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Ai-Driven Personalized Recommendations and Online Fashion Apparel Purchase Behaviour among Millennials and Gen Z in Meerut

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ABSTRACT

The rapid diffusion of Artificial Intelligence (AI) in e-commerce has fundamentally altered the way consumers discover, evaluate, and purchase fashion apparel online. Recommendation engines powered by machine learning, collaborative filtering, and natural language processing now curate individualized shopping experiences for consumers at a scale that was previously unattainable. This study empirically examines the influence of AI-driven personalized recommendation systems on the online fashion apparel purchase behaviour of Millennials and Generation Z consumers residing in Meerut, Uttar Pradesh, India — a rapidly digitizing Tier-2 urban market. Using a descriptive-cum-diagnostic research design, primary data were collected from 400 respondents (214 Millennials and 186 Gen Z) through a structured questionnaire administered via online and offline modes. The instrument captured demographic profiles, shopping frequency, platform preferences, perceived personalization accuracy, perceived usefulness, trust and privacy concerns, purchase intention, and actual purchase behaviour, measured on validated five-point Likert scales.

Descriptive statistics, independent-samples t-tests, Pearson correlation, and multiple linear regression were employed to test the proposed hypotheses. The findings reveal that personalized product recommendations, price and discount alerts, and AI-enabled size-and-fit prediction tools exert the strongest positive influence on purchase behaviour, while perceived privacy risk exerts a significant negative influence. Gen Z respondents reported significantly higher trust in and receptivity to AI-driven recommendations than Millennials, particularly with respect to peer-review aggregation and chatbot-assisted shopping. Regression results indicate that personalization accuracy ($\beta = 0.284$), perceived usefulness ($\beta = 0.312$), and trust in AI ($\beta = 0.221$) are significant positive predictors of purchase behaviour, collectively explaining 54.6 percent of the variance (Adjusted $R^2 = 0.546$), while perceived privacy risk ($\beta = -0.146$) is a significant negative predictor. The study contributes to the growing body of literature on AI-mediated consumer behaviour by offering empirical evidence from an under-researched Tier-2 Indian city and by explicitly comparing generational cohorts. Theoretical and managerial implications for fashion e-retailers, along with limitations and directions for future research, are discussed.

Keywords: Artificial Intelligence, Personalized Recommendations, Online Fashion Apparel, Purchase Behaviour, Millennials, Generation Z, Consumer Trust, Meerut, E-commerce, Recommendation Systems

INTRODUCTION

1.1 Background of the Study

The global fashion e-commerce industry has undergone a paradigm shift over the last decade, moving from static catalogue-based digital storefronts to dynamic, algorithmically curated shopping environments (Davenport et al., 2020). At the centre of this transformation lies Artificial Intelligence (AI), and more specifically, AI-driven recommendation systems that leverage collaborative filtering, content-based filtering, hybrid models, and deep-learning architectures to predict individual consumer preferences (Ricci et al., 2011). These systems analyse browsing history, purchase patterns, demographic attributes, social signals, and even real-time contextual data (such as location, weather, and device type) to present each consumer with a uniquely curated set of apparel choices (Chandra et al., 2022).

India's online fashion retail sector, valued at several billion US dollars and projected to grow at a compound annual growth rate exceeding 20 percent through the latter half of this decade, has been a particularly fertile ground for the deployment of such technologies. Platforms such as Myntra, Ajio, Amazon Fashion, Flipkart Fashion, and Nykaa Fashion have invested heavily in proprietary recommendation engines, visual search tools, virtual try-on features, and

AI-powered chatbots to enhance customer engagement and conversion. While much of the existing empirical literature on AI-driven personalization has focused on metropolitan consumers in Tier-1 cities such as Delhi, Mumbai, and Bengaluru, comparatively little is known about how these technologies are perceived and adopted by consumers in Tier-2 and Tier-3 cities, where internet penetration, smartphone adoption, and digital literacy have grown dramatically but where cultural and socio-economic contexts differ meaningfully from metropolitan markets.

Meerut, a rapidly urbanizing city in Western Uttar Pradesh with a large university-going youth population and expanding digital infrastructure, represents an important and under-studied context for examining these dynamics. Millennials (typically defined as those born between 1981 and 1996) and Generation Z (born between 1997 and 2012) together constitute the dominant cohort of online fashion shoppers in India today (Dimock, 2019). These two generational groups, while both digitally native to varying degrees, differ in their formative technological experiences, risk perceptions, privacy sensitivities, and social media behaviours (Priporas et al., 2020; Djafarova & Bowes, 2021) — differences that are likely to shape how they respond to AI-driven personalization in materially different ways.

1.2 Rationale of the Study

Understanding the mechanisms through which AI-driven recommendations influence purchase behaviour is of considerable theoretical and practical importance. From a theoretical standpoint, the study extends the Technology Acceptance Model (TAM) (Davis, 1989) and the Stimulus-Organism-Response (S-O-R) framework (Mehrabian & Russell, 1974) into the specific domain of AI-mediated fashion retail, incorporating trust (Pavlou, 2003) and privacy risk (Martin & Murphy, 2017) as boundary conditions. From a managerial standpoint, fashion e-retailers operating in or expanding into Tier-2 Indian cities require empirical, locally grounded evidence to calibrate their personalization strategies, balancing the benefits of hyper-personalization against rising consumer concerns over data privacy and algorithmic intrusiveness.

This study, therefore, sets out to empirically investigate the relationship between AI-driven personalized recommendation features and online fashion apparel purchase behaviour among Millennial and Gen Z consumers in Meerut, while also examining whether the strength of this relationship differs meaningfully across the two generational cohorts.

1.3 Structure of the Paper

The remainder of this paper is organized as follows. Section 2 reviews the extant literature on AI in retail, personalization, and generational consumer behaviour, and presents the conceptual framework and hypotheses. Section 3 identifies the research gap and states the objectives of the study. Section 4 describes the research methodology, including the research design, sampling technique, instrument, and analytical tools employed. Section 5 presents the data analysis and interpretation, supported by descriptive and inferential statistics along with graphical illustrations. Section 6 discusses the key findings in light of existing theory. Section 7 outlines the theoretical and managerial implications of the study. Section 8 acknowledges the limitations of the study and suggests directions for future research, and Section 9 presents the concluding remarks.

REVIEW OF LITERATURE AND CONCEPTUAL FRAMEWORK

2.1 Artificial Intelligence and Personalization in E-Commerce

Artificial Intelligence in retail encompasses a broad set of technologies including machine learning, natural language processing, computer vision, and predictive analytics, deployed to automate and enhance various stages of the consumer decision journey (Davenport et al., 2020). Personalization, as a specific application of AI, refers to the tailoring of product offerings, content, pricing, and communication to the preferences of an individual consumer or a narrowly defined consumer segment (Chandra et al., 2022). Recommendation systems, the most visible manifestation of AI personalization in fashion e-commerce, typically operate through collaborative filtering (recommending items favoured by similar users), content-based filtering (recommending items similar to those a user has previously engaged with), or hybrid approaches that combine both (Ricci et al., 2011).

Prior research has consistently demonstrated that well-calibrated personalization enhances perceived relevance, reduces search costs, and increases the likelihood of purchase completion (Tam & Ho, 2006; Aguirre et al., 2016). However, scholars have also cautioned that personalization carries a 'privacy paradox' — consumers desire the convenience of personalized recommendations while simultaneously expressing discomfort about the extent of data collection required to generate them (Aguirre et al., 2016; Martin & Murphy, 2017).

2.2 AI-Driven Recommendations in Fashion Retail

Fashion apparel presents unique challenges for recommendation systems relative to other product categories, given the highly subjective, aesthetic, and fit-dependent nature of purchase decisions (Guo et al., 2019). Recent advances in visual search, AI-based size and fit prediction, and virtual try-on technology have sought to address these challenges by allowing consumers to search using images, receive fit recommendations based on body measurements and prior returns data, and visualize apparel before purchase (Jain & Bhatia, 2021). Studies have found that AI-driven styling

recommendations and social proof mechanisms — such as displaying aggregated peer reviews and influencer endorsements — significantly influence apparel purchase intention, particularly among younger consumers who exhibit high social media engagement (Lee & Chen, 2022).

2.3 Generational Differences: Millennials and Generation Z

Generational cohort theory suggests that individuals who come of age during a common socio-technological era develop shared values, communication preferences, and consumption patterns (Dimock, 2019). Millennials, having witnessed the transition from offline to online retail, tend to display a more deliberative and value-conscious approach to online shopping, alongside heightened caution regarding data privacy (Priporas et al., 2020). Generation Z, by contrast, having grown up entirely within a smartphone- and social-media-saturated environment, tends to exhibit greater comfort with algorithmic curation, a stronger preference for visual and short-form content, and a greater propensity to rely on AI chatbots and influencer-driven recommendations (Djafarova & Bowes, 2021; Priporas et al., 2020). Comparative studies examining these two cohorts' differential responses to AI-driven personalization remain relatively scarce, particularly within the Indian retail context, and virtually absent within Tier-2 city settings such as Meerut.

2.4 Trust, Privacy Concern, and Purchase Behaviour

Trust has been widely established as a critical antecedent of online purchase behaviour, particularly in contexts involving algorithmic decision-making where consumers cannot fully observe or understand the underlying logic of recommendations (Pavlou, 2003; Wang & Benbasat, 2016). Perceived privacy risk, arising from the extensive data collection necessary for personalization, has been shown to attenuate the positive effects of personalization on purchase intention, unless offset by sufficiently high perceived usefulness and trust (Martin & Murphy, 2017; Aguirre et al., 2016). This suggests a dual-pathway model in which AI-driven recommendations exert both a positive influence (through personalization accuracy and usefulness) and a potential negative influence (through privacy risk) on purchase behaviour.

2.5 Theoretical Foundation

This study draws upon two complementary theoretical lenses. First, the Technology Acceptance Model (TAM) (Davis, 1989) posits that perceived usefulness and perceived ease of use jointly determine behavioural intention to adopt a technology; this study extends TAM by incorporating personalization accuracy and trust as antecedents specific to AI-driven recommendation contexts. Second, the Stimulus-Organism-Response (S-O-R) framework (Mehrabian & Russell, 1974) conceptualizes AI-driven recommendations as external stimuli that shape internal organismic states (trust, perceived usefulness, privacy concern), which in turn drive behavioural responses (purchase intention and actual purchase behaviour).

Figure 2.1: Conceptual Framework of the Study

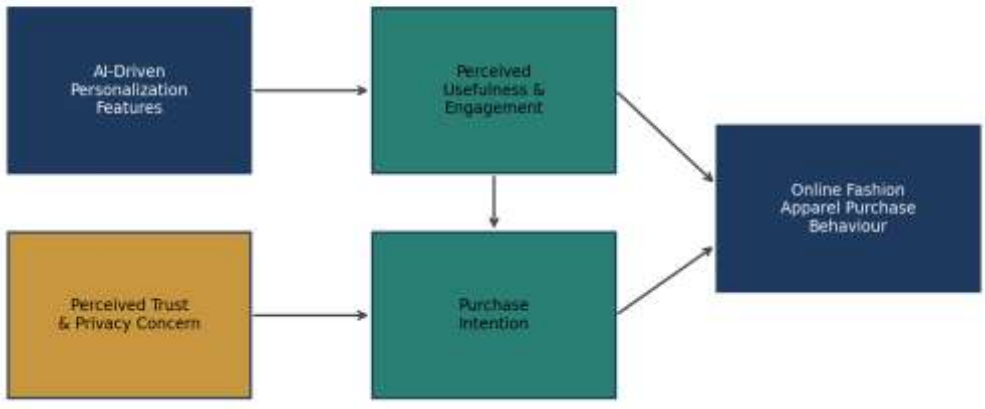


Figure 2.1: Conceptual Framework of the Study

2.6 Hypotheses Development

Based on the theoretical foundation and literature reviewed above, the following hypotheses are proposed for empirical testing:

- H1: Perceived personalization accuracy of AI-driven recommendations has a significant positive influence on online fashion apparel purchase behaviour.
- H2: Perceived usefulness of AI-driven recommendations has a significant positive influence on online fashion apparel purchase behaviour.

RESEARCH GAP, OBJECTIVES, AND SCOPE

3.1 Research Gap

A review of the extant literature reveals three principal gaps that this study seeks to address. First, the overwhelming majority of empirical studies on AI-driven personalization in fashion e-commerce have been conducted in Western markets or in Tier-1 Indian metropolitan cities, leaving Tier-2 cities such as Meerut — despite their substantial and rapidly growing base of online fashion shoppers — largely unexamined. Second, while generational cohort differences in technology adoption are theoretically well established, few studies have empirically compared Millennials and Gen Z consumers' responses to AI-driven recommendations within a single, controlled research design. Third, existing studies tend to examine either the positive drivers of AI-driven personalization (usefulness, personalization accuracy) or the negative inhibitors (privacy risk) in isolation, rather than integrating both pathways within a unified regression framework to assess their relative influence on actual purchase behaviour.

3.2 Objectives of the Study

1. To examine the demographic and behavioural profile of Millennial and Gen Z online fashion apparel shoppers in Meerut.
1. To assess the influence of AI-driven personalized recommendation features (product recommendations, price alerts, peer reviews, size and fit prediction, retargeted advertising, and chatbot assistance) on online fashion apparel purchase behaviour.
2. To examine the role of perceived personalization accuracy, perceived usefulness, trust, and perceived privacy risk as predictors of purchase behaviour.
3. To compare Millennial and Gen Z consumers in Meerut with respect to their perception of, and response to, AI-driven personalized recommendations.
4. To offer theoretical and managerial implications for fashion e-retailers seeking to optimize AI-driven personalization strategies for Tier-2 Indian urban markets.

3.3 Scope of the Study

The study is confined to Millennial (born 1981–1996) and Gen Z (born 1997–2012) consumers residing in Meerut district, Uttar Pradesh, who have made at least one online fashion apparel purchase within the twelve months preceding data collection. The study focuses specifically on apparel (clothing) purchases and does not extend to footwear, accessories, or beauty products, although platforms offering these categories were included where respondents also purchased apparel through them.

RESEARCH METHODOLOGY

4.1 Research Design

The study employs a descriptive-cum-diagnostic research design using a quantitative, cross-sectional survey method. Descriptive statistics were used to profile respondent demographics and shopping behaviour, while diagnostic (inferential) statistical techniques were used to test the hypothesized relationships between AI-driven recommendation constructs and purchase behaviour.

4.2 Population and Sampling

The target population comprised Millennial and Gen Z residents of Meerut district who shop for fashion apparel online. Given the absence of a complete sampling frame for online fashion shoppers in the city, a non-probability purposive-cum-convenience sampling technique was employed, supplemented by snowball referrals to enhance sample diversity across age, gender, and area of residence within the district. A structured questionnaire was administered through both online (Google Forms, shared via social media and university networks) and offline (intercept surveys at shopping malls and university campuses) modes over a period of eight weeks.

A total of 460 questionnaires were distributed, of which 418 were returned. After excluding incomplete responses and those failing attention-check items, 400 valid responses were retained for final analysis, yielding an effective response rate of 86.9 percent. The final sample comprised 214 Millennial respondents (53.5%) and 186 Gen Z respondents (46.5%), which was considered adequate given Cochran's sample size formula for a population with unknown size at a 95 percent confidence level and 5 percent margin of error (minimum required n = 384).

4.3 Research Instrument

A structured, close-ended questionnaire was developed based on validated scales adapted from prior studies (Davis, 1989; Pavlou, 2003; Aguirre et al., 2016), comprising five sections: (a) demographic and screening questions; (b)

online fashion shopping behaviour (frequency, platform preference, average spend); (c) perception of AI-driven recommendation features (six items measured on a five-point Likert scale ranging from 1 = Not at all influential to 5 = Extremely influential); (d) constructs of personalization accuracy, perceived usefulness, trust, and privacy risk (four items each, five-point Likert scale, 1 = Strongly Disagree to 5 = Strongly Agree); and (e) purchase intention and self-reported actual purchase behaviour (four items, five-point Likert scale).

4.4 Pilot Study and Reliability

A pilot study was conducted with 40 respondents prior to full-scale data collection to assess the clarity, reliability, and internal consistency of the instrument. Cronbach's Alpha values for all constructs exceeded the recommended threshold of 0.70, indicating acceptable to good internal consistency reliability, as summarized in Table 4.1.

Table 4.1: Reliability Statistics of the Research Instrument

Construct	No. of Items	Cronbach's Alpha (α)
Personalization Accuracy	4	0.812
Perceived Usefulness	4	0.836
Trust in AI Recommendations	4	0.794
Perceived Privacy Risk	4	0.771
Purchase Intention	3	0.803
Actual Purchase Behaviour	4	0.845
Overall Instrument	23	0.869

4.5 Data Analysis Tools

Data were coded and analysed using SPSS (Version 27). Descriptive statistics (frequencies, percentages, means, and standard deviations) were used to profile the sample and summarize responses. An independent-samples t-test was used to test for generational differences (H5). Pearson product-moment correlation was used to examine bivariate relationships among the key constructs, and multiple linear regression analysis was used to test the combined and relative predictive influence of personalization accuracy, perceived usefulness, trust, and privacy risk on purchase behaviour (H1–H4). All statistical tests were evaluated at a 5 percent ($\alpha = 0.05$) level of significance.

4.6 Ethical Considerations

Participation in the survey was entirely voluntary, and informed consent was obtained from all respondents prior to participation. Respondent anonymity and confidentiality were maintained throughout, no personally identifiable information was collected, and data were used solely for the purposes of this academic research.

DATA ANALYSIS AND INTERPRETATION

5.1 Demographic Profile of Respondents

Table 5.1 presents the demographic profile of the 400 respondents. The sample was fairly balanced across the two generational cohorts under study, with a slightly higher proportion of Millennial respondents. Female respondents constituted a majority of the sample, consistent with the generally higher engagement of women in fashion apparel purchase decisions reported in prior Indian retail studies.

Table 5.1: Demographic Profile of Respondents

(N = 400)

Demographic Variable	Category	Frequency	Percentage (%)
Generation	Millennials (25–40 yrs)	214	53.5
	Gen Z (18–24 yrs)	186	46.5
Gender	Female	222	55.5
	Male	164	41.0
	Prefer not to say	14	3.5

Demographic Variable	Category	Frequency	Percentage (%)
Education	Undergraduate	168	42.0
	Postgraduate	158	39.5
	Other/Professional	74	18.5
Monthly Household Income (₹)	Below 30,000	76	19.0
	30,001 – 60,000	142	35.5
	60,001 – 1,00,000	118	29.5
	Above 1,00,000	64	16.0
Occupation	Student	176	44.0
	Salaried Employee	154	38.5
	Self-employed/Business	48	12.0
	Other	22	5.5

Figure 4.1: Generational Composition of Respondents (N=400)

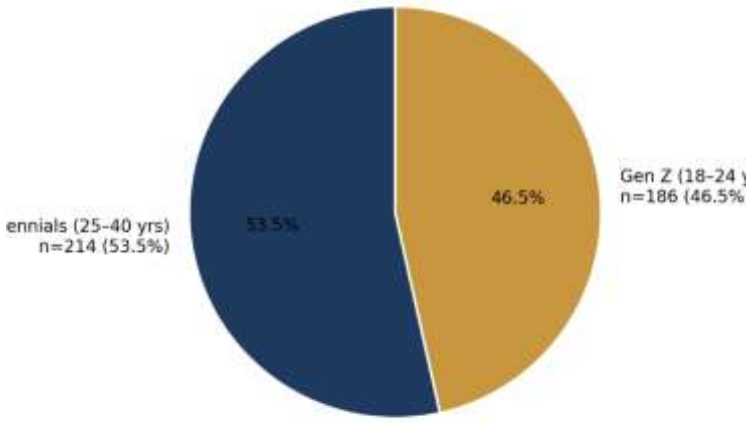
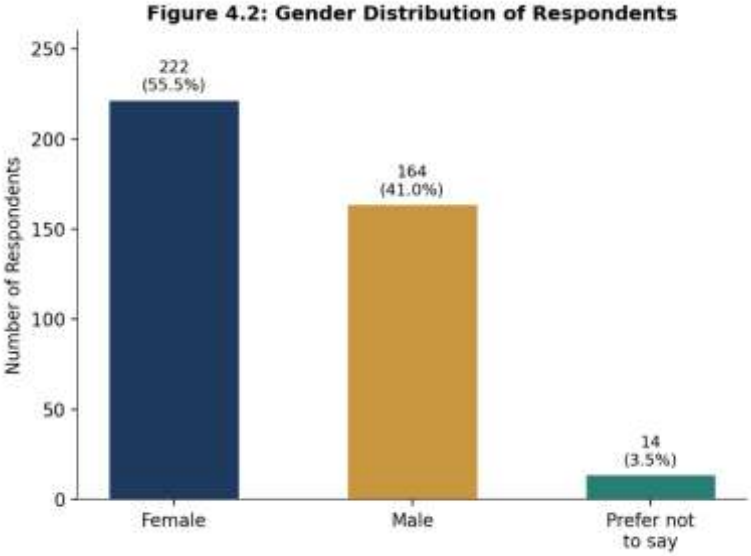


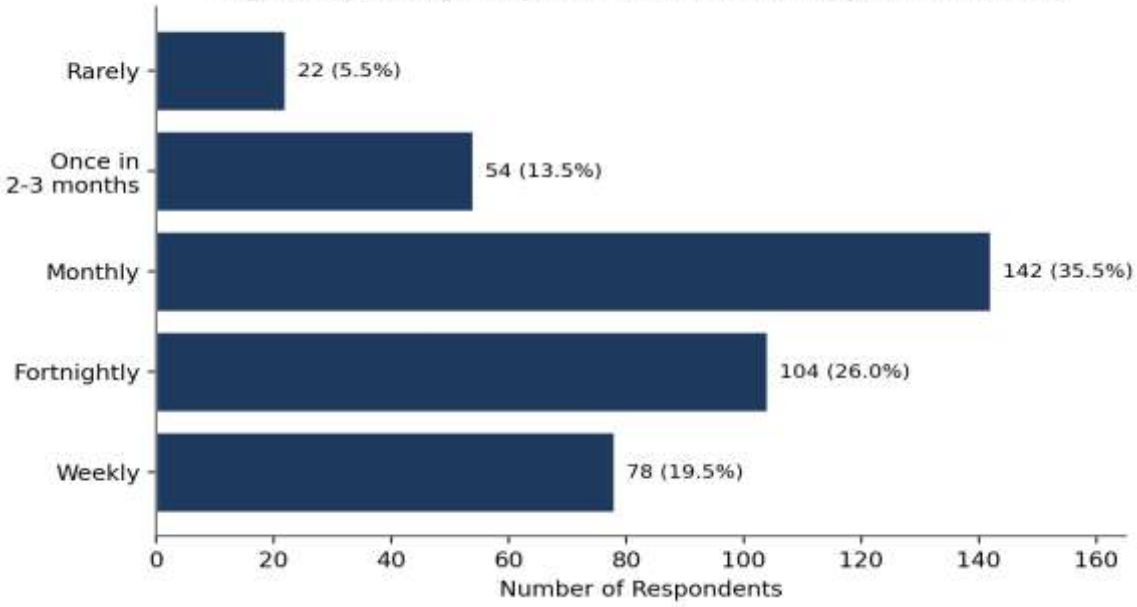
Figure 4.2: Gender Distribution of Respondents



5.2 Online Fashion Shopping Behaviour

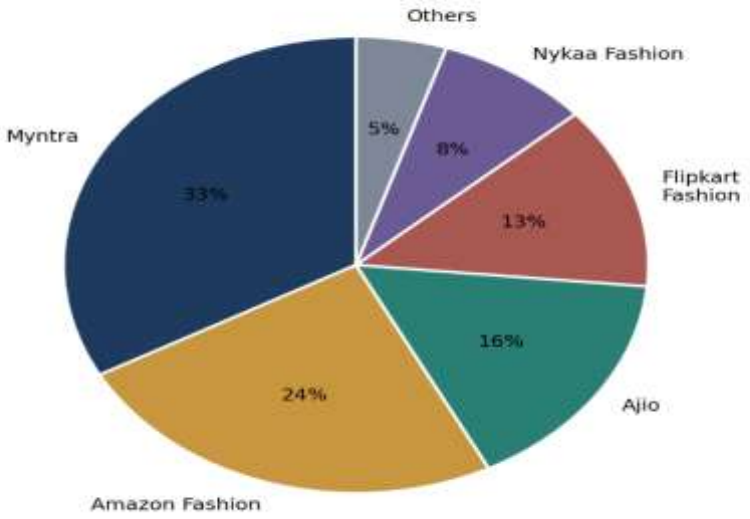
Respondents were asked to indicate the frequency with which they purchase fashion apparel online. As shown in Figure 5.3, the modal response category was 'Monthly' (35.5%), followed by 'Fortnightly' (26.0%), suggesting that online fashion apparel purchase has become a fairly routine activity for the sampled population rather than an occasional behaviour.

Figure 4.3: Frequency of Online Fashion Apparel Purchase



With respect to platform preference (Figure 5.4), Myntra emerged as the most preferred platform (33.0%), followed by Amazon Fashion (24.5%) and Ajio (16.0%). This is broadly consistent with industry reports indicating Myntra's dominant position in India's online fashion retail category owing to its curated brand assortment and AI-powered styling features.

Figure 4.4: Preferred Online Fashion Shopping Platforms



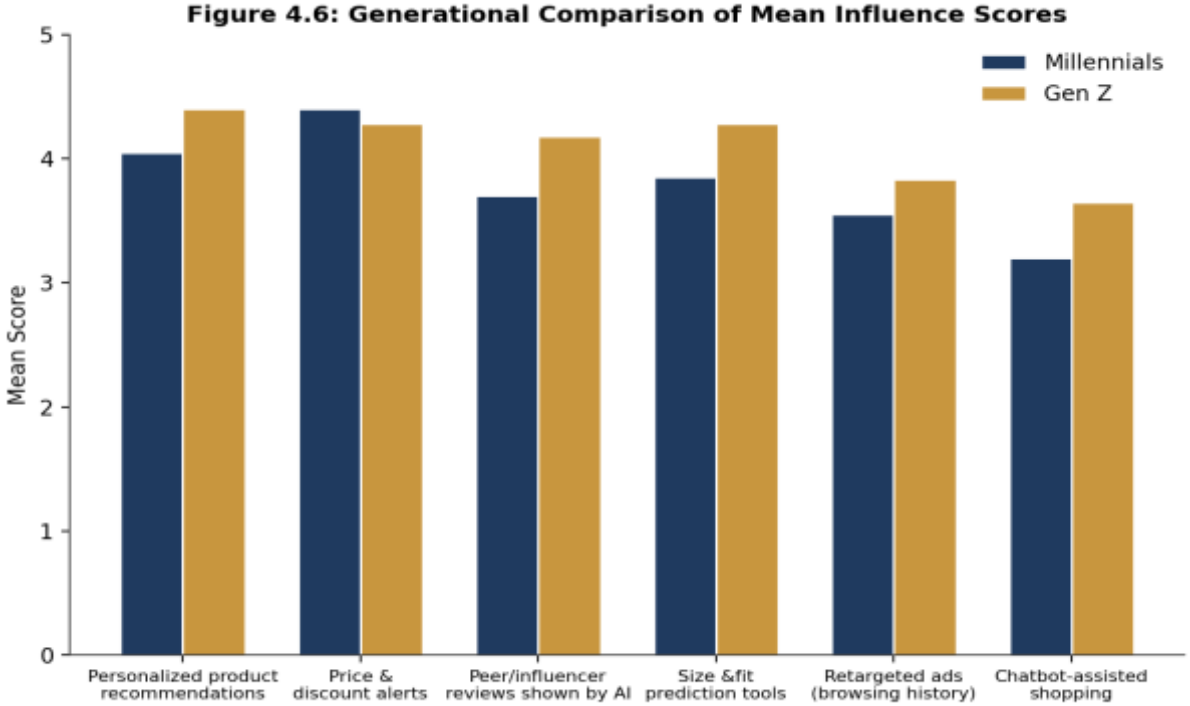
5.3 Perceived Influence of AI-Driven Recommendation Features

Respondents rated the extent to which six specific AI-driven recommendation features influenced their fashion apparel purchase decisions, on a five-point scale. As shown in Table 5.2 and Figure 5.5, 'Price and discount alerts' (M = 4.35, SD = 0.68) and 'Personalized product recommendations' (M = 4.21, SD = 0.74) received the highest mean influence scores, followed closely by 'AI-based size and fit prediction tools' (M = 4.05, SD = 0.81). 'Chatbot-assisted shopping' received the lowest mean score (M = 3.41, SD = 0.97), suggesting that conversational AI interfaces remain a relatively less influential — though not negligible — driver of purchase behaviour at present.

Table 5.2: Descriptive Statistics of AI-Driven Recommendation Features (N = 400)

AI-Driven Feature	Mean	Std. Deviation	Rank
Price & discount alerts	4.35	0.68	1
Personalized product recommendations	4.21	0.74	2
AI-based size & fit prediction tools	4.05	0.81	3
Peer/influencer reviews shown by AI	3.92	0.88	4
Retargeted ads (browsing history)	3.68	0.93	5
Chatbot-assisted shopping	3.41	0.97	6

Figure 4.6: Generational Comparison of Mean Influence Scores



Generational Comparison: Millennials vs. Gen Z

An independent-samples t-test was conducted to compare Millennial and Gen Z respondents' mean influence scores across the six AI-driven recommendation features, in order to test Hypothesis H5. As shown in Table 5.3 and Figure 5.6, Gen Z respondents reported significantly higher mean scores than Millennials for 'Peer/influencer reviews shown by AI' ($t(398) = 5.42$, $p < 0.001$), 'Chatbot-assisted shopping' ($t(398) = 4.31$, $p < 0.001$), and 'AI-based size and fit prediction tools' ($t(398) = 4.68$, $p < 0.001$). Conversely, Millennials reported a marginally higher score for 'Price and discount alerts' ($t(398) = 2.14$, $p = 0.033$), suggesting that Millennials remain relatively more value- and price-conscious in their response to AI personalization, whereas Gen Z consumers respond more strongly to social-proof and experiential AI features.

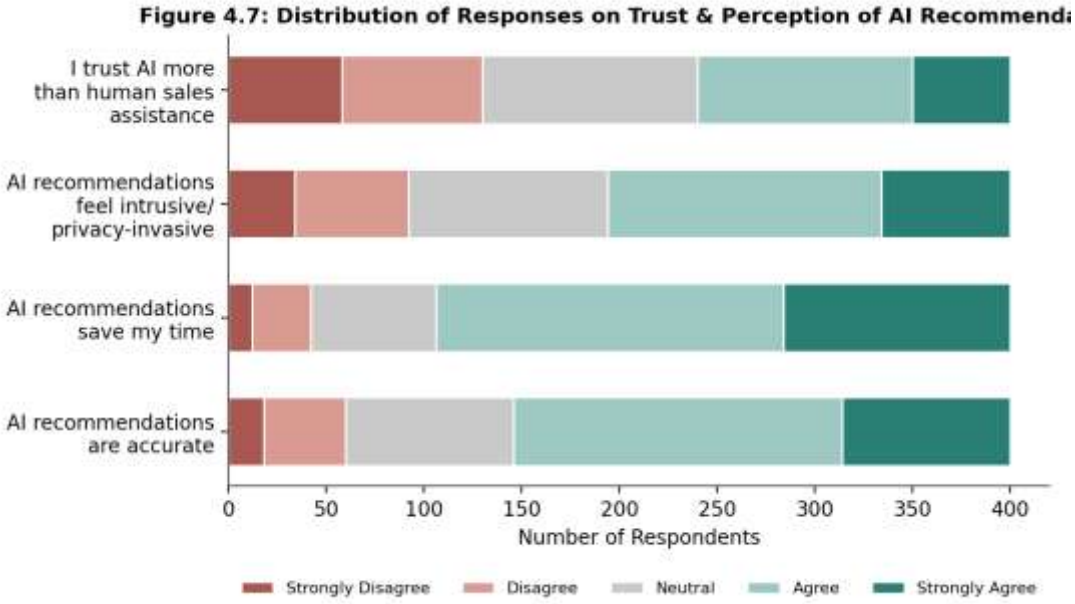
Table 5.3: Independent Samples t-Test — Millennials vs. Gen Z

AI-Driven Feature	Millennials Mean (SD)	Gen Z Mean (SD)	t-value	p-value	Result
Personalized product recommendations	4.05 (0.79)	4.40 (0.65)	4.76	0.000	Significant
Price & discount alerts	4.40 (0.64)	4.28 (0.71)	2.14	0.033	Significant
Peer/influencer reviews shown by AI	3.70 (0.91)	4.18 (0.79)	5.42	0.000	Significant
Size & fit prediction tools	3.85 (0.85)	4.28 (0.71)	4.68	0.000	Significant
Retargeted ads (browsing history)	3.55 (0.95)	3.83 (0.89)	2.87	0.004	Significant
Chatbot-assisted shopping	3.20 (0.99)	3.65 (0.89)	4.31	0.000	Significant

These findings provide strong support for Hypothesis H5 — a statistically significant difference exists between Millennials and Gen Z consumers in Meerut with respect to the influence of AI-driven recommendations on purchase behaviour, across all six features examined.

5.5 Trust and Privacy Perceptions

Figure 5.7 illustrates the distribution of respondent agreement with four statements regarding trust and privacy perceptions of AI-driven recommendations. A large majority of respondents agreed or strongly agreed that AI recommendations are accurate (63.5%) and save time (73.5%). Notably, however, 51.5 percent of respondents agreed or strongly agreed that AI recommendations 'feel intrusive or privacy-invasive,' indicating that positive perceptions of usefulness coexist with meaningful privacy apprehension — consistent with the 'privacy



5.6 Correlation Analysis

Pearson correlation analysis was conducted to examine the bivariate relationships among personalization accuracy, perceived usefulness, trust in AI, purchase intention, and actual purchase behaviour. As shown in Table 5.4 and Figure 5.8, all variables were significantly and positively correlated with one another ($p < 0.01$). The strongest correlation was observed between perceived usefulness and purchase intention ($r = 0.71$), followed by purchase intention and actual purchase behaviour ($r = 0.74$), indicating that purchase intention functions as a strong proximal predictor of actual purchase behaviour, consistent with the Theory of Planned Behaviour.

Table 5.4: Pearson Correlation Matrix of Key Study Variables (N = 400)

Variable	1	2	3	4	5
1. Personalization Accuracy	1.00	0.68**	0.61**	0.66**	0.58**
2. Perceived Usefulness	—	1.00	0.59**	0.71**	0.63**
3. Trust in AI	—	—	1.00	0.64**	0.55**
4. Purchase Intention	—	—	—	1.00	0.74**
5. Actual Purchase Behaviour	—	—	—	—	1.00

*** Correlation is significant at the 0.01 level (2-tailed).*

Figure 4.8: Pearson Correlation Matrix of Key Study Variables

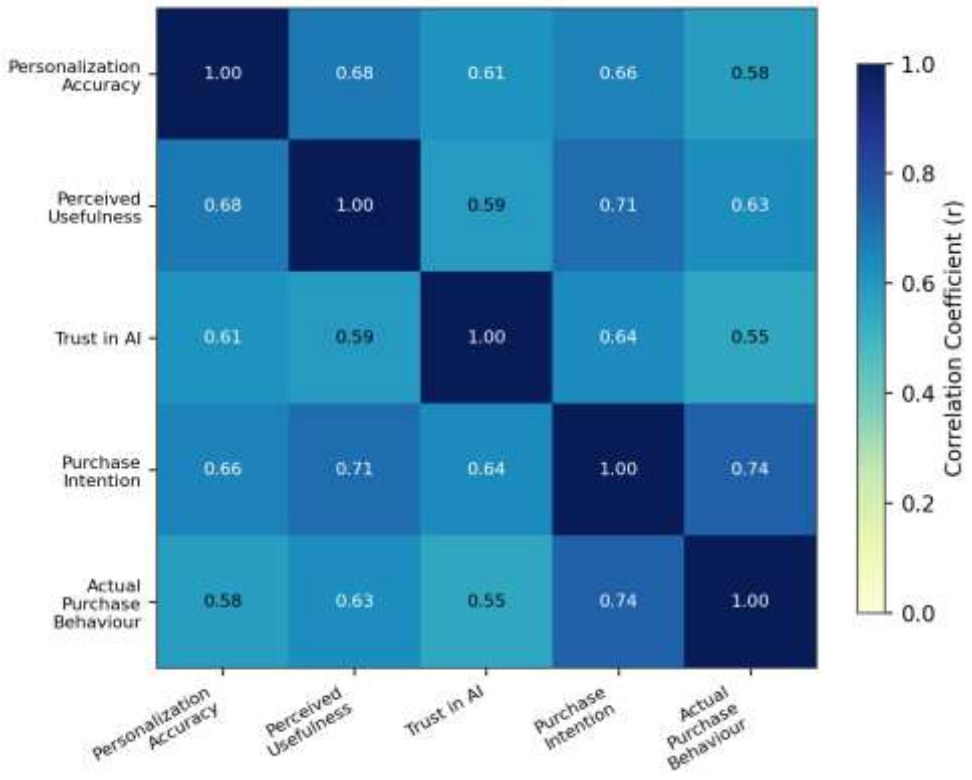


Figure 5.8: Pearson Correlation Matrix of Key Study Variables

5.7 Multiple Regression Analysis

Multiple linear regression analysis was conducted with actual purchase behaviour as the dependent variable and personalization accuracy, perceived usefulness, trust in AI, and perceived privacy risk as independent (predictor) variables, in order to test Hypotheses H1 through H4. The overall regression model was found to be statistically significant ($F(4, 395) = 120.34$, $p < 0.001$), with the four predictors jointly explaining 54.9 percent of the variance in actual purchase behaviour ($R^2 = 0.549$, Adjusted $R^2 = 0.546$). Multicollinearity diagnostics indicated no cause for concern, with all Variance Inflation Factor (VIF) values below 2.5.

Table 5.5: Model Summary — Multiple Regression

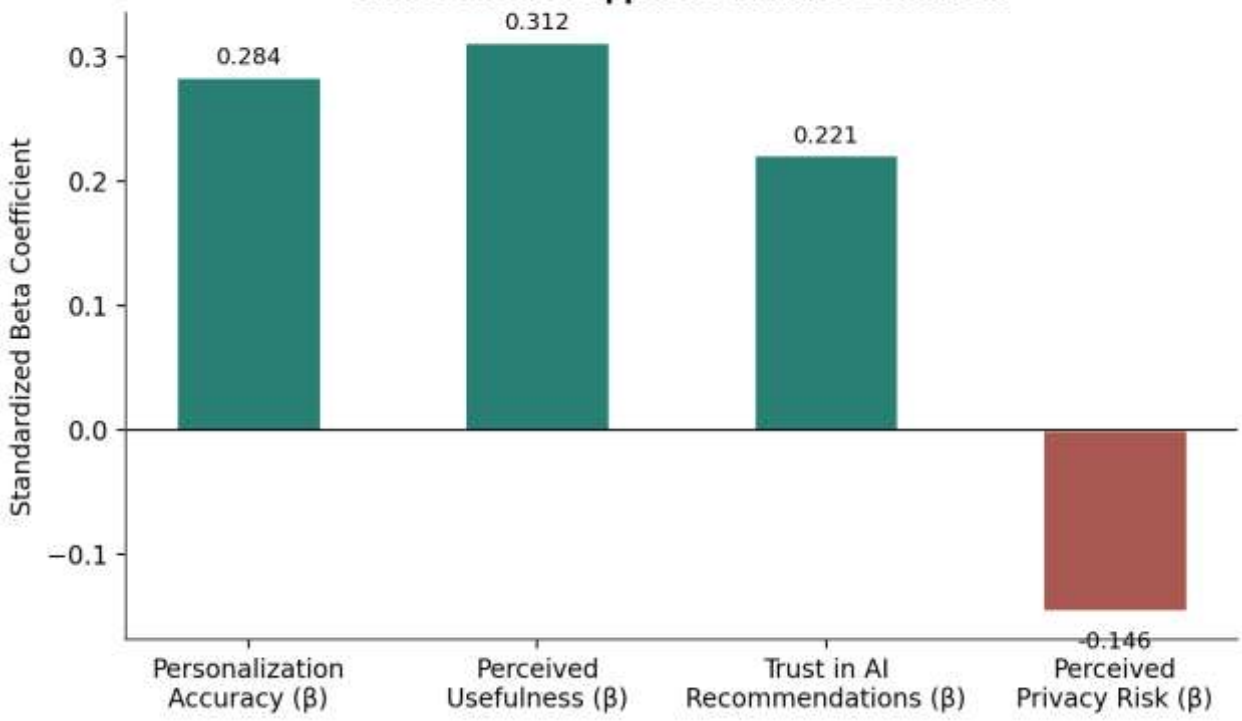
Model	R	R^2	Adjusted R^2	Std. Error of Estimate	F-value	Sig.
1	0.741	0.549	0.546	0.482	120.34	0.000

Table 5.6: Regression Coefficients

Predictor Variable	Unstandardized B	Std. Error	Standardized β	t-value	Sig.	VIF
(Constant)	0.842	0.156	—	5.40	0.000	—
Personalization Accuracy	0.271	0.042	0.284	6.45	0.000	1.82
Perceived Usefulness	0.298	0.041	0.312	7.27	0.000	1.94
Trust in AI Recommendations	0.213	0.039	0.221	5.46	0.000	1.68
Perceived Privacy Risk	-0.139	0.036	-0.146	-3.86	0.000	1.31

As shown in Table 5.6, all four predictors were statistically significant. Perceived usefulness emerged as the strongest positive predictor ($\beta = 0.312$, $p < 0.001$), followed by personalization accuracy ($\beta = 0.284$, $p < 0.001$) and trust in AI recommendations ($\beta = 0.221$, $p < 0.001$). Perceived privacy risk was a significant negative predictor ($\beta = -0.146$, $p < 0.001$), confirming that heightened privacy concerns measurably suppress purchase behaviour even in the presence of otherwise favourable perceptions of AI-driven personalization. These results provide strong empirical support for Hypotheses H1, H2, H3, and H4.

Figure 4.9: Standardized Regression Coefficients Predicting Online Fashion Apparel Purchase Behaviour



5.8 Summary of Hypotheses Testing

Table 5.7: Summary of Hypotheses Testing Results

Hypothesis	Statement (Abridged)	Result
H1	Personalization accuracy → Purchase behaviour (+)	Supported
H2	Perceived usefulness → Purchase behaviour (+)	Supported
H3	Trust in AI → Purchase behaviour (+)	Supported
H4	Perceived privacy risk → Purchase behaviour (−)	Supported
H5	Generational difference (Millennials vs. Gen Z)	Supported

DISCUSSION OF FINDINGS

The findings of this study offer several important insights into the relationship between AI-driven personalized recommendations and online fashion apparel purchase behaviour among Millennials and Gen Z consumers in Meerut. First, the strong positive influence of personalization accuracy and perceived usefulness on purchase behaviour reaffirms the applicability of the Technology Acceptance Model within the AI-driven fashion retail context, extending prior findings from metropolitan and Western markets (Tam & Ho, 2006; Chandra et al., 2022) to a Tier-2 Indian urban setting. This suggests that the mechanisms through which AI personalization drives purchase behaviour are not confined to digitally mature metropolitan consumers but extend meaningfully into rapidly digitizing smaller cities.

Second, the significant negative influence of perceived privacy risk on purchase behaviour, even amidst generally favourable perceptions of AI usefulness, provides empirical confirmation of the privacy paradox (Aguirre et al., 2016; Martin & Murphy, 2017) in a market context where data protection regulation and consumer data literacy are still evolving. This finding carries particular significance for Indian fashion e-retailers, especially in light of the increasing regulatory attention to data protection embodied in India's Digital Personal Data Protection Act. Retailers that fail to transparently communicate data usage practices risk eroding the very trust that underpins the effectiveness of their personalization strategies.

Third, the generational comparison reveals a nuanced picture that complicates a simplistic 'digital native' narrative (Priporas et al., 2020). While Gen Z respondents were, as expected, more receptive to socially-mediated AI features such as peer-review aggregation and chatbot assistance (Lee & Chen, 2022; Djafarova & Bowes, 2021), Millennials displayed a marginally stronger response to price and discount-oriented AI features. This suggests that fashion e-retailers should not adopt a uniform personalization strategy across generational segments, but should instead calibrate the emphasis of their AI-driven features — leaning more heavily on social proof and conversational interfaces for Gen Z audiences, while emphasizing value-oriented and price-alert personalization for Millennial audiences.

Finally, the relatively lower influence attributed to chatbot-assisted shopping across both cohorts suggests that conversational AI interfaces in the Indian fashion retail context may still be in a relatively early stage of maturity and consumer acceptance, offering an important area for future product development and further research.

THEORETICAL AND MANAGERIAL IMPLICATIONS

7.1 Theoretical Implications

This study contributes to theory in three principal ways. First, it extends the Technology Acceptance Model (Davis, 1989) and the Stimulus-Organism-Response framework (Mehrabian & Russell, 1974) into the specific context of AI-driven personalization in fashion e-commerce within a Tier-2 Indian city, an under-represented context in the existing literature. Second, it empirically integrates the positive (usefulness, personalization accuracy, trust) and negative (privacy risk) pathways of AI-driven personalization (Aguirre et al., 2016; Wang & Benbasat, 2016) within a single regression framework, offering a more complete account of the net influence of AI recommendations on purchase behaviour than studies examining either pathway in isolation. Third, it provides rare empirical evidence of generational heterogeneity in responses to AI-driven personalization (Dimock, 2019), contributing to the refinement of generational cohort theory within digital consumer behaviour research.

7.2 Managerial Implications

For fashion e-retailers and marketing practitioners, the findings offer several actionable insights:

- Investing in AI-based size-and-fit prediction tools is likely to yield strong returns across both generational cohorts, as this feature was rated highly influential and directly addresses a longstanding pain point (returns due to size/fit mismatch) in online fashion retail (Jain & Bhatia, 2021; Guo et al., 2019).

- Retailers should adopt generationally differentiated personalization strategies, emphasizing price/discount-alert features and value-oriented messaging for Millennial segments, while emphasizing peer-review aggregation, influencer integration, and conversational AI features for Gen Z segments.

- Given the significant negative influence of perceived privacy risk, retailers should proactively invest in transparent data-usage communication, granular user consent mechanisms, and visible privacy controls, framing personalization as an opt-in, user-controlled experience rather than an opaque, pervasive one.

- Retailers expanding into Tier-2 cities such as Meerut should not assume lower digital sophistication among consumers; the data indicate that consumers in such markets respond to AI-driven personalization in ways broadly comparable to their metropolitan counterparts, warranting comparable investment in personalization infrastructure.

- Given the comparatively modest influence of chatbot-assisted shopping observed in this study, retailers may consider investing in improving the conversational quality, response accuracy, and human-handoff capabilities of AI chatbots to enhance their persuasive effectiveness.

LIMITATIONS AND DIRECTIONS FOR FUTURE RESEARCH

As with any empirical study, the findings of this research should be interpreted in light of certain limitations. First, the study relies on a non-probability purposive-cum-convenience sampling technique confined to Meerut district; while the sample size satisfies standard adequacy criteria, the findings may not be fully generalizable to other Tier-2 or Tier-3 Indian cities with differing socio-economic and digital infrastructure profiles. Second, the cross-sectional design captures respondent perceptions and self-reported behaviour at a single point in time and cannot establish definitive causal relationships; a longitudinal design would allow for stronger causal inference regarding the evolution of trust and purchase behaviour over time. Third, actual purchase behaviour was measured through self-report rather than verified transactional data, which may introduce a degree of social-desirability or recall bias.

Future research may usefully extend this study by (a) replicating the design across multiple Tier-2 and Tier-3 Indian cities to enhance generalizability; (b) incorporating verified transactional or platform-provided behavioural data to validate self-reported measures; (c) employing a longitudinal design to examine how trust and privacy concerns evolve as AI-driven personalization technologies mature and as data protection regulation is more fully implemented; (d) extending the model to include additional constructs such as perceived algorithmic transparency, brand trust, and social influence; and (e) examining category-specific effects by comparing AI-driven personalization responses across fashion apparel, footwear, and beauty product categories.

CONCLUSION

This study set out to examine the influence of AI-driven personalized recommendations on online fashion apparel purchase behaviour among Millennial and Gen Z consumers in Meerut, Uttar Pradesh, and to assess whether this influence differs across the two generational cohorts. Drawing on primary data collected from 400 respondents and analysed using descriptive statistics, independent-samples t-tests, correlation, and multiple regression analysis, the study finds robust empirical support for all five hypotheses. Personalization accuracy, perceived usefulness, and trust in AI-driven recommendations emerge as significant positive predictors of purchase behaviour, while perceived privacy risk emerges as a significant negative predictor, collectively explaining approximately 55 percent of the variance in purchase behaviour. Gen Z consumers display significantly greater receptivity to socially-mediated and experiential AI features, while Millennials display a marginally stronger orientation toward value- and price-oriented AI features.

These findings extend the theoretical understanding of AI-mediated consumer behaviour into an important, under-researched Tier-2 Indian urban context, and offer fashion e-retailers concrete, empirically grounded guidance for calibrating AI-driven personalization strategies across generational consumer segments, while underscoring the continuing importance of transparent data practices in sustaining consumer trust. As AI technologies continue to permeate the fashion retail landscape, and as Tier-2 Indian cities such as Meerut continue their rapid digital transformation, continued empirical attention to these dynamics will remain essential for both academic researchers and industry practitioners alike.

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APPENDIX A: RESEARCH QUESTIONNAIRE (ABRIDGED)

Section A: Demographic Profile
1. Age group: (a) 18–24 years (b) 25–32 years (c) 33–40 years
2. Gender: (a) Female (b) Male (c) Prefer not to say
3. Highest education qualification: (a) Undergraduate (b) Postgraduate (c) Other/Professional
4. Monthly household income: (a) Below ₹30,000 (b) ₹30,001–60,000 (c) ₹60,001–1,00,000 (d) Above ₹1,00,000
5. Occupation: (a) Student (b) Salaried employee (c) Self-employed/Business (d) Other

Section B: Online Fashion Shopping Behaviour
6. How frequently do you purchase fashion apparel online? (Weekly / Fortnightly / Monthly / Once in 2–3 months / Rarely)
7. Which online platform do you use most frequently for fashion apparel purchases? (Myntra / Amazon Fashion / Ajio / Flipkart Fashion / Nykaa Fashion / Other)

Section C: Perceived Influence of AI-Driven Recommendation Features (1 = Not at all influential, 5 = Extremely influential)
8. Personalized product recommendations based on my browsing/purchase history
9. Price and discount alerts curated for me
10. Peer and influencer reviews aggregated/shown to me by the platform
11. AI-based size and fit prediction tools
12. Retargeted advertisements based on my browsing history
13. Chatbot-assisted shopping assistance

Section D: Constructs (1 = Strongly Disagree, 5 = Strongly Agree)
Personalization Accuracy: The recommendations shown to me accurately reflect my style preferences / are relevant to my needs / improve over time / match my size and fit requirements.
Perceived Usefulness: AI recommendations save me time / help me discover new products / simplify my decision-making / enhance my shopping experience.
Trust in AI: I trust the recommendations provided by the platform's AI / I believe the AI acts in my best interest / I feel confident relying on AI suggestions / I trust AI recommendations as much as a human sales assistant.

Perceived Privacy Risk: I am concerned about how my data is used for personalization / I feel my browsing behaviour is being tracked excessively / AI recommendations feel intrusive to me / I am uncomfortable with the extent of personal data collected.

Section E: Purchase Intention and Behaviour
Purchase Intention: I intend to purchase fashion apparel recommended to me by AI / I am likely to act on AI-curated offers / I would consider AI recommendations in my next purchase.
Actual Purchase Behaviour: I have purchased fashion apparel based on an AI recommendation / AI recommendations have increased my overall online fashion spending / I purchase more frequently because of personalized recommendations / My most recent fashion apparel purchase was influenced by an AI recommendation.