients (β), t-value, and p-value. Based on the findings, attitudes ($\beta = 0.283$, $t = 3.063$, $p = 0.002$), perception of behavioral control ($\beta = 0.182$, $t = 2.476$, $p = 0.013$), and subjective norms ($\beta = 0.391$, $t = 5.075$, $p < 0.001$) positively influence webrooming behavior. Consequently, all hypothesized relationships are supported.

There is empirical evidence from various authors (Geisser, 1974; Stone, 1974) that an effective model should possess the capability to predict outside the sample data, thus highlighting the external validity of the research. The external validity is measured in terms of the $Q^2$ index, whereby positive values greater than zero signify satisfactory predictive ability (Chin, 1998). In this case, the prediction capabilities of the PLS-SEM were analyzed

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through the use of PLS-Predict on the Smart-PLS software through the comparison of the Root Mean Square Error (RMSE) of both the PLS-SEM and linear model (LM) models.

The $Q^2$ Predict value of each of the indicators of webrooming behavior (WB1-WB8), as shown in Table 6, is positive and falls between 0.221 and 0.349, thus validating the predictive relevance of the proposed model. Furthermore, in comparing the prediction error, it is clear that the proposed model outperforms the benchmark model since the PLS-SEM RMSE values are smaller than the LM RMSE values for most indicators.

**Control Variables**

The current study has also analyzed the effect of selected socio-demographic factors such as gender, age, annual income of the family, educational qualifications, occupation, and residence as control variables. It can be seen from the results obtained that education was the only significant control factor, whereas other factors had no significant impact on the dependent variables.

Our findings for education are statistically significant (0.021), showing that educated people are more likely to conduct webrooming activities. This may be attributed to the fact that they have a greater ability in information processing and comparing alternative products available in online and offline modes. Educated consumers are generally more aware of digital platforms and process better analytical skills, which enhances their tendency to search online and purchase offline.

On the other hand, the insignificant effects of age, gender, income, occupation, and residential status indicate that these demographic factors do not play a substantial role in influencing webrooming behavior in the present study.

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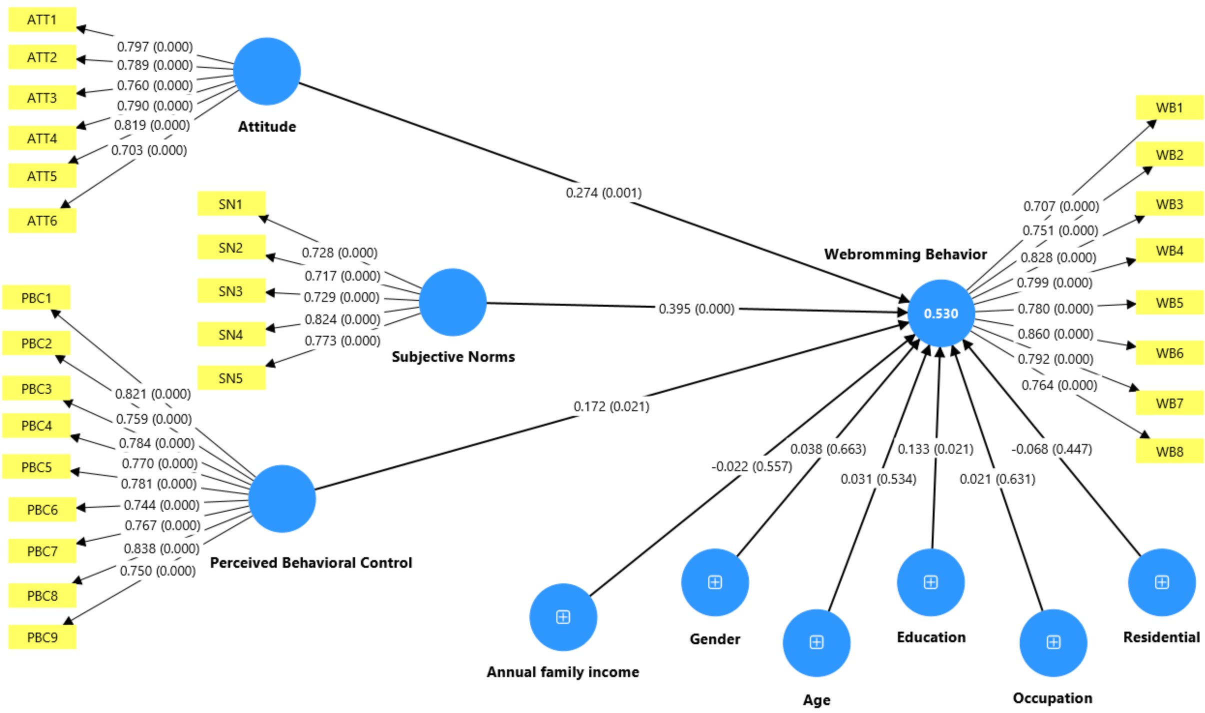


Figure 3. Proposed Model by Using PLS-SEM.

**Table 5** Hypothesis Testing.

| Hypothesis | Std β | S.D. | t Stat | $F^2$ | $R^2$ | p Values | Remarks |
|---|---|---|---|---|---|---|---|
| ATT→WB | 0.283 | 0.092 | 3.063 | 0.101 | | 0.002 | Supported |
| PBC→WB | 0.182 | 0.073 | 2.476 | 0.046 | | 0.013 | Supported |
| SN→WB | 0.391 | 0.077 | 5.075 | 0.170 | 0.503 | 0.000 | Supported |

**Source:** Compiled by the author based on results extracted from Smart PLS.

**Note:** PBC: Perceived Behavioral Control; ATT: Attitude; SN: Subjective Norms; WB: Webrooming Behavior.

**Table 6** Predictive Power or Generalisability of Model.

| Dependent Variables | $Q^2$ Predict | PLS-SEM_RMSE | LM_RMSE |
|---|---|---|---|
| WB1 | 0.301 | 0.871 | 0.902 |

| | | | |
|---|---|---|---|
| WB2 | 0.253 | 0.793 | 0.822 |
| WB3 | 0.300 | 0.816 | 0.839 |
| WB4 | 0.221 | 0.851 | 0.876 |
| WB5 | 0.258 | 0.801 | 0.809 |
| WB6 | 0.349 | 0.763 | 0.785 |
| WB7 | 0.260 | 0.879 | 0.876 |
| WB8 | 0.292 | 0.744 | 0.768 |

**Source:** Extracted from Smart PLS.

Note: LM: Linear model; PLS-SEM: Partial Least Squares Structural Equation Modeling; RMSE: Root Mean Squared error; WB: Webrooming Behavior.

## Discussion and Conclusion

This research will be carried out with the aim of identifying how the webrooming behavior of customers is affected by the three key factors of the Theory of Planned Behavior: subjective norm, attitude, and perceived behavioral control. The outcomes give empirical evidence to support that TPB can be used when explaining the willingness of consumers to carry out online searches first, before they make offline purchases.

First, as hypothesized, attitude really does, in a significant and favorable kind of way, influence webrooming behavior. According to Gopi et al. (2024), the use of multiple channels positively influences consumers' attitudes toward cross-channel shopping behaviors before purchase. As per the results, the consumer's attitude towards the activity and actual participation in it will depend on the consumer's perception that online information search is useful, convenient, and beneficial. These results align with earlier studies (Arora & Sahney, 2018; 2019; Flavian et al., 2020) that indicate that a favorable review of online search can boost consumer confidence and improve the effectiveness of decision-making during in-store purchases. Consumers are most likely to blend both online and offline channels when they perceive that online investigation improves the purchase experience (Gopi et al., 2024).

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Secondly, the study finds that webrooming practice is positively related to subjective norms. The implication from such an observation is that consumers' preference for channels seems largely influenced by socialization. People will engage in webrooming activities when they think those close to them, their relatives and colleagues, also prefer to do so. In line with the literature, the results find that normative beliefs and social pressure can have a big influence on cross-channel purchasing decisions (Arora & Sahney, 2019; Sahu et al., 2020). The results obtained are consistent with the findings by Arora and Sahney (2018), who found that subjective norms motivate consumers to participate in webrooming, and knowledge about webrooming motivates consumers to successfully perform the behavior. The impact of subjective norms on consumer behavior is further reinforced by the growing significance of social contacts and shared experiences in the digital world.

Third, webrooming behavior is found to be significantly positively impacted by perceived behavioral control. These findings show that individuals who believe themselves to be able to use many channels due to having enough information, technology skills, and enough resources tend to use webrooming. This study aligns with previous literature findings indicated that ease of consumers in switching between different online and offline platforms makes them adaptive to webrooming behavior (Arora & Sahney, 2018), and also confirms the assumptions in theory that the perception of ease/difficulty to perform an activity influences actual performance (Ajzen, 1991). The findings obtained by us are consistent with other research conducted in this field (Arora & Sahney, 2018; 2019), which proves that webrooming is most probable for consumers who can use multiple media sources, have a good attitude towards them, and feel socially supported. In the final analysis, webrooming affects consumer behavior during the purchase decision process in terms of time saving and improving decision-making ability.

Another finding from the study is that educational qualification shows a significant effect on webrooming behavior. The results indicate that people with higher educational levels tend to be more involved in these webrooming activities. It could be that people with higher

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education are better informed about how to handle different forms of information prior to making purchasing decisions, hence becoming more engaged in the process of webrooming.

**Implications**

**Theoretical Implication**

This paper contributes to the current literature on the subject of webrooming behavior by increasing the application of the theory of planned behavior as an attempt to better understand the consumer decision-making process regarding the adoption of the webrooming strategy. Even though earlier research has mostly placed emphasis on the practical, functional advantages such as information access and convenience (Arora & Sahney, 2018; 2019; Aw, 2020), this present work looks more into the deeper psychological forces behind it. What stands out most in our findings is that subjective norms, such as social pressure and peer influence, really steer customers' choice of channel during buying, and that cannot be ignored while determining consumer behavior by marketers.

Additionally, this study seems to back up the idea that webrooming is based on logical reasoning or utility-based logic. It's more like it gets shaped by social connections, cognitive appraisals, and also by how consumers judge their own ability to use different channels effectively, as if their perceived skill matters a lot. The reliability of this model is strengthened by adding demographic characteristics as control variables, and suggests that the associations among them still have a more or less significant impact on webrooming behavior. All things considered, the study shows a fairly sound theoretical base, and it is also backed up empirically. It helps us understand webrooming behavior better, and it gives a strong basis for further investigation in this area.

**Practical Implication**

From the results of the current study, it becomes clear that several psychological factors can significantly impact consumers' webrooming activity, which can help marketers and retailers a lot. In practice, retailers might want to focus on improving customers' attitudes by

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providing online product details that are accurate, full, and dependable, since this kind of information tends to push customers to do some online investigation before they commit to an offline purchase (Arora & Sahney, 2018; 2019). In terms of social influence, businessmen may take advantage of positive customer reviews, ratings, and referrals to earn the trust of consumers to an extent and, sort of, direct consumer perceptions in a positive way because subjective criteria do affect consumers' behavior significantly (Arora & Sahney, 2019). Beyond that, companies should also see to it that their websites stay user-friendly, the information is easy to reach, and the shift between browsing online and buying in-store is smooth, since these factors can boost customer confidence and support webrooming behavior (Aw, 2020).

Webrooming can be a strong option for shoppers to decide with more certainty and to purchase after they feel well-informed. Customers can reduce uncertainty and improve the quality of their decisions by using online platforms to obtain information and offline stores to physically assess products (Arora & Sahney, 2018; Aw, 2020). In addition to saving time and effort, this integrated strategy raises customer satisfaction with purchase results. Overall, the study indicates that businesses may better promote webrooming behavior and improve the entire buying experience by matching online information with real experiences and attending to customers' psychological needs.

## Limitations and Future Research Direction

Even though this research is a valuable addition to the literature on webrooming behavior, there are some limitations that may need to be addressed in future research. First, the findings may not be generalizable as much as they could be because of the type of sample collected in Haryana, which was based on convenience sampling. Secondly, because of the cross-sectional nature of the data collected, causal inference becomes difficult, and hence longitudinal investigation of the data would yield a better understanding of webrooming behavior trends over time (Hair et al., 2007). Third, this study did not look at demographic groups separately; future research can investigate how variations in age, gender, income, and other factors affect webrooming behavior in various circumstances. Moreover, the research is grounded in the Theory of Planned Behavior, focusing on the basic elements; future models can take into consideration additional variables. Finally, future studies can concentrate on experiential product categories, including jewelry, apparel, cosmetics, and perfume, where physical evaluation has a greater influence on webrooming behavior.

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