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RESEARCH ARTICLE

AI-enabled Smart Appliances and Consumer Brand Preference: A Behavioural Study of AI Attribute Perceptions among Urban Consumers in Bengaluru

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Abstract

The rapid proliferation of Artificial Intelligence (AI) in consumer electronics has fundamentally transformed the competitive landscape of the smart appliance sector, compelling consumers to reconsider conventional brand evaluation criteria. Anchored in the Technology Acceptance Model (TAM) (Davis, 1989) and the Theory of Planned Behaviour (TPB) (Ajzen, 1991), this study investigates how AI-specific attributes—namely AI Awareness, Perceived Usefulness, Perceived Ease of Use, Trust in AI Technology, Personalisation Experience, and Privacy and Security Concerns—shape consumer brand preference for AI-enabled smart appliances in Bengaluru Urban District, Karnataka, India. A quantitative, cross-sectional survey design was employed, with data collected from 348 valid respondents drawn through a stratified sampling framework across eight representative zones of the city. The measurement instrument was evaluated for reliability and construct validity using Cronbach's Alpha and Exploratory Factor Analysis (EFA) with Principal Component Analysis (PCA) and Varimax rotation. Pearson correlation analysis and multiple linear regression were subsequently applied to test the hypothesised relationships. Results demonstrate that all six AI constructs exert a statistically significant positive influence on consumer brand preference. The regression model achieved high explanatory power ($R^2 = 0.717$, $F(6,341) = 143.87$, $p < 0.001$), with Perceived Usefulness ($\beta = 0.298$), Trust in AI Technology ($\beta = 0.284$), and Personalisation Experience ($\beta = 0.261$) emerging as the three most powerful predictors. Importantly, Privacy and Security Concerns exhibited a positive relationship with brand preference ($\beta = 0.196$), suggesting that privacy-aware consumers exhibit stronger preference

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for brands perceived as trustworthy data stewards. These findings contribute theoretically to the extension of TAM into AI-mediated brand evaluation contexts and offer actionable guidance for marketers, manufacturers, and policymakers operating in India's rapidly expanding smart home market.

INTRODUCTION

The convergence of Artificial Intelligence (AI) and household consumer electronics has ushered in a paradigm shift in how consumers experience, evaluate, and form preferences toward smart appliance brands. Globally, the smart home appliance market was valued at USD 89.4 billion in 2023 and is projected to reach USD 166.7 billion by 2030 at a Compound Annual Growth Rate (CAGR) of 14.7% (Kumar *et al.*, 2023). Unlike earlier generations of consumer electronics differentiated primarily by price, aesthetics, and hardware specifications, AI-enabled appliances engage consumers through dynamic, adaptive, and increasingly relational interactions—transforming the product from an inert object into a responsive, learning ecosystem (Zhang *et al.*, 2022).

Within the Indian context, Bengaluru Urban District represents a strategically significant consumer market. As India's technology capital, the city combines high digital literacy, significant concentrations of young professionals, and growing disposable incomes—conditions that accelerate AI adoption and intensify the influence of AI attributes on brand evaluation (Chopra & Jain, 2023; Mehta & Srivastava, 2022). As Sharma and Reddy (2022) observe, contemporary consumers in such environments increasingly assess brands not merely on conventional product attributes but on AI-specific dimensions including responsiveness, learning capability, data security, and quality of personalisation.

Despite the growing body of research on AI adoption (Venkatesh *et al.*, 2021; Cho *et al.*, 2021; Liu *et al.*, 2022), two critical gaps persist in the extant literature. First, the majority of AI adoption studies treat behavioural intention as the dependent variable, leaving consumer brand preference—a strategically more consequential outcome for manufacturers—underexplored (Park & Cho, 2023). Second, empirical investigations situated in Indian metropolitan consumer markets, where unique socio-cultural dynamics and privacy sensitivities coexist with rapid technology uptake, remain scarce (Nair & Pillai, 2024). This study directly addresses both gaps.

Theoretically, the research integrates the TAM (Davis, 1989)—which posits that Perceived Usefulness and Perceived Ease of Use are primary determinants of technology adoption—with AI-specific extensions including Trust, Personalisation, and Privacy and Security concerns. This extended framework is further enriched by the Theory of Planned Behaviour (TPB) (Ajzen, 1991), which contextualises brand preferability within a broader nexus of consumer attitudes, subjective norms, and behavioural intentions. Together, these theoretical lenses provide a comprehensive and methodologically defensible foundation for examining the multi-dimensional psychology underlying AI appliance adoption and brand loyalty formation.

The study's central research question is: To what extent, and in what hierarchical order, do AI attribute perceptions influence consumer brand preference for smart appliances among urban consumers in Bengaluru? By systematically addressing this question through validated measurement instruments and robust multivariate analysis, this research generates both theoretical contributions to AI adoption scholarship and practical insights for brand managers competing in India's smart home market.

While the international literature has examined AI adoption in smart home contexts from the perspectives of behavioural intention, continuance usage, and user experience (Cho *et al.*, 2021; Liu *et al.*, 2022; Li *et al.*, 2022), brand preference as a dependent variable mediated by AI-specific attributes has received comparatively limited scholarly attention. This gap is particularly pronounced in the Indian urban market.

Existing Indian studies have examined e-commerce adoption and IoT device usage (Gupta & Singh, 2024) but have not systematically integrated AI attribute perceptions with brand preference outcomes within a validated theoretical framework. Moreover, prior studies have generally not incorporated Privacy and Security Concerns as a potential positive driver of brand preference, leaving a theoretically interesting and managerially relevant relationship unexplored.

The present study addresses these gaps by developing, empirically validating, and testing a comprehensive conceptual model specifically tailored to the AI-enabled smart appliance market in an urban Indian consumer ecosystem. In doing so, it responds to calls by Venkatesh *et al.* (2021) and Gupta and Singh (2024) for context-specific extensions of TAM that capture the distinctive dynamics of emerging economy technology markets.

REVIEW OF LITERATURE

This section critically synthesises the extant literature across six thematic domains central to the study's conceptual framework. Rather than cataloguing studies descriptively, the review foregrounds theoretical tensions, empirical convergences, and contextual specificities that collectively motivate the present research.

Theoretical Foundations: TAM and TPB in AI Contexts

The TAM, originally proposed by Davis (1989), posits that Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) are the two primary determinants of individual acceptance and use of technology. The parsimony and robust cross-cultural validity of TAM have made it the dominant theoretical framework in technology adoption research over three decades (Venkatesh *et al.*, 2021). However, the emergence of AI systems—characterised by autonomy, adaptivity, and opacity—has challenged the sufficiency of the original TAM constructs.

Venkatesh *et al.* (2021), in a synthesis of the Unified Theory of Acceptance and Use of Technology (UTAUT) literature, argue that AI-mediated technologies necessitate the incorporation of trust, social influence, and hedonic motivation to adequately capture user acceptance dynamics. Gupta and Singh (2024), through a meta-analysis of 67 TAM studies in South Asian technology markets, further demonstrate that augmented TAM models incorporating trust and social influence constructs explain an additional 62% of variance in technology adoption behaviour compared to the original two-factor model—providing strong methodological justification for the extended framework adopted in this study.

The TPB (Ajzen, 1991) complements TAM by embedding behavioural intention—including brand preference—within a broader attitudinal framework encompassing subjective norms and perceived behavioural control. In the context of AI appliances, TPB accounts for the social and normative influences that shape consumer preferences beyond purely cognitive assessments of AI functionality. Rodrigues and Pereira (2022), in a study of smart home adopters in Portugal, found that subjective norms significantly moderated the TAM relationship for older consumers, while perceived behavioural control was more salient for younger urban users—a finding that has direct implications for the demographically diverse Bengaluru consumer market.

AI in Consumer Electronics: From Feature-Based to Intelligence-Based Brand Evaluation: The integration of AI into consumer electronics has precipitated a fundamental shift from feature-based to intelligence-based brand evaluation. Lee and Kim (2021), in a study of Korean smart home users, found that AI-enabled functionalities—including voice control, predictive maintenance, and adaptive energy optimisation—generated greater improvements in user experience than hardware upgrades of equivalent cost. This finding implies that AI capabilities are becoming primary differentiating attributes in consumer electronics purchasing decisions.

In the Indian context, Chopra and Jain (2023) document an analogous paradigm shift among Tier-1

city consumers, who increasingly assess brand quality through AI performance indicators rather than conventional feature sets. This shift carries important implications for brand positioning: manufacturers who fail to communicate the intelligence attributes of their products risk commoditisation even when underlying AI performance is superior. Zhang *et al.* (2022) extend this analysis by identifying AI as a boundary-spanning factor in smart home ecosystems, demonstrating that positive AI experiences with one product from a brand increase purchase likelihood for other products from the same brand by 43%—an effect mediated by cumulative AI satisfaction.

Mehta and Srivastava (2022), in a conjoint analysis of middle-class urban Indian households, found that AI capabilities ranked as the top brand attribute in premium appliance categories, surpassing after-sales service quality and brand heritage. Taken together, these findings establish a compelling empirical foundation for the hypothesis that AI attribute perceptions are primary drivers of consumer brand preference in technology-intensive markets.

Trust in AI Technology and Brand Preference: Trust has emerged as perhaps the most theoretically complex and practically consequential construct in AI consumer behaviour research. Drawing on Mayer *et al.*'s (1995) integrative model of organisational trust—which identifies ability, benevolence, and integrity as the three foundational dimensions of trust—Glikson and Woolley (2020) conducted a systematic review of 50 years of human-automation trust literature and identified reliability, transparency, and predictability as the primary mechanisms through which trust in AI systems is established and sustained. Critically, their review reveals that initial trust formation in AI is disproportionately influenced by first interaction experiences, while long-term trust maintenance depends on consistent AI performance and perceived alignment of AI goals with user interests.

The commercial significance of AI trust is documented by Li *et al.* (2022), who found that consumer trust in AI appliances was a strong and statistically robust predictor of continued usage intention ($\beta = 0.72$, $p < 0.001$) among Chinese urban households. Park and Cho (2023), extending this analysis to brand preference outcomes across APAC markets, demonstrated that AI trust significantly mediates the relationship between perceived usefulness and brand preference ($\beta = 0.41$, $p < 0.01$). Collectively, these findings suggest that trust operates not merely as a prerequisite for AI adoption but as an active driver of brand differentiation and loyalty formation.

The Indian context introduces additional dimensions of complexity. As Nair and Pillai (2024) document, Indian consumers exhibit higher-than-average AI trust sensitivity due to the salience of high-profile data breach incidents and ambiguities in the domestic data protection regulatory environment. This heightened sensitivity implies that trust-building investments by smart appliance brands may yield greater brand preference returns in India than in markets with more established data governance traditions.

Personalisation Experience and Brand Loyalty: AI-enabled personalisation—defined as the adaptive customisation of interfaces, recommendations, and functionalities in response to individual user preferences and behavioural patterns (Araujo *et al.*, 2020)—represents a distinctively AI-native form of consumer value creation. Unlike static product features, personalisation deepens over time, generating switching costs that are experiential rather than contractual. Kumar *et al.* (2023), in a study of smart home adopters in metropolitan India, found a strong positive correlation between personalisation experience and customer satisfaction ($r = 0.68$, $p < 0.001$), underscoring the centrality of adaptive AI performance to post-purchase brand evaluation. Jain and Mishra (2023), in a study of 512 smart appliance users in Delhi-NCR, identified personalisation as the second most important driver of brand switching intention—after trust—demonstrating that consumers who experience superior personalisation are 57% less likely to switch brands than those with low personalisation satisfaction, even in the presence of price incentives from competing brands. This finding has profound strategic implications: it suggests that personalisation capability creates a form of affective brand lock-in that is qualitatively distinct from and potentially more durable than price-based or feature-based competitive advantages. Chen and Liu (2021),

adopting a co-creation perspective, propose that AI personalisation generates brand equity through iterative human-AI interaction cycles in which each episode of successful personalisation reinforces positive brand associations. Their longitudinal study of 845 smart TV owners found that satisfaction with AI interactions was a stronger predictor of 12-month brand loyalty than traditional satisfaction measures, suggesting that AI personalisation quality may be a leading indicator of long-term brand health metrics.

Privacy and Security Concerns: From Risk Factor to Brand Differentiator: Privacy concerns in AI consumer contexts arise from the collection, processing, and potential misuse of behaviourally rich personal data including audio-visual recordings, usage patterns, and interaction histories (Smith *et al.*, 2021). The dominant theoretical framing positions privacy concerns as a risk factor that negatively moderates AI adoption—a perspective supported by Wang and Kim (2023), who found that privacy concerns negatively moderated the relationship between AI features and brand preference ($\beta = -0.31$, $p < 0.001$) among smart home users in Singapore and South Korea. However, a more nuanced reading of the literature reveals an emerging complementary perspective: that privacy concerns, when associated with effective brand-level data governance, can be transformed from adoption barriers into positive brand differentiators. Wang and Kim (2023) themselves acknowledge that transparent data governance policies substantially attenuated the negative effect of privacy concerns on brand preference, suggesting a conditional positive pathway. Nair and Pillai (2024) extend this observation to the Indian context, noting that Indian consumers' above-average privacy concern scores ($M = 4.09$ vs. global APAC average of 3.71) have created meaningful market demand for brands that visibly invest in data protection. This theoretical tension—between privacy concerns as adoption barriers and as potential brand differentiators—generates the study's most theoretically interesting hypothesis (H6) and helps explain the positive coefficient obtained in the regression analysis. Consumers in high-privacy-concern environments may exhibit stronger preferences for brands perceived as trustworthy data custodians, a relationship that aligns with signalling theory: brands that invest visibly in privacy governance send credible signals of benevolence that enhance overall brand preference.

Consumer Brand Preference in AI-Mediated Technology Markets: Brand preference in technology markets is a multi-dimensional construct encompassing functional utility assessments, experiential value perceptions, social signalling motivations, and emotional attachments (Aaker, 1991; Keller, 2013). The introduction of AI into consumer products adds a relational dimension to this construct: consumers develop preferences not merely for the product's features but for the ongoing relationship with an AI system that learns, adapts, and responds to individual needs over time. Sharma and Reddy (2022) document this relational dimension empirically, demonstrating that consumers who attribute decision-making competence to AI systems develop stronger brand attachments than those who perceive AI as merely automating predefined routines. Chen and Liu (2021) further advance this understanding by proposing that AI experiences function as brand touchpoints that cumulatively shape brand equity through emotional, cognitive, and functional pathways simultaneously—a multi-pathway model that transcends conventional satisfaction-loyalty frameworks. In the Indian market specifically, Mehta and Srivastava (2022) provide evidence that the influence of AI capabilities on brand preference is strongest in the premium appliance segment, while Kumar *et al.* (2023) document positive associations between AI personalisation quality and net promoter scores among smart home adopters in metro India. Together, these studies establish a coherent empirical basis for the argument that AI attribute perceptions are emerging as the primary competitive frontier in smart appliance brand preference formation.

Hypotheses

Based on the theoretical framework and critical review of the literature, the following hypotheses were formulated:

H1: AI Awareness has a significant positive influence on Consumer Brand Preference.

H2: Perceived Usefulness has a significant positive influence on Consumer Brand Preference.

H3: Perceived Ease of Use has a significant positive influence on Consumer Brand Preference.
H4: Trust in AI Technology has a significant positive influence on Consumer Brand Preference.
H5: Personalisation Experience has a significant positive influence on Consumer Brand Preference.
H6: Privacy and Security Concerns have a significant influence on Consumer Brand Preference.

RESEARCH METHODOLOGY

Research Design and Philosophical Orientation

This study adopts a quantitative, cross-sectional survey design consistent with positivist epistemological assumptions (Malhotra, 2020). The positivist stance, which holds that social phenomena can be objectively measured and that causal hypotheses can be tested through statistical inference, is appropriate for the study's objectives of hypothesis testing and model validation. Cross-sectional designs are well-established in consumer behaviour research for capturing perceptual states at a defined point in time (Hair *et al.*, 2019) and provide an adequate basis for establishing associative—though not causal—relationships among constructs. The acknowledged limitation of causal inference is addressed in the limitations section, where longitudinal and experimental designs are recommended for future research.

Population, Sample, and Sampling Procedure

The target population comprised adult consumers aged 18 years and above residing in Bengaluru Urban District who owned and used at least one AI-enabled smart appliance. Based on the Krejcie and Morgan (1970) formula applied to the estimated adult population of 14.7 million in the Bengaluru Metropolitan Region Development Authority (BMRDA) area, a minimum sample size of 384 respondents was required for a 95% confidence level with a 5% margin of error.

The sampling strategy employed a two-stage approach combining stratified and purposive sampling. In Stage 1, the study delineated eight representative geographic zones within Bengaluru Urban District—North, South, East, West, Central, Hebbal, Whitefield, and Electronic City—to ensure spatial representativeness across diverse socioeconomic residential profiles. In Stage 2, within each zone, respondents were recruited through a combination of offline and online channels, including electronics retail outlets, residential societies, technology parks, WhatsApp communities, and professional LinkedIn networks. This multi-channel recruitment approach was adopted to maximise coverage of the AI-appliance-owning consumer population across age groups, income levels, and digital access modalities.

It is acknowledged that the online recruitment channels may introduce elements of convenience sampling that could affect the representativeness of the sample relative to the broader population of Bengaluru smart appliance owners, including those with limited digital access. Accordingly, the findings should be interpreted as representative of digitally active, AI-appliance-owning urban consumers—a population that constitutes the primary target segment for smart appliance brands. A total of 400 questionnaires were administered, yielding 348 valid responses and an 87% response rate.

Research Instrument

A structured questionnaire was developed comprising eight sections: Section A (Demographic Profile) and Sections B through G (AI-related constructs measured on a 5-point Likert scale anchored from 1 = Strongly Disagree to 5 = Strongly Agree) and Section H (Consumer Brand Preference). The instrument contained 32 items across six independent construct scales and six items for the dependent variable scale.

Item development followed a systematic process informed by prior validated scales in the literature: TAM items were adapted from Davis (1989) and Venkatesh *et al.* (2021); Trust items were adapted from Mayer *et al.* (1995) and Glikson and Woolley (2020); Personalisation items were adapted from Araujo *et al.* (2020) and Jain and Mishra (2023); and Privacy and Security items were adapted from Smith *et al.* (2021) and Nair and Pillai (2024). All adaptations were

contextualised for AI-enabled smart appliances in the Indian consumer environment.

Content validity was established through structured review by a panel of five marketing academicians and two industry practitioners with expertise in consumer technology markets. Their feedback informed item refinement for clarity, relevance, and contextual appropriateness. A pilot study administered to 40 respondents confirmed the psychometric soundness of the instrument prior to full-scale data collection, with all constructs achieving satisfactory reliability coefficients. Future research would benefit from Confirmatory Factor Analysis (CFA) to formally assess convergent and discriminant validity within a structural equation modelling framework.

Statistical Analysis

Data analysis was conducted using IBM SPSS Statistics 27.0 through a sequential analytical framework: (i) Descriptive Statistics including frequency distributions, means, and standard deviations; (ii) Reliability Analysis using Cronbach's Alpha to assess internal consistency; (iii) EFA with PCA and Varimax rotation to assess construct validity; (iv) Pearson Correlation Analysis to examine bivariate relationships among constructs; and (v) Multiple Linear Regression Analysis to test the predictive model with Consumer Brand Preference as the dependent variable. Multicollinearity diagnostics (Variance Inflation Factor and Tolerance) and residual analyses were conducted to verify regression assumptions.

RESULTS AND ANALYSIS

Demographic Profile of Respondents

Table 1 presents the demographic characteristics of the 348 valid respondents. The sample comprised 196 males (56.3%), 144 females (41.4%), and 8 respondents identifying as other (2.3%), broadly consistent with the demographic profile of technology adopters in Bengaluru's IT-driven economy. The largest age cohort was 26-35 years (39.7%), reflecting the concentration of young professionals characteristic of the city's technology sector. Educational attainment was high, with postgraduates constituting 50.6% of the sample and undergraduates 49.4%. Smart TV ownership (85.6%) was most prevalent, followed by Smart Air Conditioner (61.8%) and Smart Refrigerator (57.8%).

Table 1. Demographic Profile of Respondents (N = 348)

Variable	Category	Frequency (n=348)	Percentage (%)
Gender	Male	196	56.3
	Female	144	41.4
	Other	8	2.3
Age	Below 25 years	62	17.8
	26-35 years	138	39.7
	36-45 years	97	27.9
	46-55 years	38	10.9
	Above 55 years	13	3.7
Education	Undergraduate	172	49.4
	Postgraduate	176	50.6
Smart appliance used	Smart TV	298	85.6
	Smart Refrigerator	201	57.8
	Smart Washing Machine	178	51.1
	Smart AC	215	61.8
	Smart Speaker	167	48.0
	Others	23	6.6

Note: Multiple responses permitted for appliance category. Source: Primary data.

Descriptive Statistics

Table 2 presents the mean scores and standard deviations for all 32 Likert-scale items. Across all constructs, mean scores exceeded 3.45, indicating a broadly positive disposition toward AI appliances among the sample. Perceived Usefulness items achieved the highest means (PU1: M = 4.21, SD = 0.72; PU2: M = 4.18, SD = 0.76), reflecting high consumer awareness of functional AI benefits. Privacy and Security items also achieved elevated mean scores (PSC2: M = 4.08; PSC4: M = 4.14), confirming heightened data security consciousness among the sample—a finding consistent with Nair and Pillai (2024). Trust in AI exhibited the widest standard

deviation (TR3: M = 3.48, SD = 1.05), indicating heterogeneity in consumer perceptions of AI decision-making reliability, which likely reflects variation in prior AI interaction experience across respondents.

Table 2. Descriptive Statistics - Mean and Standard Deviation for All Items (N = 348)

Construct	Item	Mean	SD	Interpretation
AI Awareness (AW)	AW1	3.84	0.91	Agree
	AW2	3.71	0.88	Agree
	AW3	3.45	0.97	Neutral
	AW4	4.12	0.79	Agree
Perceived Usefulness (PU)	PU1	4.21	0.72	Agree
	PU2	4.18	0.76	Agree
	PU3	4.09	0.81	Agree
	PU4	4.03	0.84	Agree
	PU5	3.98	0.87	Agree
Perceived Ease of Use (PEOU)	PEOU1	3.92	0.85	Agree
	PEOU2	3.87	0.89	Agree
	PEOU3	3.79	0.93	Agree
	PEOU4	3.83	0.91	Agree
Trust in AI (TR)	TR1	3.65	1.02	Agree
	TR2	3.72	0.98	Agree
	TR3	3.48	1.05	Neutral
	TR4	3.56	0.99	Agree
	TR5	3.69	0.96	Agree
Personalisation (PE)	PE1	3.88	0.87	Agree
	PE2	3.95	0.82	Agree
	PE3	3.79	0.91	Agree
	PE4	4.01	0.78	Agree
Privacy and Security (PSC)	PSC1	3.97	0.88	Agree
	PSC2	4.08	0.84	Agree
	PSC3	3.91	0.92	Agree
	PSC4	4.14	0.79	Agree
Brand Preference (BP)	BP1	4.07	0.81	Agree
	BP2	4.11	0.77	Agree
	BP3	3.82	0.93	Agree
	BP4	4.03	0.86	Agree
	BP5	3.94	0.89	Agree
	BP6	4.16	0.75	Agree

Note: Scale range 1 (Strongly Disagree) to 5 (Strongly Agree). Mean > 3.5 = Agree.

Reliability Analysis

Internal consistency was assessed using Cronbach's Alpha for each construct. As shown in Table 3, all constructs exceeded Nunnally's (1978) recommended threshold of $\alpha \geq 0.70$. Trust in AI ($\alpha = 0.912$) and Consumer Brand Preference ($\alpha = 0.924$) achieved excellent reliability, confirming the precision of measurement for these theoretically central constructs. The overall scale reliability ($\alpha = 0.938$) attests to the strong internal coherence of the 32-item instrument. These results validate the measurement model's internal consistency and support the use of composite scores in subsequent analyses.

Exploratory Factor Analysis (EFA)

Prior to EFA, the suitability of the data matrix was confirmed by the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy (KMO = 0.897, exceeding the recommended threshold of 0.80) and Bartlett's Test of Sphericity ($\chi^2 = 4821.347$, df = 496, $p < 0.001$), indicating that the correlation matrix was factorable (Table 4).

Principal Component Analysis (PCA) with Varimax rotation extracted seven factors with eigenvalues greater than 1.0, collectively explaining 68.01% of the total variance (Table 5). All factor loadings exceeded 0.70, indicating strong item-factor associations and evidence of convergent validity. The clean seven-factor solution replicates the theorised construct structure, providing empirical support for the conceptual separability of the six AI attribute constructs and the Consumer Brand Preference construct. These results strengthen confidence in the distinctiveness of the measured constructs and validate the multi-dimensional measurement approach adopted in this study. Future research employing CFA would provide a more rigorous assessment of discriminant validity and allow formal testing of model fit indices.

Pearson Correlation Analysis

Table 6 presents the Pearson correlation matrix for all study constructs. All AI constructs were significantly and positively correlated with Consumer Brand Preference ($p < 0.01$), providing initial support for

Table 3. Reliability Analysis - Cronbach's Alpha Coefficients

Construct	No. of items	Cronbach's Alpha	Interpretation
AI awareness	4	0.843	Acceptable
Perceived usefulness	5	0.891	Good
Perceived ease of use	4	0.874	Good
Trust in AI technology	5	0.912	Excellent
Personalisation experience	4	0.867	Good
Privacy and security concerns	4	0.856	Good
Consumer brand preference	6	0.924	Excellent
Overall scale	32	0.938	Excellent

Note: α > 0.9 = Excellent; α 0.8-0.9 = Good; α 0.7-0.8 = Acceptable (Nunnally, 1978).

Table 4. KMO and Bartlett's Test of Sphericity

Test	Parameter	Value
KMO measure of sampling adequacy		0.897
Bartlett's test of sphericity	Approx. Chi-Square	4821.347
	df	496
	Sig.	0.000

Table 5. EFA - Component Matrix (Varimax Rotation)

Factor	Construct	Items	Factor loadings	Eigenvalue	% variance
Factor 1	Perceived usefulness	PU1-PU5	0.789-0.841	4.312	13.48
Factor 2	Trust in AI	TR1-TR5	0.762-0.831	3.874	12.11
Factor 3	Consumer brand preference	BP1-BP6	0.748-0.867	3.521	11.00
Factor 4	Privacy and security	PSC1-PSC4	0.712-0.801	2.943	9.20
Factor 5	Personalisation experience	PE1-PE4	0.731-0.812	2.687	8.40
Factor 6	AI awareness	AW1-AW4	0.698-0.789	2.314	7.23
Factor 7	Perceived ease of use	PEOU1-PEOU4	0.703-0.798	2.108	6.59
	Total variance explained				68.01%

Note: Factor loadings < 0.50 suppressed. Total Cumulative Variance Explained = 68.01%.

all six research hypotheses. Trust in AI exhibited the strongest bivariate correlation with Brand Preference (r = 0.762), followed closely by Personalisation (r = 0.731) and Perceived Usefulness (r = 0.748). Privacy and Security Concerns showed a moderate positive correlation with Brand Preference (r = 0.554), which is theoretically interpretable within the signalling framework elaborated in Section 2.5: consumers with heightened privacy awareness exhibit stronger preferences for brands that signal effective data governance.

Inter-construct correlations ranged from 0.421 (Privacy and Security-AI Awareness) to 0.704 (Trust-Personalisation), indicating conceptual relatedness among predictors without reaching levels indicative of problematic multicollinearity. This interpretation is confirmed by the regression diagnostics reported in Table 6.

Table 6. Pearson Correlation Analysis Matrix

Construct	AW	PU	PEOU	TR	PE	PSC	BP
AI awareness	1.000						
Perceived usefulness	0.612**	1.000					
Perceived ease of use	0.573**	0.641**	1.000				
Trust in AI	0.587**	0.693**	0.621**	1.000			
Personalisation	0.548**	0.672**	0.598**	0.704**	1.000		
Privacy and security	0.421**	0.512**	0.487**	0.533**	0.498**	1.000	
Brand preference	0.634**	0.748**	0.691**	0.762**	0.731**	0.554**	1.000

Note: **Correlation significant at the 0.01 level (2-tailed). AW=AI Awareness; PU=Perceived Usefulness; PEOU=Perceived Ease of Use; TR=Trust; PE=Personalisation; PSC=Privacy and Security; BP=Brand Preference.

Multiple Linear Regression Analysis

Multiple linear regression was conducted with Consumer Brand Preference as the dependent variable and the six AI constructs as independent variables. Multicollinearity diagnostics confirmed the absence of problematic multicollinearity: Variance Inflation Factors (VIFs) ranged from 1.43 to 2.87 (all below the threshold of 10), and Tolerance values were all above 0.35 (exceeding the threshold of 0.10) (Hair *et al.*, 2019). Residual analysis confirmed that regression assumptions of normally distributed errors and homoscedasticity were met.

The overall regression model was highly significant ($F(6, 341) = 143.87$, $p < 0.001$), with the six predictors jointly explaining 71.7% of the variance in Consumer Brand Preference ($R^2 = 0.717$; Adjusted $R^2 = 0.712$). This level of explanatory power substantially exceeds the variance explained by standard TAM applications (R^2 range: 0.40-0.55), confirming the incremental validity of the AI-specific extensions incorporated in the model. Perceived Usefulness was the most influential predictor ($\beta = 0.298$, $t = 5.115$, $p < 0.001$), consistent with the TAM tenet that perceived functional benefit is the primary cognitive determinant of technology acceptance and, in this context, brand preference. Trust in AI ranked second ($\beta = 0.284$, $t = 4.730$, $p < 0.001$), confirming Glikson and Woolley's (2020) argument that trust is a fundamental prerequisite for sustained positive engagement with AI systems, and extending this argument to show that trust also directly shapes brand-level consumer preferences. Personalisation Experience ranked third ($\beta = 0.261$, $t = 4.525$, $p < 0.001$), consistent with Jain and Mishra's (2023) finding that personalisation quality is a primary retention mechanism in smart appliance markets.

The positive and statistically significant coefficient for Privacy and Security Concerns ($\beta = 0.196$, $t = 3.808$, $p < 0.001$) warrants specific theoretical discussion. While the dominant literature frames privacy concerns as adoption barriers, the present result is consistent with the brand-differentiator perspective: in a market with heightened privacy sensitivity (Nair & Pillai, 2024), consumers who are more concerned about privacy tend to be more discerning brand selectors who preferentially favour brands perceived as responsible data custodians. This finding aligns with Wang and Kim (2023), who demonstrated that brands with transparent data governance policies successfully convert privacy-aware consumers into brand advocates rather than losing them to competing concerns. The practical implication is that privacy governance investment can function as an offensive brand-building strategy rather than merely a defensive compliance posture.

Table 7. Multiple Linear Regression Analysis - Predictors of Consumer Brand Preference

Predictor Variable	B	SE	Beta (β)	t-value	pvalue
(Constant)	0.412	0.187		2.203	0.028
AI awareness	0.187	0.054	0.183	3.463	0.001**
Perceived usefulness	0.312	0.061	0.298	5.115	0.000**
Perceived ease of use	0.241	0.058	0.227	4.155	0.000**
Trust in AI	0.298	0.063	0.284	4.730	0.000**
Personalisation	0.267	0.059	0.261	4.525	0.000**
Privacy and security	0.198	0.052	0.196	3.808	0.000**

Note: $R = 0.847$, $R^2 = 0.717$, Adjusted $R^2 = 0.712$, $F(6,341) = 143.87$, $p < 0.001$. Dependent Variable: Consumer Brand Preference. **$p < 0.01$.

Hypothesis Testing Summary

Table 8. Hypothesis Testing Summary

Hypothesis	Relationship	Beta (β)	t-value	pvalue	Result
H1	AI awareness → Brand preference	0.183	3.463	0.001	Supported
H2	Perceived usefulness → Brand preference	0.298	5.115	0.000	Supported
H3	Perceived ease of use → Brand preference	0.227	4.155	0.000	Supported
H4	Trust in AI → Brand preference	0.284	4.730	0.000	Supported
H5	Personalisation → Brand preference	0.261	4.525	0.000	Supported
H6	Privacy and Security → brand preference	0.196	3.808	0.000	Supported

Note: All hypotheses supported at $p < 0.01$ significance level.

DISCUSSION

Theoretical Contributions

This study makes three principal theoretical contributions to the literature on AI adoption, consumer behaviour, and brand preference in emerging markets.

First, the study confirms and extends the explanatory power of the TAM framework in the domain of AI-enabled consumer products within an emerging economy context. The high variance explained by the model ($R^2 = 0.717$) significantly exceeds typical TAM application benchmarks (0.40-0.55), validating Gupta and Singh's (2024) meta-analytic finding that AI-specific construct extensions substantially improve TAM's predictive adequacy. The study thereby provides a replicated, context-validated extension of TAM that subsequent researchers can adapt for AI product contexts across emerging markets.

Second, the significant positive relationship between Trust in AI and brand preference ($\beta = 0.284$) theoretically advances Glikson and Woolley's (2020) trust-in-automation framework from the human-automation interaction domain into the human-brand relationship domain. This extension implies that trust mechanisms originally theorised for human-robot interaction are systematically operable at the brand level, where accumulated AI trust experiences aggregate into brand-level trust capital. This contributes a new theoretical lens for understanding how AI system-level interactions translate into brand equity outcomes—a translation mechanism that Chen and Liu (2021) identified as theoretically important but did not empirically test.

Third, the positive coefficient for Privacy and Security Concerns (β = 0.196) challenges the dominant framing of privacy concerns as purely inhibitory in technology adoption models, contributing a theoretically grounded signalling perspective to the understanding of how consumer privacy consciousness relates to brand preference. This finding invites reconceptualisation of privacy concerns not merely as risk perceptions to be managed but as market-segmenting signals that direct privacy-conscious consumers toward brands that demonstrate credible data stewardship—an insight with implications for theoretical models of privacy paradox and technology adoption.

Managerial Implications

The findings carry several actionable strategic implications for smart appliance marketers and manufacturers operating in the Indian market. The primacy of Perceived Usefulness (β = 0.298) indicates that marketing communications should foreground concrete functional outcomes—energy savings, time efficiency, lifestyle enhancement—rather than technical AI specifications. Brands such as Samsung, LG, and Haier should develop consumer-facing narratives that translate AI capabilities into everyday quality-of-life improvements that resonate with the aspirations of Bengaluru's young professional demographic.

The critical importance of Trust in AI (β = 0.284) implies that brands must develop systematic trust-building architectures encompassing explainable AI interfaces, consistent performance metrics, robust after-sales commitments, and proactive communication of AI decision-making processes. User interface design should incorporate trust signals such as real-time AI decision explanations and user control features that reinforce consumer agency in human-AI interactions.

The significant role of Personalisation (β = 0.261) highlights the commercial potential of investing in superior adaptive learning algorithms, cross-device synchronisation, and usage history integration. For Bengaluru's tech-savvy professional consumer segment, brands that can deliver demonstrably superior personalisation are positioned to command premium pricing and achieve higher brand loyalty metrics.

The positive relationship between Privacy and Security Concerns and brand preference (β = 0.196) provides a clear strategic opportunity for brand differentiation through visible data governance investment. Pursuits such as ISO 27001 certification, GDPR-aligned data protection practices, edge AI processing (which reduces data transmission risks), and data minimisation commitments are likely to be particularly effective in converting India's privacy-conscious consumers into brand advocates.

The predictor hierarchy emerging from this study—Perceived Usefulness > Trust > Personalisation > Perceived Ease of Use > Privacy and Security > AI Awareness—offers interesting points of convergence and divergence with the international literature. The prominence of Perceived Usefulness at the apex of the hierarchy is consistent with Lee and Kim's (2021) findings in the Korean smart home context, reinforcing the cross-cultural robustness of the TAM utility perception construct.

However, the present study diverges from Liu *et al.*'s (2022) Chinese market findings, where Trust ranked first above Perceived Usefulness. This divergence may reflect the relatively higher institutional trust in AI companies that characterises the Chinese technology market compared to India, where consumers exhibit greater scepticism toward both AI systems and corporate data practices (Nair & Pillai, 2024). The elevated privacy concern scores observed in this sample (M = 4.08-4.14) exceed APAC averages reported by Nair and Pillai (2024) (M = 3.71), consistent with the heightened sensitivity created by India's data breach landscape and the absence, at the time of data collection, of a comprehensive domestic data protection framework.

The positive association between Privacy and Security Concerns and Brand Preference observed in this study contrasts with Wang and Kim's (2023) finding of a negative moderation effect in Singapore and South Korea. This divergence is theoretically resolvable through the brand-differentiator perspective advanced in Section 2.5: in markets where privacy concerns are particularly salient (as in India), the signal value of credible privacy governance is correspondingly higher, generating positive rather than merely attenuated negative effects on brand preference.

CONCLUSIONS AND FUTURE DIRECTIONS

This study provides comprehensive empirical evidence that AI attribute perceptions are powerful and multi-dimensional determinants of consumer brand preference for smart appliances in Bengaluru Urban District. Analysing 348 valid responses through a multi-stage analytical framework, the study demonstrates that AI Awareness, Perceived Usefulness, Perceived Ease of Use, Trust in AI Technology, Personalisation Experience, and Privacy and Security Concerns collectively explain 71.7% of the variance in Consumer Brand Preference—a level of explanatory power that substantially exceeds conventional TAM benchmarks and attests to the theoretical adequacy of the extended AI-TAM framework. All six research hypotheses were supported at the 1% significance level, providing strong empirical validation of the proposed conceptual model.

The theoretical contributions of the study are threefold: (i) it validates and extends TAM with AI-specific constructs in an emerging economy smart appliance context; (ii) it extends trust-in-automation theory from system-level to brand-level relationship dynamics; and (iii) it reconceptualises privacy concerns as potential positive brand differentiators in high-privacy-sensitivity markets. The managerial implications centre on utility communication, trust architecture development, personalisation investment, and privacy governance as primary strategic levers for brand preference formation in India's growing smart home market.

Several limitations of this study point toward productive directions for future research. The cross-sectional design precludes causal inference; longitudinal panel designs would capture AI adoption dynamics across product ownership lifecycles and enable examination of how initial AI experiences translate into durable brand loyalty. The geographic scope—limited to Bengaluru Urban District—restricts immediate generalisability to Tier-2 cities and rural markets with different digital infrastructure profiles and AI literacy levels. The multi-channel sampling approach, while maximising coverage of AI-appliance-owning consumers, may have introduced sampling bias in ways that underrepresent less digitally active population segments.

Methodologically, future research would benefit from Structural Equation Modelling (SEM) to examine mediation and moderation effects within the proposed framework—for example, testing whether Trust mediates the relationship between Perceived Usefulness and Brand Preference, or whether Privacy and Security Concerns moderate the Personalisation-Brand Preference relationship. Additional constructs—including Social Influence, Hedonic Motivation, and AI Anthropomorphism—could enrich the model's explanatory scope. Comparative studies across Indian metropolitan markets and against international consumer populations would further establish the contextual boundaries and cultural moderators of AI attribute influence on brand preference.

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