



The Impact of AI-Enabled Customer Interaction on Consumer Buying Intention towards Housing Properties in Bangalore: Evidence from Adoption, Regression and Correlation Analysis

Ajay Kumar Naik .M

Faculty of Management and Commerce Ramaiah University of Applied Sciences,
Gnanagangothri Campus, MSR Nagar, Bengaluru-560054, India Email- ajaykumarnaik1472@gmail.com

Dr.Vaishaly Bopaiah G

Faculty of Management and Commerce Ramaiah University of Applied Sciences, Gnanagangothri Campus,
MSR Nagar, Bengaluru-560054, India
Email- Vaishalybopaiahg.ms.mc@msruas.ac.in.

How to Cite this Article:

.M, A. K. N. (2026). The Impact of AI-Enabled Customer Interaction on Consumer Buying Intention towards Housing Properties in Bangalore: Evidence from Adoption, Regression and Correlation Analysis. International Journal of Creative and Open Research in Engineering and Management, 2(10), 1-9.
<https://doi.org/10.55041/ijcope.v2i10.071>

License:

This article is published under the terms of the Creative Commons Attribution 4.0 International License (CC BY 4.0), which permits unrestricted use, distribution, and reproduction in any medium, provided the original author(s) and the source are credited.

© The Author(s). Published by International Journal of Creative and Open Research in Engineering and Management.



<https://doi.org/10.55041/ijcope.v2i10.071>

ABSTRACT:

AI-enabled customer interaction, delivered through recommendation systems, chatbots and virtual assistants, is increasingly used by housing and real-estate platforms to engage prospective buyers. Housing is a high-value, high-involvement purchase in which trust and accurate information matter, yet evidence on how AI-enabled interaction relates to buying intention in an Indian metropolitan market such as Bangalore remains limited. This study examines the adoption and usage of AI-enabled customer interaction tools among prospective housing buyers, their impact on and relationship with buying intention, and the challenges buyers report. A quantitative, cross-sectional survey was conducted with a structured five-point Likert questionnaire, and 214 valid responses collected between 19 and 25 August 2026 were analysed with IBM SPSS Statistics and jamovi using descriptive statistics, Cronbach's alpha, one-sample t tests, multiple linear regression, and Pearson and Spearman correlation. Adoption was moderate-to-high (item means 3.26–3.48; composite = 3.373; $\alpha = .849$). AI-enabled interaction was significantly and positively correlated with buying intention (Pearson $r = .337$; Spearman $\rho = .349$; $p < .001$). A regression of the five AI items on the outcome was significant but explained a modest share of variance ($R^2 = .056$; $F(5, 208) = 2.490$; $p = .032$), and no individual item was a significant unique predictor. The most prominent challenges were a preference for human interaction at final negotiation ($M = 3.36$) and technical issues ($M = 3.27$); the challenge scale was reliable ($\alpha = .792$). Three of four hypotheses were supported and one was partly supported. The

study extends AI-marketing research to the housing context and supports a hybrid AI-plus-human approach: AI for search and first enquiries, human contact for negotiation, and reliable technology throughout. Because the design is cross-sectional, the findings describe association rather than causation.

KEYWORDS: AI-enabled customer interaction, Chatbots, Recommendation systems, Buying intention, Housing properties, Real estate, Bangalore.

INTRODUCTION:

Artificial intelligence (AI) has moved from the back end of business systems to the front end of consumer interaction. Recommendation engines suggest what a consumer should view next, chatbots answer questions at any hour, and virtual assistants guide users through search, comparison and enquiry.



In retail, banking, hospitality and travel these tools are now routine touchpoints¹, and real estate is following the same path: housing platforms and developers increasingly use AI to answer buyer queries, shortlist properties and personalise the search experience.

Housing, however, is not an ordinary purchase. It is a high-value, high-involvement and largely irreversible decision in which trust, accurate information and timely responses weigh heavily on the buyer. The market is characterised by information asymmetry, high transaction values and long decision cycles, and regulatory developments such as the Real Estate (Regulation and Development) Act, 2016 have raised the emphasis on transparent project information². Whether an AI-enabled interaction genuinely builds a buyer's intention to purchase, or is offset by concerns such as impersonal responses, technical faults and a preference for dealing with a human negotiator, is therefore an open empirical question. Research on AI touchpoints shows that personalisation aids purchase evaluation while privacy and transparency concerns can undermine trust³, and research on virtual shopping assistants indicates that purchase decisions are strongest at a medium level of algorithmic autonomy⁴. AI interaction is thus neither uniformly beneficial nor uniformly resisted; its effect depends on how it is designed and where in the decision journey it is used.

Three streams of theory frame the question. The Technology Acceptance Model (TAM) explains adoption through perceived usefulness and ease of use⁵; the Theory of Planned Behaviour treats intention as the immediate antecedent of behaviour⁶; and the Unified Theory of Acceptance and Use of Technology (UTAUT) adds performance expectancy, effort expectancy, social influence and facilitating conditions⁷. Together they suggest that a buyer who finds an AI tool useful and easy to use is more likely to keep using it, and that a favourable experience can strengthen the intention to act on what it recommends, while slow, inaccurate or unresponsive tools weaken it.

Despite the growth of AI-marketing research, the existing literature has important shortcomings. First, most studies concentrate on retail, banking, hospitality, fashion and e-commerce rather than housing. Second, empirical evidence from Bangalore, widely regarded as India's technology capital with an active residential property market, or from Indian housing buyers in general is limited. Third, adoption, buying intention and AI-related challenges are rarely examined together in one respondent group. Against this background, the objectives of the present study are: (i) to assess the level of adoption and usage of AI-enabled customer interaction tools among prospective housing buyers in Bangalore; (ii) to examine the impact of AI-enabled customer interaction on consumers' buying intention towards housing properties; (iii) to determine the relationship between AI-enabled customer interaction and buying intention; and (iv) to identify the challenges or limitations consumers face when interacting with AI-enabled tools in the housing purchase process.

LITERATURE REVIEW:

This section reviews fourteen recent studies (2020–2026) on AI in marketing and consumer behaviour, summarised in Table 1, together with the foundational technology-acceptance theories. The studies are grouped by theme rather than by country because their sectors and contexts differ widely. Where the findings of a study were available they are reported; for the remaining studies only the focus and its relevance to the present research are described.

AI Positioning, Trust and Technology Adoption

Zaman and colleagues studied AI-driven brand positioning and smart-product adoption and found that perceived usefulness mediates the path from AI positioning to adoption, while digital trust strengthens the effect⁸. Trust and perceived usefulness are therefore plausible drivers of housing buyers' use of AI tools. Chiu and Chen examined travellers' accommodation intention towards smart hotels using SEM and fsQCA and reported that novelty, efficacy and compatibility lead to perceived value, which in turn leads to accommodation intention⁹. Accommodation is the closest reviewed context to housing, and the study shows how technology attributes translate into intention through perceived value.

Chatbots, Voice Assistants and Virtual Shopping Assistants

Mahajan reported a TAM-based chain from anthropomorphism to perceived usefulness and ease of use, then to acceptance and purchase intention, for voice assistants¹⁰, a chain directly relevant to virtual assistants on housing platforms. Misra and colleagues found that purchase decisions are strongest at a medium level of algorithmic decision



autonomy, introducing a boundary condition: more automation does not automatically produce stronger purchase decisions⁴. Khan and colleagues investigated the effectiveness of AI in building customer loyalty with chatbots as a mediating touchpoint in the tourism sector of Pakistan¹¹.

Personalisation, Purchase Intention and Their Boundaries

Truong found that personalisation and interaction mediate the link between AI perceptions and purchase intention among Generation Z fashion consumers in Vietnam¹². Karim and colleagues reported that personalisation aids purchase evaluation in e-commerce, whereas privacy and transparency concerns undermine trust³. Nahar and colleagues examined the effect of AI features on customer satisfaction and purchase intention in the Bangladeshi food industry¹³, and Ju examined perceptions, experiences and behavioural intention towards generative-AI-supported fashion customisation¹⁴. Both place intention as the outcome of AI-related experiences, supporting the outcome chosen here.

AI in Other Sectors

Malali and Gopalakrishnan provided an overview of AI technologies in the Indian banking and financial industry, one of the few India-anchored sources in the set¹. Further studies address employee satisfaction with AI features in online fashion companies¹⁵, AI-driven sustainable innovation and consumer behaviour¹⁶, AI-powered refrigerators and purchase intention¹⁷, and AI-driven behavioural insights in smart kitchens¹⁸. These studies confirm the breadth of AI research across products and services, but none is set in housing.

Theoretical Foundations

TAM proposes that perceived usefulness and ease of use determine attitudes and intention to use a technology⁵; in this study, ease of use (AI2) and the use of chatbots and recommendation tools (AI1, AI3) map onto this logic. The Theory of Planned Behaviour holds that intention, shaped by attitude, subjective norms and perceived control, is the proximal predictor of behaviour⁶, which justifies buying intention as the outcome. UTAUT allows technical issues (CL2) to be read as a shortfall in facilitating conditions and accuracy problems (CL3) as a shortfall in performance expectancy⁷. Across the reviewed literature the common themes are perceived usefulness, ease of use, personalisation, trust, satisfaction, human interaction, purchase intention and AI transparency, with effects moderated by privacy concerns and a persistent preference for human contact at key decision points.

Table 1. Summary of reviewed literature on AI-enabled customer interaction and purchase intention

No.	Author(s) (Year)	Focus & Context	Key Findings	Gap / Contribution to Study
1	Zaman et al. (2026)	AI brand positioning, digital trust and smart-product adoption	Perceived usefulness mediates AI positioning → adoption; digital trust strengthens the effect.	Not housing; supports trust and usefulness as adoption drivers.
2	Truong (2026)	Integrated AI technologies; Gen Z fashion purchase (Vietnam)	Personalisation and interaction mediate AI perceptions → purchase intention.	Fashion context; supports intention as outcome.
3	Mahajan (2023)	Voice assistants and purchase intention	Anthropomorphism → usefulness / ease of use → acceptance → purchase intention.	TAM chain relevant to virtual assistants.
4	Chiu & Chen (2025)	Smart-hotel adoption (SEM + fsQCA)	Novelty, efficacy, compatibility → perceived value → accommodation intention.	Accommodation-adjacent; not property purchase.



No.	Author(s) (Year)	Focus & Context	Key Findings	Gap / Contribution to Study
5	Karim, Rathore & Bhakne (2026)	AI touchpoints and purchase intent (e-commerce)	Personalisation aids evaluation; privacy and transparency concerns undermine trust.	Benefits and concerns coexist; no housing data.
6	Misra, Kapoor & Sanjeev (2026)	AI-enhanced virtual shopping assistants	Purchase decisions strongest at medium algorithmic autonomy.	Boundary condition on AI → purchase link.
7	Khan et al. (2023)	AI, chatbot mediation and loyalty (Pakistan tourism)	Focus: chatbot as mediating touchpoint; findings not summarised.	Chatbot as customer touchpoint.
8	Nahar et al. (2026)	AI features, satisfaction and purchase intention (Bangladesh food industry)	Focus: intention as outcome of AI features; findings not summarised.	Supports outcome choice; not housing.
9	Ju (2026)	Generative-AI fashion customisation services	Focus: perceptions, experiences and behavioural intention; findings not summarised.	Supports intention as outcome.
10	Malali & Gopalakrishnan (2020)	AI in Indian banking and finance	Overview of AI-powered technologies.	India-anchored, but not housing.
11	Gaur (2024)	Employee satisfaction with AI features in online fashion firms (SEM, WEBQUAL)	Focus: employee, not consumer, satisfaction.	Shows breadth of AI research.
12	Jain (2025)	AI-driven sustainable innovation and consumer behaviour	Exploratory focus on influence of AI-driven innovation.	Sector-general; no housing.
13	Li (2025)	AI-powered refrigerators and purchase intention (case study)	Company case; intention as outcome.	Single-company product case.
14	Nikitha & Renushree (2026)	AI-driven behavioural insights in smart kitchens	Focus: consumer decision-making with AI insights.	India-set, but not housing.

Source: Compiled by the authors from the reviewed literature.

RESEARCH GAPS:

- **Contextual gap:** Most prior studies on AI-enabled customer interaction focus on retail, banking, hospitality, fashion and e-commerce; housing and real estate are comparatively under-researched^{3,9,12}.
- **Geographic gap:** Limited empirical evidence exists from Bangalore or from Indian housing buyers specifically; India-anchored AI work is concentrated in banking and consumer products^{1,18}.
- **Integration gap:** Few studies combine AI adoption and interaction, buying intention and AI-related challenges within a single housing-purchase context.
- **Balance gap:** Studies tend to report either the benefits of AI or its concerns^{3,10}; fewer place them side by side in the same respondent group.

PROBLEM STATEMENT:

AI-enabled customer interaction tools are being adopted by housing and real-estate platforms in Bangalore, but the extent of buyer adoption and its actual relationship with buying intention are not well understood. It is unclear how strongly AI-enabled interaction relates to buying intention once challenges such as technical issues, difficulty obtaining accurate answers and a preference for human interaction are taken into account. The study therefore addresses the following research questions:

- **RQ1:** What is the level of adoption and usage of AI-enabled customer interaction tools among prospective housing buyers in Bangalore?
- **RQ2:** Does AI-enabled customer interaction significantly impact consumer buying intention towards housing properties?
- **RQ3:** What is the relationship between AI-enabled customer interaction and consumers' buying intention towards housing properties?
- **RQ4:** What challenges or limitations do consumers face when interacting with AI-enabled tools in the housing property buying process?



CONCEPTUAL FRAMEWORK AND HYPOTHESES DEVELOPMENT:

The framework in Figure 1 positions AI-enabled customer interaction as the focal construct and buying intention as the outcome. Adoption and usage (Objective 1) describes the level of the focal construct. Challenges and limitations are treated as a separate dimension assessed under Objective 4. Perceived trust and consumer satisfaction are shown as proposed mediators for future testing; they were not measured in this study.

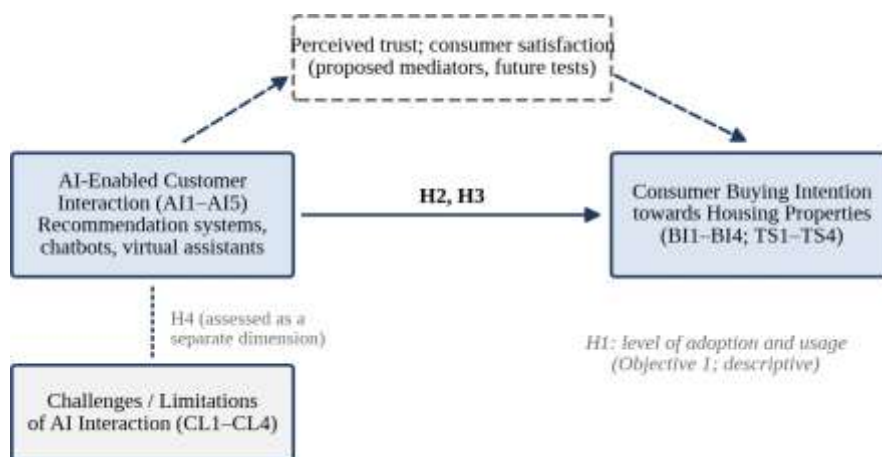


Figure 1. Conceptual framework of the study

Source: Developed by the authors.

H1 follows technology-acceptance logic and the adoption evidence, in which perceived usefulness and ease of use drive uptake^{5,8}, together with the technology literacy of Bangalore's buyers. H2 and H3 draw on the links from AI interaction to purchase intention through personalisation and perceived usefulness^{10,12}. H4 reflects the reported concerns about privacy, transparency, accuracy and human contact^{3,4}. Accordingly, the following hypotheses were formulated:

- **H1:** AI-enabled customer interaction tools are adopted and used at a moderate-to-high level among prospective housing buyers in Bangalore.
- **H2:** AI-enabled customer interaction has a significant positive impact on consumer buying intention towards housing properties.
- **H3:** There is a significant positive relationship between AI-enabled customer interaction and consumers' buying intention towards housing properties.
- **H4:** Consumers face significant challenges or limitations (for example, technical issues and preference for human interaction) when interacting with AI-enabled tools in the housing property buying process.

RESEARCH METHODOLOGY:

Research Design

The study adopts a quantitative, cross-sectional survey design. A structured questionnaire was administered once to each respondent and the responses were coded numerically. The design suits objectives that involve measuring levels (Objectives 1 and 4) and testing associations (Objectives 2 and 3), but because measurement occurs at a single point in time it supports statements about association, not causation¹⁹.

Population, Sampling and Sample Size

The target population comprised prospective housing buyers and consumers evaluating housing properties in Bangalore. Responses were collected through an online structured questionnaire, a non-probability approach²⁰, between 19 and 25 August 2026. After screening, 214 valid responses were retained with no missing values on the analysed variables. Most responses arrived towards the end of the seven-day window (timestamp skewness = -2.297). With 214 cases, the five-predictor regression has 208 residual degrees of freedom, and the sample can detect a correlation of about 0.19 at the 5% level with 80% power, below the observed correlation of 0.337.



Measurement Instrument

The questionnaire recorded respondent age group and then presented statements on a five-point Likert scale (1 = strongly disagree; 5 = strongly agree) in four item blocks (Table 2), drawn from the literature on AI adoption, purchase intention and AI-related concerns. Buying intention was captured by two four-item blocks: BI1–BI4, whose mean (BI_Mean) is used in the correlation analysis, and TS1–TS4, whose first item (TS1) served as the dependent variable in the SPSS regression. Both blocks are treated as measures of the buying-intention outcome.

Table 2. Operationalisation of the research constructs

Construct	Code	Role in model	Items	Sample item
AI-enabled customer interaction (adoption and usage)	AI1–AI5	Focal / independent	5	I frequently use AI chatbots / virtual assistants when browsing housing property websites or apps.
Buying intention (composite)	BI1–BI4	Outcome (correlation)	4	I would recommend housing platforms that use AI-enabled interaction to others (BI4).
Buying-intention scale	TS1–TS4	Outcome (regression; TS1)	4	Item wording not contained in the output files; $\alpha = .816$.
Challenges and limitations	CL1–CL4	Additional dimension	4	I prefer human interaction for final negotiation or decision-making stages.

Source: Survey instrument developed by the authors (Appendix wording available from the output files; item AI5 is recorded as an 'other AI-interaction feature').

Tools of Analysis

IBM SPSS Statistics²¹ was used for descriptive statistics, reliability analysis, the item-level correlation matrix and multiple linear regression (Enter method); jamovi²² was used for the construct-level Pearson and Spearman correlation and for the descriptive and reliability analysis of the challenge items. Internal consistency was judged against the conventional minimum of 0.70 for Cronbach's alpha^{23,24}. Supplementary computations (one-sample t tests against the scale midpoint of 3.0, confidence intervals, variance inflation factors and Cohen's d ²⁵) were calculated from the reported summary statistics and correlation matrix and are labelled as supplementary. The decision rule was to reject the null hypothesis when $p < .05$. Construct validity was not tested with factor analysis.

Ethical Considerations

Participation was voluntary and responses were collected for academic purposes only. No information that identifies respondents was retained in the analysed dataset, results are reported in aggregate, and the study follows the university's research-ethics expectations.

RESULTS:

Profile of Respondents

Table 3 shows that the sample is a working-age, professional group. Respondents aged 35–44 (54.7%) and 25–34 (33.2%) together make up 87.9% of the sample, and only two respondents (0.9%) are aged 55 or above, too few for group-level inference. Men outnumber women by about 2.9 to 1 (74.3% versus 25.7%). Almost all respondents are self-employed (48.6%) or employed (45.3%), and 72.9% earn ₹1 lakh or more per month.

Table 3. Demographic profile of respondents (N = 214)

Variable	Category: n (%)
Age group	25–34: 71 (33.2); 35–44: 117 (54.7); 45–54: 24 (11.2); 55 and above: 2 (0.9)
Gender	Male: 159 (74.3); Female: 55 (25.7)
Occupation	Self-employed: 104 (48.6); Employed: 97 (45.3); Others: 13 (6.1)
Monthly income	₹1–2 lakh: 111 (51.9); ₹50,000–1 lakh: 58 (27.1); ₹2–3 lakh: 41 (19.2); Above ₹3 lakh: 4 (1.9)

Source: Primary survey data (N = 214). Income counts for the two smaller bands are derived from the reported percentages.

Objective 1: Adoption and Usage of AI-Enabled Customer Interaction Tools

All 214 cases were valid. The five-item scale is reliable ($\alpha = .849$; standardised $\alpha = .851$), and the mean inter-item correlation is .533 (range .366–.648), indicating items that are related but not redundant. As Table 4 and Figure 2 show, every item mean lies above the neutral midpoint, from 3.26 for recommendation systems (AI1) to 3.48 for preference for AI over a human agent in initial enquiries (AI4) and other AI-interaction features (AI5). The composite AI_Mean of 3.373 (SD = 0.917; 95% CI 3.25–3.50) exceeds 3.0 significantly, $t(213) = 5.95$, $p < .001$, $d = 0.41$, a small-to-moderate effect. Friedman's test shows that item means differ statistically ($\chi^2 = 13.359$, $p = .010$) but



negligibly in practice (Kendall's $W = .006$), and Tukey's test for nonadditivity is not significant ($p = .472$), supporting averaging the items into one composite. Because means fall between neutral and agree, adoption is best described as moderate-to-high rather than very high. **H1 is supported.**

Table 4. Adoption and usage of AI-enabled interaction tools: item statistics and tests against the midpoint of 3.0

Item	Mean	SD	95% CI	t (213)	p	Cohen's d
AI1 Recommendation systems	3.26	1.310	3.08–3.44	2.90	.004	0.20
AI2 Ease of use	3.33	0.976	3.20–3.46	4.95	< .001	0.34
AI3 Chatbots / virtual assistants	3.32	1.192	3.16–3.48	3.93	< .001	0.27
AI4 Prefer AI for initial enquiry	3.48	1.108	3.33–3.63	6.34	< .001	0.43
AI5 Other AI-interaction feature	3.48	1.194	3.32–3.64	5.88	< .001	0.40
AI_Mean (composite)	3.373	0.917	3.25–3.50	5.95	< .001	0.41

Source: SPSS output; *t* tests, CIs and *d* are supplementary computations from reported means and SDs (two-tailed).

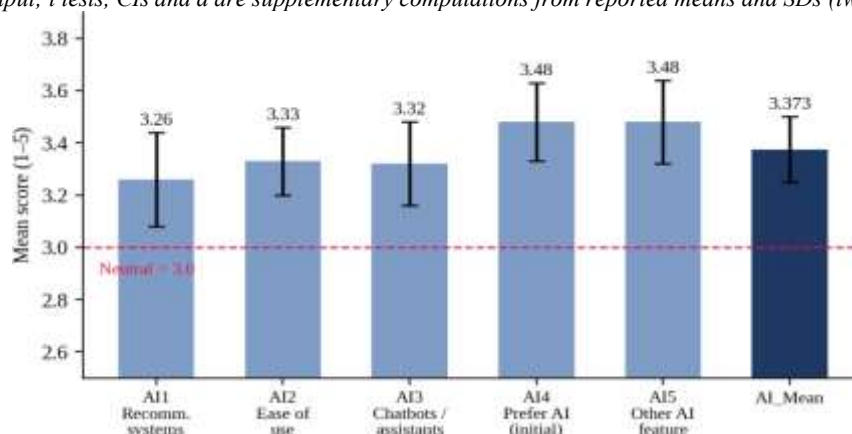


Figure 2. Mean adoption and usage scores with 95% confidence intervals

Source: SPSS output; prepared by the authors.

Objective 2: Impact of AI-Enabled Customer Interaction on Buying Intention

A multiple linear regression (Enter method) was estimated with AI1–AI5 as predictors and TS1 as the dependent variable. The four-item scale to which TS1 belongs is reliable ($\alpha = .816$). TS1 correlates positively with all five predictors ($r = .130$ – $.222$). The model is statistically significant, $F(5, 208) = 2.490$, $p = .032$, but the five items together account for only 5.6% of the variance ($R = .238$; $R^2 = .056$; adjusted $R^2 = .034$; Cohen's $f^2 \approx 0.06$, a small effect), and the standard error of the estimate (1.336) is large on a five-point scale (Table 5). No individual predictor reaches the 5% level. The closest is AI4, preference for AI over a human agent for initial enquiries ($B = 0.212$; $\beta = 0.173$; $p = .062$), while AI1 and AI5 carry small negative partial coefficients close to zero (Figure 3). Collinearity does not explain this pattern: variance inflation factors range from 1.84 to 2.25 (tolerance .445–.543), so the items simply overlap in what they explain (mean inter-item $r = .53$).

Table 5. Multiple regression of TS1 on AI1–AI5 (SPSS, Enter method; N = 214)

Predictor	B	Std. error	Beta	t	Sig.
(Constant)	1.852	.372	—	4.981	< .001
AI1 Recommendation systems	-.033	.099	-.032	-.334	.739
AI2 Ease of use	.135	.128	.097	1.059	.291
AI3 Chatbots / virtual assistants	.069	.104	.061	.663	.508
AI4 Prefer AI for initial enquiry	.212	.113	.173	1.878	.062
AI5 Other AI-interaction feature	-.033	.115	-.029	-.283	.778

Model: $R = .238$; $R^2 = .056$; adjusted $R^2 = .034$; $F(5, 208) = 2.490$, $p = .032$. Source: SPSS output.

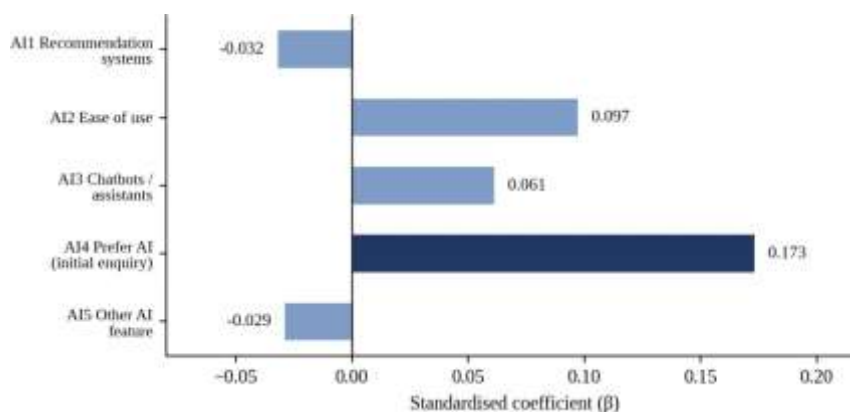


Figure 3. Standardised regression coefficients (dependent variable: TS1)

Source: SPSS output; prepared by the authors.

A single-item outcome is noisier than a scale, which lowers the achievable R^2 . As a supplementary check, the regression was recomputed with the mean of TS1–TS4 as the dependent variable (Table 6). The fit improves ($R^2 = .160$; adjusted $R^2 = .140$; $F(5, 208) = 7.91$; $p < .001$), with AI4 ($\beta = 0.224$) and AI3 ($\beta = 0.211$) emerging as significant positive predictors and AI1 as a significant negative one ($\beta = -0.206$), suggesting that the modest explanatory power of the single-item model is partly a measurement issue. **H2 is partly supported:** the model is significant and the direction is positive, but the effect is small and no item is a significant unique predictor in the SPSS model.

Table 6. Supplementary regression of the TS1–TS4 composite on AI1–AI5

Predictor	B	Std. error	Beta	t	Sig.
AI1 Recommendation systems	-.149	.065	-.206	-2.28	.024
AI2 Ease of use	.157	.084	.162	1.87	.064
AI3 Chatbots / virtual assistants	.168	.068	.211	2.45	.015
AI4 Prefer AI for initial enquiry	.191	.074	.224	2.58	.010
AI5 Other AI-interaction feature	.043	.075	.054	0.57	.569

Model: $R = .400$; $R^2 = .160$; $F(5, 208) = 7.91$, $p < .001$. Source: computed from the submitted correlation matrix and item SDs (supplementary).

Objective 3: Relationship between AI-Enabled Interaction and Buying Intention

AI_Mean ($M = 3.373$; $SD = 0.917$) and BI_Mean ($M = 3.237$; $SD = 0.936$) are both above the neutral midpoint (BI_Mean: $t(213) = 3.70$, $p < .001$, $d = 0.25$), although intention is somewhat lower than adoption. As Table 7 shows, the two composites are significantly and positively correlated (Pearson $r = .337$, $p < .001$; Spearman $\rho = .349$, $p < .001$). The 95% confidence interval for r runs from .212 to .451, a medium effect²⁵ implying that about 11.4% of the variance in buying intention is shared with AI-enabled interaction. The agreement between the Pearson and Spearman coefficients shows that the result does not depend on normality or outliers.

Table 7. Correlation between AI-enabled interaction and buying intention, and construct-level relationships

Pair	r / ρ	95% CI	p	Source
AI_Mean and BI_Mean (Pearson)	.337	.212–.451	< .001	jamovi
AI_Mean and BI_Mean (Spearman)	.349	—	< .001	jamovi
AI_Mean and TS_Mean	.328	.203–.443	< .001	Supplementary
AI_Mean and CL_Mean	.298	.170–.415	< .001	Supplementary
TS_Mean and CL_Mean	.324	.198–.439	< .001	Supplementary

Note: $N = 214$; $df = 212$. Source: jamovi output and SPSS item-level correlation matrix (Output 8).

The item-level matrix reinforces this picture (Table 8, Figure 4). Of the 20 pairs between AI and BI items, 19 are significant at 5% and 15 at 1%, with coefficients from .105 to .305 (mean .217); the only non-significant pair is AI3 with BI4 ($r = .105$, $p = .124$). AI4 has the strongest and most consistent links with the intention items (.221–.305), followed by AI5 (.210–.254), and AI1 is the weakest (.144–.224). Across the full 17-item matrix, 123 of 136 correlations (90.4%) are significant, with strong within-scale and moderate between-scale correlations, as expected of



four related but distinct constructs. **H3 is supported**, and the null hypothesis of no relationship is rejected. The result describes association only, since price, location and trust were not controlled.

Table 8. Pearson correlations between AI items and BI items, r (two-tailed p)

Item	BI1	BI2	BI3	BI4
AI1	.224 (< .001)	.144 (.035)	.151 (.027)	.178 (.009)
AI2	.159 (.020)	.291 (< .001)	.247 (< .001)	.253 (< .001)
AI3	.201 (.003)	.162 (.018)	.265 (< .001)	.105 (.124)
Item	BI1	BI2	BI3	BI4
AI4	.221 (.001)	.305 (< .001)	.226 (< .001)	.288 (< .001)
AI5	.231 (< .001)	.227 (< .001)	.254 (< .001)	.210 (.002)

Source: SPSS Output 8 ($N = 214$).

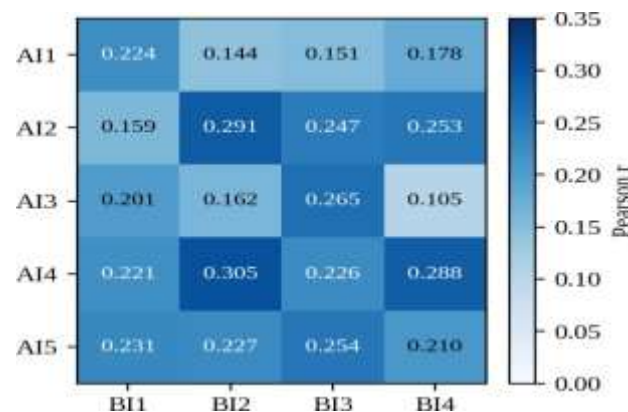


Figure 4. Heat map of correlations between AI items and BI items

Source: SPSS Output 8; prepared by the authors.

Objective 4: Challenges and Limitations of AI-Enabled Interaction

Table 9 and Figure 5 rank the four challenges. Preference for human interaction at final negotiation or decision-making (CL4; $M = 3.36$) is the most prominent, followed by technical issues (CL2; $M = 3.27$). Both are significantly above neutral (CL4: $t = 4.67$, $p < .001$, $d = 0.32$; CL2: $t = 4.07$, $p < .001$, $d = 0.28$). Difficulty obtaining accurate answers to complex questions (CL3; $M = 3.11$) and AI tools missing specific requirements (CL1; $M = 2.99$) do not differ from neutral, and CL1 shows the widest disagreement ($SD = 1.453$). The composite challenge score ($M = 3.183$; $SD = 0.942$) is significantly above neutral, $t(213) = 2.84$, $p = .005$, $d = 0.19$. The gap between the highest and lowest means is only

0.37 points, so the challenges are moderate rather than severe.

Table 9. Descriptive statistics and ranking of challenge items ($N = 214$)

Rank	Challenge / limitation	Mean	SD	95% CI	p	Result
1	CL4 Prefer human interaction at final negotiation	3.36	1.142	3.21–3.52	< .001	Above neutral
2	CL2 Technical issues reduce confidence	3.27	0.970	3.14–3.40	< .001	Above neutral
3	CL3 Difficulty with accurate answers to complex questions	3.11	1.185	2.95–3.27	.176	Not different
4	CL1 AI fails to understand specific requirements	2.99	1.453	2.79–3.19	.920	Not different
—	CL_Mean (composite)	3.183	0.942	3.06–3.31	.005	Above neutral

Source: jamovi and SPSS output; t tests against 3.0 are supplementary computations.

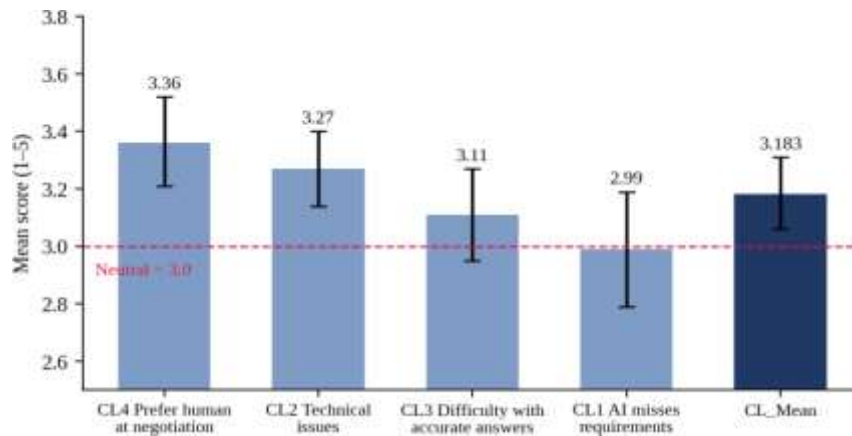


Figure 5. Mean scores of the four challenge items with 95% confidence intervals

Source: jamovi and SPSS output; prepared by the authors.

Of the 214 respondents, 93 (43.5%) agree or strongly agree that they prefer a human at the final stage, 79 (36.9%) are neutral and 42 (19.6%) disagree or strongly disagree (Figure 6). The mean preference is similar across age groups (25–34: 3.34; 35–44: 3.36; 45–54: 3.54), with no significant difference (one-way ANOVA $F = 0.301$, $p = .74$; Kruskal–Wallis $H = 0.968$, $p = .616$); the 55-and-above group ($n = 2$) is not interpretable. The challenge scale is reliable ($\alpha = .792$), and deleting any item would lower alpha (CL1 .719; CL2 .751; CL3 .764; CL4 .723), so all four items are retained.

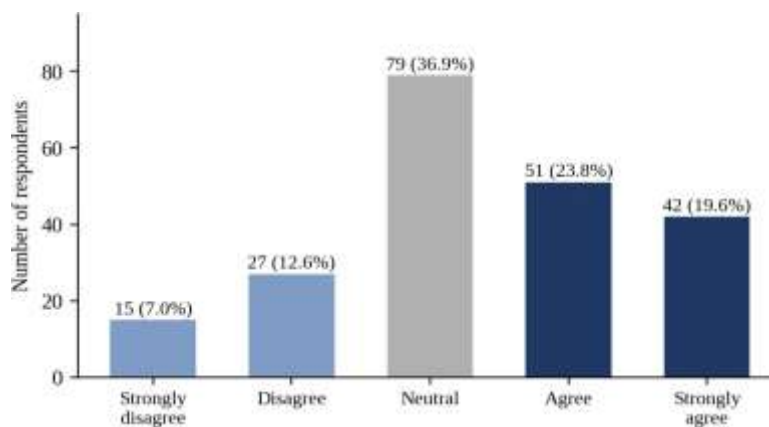


Figure 6. Distribution of responses on CL4 (prefer human interaction at final negotiation)

Source: Response data underlying SPSS Output 3; prepared by the authors.

The challenge items correlate positively with the AI items (16 of 20 significant; mean $r = .186$), most strongly AI3 (chatbot use) with CL3 (.280) and AI1 with CL1 (.275); the more buyers use these tools, the more they notice their limits. CL4 also correlates positively with willingness to recommend AI-enabled platforms (BI4: $r = .326$), showing that preferring a human negotiator does not imply rejecting AI. **H4 is supported with qualification**, because the composite and the two leading challenges are significant while two of the four challenges do not differ from neutral. Table 10 summarises scale reliability and Table 11 the hypothesis decisions.

Table 10. Reliability of the study scales

Scale	Items	Cronbach's α	Standardised α	Verdict
AI-enabled interaction (AI1–AI5)	5	.849 (SPSS)	.851	Good
Four-item scale (TS1–TS4)	4	.816 (SPSS)	.821	Good
Buying intention (BI1–BI4)	4	Not separately reported	.812 (computed)	Good
Scale	Items	Cronbach's α	Standardised α	Verdict
Challenges (CL1–CL4)	4	.792 (jamovi)	.799	Acceptable

Thresholds: 0.70 acceptable; 0.80 good; 0.90 excellent. Source: SPSS and jamovi output.



Table 11. Summary of hypothesis testing

Hypothesis	Test and key result	Decision
H1	Item means 3.26–3.48 all above 3.0; AI_Mean = 3.373, $t(213) = 5.95$, $p < .001$; $\alpha = .849$	Supported
H2	$R^2 = .056$, $F(5, 208) = 2.490$, $p = .032$; no individual predictor significant (AI4 $p = .062$); composite check $R^2 = .160$	Partly supported
H3	Pearson $r = .337$, Spearman $\rho = .349$, both $p < .001$; 19 of 20 item pairs significant	Supported
H4	CL4 = 3.36 and CL2 = 3.27 above neutral; CL3 and CL1 not different; CL_Mean = 3.18, $p = .005$	Supported with qualification

Source: Compiled by the authors from the SPSS and jamovi analyses.

DISCUSSION:

Moderate-to-high adoption, led by convenience. All five adoption items sit between neutral and agree, and the highest-rated statements concern preferring AI for initial enquiries (3.48) and ease of use (3.33). Ease of use scoring above neutral is consistent with the acceptance logic in which ease of use and usefulness drive adoption^{5,10}, and the preference for AI at the enquiry stage suggests that buyers see it as a convenient first point of contact, in line with the usefulness-and-trust drivers of adoption⁸. Recommendation-system use had the lowest mean and the widest spread ($SD = 1.310$), indicating uneven adoption: some buyers use these tools heavily and others rarely.

A real but modest link with buying intention. AI-enabled interaction is positively associated with intention ($r = .337$), which agrees with studies reporting positive links between AI-enabled experiences and purchase or behavioural intention^{10,12–14}. Yet the regression explains only 5.6% of the variance in the single-item outcome, and no item is a unique predictor. This is consistent with the literature's emphasis on mediating and boundary factors such as trust, personalisation, perceived value and algorithmic autonomy^{4,9,12}: a direct model containing only usage and preference items should be expected to explain a limited share of variance. The larger R^2 for the composite outcome (.160) indicates that measurement noise in single-item outcomes understates the relationship, and that chatbot use (AI3) and preference for AI at enquiry (AI4) carry the clearest positive links. The negative coefficient for AI1 in the composite model should be read cautiously, as it emerges in a model whose predictors overlap substantially.

Human contact remains valued at the decision point. The leading challenge, a preference for a human at final negotiation, echoes the reported persistence of human contact at key decision points and the boundary conditions on algorithmic autonomy^{3,4}. Housing involves large sums and contractual commitment, and buyers appear to want an accountable person for price discussion. Technical reliability ranks second, consistent with the facilitating-conditions element of UTAUT⁷. The positive correlations between AI use and the challenge items suggest that heavier users are more aware of limitations, and the positive link between CL4 and willingness to recommend AI platforms shows that the two attitudes coexist rather than compete: preferring a human negotiator complements, rather than replaces, use of AI in the early stages.

Convergence across analyses. The regression, correlation and challenge results point the same way: AI helps at discovery and first enquiry, is associated with stronger intention, but is one contributor among many, and it works best alongside human contact and reliable technology.

IMPLICATIONS:

Managerial Implications

- Deploy chatbots and virtual assistants where they are preferred, at initial enquiries, for availability, amenity, price-range and location queries and for shortlisting (preference for AI at enquiry scored 3.48).
- Keep a visible human hand-off: with 43.5% preferring a human at final negotiation, provide a one-click route from the assistant to a sales executive, with the conversation history carried over.
- Invest in reliability, since technical issues rank second (3.27): monitor response times and errors and set service-level targets for the AI layer.
- Improve handling of complex and specific requirements. Although CL1 and CL3 are near neutral, their wide spread shows that a sizeable group is dissatisfied; review failed conversations and extend coverage of financing and legal-clarity questions.
- Position AI as support to the buyer journey, not a substitute for trust built through people, site visits and transparent information, because its direct effect on intention is modest.



Academic Implications

- The study extends AI-marketing research, largely concentrated in retail, banking, hospitality and fashion, to housing and real estate in an Indian metro.
- It provides within-sample evidence on adoption, buying intention and challenges together, so that benefits and concerns can be read side by side.
- It shows that a modest direct effect ($R^2 = .056$ on a single item; $.160$ on a composite) is the realistic expectation, pointing future models towards mediators such as trust and satisfaction and moderators such as property complexity.

Practical Implications for AI-Tool Designers

- Design for graceful escalation when the tool cannot answer, make recommendation logic understandable given the emphasis on transparency and trust³, and test tools with heavier users, who are most likely to detect gaps.

CONCLUSION:

This study examined how AI-enabled customer interaction relates to consumer buying intention towards housing properties in Bangalore, using 214 valid responses from prospective buyers. Adoption of recommendation systems, chatbots and virtual assistants is moderate-to-high. AI-enabled interaction is significantly and positively associated with buying intention ($r = .337$, $p < .001$), although a regression of the five AI items explains only a small share of the outcome ($R^2 = .056$, $p = .032$). Buyers report moderate challenges, chiefly a preference for human interaction at final negotiation (3.36) and technical issues (3.27). Taken together, the evidence supports a hybrid approach for housing: AI for discovery and first enquiry, people for negotiation and commitment, and reliable technology throughout. Because the design is cross-sectional, the findings describe association rather than proven causation.

LIMITATIONS OF THE STUDY:

- The cross-sectional design captures perceptions at one point in time and cannot establish causality; the regression and correlation results describe association.
- Findings are specific to Bangalore's housing context and to the 19–25 August 2026 survey window, and the online non-probability sample may favour digitally comfortable respondents²⁰.
- The sample is skewed towards men (74.3%) and ages 25–44 (87.9%); older buyers are under-represented ($n = 2$ aged 55 or above).
- Self-reported Likert data may be affected by social-desirability and common-method bias^{26,27}.
- Only AI interaction and challenges were modelled; price, location, income, trust and brand may also influence buying intention, and the direct model has limited explanatory power.
- Construct validity was not tested with factor analysis, the challenge scale has four items, buying intention is captured by two four-item blocks (the regression uses the single item TS1), and several supplementary statistics were computed from summary statistics and therefore carry rounding error.

FUTURE SCOPE:

- Test perceived trust and consumer satisfaction as mediating or moderating variables in the AI-to-intention link.
- Examine property complexity and price band as moderators of the AI–intention relationship.
- Study demographic differences among housing buyers, including older buyers and first-time versus repeat buyers.
- Investigate the human–AI hand-off at the negotiation stage through qualitative or experimental designs.
- Extend the sample to multiple cities and use longitudinal designs to test causal direction, applying factor analysis and structural equation modelling to validate the constructs.

CONFLICT OF INTEREST:

The authors declare no conflicts of interest regarding this investigation.



ACKNOWLEDGMENTS:

The authors thank the Department of Management Studies, Faculty of Management and Commerce, M S Ramaiah University of Applied Sciences, Bengaluru, for its academic support, and sincerely acknowledge the prospective housing buyers who participated in the survey.

REFERENCES:

1. Malali AB, Gopalakrishnan S. Application of artificial intelligence and its powered technologies in the Indian banking and financial industry: An overview. 2020.
2. Government of India. The Real Estate (Regulation and Development) Act, 2016. New Delhi: Government of India; 2016.
3. Karim MA, Rathore K, Bhakne T. Impact of artificial intelligence on consumer buying behavior: Personalization, algorithmic decision-making, and purchase intent. 2026.
4. Misra RR, Kapoor S, Sanjeev MA. The impact of personalisation algorithms on consumer engagement and purchase behaviour in AI-enhanced virtual shopping assistants. 2026.
5. Davis FD. Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*. 1989; 13(3):319–340. doi.org/10.2307/249008
6. Ajzen I. The theory of planned behavior. *Organizational Behavior and Human Decision Processes*. 1991; 50(2):179–211.
7. Venkatesh V, Morris MG, Davis GB, Davis FD. User acceptance of information technology: Toward a unified view. *MIS Quarterly*. 2003; 27(3):425–478. doi.org/10.2307/30036540
8. Zaman HMF, Xu Y, Nguyen TTN, Pasha MA, Nguyen ATL. AI-driven brand positioning and smart product adoption: The roles of perceived usefulness and digital trust. 2026.
9. Chiu F-R, Chen Y-K. Travelers' accommodation intention towards smart hotels: A two-stage analysis using SEM and fsQCA. 2025.
10. Mahajan M. Speak, assist, purchase: Exploring the impact of voice assistants on consumer purchase intention. 2023.
11. Khan A, Abdul Hamid AB, Mat Saad N, Hussain Z, Arif AR. Effectiveness of artificial intelligence in building customer loyalty: Investigating the mediating role of chatbot in the tourism sector of Pakistan. 2023.
12. Truong TMT. Integrated AI technologies and fashion purchase intentions among Generation Z consumers in Vietnam. 2026.
13. Nahar N, Tafsirun U, Tanchangya T, Siddiqi KO, Naher K, Islam N, Hossan MA. The impact of AI features on customer satisfaction and purchase intention in the Bangladeshi food industry. 2026.
14. Ju A. Consumers' perceptions, experiences, and behavioral intention toward generative AI-supported fashion customization services (GAIFCS). 2026.
15. Gaur V. An empirical study on employee satisfaction with AI and technology-enabled features in online fashion companies using SEM and WEBQUAL. 2024.
16. Jain R. Exploring the influence of AI-driven sustainable innovation on consumer behavior. 2025.
17. Li M. The impact of AI-powered refrigerators on consumer purchase intentions: A case study of HA company. 2025.
18. Nikitha K, Renushree S. AI-driven behavioral insights and consumer decision-making in smart kitchen environments. 2026.
19. Setia MS. Methodology series module 3: Cross-sectional studies. *Indian Journal of Dermatology*. 2016; 61(3):261–264. doi.org/10.4103/0019-5154.182410
20. Etikan I, Musa SA, Alkassim RS. Comparison of convenience sampling and purposive sampling. *American Journal of Theoretical and Applied Statistics*. 2016; 5(1):1–4. doi.org/10.11648/j.ajtas.20160501.11
21. IBM Corp. IBM SPSS Statistics [Computer software]. Armonk, NY: IBM Corp.
22. The jamovi project. jamovi [Computer software]. <https://www.jamovi.org>
23. Cronbach LJ. Coefficient alpha and the internal structure of tests. *Psychometrika*. 1951; 16(3):297–334.
24. Nunnally JC. *Psychometric theory*. 2nd ed. New York: McGraw-Hill; 1978.
25. Cohen J. *Statistical power analysis for the behavioral sciences*. 2nd ed. Hillsdale, NJ: Lawrence Erlbaum Associates; 1988.
26. Krumpal I. Determinants of social desirability bias in sensitive surveys: A literature review. *Quality & Quantity*. 2013; 47(4):2025–2047. doi.org/10.1007/s11135-011-9640-9
27. Podsakoff PM, MacKenzie SB, Lee JY, Podsakoff NP. Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology*. 2003; 88(5):879–903. doi.org/10.1037/0021-9010.88.5.879