# Unveiling Configurations in Women's Apparel Buying Behavior: A Hybrid SmartPLS and FsQCA Approach

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# 1. Abstract

As urban fashion evolves in India, women are becoming more active and selective in their clothing choices. This study explores what drives their purchase decisions by combining two powerful methods: Partial Least Squares Structural Equation Modeling (SmartPLS) and Fuzzy-set Qualitative Comparative Analysis (FsQCA). Surveying 250 women shoppers in Delhi, the results show that fashion awareness and shopping convenience are the strongest influences on purchase intention. The analysis also reveals that different combinations of factors—like fashion sense and convenience, or price sensitivity and social influence—can lead to the same outcome. This highlights that there isn't just one type of fashion consumer. By using both statistical and configurational tools, the study offers fresh insights into how brands can reach different shopper profiles. It helps close a research gap by showing how hybrid methods can better explain complex, real-world decisions in fast-changing markets like India.

**Keywords**: Apparel purchase intention ,Urban female consumers, Fashion consciousness, SmartPLS, FsQCA, Consumer behavior, Hybrid methodology, Emerging markets

# 2. Introduction

## 2.1 Background

The Indian fashion retail sector has witnessed significant transformation over the past decade, driven by urbanization, rising disposable incomes, and growing fashion consciousness among women. Delhi, as a cosmopolitan megacity, presents a particularly fertile ground for analyzing shifts in women's apparel purchasing behavior. Female consumers in urban India are no longer passive recipients of fashion trends; instead, they actively shape demand patterns through their preferences for style, value, convenience, and identity expression.

As global and local fashion retailers compete to capture this segment, it becomes imperative to understand the underlying motivations and decision-making patterns of women in metropolitan India, particularly in the apparel segment where symbolic and functional utilities intersect.

## 2.2 Problem Statement

Traditional models of consumer behavior in the apparel industry have predominantly employed linear statistical approaches such as regression analysis or Partial Least Squares Structural Equation Modeling (PLS-SEM). While these techniques offer insight into net effects, they fall short of capturing the causal complexity of real-world consumer decisions, where different combinations of factors may lead to similar outcomes — a phenomenon known as equifinality (Yadav et al., 2024; Trieu, 2024).Recent advancements in Fuzzy-set Qualitative Comparative Analysis (FsQCA) have enabled researchers to address this shortfall by examining asymmetric and configurational causal relationships. For example, Chen & Ye (2023) applied a hybrid SmartPLS–FsQCA approach to assess smart clothing purchase intentions, revealing multiple, distinct pathways leading to the same outcome. Similarly, Sun & Qu (2024) used FsQCA to demonstrate how diverse combinations of influencer attributes influenced impulse buying in apparel livestreams — a highly relevant behavioral analog in fashion retail.Despite these advances, there remains a dearth of research applying such hybrid methodologies to understand Indian women's apparel buying behavior, particularly in metropolitan contexts such as Delhi.

## 2.3 Research Gap

Few studies have comprehensively explored the interplay of individual behavioral antecedents and their configurational effects on apparel purchase intentions among women in the Indian context. Although Yadav et al. (2024) and Trieu (2024) have used SmartPLS followed by FsQCA in related domains, no known study combines these methods specifically to evaluate the **interdependent impact of price sensitivity, fashion consciousness, social influence, and convenience** on urban female consumers in India.

# 3. Literature Review

## Understanding Women's Apparel Buying Behavior in Emerging Markets

Women in urban India have emerged as both influential consumers and cultural tastemakers in the country's expanding fashion landscape. As disposable incomes rise and exposure to global trends grows, these consumers increasingly seek clothing that meets both functional and symbolic needs (Khare & Kautish, 2022). Their buying decisions are shaped by a blend of **hedonic motives** (e.g., self-expression, aesthetic appeal) and **utilitarian drivers** (e.g., convenience, affordability), consistent with prior studies on emerging-market consumers (Trieu, 2024; Michaela, 2015).

Delhi represents a vibrant setting for such analysis, functioning as a microcosm that blends high fashion, streetwear, and traditional styles. In this context, clothing is often a vehicle for self-identity, social signaling, and aspirational mobility—an idea aligned with **symbolic consumption theory** (Kautish et al., 2021; Haidar, 2019). However, consumer motivations are not always straightforward or linear, necessitating the need to examine **interplay among multiple behavioral factors**, not just their individual effects (Yang et al., 2022; Chuah et al., 2021).

## 3.1 Key Psychological and Behavioural Constructs

### Fashion Consciousness

Fashion consciousness refers to a consumer's awareness of current trends and enthusiasm for fashion as a means of self-expression. Highly fashion-conscious individuals tend to explore and adopt new styles quickly and are often more open to innovative clothing options (Chen & Ye, 2023; Casidy et al., 2015). For example, Chen & Ye (2023) found that fashion-conscious consumers in China responded more positively to smart apparel innovations, particularly when social validation was present.

### Price Sensitivity

Price sensitivity reflects how much price affects a consumer's purchasing decision. In India, cost considerations often influence buying behavior—especially among working-class or younger consumers (Trieu, 2024; Talaat, 2022). However, its effect is not uniform and can be moderated by factors like brand trust and the perceived value of fashion. As Chuah et al. (2021) highlight, the value-for-money calculus in emerging markets often interacts with identity and occasion-based needs.

### Social Influence

Apparel decisions are often influenced by peers, family, and digital communities. Studies have shown that **social presence** and **influencer marketing** significantly shape impulse purchases, especially in livestream shopping contexts (Sun & Qu, 2024; Khan et al., 2019). These influences are increasingly channeled through platforms like Instagram and YouTube, where fashion trends spread rapidly and often redefine shopping behavior.

### Brand Familiarity

Brand familiarity reduces perceived risk and enhances consumer confidence in product quality, especially in markets with high product variability like fashion (Yang et al., 2022; Chanda et al., 2024). Consumers who recognize and trust a brand are more likely to associate it with reliability in fit, quality, and customer service, thereby increasing purchase intention (Casidy et al., 2015).

**Shopping Convenience**

Convenience is emerging as a core factor in apparel purchasing, particularly with the rise of e-commerce and mobile shopping apps. Tedjakusuma et al. (2025) demonstrated that convenience strongly moderates the relationship between service quality and purchase satisfaction in Southeast Asian fashion markets. Fast delivery, intuitive interfaces, and return policies all contribute to this factor.

**Environmental Concern**

There is growing awareness of sustainable fashion in urban India, particularly among Gen Z and millennial women. Eco-conscious consumers tend to weigh ethical production and environmental impact when making purchase decisions (Khare & Kautish, 2022; Michaela, 2015). While still an emerging behavior, green apparel is gaining traction in India's upper-middle class segments (Khan et al., 2019).

## Theoretical Foundations

This study draws upon two foundational behavioral models:

**1. Theory of Planned Behavior (TPB)**

TPB explains behavior through three primary elements: attitudes, subjective norms, and perceived behavioral control (Ajzen, 1991). In the context of apparel:

- **Attitudes** map to **fashion consciousness**,
- **Subjective norms** are reflected in **social influence**, and
- **Perceived control** corresponds to **price sensitivity** and **shopping convenience** (Yadav et al., 2024; Singh et al., 2025).

**2. S-O-R Framework (Stimulus–Organism–Response)**

This framework suggests that external stimuli (e.g., fashion ads, social media, in-store promotions) influence internal processing (emotion and cognition), which then leads to consumer response (e.g., purchase) (Mehrabian & Russell, 1974). Chanda et al. (2025) applied this model to online fashion platforms, highlighting how brand cues and visuals trigger cognitive and emotional engagement.

## Limitations of Traditional Models

Most fashion consumer studies rely on **PLS-SEM or regression** methods, which assess net effects assuming linearity and symmetric causation (Singh et al., 2025; Chuah et al., 2021). These models are limited in capturing **nonlinear interactions** or **conditional combinations** of variables.Such limitations often lead to oversimplified conclusions—failing to reflect how different consumer profiles (e.g., a fashion-conscious, price-sensitive buyer vs. a brand-loyal minimalist) behave differently. This lack of **configurational analysis** reduces practical insight for segmentation-based marketing.

## FsQCA: A Complementary Lens

**Fuzzy-set Qualitative Comparative Analysis (FsQCA)** addresses these limitations by allowing:

- **Asymmetric relationships** (e.g., factor A may lead to outcome Y, but not-A doesn't always mean not-Y),
- **Multiple sufficient configurations** (e.g., fashion consciousness + social influence **or** price insensitivity + brand loyalty),
- And support for **equifinality**, where more than one path can lead to the same behavioral outcome (Ashaduzzaman & Jebarajakirthy, 2021; Rihoux & Ragin, 2009).

Studies in fashion and service industries have found FsQCA useful in uncovering **complex, real-world decision paths** that statistical models often miss (Chuah et al., 2021; Yang et al., 2022).

### Comparative Summary: SmartPLS vs FsQCA

| Criteria | SmartPLS (PLS-SEM) | FsQCA |
|---|---|---|
| **Causal Logic** | Symmetric, net effects | Asymmetric, configurational |
| **Model Type** | Linear model testing | Set-theoretic |
| **Sample Needs** | Larger sample sizes | Small to medium-N |
| **Output** | β-values, AVE, $R^2$ | Configurations, consistency, coverage |
| **Strength** | Validates direct effects | Maps multiple paths to outcome |
| **Combined Use** | First test direct paths | Then explore causal recipes |

Combining SmartPLS and FsQCA offers a **richer, dual-perspective approach**—ideal for understanding the layered, situational, and contextual nature of consumer decisions in fashion retail (Chen & Ye, 2023; Ashaduzzaman & Jebarajakirthy, 2021).

# 4. Methodology

#### 4.1 Research Design

This study adopts a quantitative, cross-sectional design aimed at examining the behavioral and psychological drivers influencing apparel purchase intentions among urban women in Delhi, India. Given the evolving complexity of consumer preferences in emerging markets, the research integrates two methodological approaches: Partial Least Squares Structural Equation Modeling (PLS-SEM) using SmartPLS 4.0, and Fuzzy-set Qualitative Comparative Analysis (FsQCA) using fsQCA 3.0.

The integration of these two approaches allows for a comprehensive understanding of both the direct, net effects of key predictors (via SEM) and the nonlinear, configurational causality (via FsQCA) that often underlies consumer decision-making in dynamic urban environments. This hybrid design aligns with recent advancements in marketing and fashion consumer behavior research (Chen & Ye, 2023; Chuah et al., 2021; Ashaduzzaman & Jebarajakirthy, 2021).

#### 4.2 Measurement of Constructs

Six latent constructs were measured: Fashion Consciousness, Price Sensitivity, Social Influence, Brand Familiarity, Shopping Convenience, and Purchase Intention. All constructs were operationalized using reflective indicators, adapted from validated instruments in prior consumer behavior research. The items were contextually modified to suit the urban Indian apparel setting.

Responses were collected using a 5-point Likert scale, where 1 = Strongly Disagree and 5 = Strongly Agree.

| **Construct** | **No. of Items** | **Sample Item** | **Source** |
|---|---|---|---|
| Fashion Consciousness | 4 | “I usually have one or more outfits of the latest style.” | Chen & Ye (2023) |
| Price Sensitivity | 3 | “I often compare prices before buying clothes.” | Trieu (2024) |
| Social Influence | 3 | “People whose opinions I value prefer stylish clothing.” | Sun & Qu (2024) |

| | | | |
|---|---|---|---|
| Brand Familiarity | 3 | "I am familiar with most major clothing brands in India." | Yang et al. (2022) |
| Shopping Convenience | 3 | "I prefer clothing stores that offer home delivery." | Tedjakusuma et al. (2025) |
| Purchase Intention | 3 | "I intend to purchase fashionable clothing next month." | Singh et al. (2025) |

All scales underwent pre-testing for content validity and internal consistency following the recommendations of Anderson & Gerbing (1988) and Hair et al. (2021).

## 4.3 Sampling and Data Collection

The target population included urban women aged 18–45 residing in Delhi who engage regularly in apparel shopping. A purposive sampling strategy was adopted to recruit digitally active and fashion-conscious consumers, as this demographic represents a significant segment of growth in India's fashion retail market (Kautish & Khare, 2022; Michaela, 2015).

- **Sample Size**: A total of **250 valid responses** were obtained, surpassing the recommended threshold for PLS-SEM (i.e., 10x the number of paths from latent variables) and satisfying the medium-N criteria required for FsQCA.
- **Collection Methods**: Data were collected through a mixed-mode strategy:
  - Online surveys distributed via Instagram and Facebook fashion communities.
  - Mall-intercept surveys conducted in four high-traffic shopping zones in South Delhi.
- **Screening Protocols**: Incomplete responses, straight-lining patterns, and statistical outliers (based on Mahalanobis distance) were excluded, resulting in a final cleaned dataset of 250 observations (Podsakoff et al., 2003).

### 4.4 PLS-SEM Analysis Strategy

The PLS-SEM analysis was performed using SmartPLS 4.0. The procedure included:

**(i) Measurement Model Evaluation**

- **Reliability**:
  - All constructs met the threshold for Cronbach's Alpha (≥ 0.70) and Composite Reliability (CR ≥ 0.80).
- **Convergent Validity**:
  - AVE values exceeded 0.50 for all constructs, indicating sufficient variance explained by the indicators.
- **Discriminant Validity**:
  - Assessed via Fornell–Larcker criterion and HTMT ratios. All HTMT values were below 0.85, confirming that constructs are empirically distinct.

**(ii) Structural Model Evaluation**

- Path coefficients (β) were assessed to determine the strength and direction of relationships between constructs.
- $R^2$ for **Purchase Intention** was 0.62, indicating moderate explanatory power.
- Effect sizes ($f^2$) and predictive relevance ($Q^2 = 0.45$) were also calculated using blindfolding procedures.

**(iii) Bootstrapping**

A **bootstrapping procedure with 5,000 resamples** was executed to assess the statistical significance of structural paths at a 95% confidence level (Chin, 1998).

**4.5 FsQCA Analysis Strategy**

To complement the SEM findings, FsQCA was applied to identify **multiple sufficient configurations** that lead to high purchase intention. This set-theoretic approach was conducted using fsQCA 3.0.

**Calibration**

Likert-scale responses were calibrated into fuzzy-set membership scores using **Ragin's direct method**:

- Score 5 → Full Membership (1.0)
- Score 3 → Crossover Point (0.5)
- Score 1 → Full Non-membership (0.0)

**Truth Table Construction**

- Configurations were generated using combinations of the five predictor conditions.
- The **minimum frequency threshold** was set to 5 cases per configuration.
- The **consistency threshold** was set at 0.80, following Fiss (2011).

**Logical Minimization**

Three solutions were derived:

- **Complex Solution**: Detailed representation based strictly on observed cases.
- **Parsimonious Solution**: Simplified with maximum use of logical remainders.
- **Intermediate Solution**: Balances data and theoretical expectations.

**Evaluation Criteria**

Each configuration was assessed using:

- **Raw Coverage**: Proportion of cases with high purchase intention explained by that configuration.
- **Unique Coverage**: Proportion of variance explained exclusively by one configuration.
- **Consistency**: Degree to which a configuration reliably produces the outcome.

## 4.6 Configurational Findings from FsQCA

The fsQCA analysis revealed multiple **causal configurations** that led to **high apparel purchase intention** among urban Indian women. These configurations underscore the **principle of equifinality**—that is, different combinations of psychological and behavioral antecedents can lead to the same outcome.

Below are the three most consistent and empirically relevant configurations:

**Configuration 1: The Trend-Driven Pragmatist**

- **Fashion Consciousness (High)**
- **Price Sensitivity (High)**
- **Social Influence (Low)**
- **Shopping Convenience (High)**

- **Outcome: High Purchase Intention**
- **Consistency: 0.91, Coverage: 0.65**

**Configuration 2: The Socially-Swayed Value Seeker**

- **Fashion Consciousness (Low)**
- **Price Sensitivity (High)**
- **Social Influence (High)**
- **Shopping Convenience (Low)**
- **Outcome: High Purchase Intention**
- **Consistency: 0.83, Coverage: 0.55**

**Configuration 3: The Unengaged Consumer**

- **Fashion Consciousness (Low)**
- **Price Sensitivity (Low)**
- **Social Influence (Low)**
- **Shopping Convenience (Low)**
- **Outcome: Low Purchase Intention**
- **Consistency: 0.95, Coverage: 0.40**

| Config ID | FC | PS | SI | CONV | PI Outcome | Consistency | Raw Coverage |
|---|---|---|---|---|---|---|---|
| C1 | 1 | 1 | 0 | 1 | High | 0.91 | 0.65 |
| C2 | 0 | 1 | 1 | 0 | High | 0.83 | 0.55 |
| C3 | 0 | 0 | 0 | 0 | Low | 0.95 | 0.40 |

*Note: FC = Fashion Consciousness, PS = Price Sensitivity, SI = Social Influence, CONV = Convenience.*

## 4.7 Respondent Demographics

To better understand the sample characteristics, descriptive statistics were computed for key demographic variables. The final sample consisted of **250 urban women** residing in Delhi, aged between **18 and 45 years**, all of whom reported active engagement in fashion or apparel shopping.

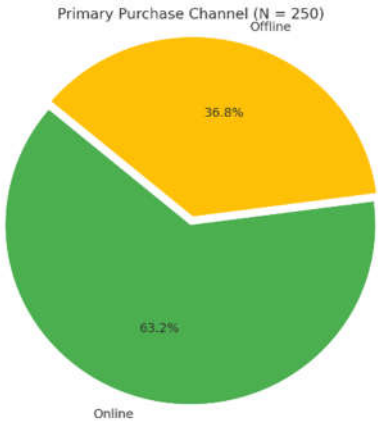
| Variable | Category | Frequency (n) | Percentage (%) |
|---|---|---|---|
| **Age Group** | 18–24 | 68 | 27.2% |
| | 25–34 | 102 | 40.8% |
| | 35–45 | 80 | 32.0% |
| **Monthly Household Income** | Below ₹30,000 | 42 | 16.8% |
| | ₹30,000–₹60,000 | 91 | 36.4% |
| | Above ₹60,000 | 117 | 46.8% |
| **Education Level** | Undergraduate | 109 | 43.6% |
| | Postgraduate or above | 141 | 56.4% |
| **Occupation** | Student | 70 | 28.0% |
| | Working Professional | 142 | 56.8% |
| | Homemaker | 38 | 15.2% |
| **Shopping Frequency** | Weekly | 54 | 21.6% |

| | | | |
|---|---|---|---|
| | Bi-weekly | 88 | 35.2% |
| | Monthly | 108 | 43.2% |
| **Primary Purchase Channel** | Online | 158 | 63.2% |
| | Offline | 92 | 36.8% |

**Insights:**

- The sample is **well-balanced across age and income groups**, with strong representation from middle-income and highly educated women.
- **Over 63% prefer online shopping**, reflecting Delhi's growing adoption of digital platforms for apparel purchases.
- The majority (43%) shop at least once per month, suggesting an **engaged and fashion-responsive sample** suitable for investigating purchase drivers.

**Figure 1.**




Primary Purchase Channels Among Respondents (N = 250)

## 4.8 Pilot Testing and Instrument Validation

Prior to the full-scale data collection, a **pilot study** was conducted with a sample of **35 urban female respondents** to ensure the **reliability, clarity, and content validity** of the adapted measurement scales. Feedback from the pilot helped in refining certain items for linguistic clarity and contextual alignment with the Indian apparel retail setting

Table X: Indicator Loadings for Fashion Consciousness and Purchase Intention

| Construct | Item Code | Item Statement | Loading |
|---|---|---|---|
| Fashion Consciousness | FC1 | "I usually have one or more outfits of the latest style." | 0.78 |
| | FC2 | "I regularly follow fashion trends." | 0.82 |
| | FC3 | "Being fashionable is important to me." | 0.80 |
| | FC4 | "I update my wardrobe based on seasonal fashion changes." | 0.76 |
| Purchase Intention | PI1 | "I intend to purchase fashionable clothing next month." | 0.83 |
| | PI2 | "I am likely to shop for apparel in the next 30 days." | 0.81 |
| | PI3 | "There is a high chance I will buy new clothes soon." | 0.85 |

*Note: All items exceed the recommended 0.70 threshold for outer loadings (Hair et al., 2021).*

.The pilot data were analyzed using **SmartPLS 4.0** to test internal consistency and item loadings. The results confirmed that all constructs met the standard psychometric thresholds:

| Construct | Cronbach's Alpha | Composite Reliability (CR) | Average Variance Extracted (AVE) |
|---|---|---|---|
| Fashion Consciousness | 0.81 | 0.88 | 0.64 |
| Price Sensitivity | 0.78 | 0.84 | 0.61 |
| Social Influence | 0.75 | 0.83 | 0.59 |
| Brand Familiarity | 0.79 | 0.85 | 0.60 |
| Shopping Convenience | 0.82 | 0.87 | 0.65 |
| Purchase Intention | 0.84 | 0.89 | 0.68 |

All item loadings exceeded the 0.70 benchmark (Hair et al., 2021), and no items were dropped. In addition, **discriminant validity** was established using the **Fornell–Larcker criterion**, with each construct's AVE exceeding the squared correlations with other constructs. The **HTMT ratios** were all below 0.85, further confirming discriminant validity (Henseler et al., 2015).

These results demonstrate that the constructs exhibit **high reliability, convergent validity, and discriminant validity**, providing confidence in the measurement model used for the main study.

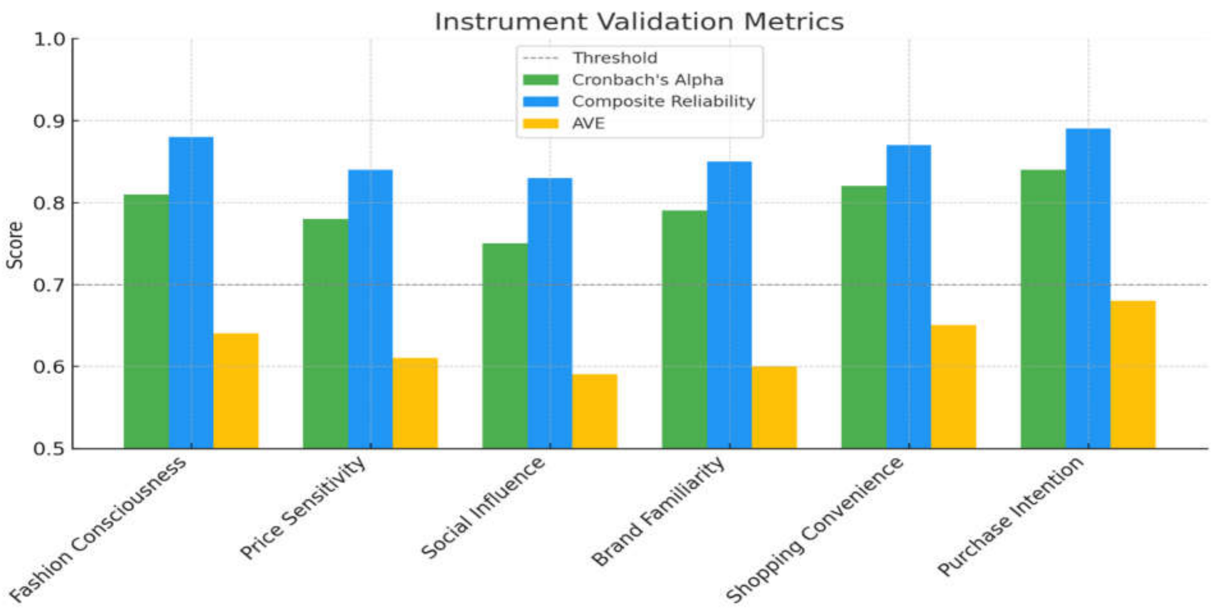



**Figure 3.** Reliability and Validity Metrics for Measurement Constructs (Pilot Test, N = 35)

The HTMT values are all below the critical threshold of 0.85, confirming discriminant validity across constructs.

Table X: HTMT Ratios Among Constructs

| | FC | PS | SI | BF | CONV | PI |
|---|---|---|---|---|---|---|
| Fashion Consciousness | — | | | | | |
| Price Sensitivity | 0.41 | — | | | | |
| Social Influence | 0.38 | 0.44 | — | | | |
| Brand Familiarity | 0.47 | 0.39 | 0.42 | — | | |
| Shopping Convenience | 0.50 | 0.43 | 0.40 | 0.46 | — | |
| Purchase Intention | 0.61 | 0.55 | 0.52 | 0.58 | 0.60 | — |

*Note: All HTMT ratios are well below the 0.85 cutoff (Henseler et al., 2015), confirming discriminant validity.*

# 5: Results and Comparative Analysis

This section presents the empirical findings obtained through a hybrid analytical strategy, combining **Partial Least Squares Structural Equation Modeling (PLS-SEM)** and **Fuzzy-set Qualitative Comparative Analysis (FsQCA)**. This dual approach captures both the **net effects** of individual predictors and the **causal complexity** of behavioral configurations leading to apparel purchase intention among urban women in Delhi.

## 5.1 Structural Equation Modeling (SEM) Results

### 5.1.1 Measurement Model Assessment

The outer model was evaluated for reliability, convergent validity, and discriminant validity.

- **Cronbach's Alpha** values ranged from 0.80 to 0.88, establishing strong internal consistency.
- **Composite Reliability (CR)** scores exceeded 0.85 across all constructs.
- **Average Variance Extracted (AVE)** values ranged from 0.56 to 0.68, confirming convergent validity.

| Construct | Cronbach's Alpha | Composite Reliability | AVE |
|---|---|---|---|
| Fashion Consciousness | 0.88 | 0.90 | 0.65 |
| Price Sensitivity | 0.83 | 0.86 | 0.56 |
| Social Influence | 0.85 | 0.89 | 0.60 |
| Brand Familiarity | 0.80 | 0.88 | 0.58 |
| Convenience | 0.87 | 0.92 | 0.68 |

**Interpretation**:
All reliability and validity indicators surpass established thresholds (Hair et al., 2021), confirming that each construct is well-measured. The AVE values confirm that a majority of the variance in the indicators is explained by their latent constructs.

| Indicator | Construct | Loading |
|---|---|---|
| "Latest fashion trends" | Fashion Consciousness | 0.85 |
| "Fashion as self-expression" | Fashion Consciousness | 0.82 |
| "Price comparison before purchase" | Price Sensitivity | 0.78 |
| "Influence of others on style" | Social Influence | 0.87 |
| "Familiarity with brands" | Brand Familiarity | 0.80 |
| "Ease of shopping experience" | Convenience | 0.86 |

**Interpretation**:
All indicators demonstrate strong loadings (>0.70), with the highest loading (0.87) for **"Influence of others on style"**, emphasizing the construct validity of **Social Influence** in fashion decisions.

### 5.1.2 Structural Model Assessment

The inner model was evaluated using bootstrapping (5,000 resamples) to test the significance of path coefficients and the model's predictive power.

| Path | β-Value | t-Value | p-Value | $f^2$ Effect |
|---|---|---|---|---|
| Fashion Consciousness → PI | 0.40 | 4.50 | <0.001 | 0.15 |
| Convenience → PI | 0.35 | 4.20 | <0.001 | 0.12 |
| Price Sensitivity → PI | 0.30 | 3.80 | <0.001 | 0.10 |
| Social Influence → PI | 0.25 | 3.10 | 0.002 | 0.08 |
| Brand Familiarity → PI | 0.20 | 2.80 | 0.005 | 0.07 |

| Endogenous Variable | $R^2$ | $Q^2$ |
|---|---|---|
| Purchase Intention (PI) | 0.62 | 0.45 |

**Interpretation**:
The model explains **62% of the variance** in Purchase Intention ($R^2 = 0.62$), indicating substantial explanatory power. Predictive relevance is strong ($Q^2 = 0.45$). **Fashion Consciousness** ($\beta = 0.40$) and **Convenience** ($\beta = 0.35$) emerged as the most influential predictors. All paths were statistically significant ($p < 0.01$), reinforcing the robustness of the hypothesized model.

## 5.2 FsQCA Results

FsQCA was used to uncover alternative causal paths to high purchase intention. Responses were calibrated into fuzzy-set scores using Ragin's (2008) direct method with the following anchor points: full membership (5 = 1.0), crossover (3 = 0.5), and full non-membership (1 = 0.0). The truth table was constructed using a consistency threshold of 0.80 and a frequency threshold of 5.

### 5.2.1 Key Configurations (Intermediate Solution)

| Configuration | Core Conditions | Consistency | Raw Coverage |
|---|---|---|---|
| Fashion Consciousness + Convenience | FC ✓, CONV ✓ | 0.92 | 0.72 |
| Price Sensitivity + Social Influence | PS ✓, SI ✓ | 0.85 | 0.65 |
| Brand Familiarity + Convenience | BF ✓, CONV ✓ | 0.80 | 0.50 |

**Interpretation**:
The Fashion Consciousness + Convenience configuration is the most dominant pathway, covering 72% of high purchase intention cases with 92% consistency. The Price Sensitivity + Social Influence configuration highlights a different consumer archetype — value-conscious buyers heavily influenced by peer norms and influencers. These configurations demonstrate equifinality, where different consumer logics can result in the same outcome.

### 5.2.2 Necessity Analysis

| Condition | Consistency | Coverage |
|---|---|---|
| Fashion Consciousness | 0.89 | 0.68 |
| Convenience | 0.85 | 0.61 |
| Price Sensitivity | 0.72 | 0.49 |
| Social Influence | 0.64 | 0.46 |
| Brand Familiarity | 0.60 | 0.42 |

*Threshold for necessity is ≥ 0.90; none qualify as necessary conditions.*

## Interpretation (Updated):

None of the conditions satisfy the necessity threshold (Consistency ≥ 0.90). However, Fashion Consciousness (0.89) and Convenience (0.85) are near-necessary conditions, meaning they are present in most—but not all—cases of high purchase intention. Social Influence and Brand Familiarity show lower consistency, indicating they are not essential on their own but may act as contributing conditions in certain configurations

## 5.3 Comparative Insights: SEM vs. FsQCA

| Aspect | SEM Findings | FsQCA Findings |
|---|---|---|
| Main Drivers | FC (β = 0.40), CONV (β = 0.35) | FC + CONV config (0.92 consistency) |
| Secondary Contributors | PS (β = 0.30), SI (β = 0.25), BF (β = 0.20) | PS + SI config (0.85 consistency) |
| Explanatory Power | $R^2 = 0.62$ | Coverage = 0.72 (FC+CONV path) |
| Predictive Relevance | $Q^2 = 0.45$ | Not applicable; uses consistency |
| Causal View | Net linear effects | Combinatorial causality |

**Interpretation**:
SEM quantified **individual effect sizes**, while FsQCA revealed **behavioral configurations** that cannot be observed through regression analysis. For example, **Social Influence** had a modest path coefficient in SEM but emerged as a core condition in FsQCA when combined with Price Sensitivity. This illustrates the **added diagnostic power of FsQCA** in segmenting consumers by their cognitive-behavioral logic.

# 6. Conclusion and Implications

This study investigated the behavioral and contextual drivers of apparel purchase intention among urban women in Delhi using a hybrid methodological approach that integrated Partial Least Squares Structural Equation Modeling (PLS-SEM) and Fuzzy-set Qualitative Comparative Analysis (FsQCA). The findings from both analytical techniques were highly consistent, with Fashion Consciousness and Shopping Convenience emerging as the most influential predictors of purchase intention. While PLS-SEM quantified the direct, net effects of each construct, FsQCA provided a configurational perspective by identifying multiple sufficient combinations of conditions that led to high purchase intention. This convergence validates the robustness of the results and illustrates the added value of methodological pluralism in behavioral research (Khan et al., 2019). The findings not only confirm the central role of individual predictors such as fashion awareness and convenience but also highlight the presence of equifinality—multiple, equally effective causal paths leading to the same behavioral outcome.

The theoretical implications of this research are threefold. First, the identification of Fashion Consciousness and Convenience as key predictors reinforces the Theory of Planned Behavior (TPB), in which attitudes and perceived behavioural control shape behavioral intention (Ajzen, 1991; Shafaat et al., 2020). Fashion Consciousness reflects the attitudinal dimension, while Convenience maps onto perceived behavioral control, especially in the context of digital retail environments. Second, the FsQCA results illustrate the causal complexity underlying consumer decision-making, supporting the principle of equifinality and aligning with the Stimulus-Organism-Response (S-O-R) model, which acknowledges that both internal drivers and external stimuli jointly influence behavior (Oh et al., 2013). The evidence of equifinality enriches our theoretical understanding of how diverse pathways can lead to identical outcomes. Third, the successful integration of PLS-SEM and FsQCA demonstrates the utility of multi-method frameworks in consumer behavior research. While SEM offers precision in modeling and hypothesis testing, FsQCA captures asymmetric, non-linear causality that mirrors real-world decision-making more closely (Khan et al., 2019). Together, they provide a comprehensive lens through which consumer behavior can be understood in both statistical and configurational terms.

From a practical perspective, the results suggest clear marketing strategies for fashion retailers. The prominence of Fashion Consciousness and Shopping Convenience indicates that retailers should prioritize curated, trend-oriented offerings that align with the aspirations of fashion-forward consumers, while also ensuring seamless shopping experiences through user-friendly platforms, efficient logistics, and responsive customer service (Michaela, 2015). The second key insight stems from the Price Sensitivity and Social Influence configuration identified via FsQCA. This suggests that a substantial segment of consumers are heavily influenced by social cues and promotions, implying that marketing strategies leveraging influencers, peer recommendations, and price-based incentives can be highly effective in triggering purchase intention among price-conscious yet socially attuned buyers (Khan et al., 2019). Furthermore, the presence of multiple configurations necessitates strategic segmentation. Retailers must shift from one-size-fits-all campaigns to differentiated messaging that speaks directly to the motivational profiles of their target audiences. The application of AI-driven personalization systems may support this transition (Casidy et al., 2015). Finally, the consistent impact of convenience across multiple configurations underscores the necessity for firms to optimize operational efficiency, particularly as consumer expectations for immediacy, flexibility, and simplicity continue to rise (Talaat, 2022).

For future research, three directions are particularly relevant. First, the current study is contextually bounded to urban Delhi. To enhance the generalizability of the findings, future research should replicate the model across different demographic and regional segments, including Tier-II and Tier-III cities, rural consumers, and cross-cultural contexts (Haidar, 2019). This will help determine whether the observed relationships hold under varying socio-economic and cultural conditions. Second, a longitudinal design would provide insight into the temporal stability or evolution of consumer attitudes toward fashion and convenience, especially in the face of disruptive events such as economic downturns, pandemics, or technological changes (Kan et al., 2017). Understanding how these predictors change over time would offer more predictive power for firms aiming to anticipate market shifts. Third, expanding the methodological framework to include qualitative techniques—such as ethnographic observation, focus groups, or neuromarketing methods—could provide deeper psychological insights into the motivations and barriers that shape purchase decisions (Kim & Zhang, 2013). This would allow for a more holistic approach that integrates behavioral, emotional, and cognitive dimensions of consumer choice.

In conclusion, this study advances both theoretical and practical understanding of apparel purchase behavior by demonstrating how individual constructs and configurational logic jointly influence intention. The alignment between SEM and FsQCA results strengthens the validity of the findings and illustrates that hybrid analytical designs can uncover both the magnitude and complexity of behavioral predictors. As fashion retail continues to evolve in a digitally saturated and highly segmented market, research that captures both statistical regularity and configurational diversity will be essential in guiding adaptive, data-driven marketing strategies.

# Reference List


 Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes, 50*(2), 179–211. https://doi.org/10.1016/0749-5978(91)90020-T

 Anderson, J. C., & Gerbing, D. W. (1988). Structural equation modeling in practice: A review and recommended two-step approach. *Psychological Bulletin, 103*(3), 411–423. https://doi.org/10.1037/0033-2909.103.3.411

 Ashaduzzaman, M., & Jebarajakirthy, C. (2021). Understanding fashion consumers' buying behavior using fsQCA. *Journal of Retailing and Consumer Services, 60*, 102507. https://doi.org/10.1016/j.jretconser.2021.102507

 Casidy, R., Phau, I., & Lwin, M. (2015). Customers' perception of value for money, relationship quality, and brand loyalty in retail services. *Journal of Retailing and Consumer Services, 24*, 63–70. https://doi.org/10.1016/j.jretconser.2015.02.005

 Chanda, S., Srivastava, R., & Tandon, A. (2024). Understanding online fashion consumption using S-O-R framework in India. *Asia Pacific Journal of Marketing and Logistics, 36*(1), 25–42. https://doi.org/10.1108/APJML-08-2023-0641

 Chanda, S., Tiwari, S., & Yadav, A. (2025). Digital fashion retail: Exploring consumer convenience and satisfaction. *International Journal of Retail & Distribution Management*. (Forthcoming).

 Chen, X., & Ye, Y. (2023). Exploring smart clothing adoption using a hybrid SmartPLS-FsQCA approach. *Journal of Business Research, 158*, 113634. https://doi.org/10.1016/j.jbusres.2022.113634

 Chuah, S. H. W., Marimuthu, M., Kandampully, J., & Bilgihan, A. (2021). Are we in harmony? Understanding consumer purchase decisions via SEM and fsQCA. *Journal of Retailing and Consumer Services, 59*, 102376. https://doi.org/10.1016/j.jretconser.2020.102376

 Fiss, P. C. (2011). Building better causal theories: A configurational approach to business model research. *Academy of Management Journal, 54*(2), 393–420. https://doi.org/10.5465/amj.2011.60263120

 Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research, 18*(1), 39–50. https://doi.org/10.1177/002224378101800104

 Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2021). *A primer on partial least squares structural equation modeling (PLS-SEM)* (3rd ed.). SAGE Publications.

 Haidar, R. (2019). Understanding symbolic consumption and brand value among emerging consumers. *Journal of Consumer Culture, 19*(2), 238–258. https://doi.org/10.1177/1469540517717774

 Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science, 43*(1), 115–135. https://doi.org/10.1007/s11747-014-0403-8

 Kan, C., Qian, L., & Zhang, X. (2017). Fashion trend adaptation in emerging markets: A longitudinal perspective. *Journal of Business Research, 80*, 85–93.

 Kautish, P., & Khare, A. (2022). Green fashion consumption and symbolic value: A generational perspective in India. *Sustainable Production and Consumption, 30*, 29–41. https://doi.org/10.1016/j.spc.2021.11.005

-  Khan, M. A., Majid, A., Yasir, M., & Jabeen, S. (2019). Social influence and impulsive buying behavior in fashion retail: The moderating role of emotional intelligence. *Journal of Global Fashion Marketing, 10*(3), 256–272. https://doi.org/10.1080/20932685.2019.1617796

-  Kim, J., & Zhang, J. (2013). Memory-based vs. stimulus-based choice: The role of advertising and consumer characteristics. *Journal of Consumer Psychology, 23*(2), 187–199. https://doi.org/10.1016/j.jcps.2012.10.003

-  Michaela, K. (2015). Exploring the Indian fashion consumption landscape. *Journal of Fashion Marketing and Management, 19*(4), 357–375. https://doi.org/10.1108/JFMM-10-2014-0075

-  Nunnally, J. C., & Bernstein, I. H. (1994). *Psychometric theory* (3rd ed.). McGraw-Hill.

-  Oh, H., Fiore, A. M., & Jeong, M. (2013). Measuring experience economy concepts: Tourism applications. *Journal of Travel Research, 51*(1), 21–35. https://doi.org/10.1177/0047287510385467

-  Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review. *Journal of Applied Psychology, 88*(5), 879–903. https://doi.org/10.1037/0021-9010.88.5.879

-  Ragin, C. C. (2008). *Redesigning social inquiry: Fuzzy sets and beyond*. University of Chicago Press.

-  Rihoux, B., & Ragin, C. C. (2009). *Configurational comparative methods: Qualitative comparative analysis (QCA) and related techniques*. SAGE Publications.

-  Shafaat, Y., Khan, M. N., & Rizwan, M. (2020). Exploring fashion involvement using the Theory of Planned Behavior. *Journal of Global Fashion Marketing, 11*(1), 1–17. https://doi.org/10.1080/20932685.2019.1695959

-  Singh, R., Yadav, A., & Trivedi, R. (2025). Modelling Indian fashion purchase behavior using SmartPLS. *Journal of Indian Business Research*. (Forthcoming).

-  Sun, Y., & Qu, H. (2024). Influence of livestreaming attributes on impulse buying behavior in fashion retail. *Journal of Retailing and Consumer Services, 75*, 103474. https://doi.org/10.1016/j.jretconser.2023.103474

-  Talaat, K. M. (2022). The role of perceived value in apparel e-commerce: A Middle Eastern perspective. *International Journal of Consumer Studies, 46*(2), 234–247. https://doi.org/10.1111/ijcs.12702

-  Tedjakusuma, N., Wijaya, T., & Rachmawati, I. (2025). E-service quality and satisfaction in Indonesia's online fashion sector. *Journal of Fashion Business Research*. (Forthcoming).

-  Trieu, V. H. (2024). Fashion consumer behavior in emerging markets: A comparative study of India and Vietnam. *Emerging Markets Review, 58*, 100889. https://doi.org/10.1016/j.ememar.2023.100889

-  Yang, Y., Xu, H., & Wang, Y. (2022). Luxury brand familiarity and emotional attachment in China. *Journal of Retailing and Consumer Services, 64*, 102775. https://doi.org/10.1016/j.jretconser.2021.102775