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The Impact of Explainability on Trust in AI-Based Systems: An Empirical Study in Navi Mumbai

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Abstract - *Artificial intelligence (AI) tools such as ChatGPT, Gemini and Copilot are now used daily for information and decisions, yet most users cannot see how an answer was produced. This study examines whether explainability is associated with trust in AI-based systems. Primary data were collected through a structured Google Form from 101 respondents using five-point Likert items and analysed in Python(regression analysis, one-way ANOVA and the chi-square test). Perceived explainability showed a strong positive relationship with trust ($R = 0.821$, $p < 0.001$) and explained 67.5% of its variance. Familiarity, comfort and perceived transparency jointly explained 66.9% of the variance in trust, and the importance placed on explanations was positively related to willingness to rely on AI recommendations ($R = 0.609$). Mean trust differed significantly across usage-frequency and age groups, and 82.18% of respondents said they would trust AI more if it explained its decisions. The findings suggest that explainability is an important design requirement for trustworthy AI, though the results show association, not causation.*

Keywords: Explainable AI, Trust, Transparency, Human-AI interaction, Reliance on AI, Survey, Regression, ANOVA, Chi-square

INTRODUCTION

AI systems now support decisions in education, banking, shopping and healthcare. Many of them behave as "black boxes": they give an answer without showing why. Explainable AI (XAI) tries to address this by giving users reasons they can understand. Trust is central because people will rely on a system only if they believe it is dependable, and a lack of transparency is repeatedly linked with hesitation to use AI [1][2]. In India, AI adoption is growing quickly, but there is limited primary survey evidence on how everyday AI users connect explanations with trust. This paper reports a small empirical study that measures that link and tests it with basic statistical methods.

LITERATURE REVIEW

Thapa et al. (2026) surveyed consumers of Indian e-commerce platforms and found that personalization effectiveness, XAI and AI awareness significantly predicted trust in AI recommendations, explaining 61.4% of its variance, while interaction frequency did not.

Bhise and Kand (2026) reviewed model-specific and model-agnostic XAI techniques and argued that explanations must match human cognition and context, noting the lack of standard evaluation metrics and of real-world validation.

Parmar and Saran (2025) reported that XAI increases users' perceived control and understanding of AI products, although their evidence was drawn from secondary sources and trust was hard to quantify.

Pal, Yashvanth and Rao (2024) surveyed professionals, vendors and customers in Bengaluru and Mysuru and found low familiarity with explainable AI but strong interest in its potential for diagnosis.

Waghmare (2024) and Kumar et al. (2024) argue that interpretability supports clinicians' decisions, trust and regulatory compliance, while also raising concerns about accountability, bias and patient privacy.

Trivedi (2024) concludes from a systematic review that interpretability, transparency and accountability shape consumer trust and engagement.

Kumar et al. (2025) use SHAP on lending data to show how explanations can make credit decisions more transparent and open to fairness checks.

Neha (2025) surveys techniques and emphasises the trade-off between model performance and interpretability.

Bhosale (2026) cautions that popular tools such as SHAP and LIME may give plausible but not always faithful explanations in autonomous (agentic) systems.

Most of these studies are reviews or sector-specific; few measure, with simple primary data, how perceived explainability, familiarity, comfort and the demand for explanations relate to trust among general AI-tool users. This study addresses that gap.

Objectives of the Study

- To examine the relationship between perceived explainability and trust in AI.
- To analyse how familiarity with AI, comfort in using AI and perceived transparency relate to trust.
- To explore whether the importance given to explanations relates to willingness to rely on AI recommendations.
- To compare trust across usage-frequency and age groups.
- To test whether the wish for explanations (trusting AI more if it explains its decision) is associated with how often people use AI.

Research Hypotheses

Perceived Explainability

H01: There is no significant relationship between perceived explainability and trust in AI.

H11: There is a significant relationship between perceived explainability and trust in AI.

Familiarity, Comfort and Perceived Transparency

H02: There is no significant effect of familiarity, comfort and perceived transparency on trust in AI.

H12: There is a significant effect of at least one of familiarity, comfort and perceived transparency on trust in AI.

Importance of Explanations

H03: There is no significant relationship between the importance given to explanations and willingness to rely on AI recommendations.

H13: There is a significant relationship between the importance given to explanations and willingness to rely on AI recommendations.

Usage Frequency and Age

H04: There is no significant difference in mean trust across usage-frequency groups (and age groups).

H14: There is a significant difference in mean trust across at least one usage-frequency group (or age group).

Usage Group and the Wish for Explanations

H05: There is no significant association between the wish for explanations and usage group.

H15: There is a significant association between the wish for explanations and usage group.

RESEARCH METHODOLOGY

The study used a descriptive, quantitative survey design to examine whether perceived explainability is associated with trust in AI-based systems, and how familiarity with AI, comfort in using it, perceived transparency and the importance given to explanations relate to trust and to willingness to rely on AI recommendations. No variable was manipulated and all responses were collected at a single point in time. The design therefore supports the study of association between variables and not of cause and effect.

The study was conducted among users of conversational AI tools such as ChatGPT, Gemini and Copilot. The structured questionnaire was circulated online as a Google Form, so the respondents were not restricted to a single institution or workplace. Responses were received mainly from Navi Mumbai and the surrounding Mumbai Metropolitan Region, and covered students, working professionals and other users of AI tools.

A total of 101 complete responses were received and used for analysis, and no response was discarded for missing values. Convenience sampling was used. The sample was weighted towards younger and more frequent users of AI: 40 respondents (39.60%) were aged 18–24, and 54 respondents (53.47%) used AI tools daily.

Primary data were collected through a structured ten-question Google Form. The form was organised in three parts. The first recorded background information, namely age group and frequency of AI use. The second contained seven statements rated on a five-point Likert scale. The third contained a single question with the options Yes, Not sure and No, asking whether the respondent would trust AI more if it explained its decision. Participation was voluntary and responses were anonymous. Every question was compulsory, which is why the data set contains no missing values.

The study considered two background variables and seven perceptual variables. The background variables were age group, recorded in five bands from 18–24 to 55

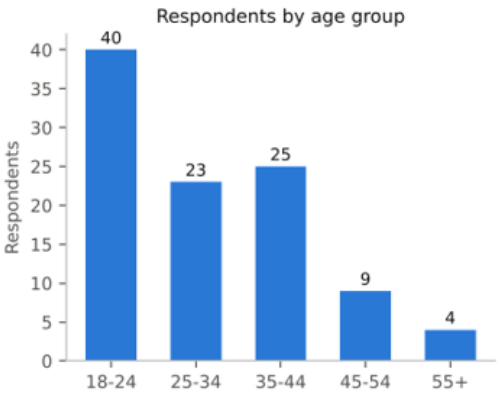
and above, and frequency of AI use, recorded at six levels from never to daily. The perceptual variables were familiarity with how AI produces its answers, comfort in using AI, perceived transparency of AI, perceived explainability, that is whether the explanations given are understandable, the importance given to explanations, trust in AI answers, and willingness to rely on AI recommendations. Trust and willingness to rely were treated as the two dependent variables of the study.

Since the constructs in this study are perceptual rather than factual, each was measured with a single self-reported statement on a five-point Likert scale instead of being scored against a correct answer. The response to the trust statement, from 1 to 5, was used as the respondent's trust score, and the response to the reliance statement as the reliance score, a higher value indicating greater trust or greater willingness to rely. Perceived explainability was measured by the statement that AI explanations are understandable. The difference between the importance given to explanations and the understandability of current explanations was treated as an indicator of an unmet need. Because each construct rests on a single item, no internal-consistency coefficient could be computed for the individual scales, and this is acknowledged as a limitation of the study.

DATA ANALYSIS

Profile of respondents

Of 101 respondents, 40 (39.60%) were aged 18-24, 23 were 25-34, 25 were 35-44, 9 were 45-54 and 4 were 55 or older. A total of 54 (53.47%) used AI tools daily and 6 never used them.



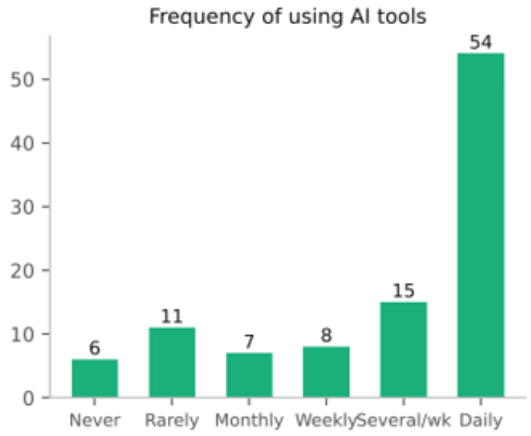


Figure 1: Respondents by age group and frequency of AI use

Descriptive statistics

All seven statements had mean scores above the neutral value of 3. Importance of explanations had the highest mean and familiarity the lowest.

Table 1: Descriptive statistics (n = 101)

Variable	Mean	SD	Median	% agree (4-5)
Familiarity (understand how AI works)	3.66	1.40	4	60.40%
Comfort using AI	3.97	1.33	4	74.26%
Perceived transparency	3.83	1.34	4	66.34%
Perceived explainability	4.33	1.32	5	83.17%
Importance of explanations	4.67	0.99	5	91.09%
Trust in AI answers	4.08	1.23	4	82.18%
Willingness to rely on AI	4.03	1.28	4	76.24%

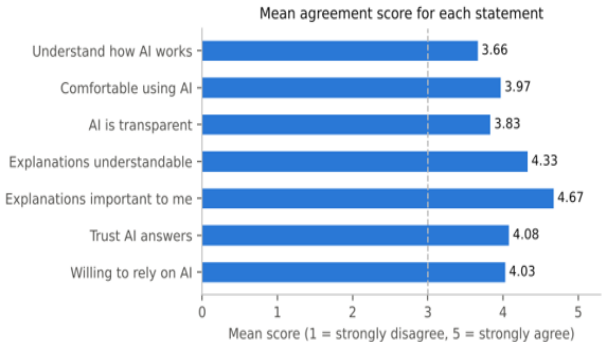


Figure 2: Mean agreement score for each statement

Regression analysis

The table below summarises three least-squares models. Each coefficient is tested for significance (t-statistic) and each model as a whole (F-statistic). It shows the fitted lines for the two simple regressions.

Table 2: Regression results

Model / predictor	b	SE	t	p-value
H1: Trust = a + b(Explainability); R = 0.821, R2 = 0.675, F = 205.32				
Perceived explainability	0.766	0.053	14.33	< 0.001
H2: Trust = a + b1(Fam) + b2(Comfort) + b3(Transp); R2 = 0.669, adj R2 = 0.659, F = 65.47				
Familiarity	0.217	0.096	2.27	0.026
Comfort	0.267	0.117	2.28	0.025
Perceived transparency	0.305	0.109	2.81	0.006
H3: Reliance = a + b(Importance); R = 0.609, R2 = 0.370, F = 58.23				
Importance of explanations	0.784	0.103	7.63	< 0.001

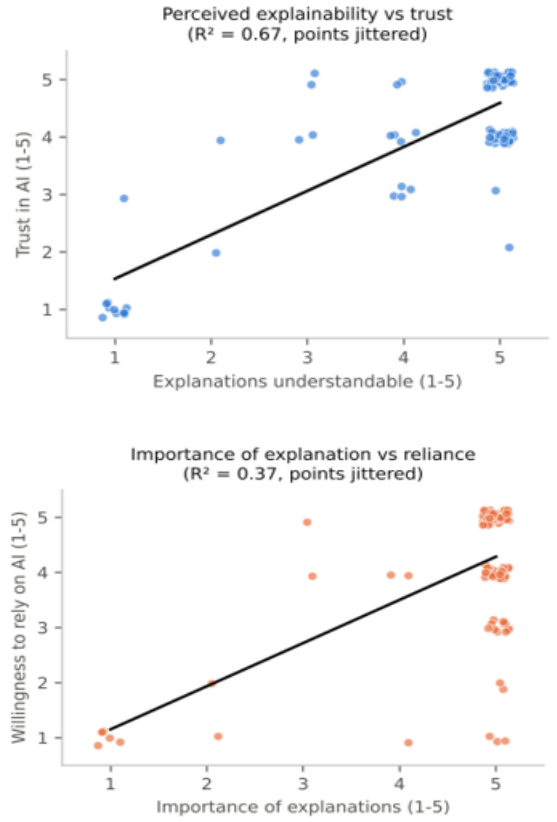


Figure 3: (a) Perceived explainability vs trust; (b) importance of explanations vs reliance (points slightly jittered; line = fitted regression)

One-way ANOVA

The table below compares mean trust across the six usage-frequency groups and the five age groups. Mean trust rose steadily with use, from 1.00 (never) to 4.67 (daily), and fell with age, from 4.65 (18-24) to 2.50 (55+). Both F-values are significant at the 5% level.

Table 3: One-way ANOVA on trust score

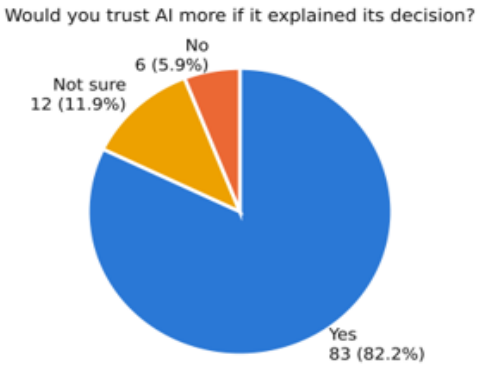
Grouping variable	SS between	SS within	df	F	p-value	Eta-sq
Usage frequency (6 groups)	90.65	60.72	5, 95	28.37	< 0.001	0.60
Age group (5 groups)	46.21	105.15	4, 96	10.55	< 0.001	0.31

Chi-square test of independence

Of 101 respondents, 83 (82.18%) said they would trust AI more if it explained how it reached a decision, 12 were not sure and 6 said no. The responses were grouped into two categories, those who would trust AI more if it explained its decision and those who would not or were undecided, so that every expected count is large enough for the test.The figure shows that the wish for explanations depends on usage group, chi-square(1) = 33.12, p < 0.001, phi = 0.57. Age band (18-24, 25-34, 35+) was also associated with the answer, chi-square(2) = 24.56, p < 0.001, although one expected count (4.10) was just below 5.

Table 4: Usage group and the wish for explanations

Group	Yes	Not Yes	% saying Yes	Test result
Frequent users (daily / several times a week)	67	2	97.10%	chi-sq = 33.12, df = 1, p < 0.001
Occasional users (weekly or less)	16	16	50.00%	



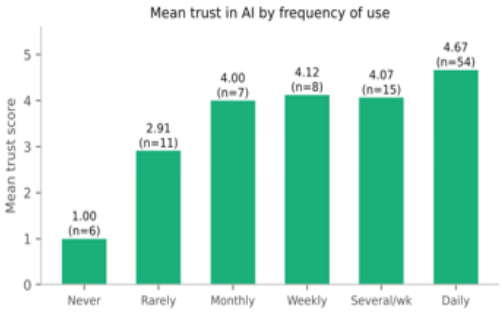


Figure 4: (a) Would trust AI more if it explained its decision (pie chart); (b) mean trust by frequency of AI use

INTERPRETATION

Perceived Explainability

H01 is rejected. Perceived explainability has a strong positive effect on trust ($R = 0.821$, $F = 205.32$, $p < 0.001$). Each one-point rise in perceived explainability is associated with a 0.77-point rise in trust, and explainability alone accounts for 67.5% of the variation in trust.

Familiarity, Comfort and Perceived Transparency

H02 is rejected. Familiarity, comfort and perceived transparency together explain 66.9% of the variation in trust, and all three coefficients are significant ($p < 0.05$). Transparency has the largest coefficient (0.305), followed by comfort (0.267) and familiarity (0.217). The predictors overlap strongly (variance inflation factors 3.50 to 4.69, below the usual limit of 5 but not low), so their separate effects should be read with caution.

Importance of Explanations

H03 is rejected. Respondents who value explanations more are more willing to rely on AI ($R = 0.609$, $p < 0.001$), and importance alone explains 37.0% of the variation in reliance. Respondents also rated the importance of explanations (mean 4.67) higher than how understandable current AI explanations are (mean 4.33), which points to an unmet need.

Usage Frequency and Age

H04 is rejected. Mean trust differs significantly across usage-frequency groups ($F = 28.37$) and age groups ($F = 10.55$). Usage frequency explains 59.89% and age 30.53% of the variation in trust (eta-squared). ANOVA shows that at least one group differs, not which; the group means show that trust is lowest among people who never or rarely use AI and among those aged 45 and above.

Usage Group and the Wish for Explanations

H05 is rejected. The wish for explanations is strongly linked with usage: 97.10% of frequent users said "Yes" against 50.00% of occasional users. Younger respondents were also more likely to say "Yes". Half of the occasional users were not convinced that explanations would raise their trust.

Key Findings

- Perceived explainability and trust are strongly and positively related ($R = 0.82$, R-squared = 0.67).
- Transparency, comfort and familiarity all help predict trust; transparency has the largest effect.
- The more respondents value explanations, the more willing they are to rely on AI ($R = 0.61$).
- 82.18% of respondents would trust AI more if it explained its decision.
- Trust is highest among daily and younger users and lowest among non-users and those aged 45 and above.
- The wish for explanations is much stronger among frequent users than occasional users.
- Importance of explanations is rated higher than how understandable current AI explanations are, indicating an unmet need.

Limitations of the Study

- The sample is small ($n = 101$), collected by convenience sampling and weighted towards young, frequent AI users.
- Many respondents gave the maximum score on most items (ceiling effect), which limits variation in the data.
- Each concept is measured with a single self-reported statement; no reliability analysis of scales was done.
- Regression, ANOVA and chi-square show association, not cause and effect; predictors overlap strongly. Some groups are very small.

FUTURE SCOPE

- Use a larger, random and more diverse sample, including rural and older users.
- Use multi-item scales and test reliability; study specific sectors such as healthcare, banking and education.
- Run experiments in which one group sees AI explanations and a control group does not, to test cause and effect.

CONCLUSION

The study finds that explainability, along with transparency, comfort and familiarity, is closely associated with trust in AI-based systems, and that people who value explanations are more willing to rely on AI. Most respondents said that explanations would increase their trust, while the gap between the importance of explanations and their current clarity suggests that AI tools can still improve. Developers and policymakers should therefore treat clear, understandable explanations as a basic part of AI design. Because the sample is limited, the results should be treated as indicative evidence and tested further on larger samples.

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