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Bridging Digital Sentiment with Physical Retail Metrics: An AI-Driven Hybrid Analysis of Consumer Behaviour in India's Innerwear and Athleisure Markets

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Abstract

Purpose: This study examines omnichannel consumer behaviour in India's innerwear and athleisure retail markets, with particular attention to the divergent dynamics of digital sentiment and physical store experience across urban tiers.

Design/Methodology/Approach: A mixed-methods framework is employed, integrating computational sentiment analysis of 1,156 publicly sourced Google Maps reviews with primary survey data from 105 respondents across Tier 1 and Tier 2 cities. Sentiment scoring was conducted using both TextBlob and a fine-tuned BERT model (nlptown/bert-base-multilingual-uncased-sentiment). Latent Dirichlet Allocation (LDA) was applied to identify thematic clusters. Hypotheses were tested via chi-square analysis using SPSS.

Findings: The analysis reveals an 88.8% positivity rate in online reviews, yet identifies critical dissatisfaction clusters—most notably staff expertise deficits (cited in 34% of negative reviews) and Tier 2 price sensitivity (71%). While 68.5% of consumers prefer in-store purchasing for tactile validation, online channels demonstrate dominance in discount-driven purchase occasions. BERT outperformed lexicon-based TextBlob in detecting sarcastic sentiment (67% accuracy) and surfacing latent themes such as 'staff impact' (23.4% topic prevalence). Regional differences in buying behaviour were statistically significant ($p = 0.01$), validating the Underwear Index as a behavioural heuristic in recessionary contexts.

Originality/Value: This study makes a novel methodological contribution by triangulating AI-driven sentiment analysis with survey instruments to produce a channel-comparative understanding of consumer behaviour. It extends Transaction Cost Economics and Veblenian conspicuous consumption theory to emerging-market retail contexts, and offers actionable frameworks for omnichannel strategy, staff training, and technology adoption in India's rapidly evolving apparel sector.

Keywords: Consumer behaviour; Sentiment analysis; Omnichannel retail; Underwear Index; BERT; Tier 1 and Tier 2 markets; Innerwear; Athleisure

JEL Classification: M31; L81; C38; O33

1. Introduction

The global apparel retail industry is undergoing a period of structural transformation, shaped by the convergence of digital commerce adoption and the enduring salience of physical store experiences. This tension is particularly pronounced in product categories—such as innerwear and athleisure—where tactile evaluation of comfort, fit, and fabric integrity remains central to purchase decisions. By 2028, the global innerwear market is projected to reach USD 90.3 billion, with India's athleisure segment expanding at a compound annual growth rate (CAGR) of

15% (Statista, 2023; IMARC, 2023). Yet macro-level growth trajectories mask significant behavioural heterogeneity: while Myntra reports a 25% annual increase in online innerwear sales, 66% of Indian consumers continue to prefer in-store purchasing for this category (Economic Times, 2023). This paradox is further complicated by India's distinctly tiered urban structure. Tier 1 metropolitan centres such as Mumbai and Delhi exhibit characteristics of digital maturity and premium brand affinity, while Tier 2 cities such as Lucknow and Nagpur are characterised by stronger price sensitivity and greater dependence on physical retail infrastructure for pre-purchase evaluation (Verma & Jain, 2022). Within this landscape, leading brands such as Jockey have adopted bifurcated channel strategies—leveraging end-of-season e-commerce discounts online while deploying augmented reality (AR) technologies in flagship stores to reduce return rates by approximately 28% (Business Today, 2023). Such strategies reflect the broader challenge facing the industry: reconciling digital scalability with the experiential trust embedded in physical retail.

Despite the proliferation of sentiment analysis research in retail and consumer behaviour, the field has not adequately addressed the integration of digital feedback with physical store performance data, particularly in an emerging market context with pronounced regional variation. Existing studies either focus exclusively on online textual data (Pang & Lee, 2008; Smith, 2019) or examine in-store experiences in isolation (Davis, 2017; Chopra, 2020), leaving a methodological and empirical gap at the intersection of these two domains.

The present study addresses this gap through a hybrid analytical framework that combines machine learning-based sentiment analysis of 1,156 Google Maps reviews with primary survey data (n = 105) spanning Tier 1 and Tier 2 respondents. Three research questions structure the inquiry:

I. Why do Tier 2 consumers exhibit significantly higher price sensitivity (71%) relative to Tier 1's brand loyalty orientation (68%), and how does this align with the Underwear Index as a behavioural indicator during periods of economic uncertainty?

II. How can retailers effectively address hygiene-related return anxiety (23% prevalence in online channels) while capitalising on the tactile advantages of physical retail?

III. What role does retail staff competence play in bridging the satisfaction gap across channels, given that 54% of upsell events are associated with knowledgeable staff, yet 34% of negative reviews cite training deficiencies?

By triangulating BERT-based contextual sentiment analysis, LDA topic modelling, and chi-square hypothesis testing on survey data, this study offers both theoretical extensions and actionable guidance for retailers operating in India's USD 21.25 billion athleisure market.

2. Literature Review

2.1 Sentiment Analysis in Retail Research

Sentiment analysis, rooted in natural language processing (NLP), has developed into a significant instrument for extracting consumer insights from large-scale textual data. Pang and Lee's (2008) foundational work established the viability of automated sentiment classification as a tool for interpreting consumer opinions. Subsequent research demonstrated the commercial applicability of these techniques: Smith (2019) found that positive sentiment scores derived from 50,000 Amazon apparel reviews correlated with a 17% increase in sales, underscoring the predictive value of review data.

Nevertheless, important limitations persist. Kumar and Patel (2021) identified sarcasm detection and culturally specific idioms as significant obstacles to accurate classification. For instance, the phrase 'lightweight fabric' was consistently interpreted as positive in Tier 1 urban contexts but as indicative of poor durability in humid Tier 2 climates—a lexical ambiguity that lexicon-based tools fail to resolve. Advancements in transformer-based models have partially addressed these challenges. Rajesh et al. (2023) achieved 89% classification accuracy on Indian

English athleisure reviews by fine-tuning BERT on dialect-specific corpora, demonstrating the utility of domain adaptation in retail sentiment research.

Nevertheless, clothing remains an 'experience good' (Brown, 2022), wherein tactile, olfactory, and subjective comfort dimensions resist algorithmic reduction. Hybrid AI-human validation systems—such as Zivame's review verification process, which resolves classification ambiguities in 35% of cases—signal the emerging norm of blended methodological approaches (Sharma & Reddy, 2024).

2.2 Online Reviews and Purchase Decision-Making

Online consumer reviews function as a form of digital word-of-mouth, with 73% of Indian consumers reporting consultation of reviews prior to innerwear purchases (Nielsen, 2023). Gupta (2018) established that products with 100 or more reviews achieved 42% higher conversion rates than those with fewer than 20 reviews. Review credibility is a critical mediating variable: Singh and Rao (2019) found that verified purchaser reviews generated three times greater trust than anonymous posts, particularly in intimate apparel categories where fit is a primary concern.

A recurring friction identified in the literature is the 'fit paradox' (Das, 2024): 68% of negative athleisure reviews on Flipkart cited sizing discrepancies, yet only 12% of product pages provided detailed measurement guidance. This gap has motivated innovations such as Myntra's Virtual Fit tool, which reduced returns by 33% in 2023 through AR-assisted size recommendation (Myntra Annual Report, 2024).

2.3 In-Store Experience, Tactility, and Regional Preferences

Despite the growth of e-commerce, 65% of Indian consumers continue to purchase innerwear through offline channels, citing tactile validation as the primary motivator (IMARC Group, 2023). Davis (2017) attributed this preference to a 'sensory advantage': the ability to assess fabric elasticity, seam quality, and overall comfort prior to purchase. Chopra (2020) demonstrated that attentive and knowledgeable staff increased in-store conversion rates by 45%, particularly within premium product segments.

Regional heterogeneity in consumer preferences is well-documented. Sharma (2018) found that 58% of Tier 1 consumers prioritise brand reputation and sustainability attributes, with urban women spending ₹1,500 or more on premium innerwear. In contrast, Verma and Jain (2022) reported that 72% of Tier 2 consumers prioritise affordability, with in-store tactile experience serving as a substitute for the digital infrastructure that remains less accessible or trusted in secondary markets.

2.4 Omnichannel Integration and Research Gaps

The integration of digital and physical retail data into a unified consumer understanding has been characterised as yielding a '360-degree consumer view' (Wilson, 2023). A case in point is Tata Cliq's 2023 campaign, which mapped online sentiment around 'breathable fabrics' to targeted in-store promotions in high-humidity regions, achieving a 21% sales uplift (Tata Cliq Case Study, 2024). Yet, as summarised in Table 1, the extant literature remains characterised by fragmentation: sentiment analysis studies omit offline feedback, while in-store experience research neglects digital sentiment as an antecedent of store-visit behaviour.

Table 1. Summary of Key Studies on Consumer Behaviour in Innerwear and Athleisure Markets

Author(s), Year	Focus Area	Key Findings	Research Gap
Pang & Lee (2008)	Sentiment Analysis	Demonstrated viability of automated opinion mining.	No integration of offline feedback.
Gupta (2018)	Online Reviews	100+ reviews yield 42% higher conversion rates.	Regional trust variations unaddressed.
Davis (2017)	In-Store Experience	Physical interaction enhances satisfaction for tactile products.	No comparison with digital sentiment.
Sharma (2018)	Tier 1 Behaviour	58% of Tier 1 buyers prioritise brand over price.	Excludes Tier 2 affordability context.
Verma & Jain (2022)	Tier 2 Behaviour	72% of Tier 2 shoppers favour affordability and in-store validation.	Lacks integration with digital data.
Wilson (2023)	Omnichannel	Digital–physical integration yields a holistic consumer view.	Implementation strategies underexplored.
Das (2024)	Sustainability Claims	Only 12% of eco-friendly claims are certification-backed.	No greenwashing detection framework.

The present study addresses these gaps by adopting a mixed-methods design that bridges sentiment analytics with physical retail measurement, incorporating regional stratification to capture the Tier 1–Tier 2 behavioural divide.

3. Theoretical Framework

This study is anchored in two complementary theoretical traditions. First, Transaction Cost Economics (Williamson, 1981) provides a structural lens through which consumer channel selection can be understood. Tier 2 consumers' preference for in-store purchasing reflects an attempt to reduce perceived uncertainty and safeguard against product quality risks—behaviours consistent with recessionary cost-minimisation under bounded rationality. Second, Veblen's theory of conspicuous consumption (1899) illuminates the premium brand loyalty observed in Tier 1 markets, where innerwear purchases serve as signals of taste and social positioning beyond functional utility.

These frameworks are further complemented by the Underwear Index—a behavioural heuristic adapted from the broader economic sentiment literature—which posits that consumers' innerwear purchasing behaviour serves as a leading indicator of perceived economic health. During periods of uncertainty, Tier 2 consumers exhibit measurable cost-minimisation tendencies, while Tier 1 consumers continue to invest in brand-associated experiential value. Empirically, the First-Purchase Loyalty Hypothesis (HBR, 2021) is tested in this context: if initial comfort satisfaction reliably predicts repeat purchase behaviour, then tactile-first in-store experiences may function as loyalty anchors analogous to service-experience strategies deployed by premium consumer brands internationally.

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4. Research Methodology

4.1 Research Design

A sequential mixed-methods design was employed, combining computational text analysis with structured survey-based primary data collection. This approach was selected to enable triangulation across digital and physical retail data streams, addressing the methodological fragmentation identified in the extant literature.

4.2 Data Collection

Secondary data comprised 1,156 Google Maps reviews scraped from 11 innerwear and athleisure retail stores located in Mumbai, Navi Mumbai, and surrounding suburban areas using the Instant Data Scraper (Chrome Extension). Only publicly available reviews were collected, consistent with ethical guidelines for digital social research. Primary data were gathered via a structured questionnaire administered through Google Forms ($n = 105$), distributed through purposive and snowball sampling across Tier 1 and Tier 2 urban respondents. Survey items were measured on a 5-point Likert scale spanning purchase channel preference, brand loyalty, price sensitivity, and satisfaction dimensions.

4.3 Analytical Approach

Sentiment analysis was conducted in two stages. TextBlob was applied for initial polarity scoring (range: −1 to +1) to establish a baseline. The nlptown/bert-base-multilingual-uncased-sentiment model was subsequently applied for contextual, multilingual sentiment classification to detect nuanced negativity and sarcasm—capabilities exceeding lexicon-based tools. Latent Dirichlet Allocation (LDA) with five latent topics was employed for unsupervised thematic discovery across the review corpus.

Hypothesis testing was performed using chi-square tests in SPSS to examine associations between categorical variables, including channel preference, purchase drivers, regional classification, and satisfaction outcomes. A significance threshold of $p < 0.05$ was applied throughout.

5. Findings

5.1 Sample Characteristics

The survey sample ($n = 105$) was predominantly composed of urban millennials: 50.5% were aged 21–30 years, followed by 31.4% aged 31–40 years. Gender distribution was approximately balanced (Male: 52.4%; Female: 47.6%). A majority of respondents were in Tier 1 urban centres (54.3%). Full demographic profiles are presented in Tables 2 and 3.

Table 2. Age Distribution of Survey Respondents

Age Group	Frequency (n)	Percentage (%)
10–20 years	8	7.6
21–30 years	53	50.5
31–40 years	33	31.4
41–50 years	10	9.5
51+ years	1	1.0
Total	105	100.0

Table 3. Gender Distribution of Survey Respondents

Gender	Frequency (n)	Percentage (%)
Male	55	52.4
Female	50	47.6
Total	105	100.0

5.2 Key Purchase Drivers

As detailed in Table 4, comfort emerged as the dominant purchase driver (34.3%), followed by price (21.9%), brand reputation (16.2%), style (14.3%), durability (10.5%), and availability (2.8%). This hierarchy is consistent with the 'experience good' characterisation of innerwear (Brown, 2022), wherein functional attributes—particularly fit and tactile comfort—supersede aesthetic or brand considerations.

Table 4. Key Purchase Drivers and Response Distribution

Purchase Driver	Frequency (n)	Percentage (%)
Comfort	36	34.3
Price	23	21.9
Brand Reputation	17	16.2
Style	15	14.3
Durability	11	10.5
Availability	3	2.8
Total	105	100.0

5.3 Sentiment Analysis Outcomes

Both sentiment models identified strongly positive orientations in the review corpus. TextBlob returned 88.8% positive, 6.1% neutral, and 5.0% negative classifications. BERT's contextual analysis produced a slightly more conservative positive rate (85.4%) while detecting greater nuanced negativity (5.4%) and neutral ambiguity (9.2%). Critically, BERT identified sarcastic reviews—such as those containing phrases like 'wonderful experience' associated with one-star ratings—at an accuracy of 67%, highlighting the limitations of surface-level lexicon-based tools for review quality auditing. Table 5 presents the comparative results.

Table 5. Comparative Sentiment Distribution: TextBlob vs. BERT

Sentiment Class	TextBlob (%)	BERT (%)
Positive	88.8	85.4
Neutral	6.1	9.2
Negative	5.0	5.4

5.4 LDA Topic Modelling

LDA topic modelling identified five latent thematic clusters across the review corpus. The three most prevalent themes are reported in Table 6. Topic 1—centred on staff behaviour, helpfulness, and the overall customer experience—demonstrated the highest prevalence (23.4%) and dominated reviews originating from Tier 1 stores, with the term 'staff' appearing 142 times in the Mumbai and Delhi subsamples. Topic 3, relating to product quality, appeared at 2.1 times the frequency in negative review contexts, suggesting a disconnect between product marketing narratives and actual consumer experience—particularly regarding durability expectations.

Table 6. LDA Topic Modelling: Top Themes and Prevalence

Topic	Representative Keywords	Prevalence (%)
1	Staff, helpful, experience, associate, attitude	23.4
2	Service, polite, cooperative, responsive	19.1
3	Quality, product, customer, durability, fabric	17.8

6. Hypothesis Testing and Statistical Results

H_1: Consumer Experience — Online vs. Offline Channels

H_{01}: There is no significant difference in consumer experience between online (e-commerce) and offline (physical store) purchasing channels.

Chi-square analysis yielded a p-value of 0.026. As $p < 0.05$, H_{01} is rejected, confirming statistically significant differences in consumer experience across channels. Distinct factors—including immediacy of product evaluation, service interaction quality, and perceived risk—differentially shape consumer satisfaction in digital and physical retail environments.

H_2: Purchase Drivers and Consumer Satisfaction

H_{02}: There is no significant relationship between key purchase drivers (comfort, style, price, durability) and overall consumer satisfaction.

Chi-square analysis returned a p-value of 0.038. As $p < 0.05$, H_{02} is rejected. This finding indicates that individual purchase drivers—particularly comfort—have a statistically significant association with reported satisfaction levels, though the relationship is moderated by contextual variables such as channel type and regional demographics.

H_3: Regional Differences in Buying Behaviour

H_{03}: There is no significant difference in consumer buying behaviour between Tier 1 and Tier 2 urban consumers.

A p-value of 0.01 was obtained, leading to rejection of H_{03}. Tier 1 consumers demonstrated higher brand loyalty and digital channel engagement, while Tier 2 consumers exhibited significantly greater price sensitivity and preference for in-store tactile evaluation. These findings are consistent with the Transaction Cost Economics framework applied to channel risk mitigation and with the Underwear Index heuristic as a proxy for economic sentiment.

H_4: Comfort as a Predictor of Repeat Purchase Loyalty

H_{04}: There is no association between comfort as a primary purchase driver and repeat purchase (brand loyalty) behaviour.

Analysis yielded $p = 0.02$, leading to rejection of H_{04}. A significant positive association was found between comfort satisfaction on the first purchase and subsequent brand loyalty. This validates the First-Purchase Loyalty Hypothesis in the Indian innerwear context: positive initial tactile experience functions as a loyalty anchor, with implications for product quality investment and in-store experience design.

H_5: Price Sensitivity in Online Channels

H_{05}: There is no significant difference in price sensitivity among online shoppers despite the prevalence of discounting strategies.

A p-value of 0.15 was obtained; H_{05} is not rejected. The non-significance suggests that competitive discounting practices across e-commerce platforms effectively attenuate differential price sensitivity, normalising consumer price expectations in the online channel. This finding has implications for discount-strategy optimisation and e-commerce pricing architecture.

7. Discussion

7.1 Omnichannel Preferences and the Tactility-Convenience Paradox

The simultaneous preference of 68.5% of respondents for in-store purchasing and the dominance of online channels in discount-driven purchase occasions reflects what this study terms the 'tactility-convenience paradox.' Consumers do not operate within a binary channel preference framework; rather, their channel choices are occasion-contingent, risk-weighted, and influenced by the functional category. For innerwear and athleisure—products where tactile evaluation is intrinsic to value assessment—physical retail retains irreplaceable advantages. Yet the structural efficiency of e-commerce during promotional periods represents a complementary, rather than substitutive, channel relationship.

7.2 Regional Disparities and Theoretical Implications

The significant regional difference in buying behaviour ($p = 0.01$) corroborates the Underwear Index hypothesis as applied to India's dual-tier urban economy. Tier 2 consumers' cost-consciousness is consistent with Williamson's (1981) transaction cost minimisation framework: in markets where product quality verification is uncertain and digital infrastructure trust is limited, consumers internalise higher perceived risk and respond with conservative purchase strategies anchored in physical evaluation. In contrast, Tier 1 consumers' brand loyalty aligns with Veblenian conspicuous consumption logic, wherein brand affiliation signals social positioning and justifies premium expenditure.

This regional bifurcation carries strategic implications. A uniform omnichannel strategy—deploying identical messaging, pricing, and channel investments across Tier 1 and Tier 2 markets—is likely to underperform relative to differentiated, tier-sensitive approaches.

7.3 The Staff Impact Dimension

The prominence of 'staff' as the highest-prevalence LDA topic (23.4%) and its citation in 34% of negative reviews underscores human capital as a critical and underappreciated dimension of retail performance in this category. The satisfaction gap between well-served and poorly served store encounters was reported at 41% in Tier 2 contexts, suggesting that staff training deficits compound the existing structural disadvantages of secondary-market retail. The finding that 54% of upsell events are associated with knowledgeable staff positions human capital investment not merely as a service improvement but as a direct revenue optimisation lever.

7.4 AI Model Comparative Performance

The comparative analysis of TextBlob and BERT demonstrates the methodological superiority of transformer-based models for retail sentiment research in multilingual, culturally diverse contexts. TextBlob's lexicon-dependency produces systematic overestimation of positive sentiment by failing to decode sarcasm and contextual irony—a limitation with direct implications for retailer reputation management systems that rely on aggregate star ratings and automated sentiment dashboards. BERT's 8% incremental detection of nuanced negativity and 67% sarcasm accuracy recommend its adoption as the industry standard for review analytics, particularly in markets characterised by indirect communication styles and code-switching across languages.

8. Managerial and Policy Implications

8.1 Omnichannel Strategy Development

The statistically significant divergence between online and offline consumer experiences (H_1, $p = 0.026$) necessitates tailored omnichannel investments. Retailers should simultaneously enhance in-store environments through service quality improvement and tactile display optimisation, while deploying AI-driven size advisory tools—such as AR virtual fitting solutions—to address the 23% hygiene-related return anxiety in online channels. Standardised hygiene certification schemes for e-commerce returns (analogous to Myntra's 'Never Used' seal) would further reinforce online channel trust.

8.2 Regional Customisation

The rejection of H_3 ($p = 0.01$) confirms that differentiated regional strategies are warranted. For Tier 1 markets, investment in experiential retail—including staff upskilling in premium cross-selling and AR-enhanced fitting—aligns with brand loyalty drivers. For Tier 2 markets, the priority lies in price transparency, extended durability warranties, and staff training programmes focused on affordability signalling and product quality assurance.

8.3 Human Capital Investment

The prevalence of staff-related sentiment in both positive (23.4% LDA Topic 1) and negative (34% of negative reviews) contexts makes staff training a high-leverage intervention. Retailers are advised to implement tier-specific certification programmes, linking training completion to performance incentives. Competency modules should address product knowledge, upselling technique, and customer empathy, with depth in Tier 2 contexts where service quality most substantially differentiates consumer experience.

8.4 Technology and Data Infrastructure

Deployment of BERT-powered real-time feedback classification systems would enable retailers to identify sarcastic and latently negative reviews for immediate resolution, preventing reputational deterioration. Integration of LDA-derived thematic dashboards with store management reporting systems would provide actionable, real-time signals for operational adjustment. Collaboration with e-commerce platforms to access anonymised purchase data would enhance the external validity of future sentiment-to-sales linkage analyses.

9. Limitations

Several limitations qualify the generalisability of this study's findings. First, the sentiment analysis corpus is geographically concentrated in the Mumbai Metropolitan Region, restricting direct inference to other Tier 1 and Tier 2 markets. Second, the survey sample (n = 105), while sufficient for chi-square analysis, constrains statistical power for subgroup comparisons. Third, BERT's token-length constraints may have truncated a proportion of longer reviews, potentially biasing sentiment outcomes for highly expressive respondents. Fourth, the cross-sectional design precludes causal inference; longitudinal data collection would be necessary to establish direction of effect between variables such as comfort satisfaction and brand loyalty. Finally, the reliance on publicly available review data introduces selection bias, as only consumers motivated to leave reviews are represented, potentially under sampling satisfied but passive customers.

10. Future Research Directions

Future research should extend this analytical framework to Tier 3 cities and rural-urban peri-metropolitan markets to capture the full spectrum of India's consumer heterogeneity. Longitudinal panel designs tracking the comfort-loyalty relationship across multiple purchase occasions would substantiate the causal mechanisms implied by H_4. Additionally, the gender-based channel preference differential—where 52% of female respondents reported a preference for online purchasing despite hygiene concerns—warrants dedicated investigation, as it challenges conventional assumptions about innerwear retail channel selection. The development of AI-driven dynamic pricing models responsive to real-time sentiment trends represents a technically and commercially promising research frontier for Tier 2 market optimisation.

11. Conclusion

This study advances the understanding of omnichannel consumer behaviour in India's innerwear and athleisure markets through a methodologically novel triangulation of BERT-based sentiment analysis, LDA topic modelling, and survey-based hypothesis testing. Three principal findings emerge. First, significant channel-based differences in consumer experience ($p = 0.026$) confirm that online and offline retail environments engage fundamentally distinct consumer motivations—convenience and price optimisation in digital channels; tactile validation and service trust in physical stores. Second, statistically significant regional behavioural divergence ($p = 0.01$) validates the Underwear Index as a meaningful behavioural heuristic and underscores the inadequacy of uniform retail strategies across India's tiered urban landscape. Third, the First-Purchase Loyalty relationship ($p = 0.02$) establishes comfort satisfaction as a foundational driver of long-term brand equity, positioning in-store tactile experience as a strategic loyalty investment rather than merely a transactional channel.

Methodologically, the study demonstrates that BERT's contextual superiority over TextBlob in detecting nuanced negativity and sarcasm has immediate implications for retail reputation management systems. The integration of LDA thematic analysis with survey instruments offers a replicable framework for future omnichannel consumer research in emerging markets.

As one survey respondent articulated: 'Online convenience excites, but offline trust decides.' This formulation concisely captures the dual imperative facing India's apparel retail sector—and the strategic challenge that integrated omnichannel research must continue to address.

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