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An Empirical Study on the Use of Generative AI for Financial Decision-Making Among Corporate Employees in Bengaluru

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Abstract: ***Generative AI tools such as ChatGPT and Gemini are now a common source of financial guidance. People will act on this guidance only if they trust it. This study looks at what shapes that trust and whether it carries over into financial decisions. We surveyed 256 corporate employees in Bengaluru. Of these, 217 had already used a generative AI tool for a financial query, and they formed the analysis sample. We used multiple linear regression to test how perceived usefulness, perceived risk and perceived transparency relate to trust. We used PLS-SEM to study the link between trust and financial decision-making, and the moderating role of financial literacy. Perceived transparency (β = 0.453) and perceived usefulness (β = 0.275) both predicted trust. Together they explained 46.5% of its variance. Perceived risk did not. Trust was positively related to financial decision-making (β = 0.112, p = 0.022), but the effect was small. Financial literacy did not moderate this relationship (β = −0.026, p = 0.494). The results suggest that AI providers are more likely to earn trust by making their tools clearly useful and open about how answers are produced. Trying to reassure users about risk seems less effective.***

Keywords: Generative AI, Trust, Financial Decision-Making, Financial Literacy, Perceived Transparency, Perceived Usefulness, PLS-SEM, Corporate Employees

I. INTRODUCTION

Ask a chatbot how to split a monthly salary between savings and a home loan. Or ask whether a tax-saving instrument is worth its lock-in period. An answer arrives within seconds. This convenience is why tools such as ChatGPT and Gemini have gone from novelty to habit. People now use them often for budgeting, investing, taxes and retirement planning. But easy access does not mean an answer is safe to act on. Financial choices have real and often lasting consequences. A person who follows poor guidance may not notice until the damage is done.

Trust links the availability of AI-generated guidance to its actual use [1]. Earlier work on robo-advisors and conversational agents shows that people weigh three things. They look at how useful the advice is, how risky it feels to depend on it, and how well they can understand where it comes from [2], [3], [4]. It is much less clear whether these perceptions shape trust in generative tools. It is also unclear whether that trust shows up in financial decision-making. What users already know about money adds another layer. A person with strong financial knowledge may treat an AI answer as one input to check. A person with less knowledge may lean on it more. This could change how far trust turns into decisions [5].

Most of the evidence comes from consumers and investors in Europe, East Asia and other markets. Studies of salaried corporate employees in India are scarce. Bengaluru is a good place to look. Its workforce is large, technology-oriented and quick to try new digital tools. That makes it a useful setting for asking how trust in AI financial guidance takes shape.

This paper asks three questions. How do perceived usefulness, perceived risk and perceived transparency influence trust in generative AI financial guidance? Is that trust related to financial decision-making? And does financial literacy change how strong this relationship is? We answer them using a survey of 256 corporate employees in Bengaluru.

II. REVIEW OF LITERATURE

A. AI as a Financial Adviser

The first body of work asks whether AI can do the job of a personal adviser. Takayanagi et al. [2] had 64 participants talk with chatbots that had different personality styles. They then assessed how well each chatbot understood the participant, how good its advice was and how much it was trusted. The doubt behind the study was twofold. Can a chatbot grasp what an individual investor needs? And does giving it a personality make it as credible as a human adviser? Other studies compare machine and human advice

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directly. These include a comparison of ChatGPT and Google Bard as substitutes for human advisers [6] and an experiment on advice from humans, machines or both [7]. Earlier work also discussed human–AI collaboration in financial planning [8].
Mirabile et al. [1] took a wider view. They followed PRISMA guidance and narrowed 430 Scopus records from 2018 to 2025 down to 114 papers. They then mapped the field using bibliometric methods. They found that studies discuss trust between people and AI in finance in scattered ways. This makes it hard for later work to build on earlier findings.

B. Acceptance, Usefulness and Perceived Risk

Technology acceptance models are the usual starting point for explaining why people adopt AI financial tools. Ming et al. [9] surveyed existing ChatGPT users with an extended acceptance model. The model added herding behaviour and social influence. They found that usefulness, herding and social influence all drove the intention to use ChatGPT for finance-related searches. Szopiński et al. [10] applied a similar model to 371 respondents from three Polish universities. Using PLS-SEM, they found that perceived ease of use, perceived usefulness and attitude were linked to actual use of AI tools in personal financial decisions.
Standard models do not explain everything. Fitriani and Basir [3] argued that they leave trust and risk perception underexplained. They surveyed 412 people who had used AI financial services. Their dual-process model separated rational trust from emotional trust. It examined how each relates to adoption, alongside satisfaction and perceived risk. Waliszewski and Warchlewska [11] took a different angle. They used international survey data to test whether age, income and education relate to satisfaction with AI-based financial planning.

C. Transparency and Explainability

Many AI models used in finance work as black boxes. The lack of clear reasoning is thought to weaken trust, accountability and regulatory compliance. Staley [4] combined a Likert-scale survey with a review of literature, case studies and regulation. The aim was to see how explainable AI can help build trust in financial services. Yue et al. [12] tackled the same problem from a technical side. They paired SHAP, which shows what drove a model's prediction, with ChatGPT, which restates the result in plain language. This lets ordinary users follow predictions that even experts find hard to explain.

D. Financial Literacy and AI Tools

Financial literacy appears in this literature both as an outcome and as a condition that shapes how AI is used. Bacha and HajMohamed [5] surveyed 121 French stock investors on five uses of ChatGPT: data analysis, risk assessment, portfolio management, forecasting and sentiment analysis. Their PLS-SEM results indicated that financial literacy moderates reliance on AI insights. Ng [13] and Praveen et al. [14] review how robo-advisors and machine learning may improve literacy, investment decisions and risk assessment. They note that long-term evidence is thin, especially in volatile markets. Evidence on trust among less experienced users is also thin. Agarwal et al. [15] point to a practical problem with current personal finance tools. These tools apply fixed rules and generic advice instead of adapting to each user.

E. Research Gap

Taken together, these studies leave several gaps. Little research looks at corporate employees in Bengaluru and how they use generative AI for financial decisions. Most work examines general consumers or investors, often outside India. Findings from those settings may not carry over to the Indian corporate context. Few studies test how perceived usefulness, risk and transparency together influence trust in generative AI financial guidance. The link between that trust and financial decision-making needs more study. The moderating role of financial literacy is also underexplored.

III. OBJECTIVES AND HYPOTHESES

The study has three objectives. (1) To assess how perceived usefulness, perceived risk and perceived transparency of generative AI influence trust in AI-generated financial guidance. (2) To analyse the relationship between that trust and financial decision-making. (3) To find out whether financial literacy changes how strongly trust affects financial decision-making. All three are studied among corporate employees in Bengaluru.
Fig. 1 shows the conceptual model. Perceived usefulness (PU), perceived risk (PR) and perceived transparency (PT) are treated as antecedents of trust. Trust is linked to financial decision-making (DM). Financial literacy (FL) is placed as a moderator of that link. We tested the following hypotheses.

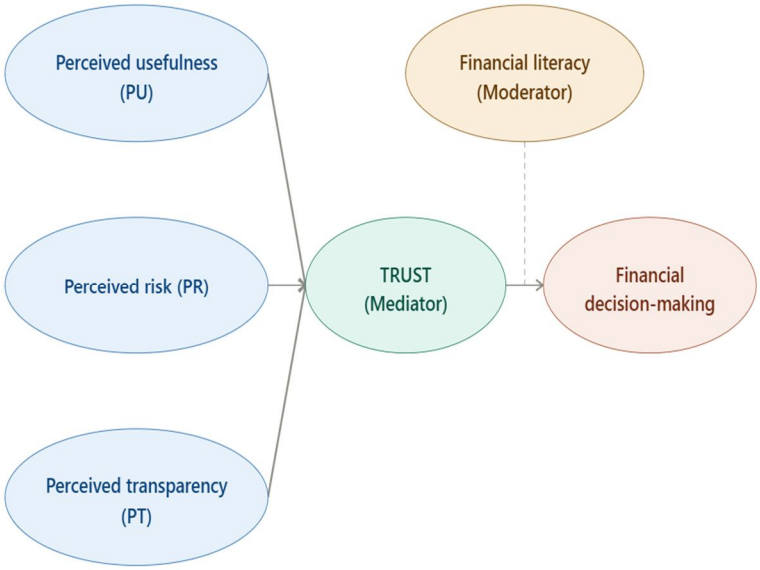


Fig. 1 Conceptual model of the study: perceived usefulness, perceived risk and perceived transparency influence trust, which relates to financial decision-making, with financial literacy as moderator

H1a: Perceived usefulness has a significant influence on trust in AI-generated financial guidance. *H1b:* Perceived risk has a significant influence on trust in AI-generated financial guidance. *H1c:* Perceived transparency has a significant influence on trust in AI-generated financial guidance. *H2:* Trust in AI-generated financial guidance has a significant positive relationship with financial decision-making. *H3:* Financial literacy significantly moderates the relationship between trust in AI-generated financial guidance and financial decision-making.

IV. RESEARCH METHODOLOGY

A. Design and Sample

The study used a quantitative, cross-sectional survey. All responses therefore reflect a single point in time. We collected data from corporate employees working in Bengaluru and kept 256 valid responses. Of these, 217 respondents (84.8%) had used a generative AI tool for a financial query or piece of advice. The constructs concern trust in such guidance and its use in decisions. So the regression and structural model analyses were run on these 217 respondents. The respondent profile in Section V-A covers all 256.

B. Instrument

We used a structured questionnaire. All construct items were rated on a five-point Likert scale. It covered six constructs: perceived usefulness, perceived risk, perceived transparency, trust in AI-generated financial guidance, financial literacy and financial decision-making. In the final measurement model, five items each measured usefulness, risk, transparency, financial literacy and decision-making. Four items measured trust. The questionnaire also collected age, gender, designation, work experience and how often respondents used generative AI for financial matters.

C. Analysis

We first summarised respondent characteristics descriptively. We then checked reliability and convergent validity using Cronbach's alpha, composite reliability and average variance extracted (AVE). Multiple linear regression was used for the first objective. PLS-SEM with a moderation (interaction) term was used for the second and third objectives. Fig. 2 shows the full structural model with item loadings.

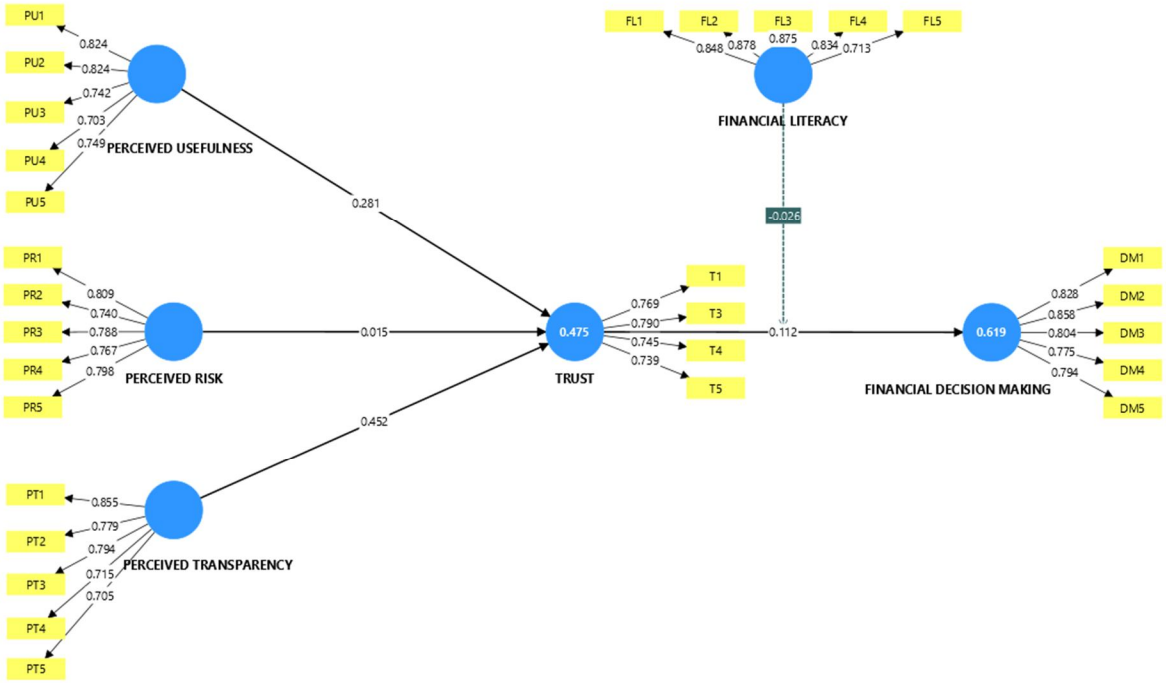


Fig. 2 Structural model with item loadings, path coefficients and R^2 values (PLS-SEM)

V. RESULTS AND DISCUSSION

A. Respondent Profile

Table I summarises the sample. Respondents were young and early in their careers. Most (87.5%) were below 35 years of age. 82.9% were at junior or mid level, and 76.9% had less than five years of experience. The sample was 57.8% male and 42.2% female. The results therefore mainly reflect the views of young, digitally active employees who do day-to-day work. They say less about senior managers.

Use of generative AI for financial matters was already common. Of the 256 respondents, 217 (84.8%) had used a generative AI tool for a financial query or piece of advice. The other 39 (15.2%) had not. Weekly use was the most common pattern (33.6%), followed by occasional use (28.5%). Only 16.8% reported daily use. So many people have tried generative AI for financial questions, but it is not yet an everyday habit for most.

TABLE I
RESPONDENT PROFILE (N = 256)

Characteristic	Distribution (%)
Age group	Below 25: 31.6; 25–34: 55.9; 35–44: 9.0; 45–54: 2.7; 55 and above: 0.8
Gender	Male: 57.8; Female: 42.2
Designation	Junior / entry-level: 39.1; Mid-level: 43.8; Senior-level: 11.7; Managerial / leadership: 5.4
Experience (years)	Less than 2: 39.8; 2–5: 37.1; 5–10: 16.0; More than 10: 7.0
Generative AI use for finance	Daily: 16.8; Weekly: 33.6; Occasionally: 28.5; Rarely: 12.5; Never used: 8.6

B. Reliability and Validity

Table II reports how well the six constructs were measured. Cronbach's alpha ranged from 0.758 to 0.888. Composite reliability ranged from 0.846 to 0.918. All values were above the usual 0.70 threshold. AVE values ranged from 0.579 to 0.692, above the 0.50 benchmark for convergent validity. Trust had the lowest values (α = 0.758, CR = 0.846, AVE = 0.579), but these are still acceptable. Item loadings were between 0.703 and 0.878 (Fig. 2).

TABLE II
CONSTRUCT RELIABILITY AND VALIDITY

Construct	**α**	**CR (ρa)**	**CR (ρc)**	**AVE**
Financial decision-making	0.871	0.871	0.906	0.660
Financial literacy	0.888	0.898	0.918	0.692
Perceived risk	0.840	0.843	0.886	0.610
Perceived transparency	0.829	0.844	0.880	0.595
Perceived usefulness	0.827	0.831	0.879	0.593
Trust	0.758	0.762	0.846	0.579

C. Determinants of Trust (Objective 1)

We estimated the regression model for trust on the 217 respondents who had used generative AI for a financial query. The model was statistically significant: $R = 0.682$, $R^2 = 0.465$, adjusted $R^2 = 0.457$, $F(3, 213) = 61.676$, $p < 0.001$. The three perceptions together explained 46.5% of the variance in trust. Variance inflation factors were between 1.450 and 2.160. This points to no serious multicollinearity. Table III gives the coefficients.

TABLE III
REGRESSION OF TRUST ON PERCEIVED USEFULNESS, RISK AND TRANSPARENCY

Predictor	B	β	t	p
(Constant)	1.042	—	5.161	<0.001
Perceived usefulness	0.258	0.275	3.799	<0.001
Perceived risk	0.011	0.012	0.196	0.845
Perceived transparency	0.422	0.453	6.149	<0.001

Perceived transparency was the strongest predictor of trust (β = 0.453, $p < 0.001$). Perceived usefulness came next (β = 0.275, $p < 0.001$). Perceived risk had no significant effect (β = 0.012, p = 0.845). So H1a and H1c are supported, and H1b is not. The fitted equation is Trust = 1.042 + 0.258(PU) + 0.011(PR) + 0.422(PT).

The role of transparency agrees with the view that opaque reasoning damages trust in financial AI [4], [12]. The role of usefulness fits acceptance studies, where usefulness drives the intention to use AI tools and their actual use [9], [10]. The lack of a risk effect is less expected, because risk perception is often described as a barrier to adoption [3]. There are two possible reasons. The sample is young and already familiar with these tools, so risk may weigh less on trust than it would for cautious first-time users. Also, people who find a tool useful and easy to understand may simply worry less about risk. Our data cannot separate these explanations. We offer them as ideas to test, not as findings.

D. Trust and Financial Decision-Making (Objective 2)

Table IV gives the structural model results. Trust had a positive and statistically significant relationship with financial decision-making (β = 0.112, t = 2.292, p = 0.022), so H2 is supported. Employees who trust AI-generated financial guidance more tend to report stronger financial decision-making. The paths from the antecedents to trust closely matched the regression results. Usefulness (β = 0.281, $p < 0.001$) and transparency (β = 0.452, $p < 0.001$) were significant. Risk was not (β = 0.015, p = 0.817). The model explained 47.5% of the variance in trust and 61.9% in financial decision-making.

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TABLE IV
STRUCTURAL MODEL RESULTS

Path	β	t	p	Result
PU → Trust	0.281	3.563	<0.001	Supported
PR → Trust	0.015	0.232	0.817	Not supported
PT → Trust	0.452	6.558	<0.001	Supported
Trust → DM	0.112	2.292	0.022	Supported
Trust × FL → DM	−0.026	0.683	0.494	Not supported

The effect is statistically reliable but small. Its size should be read with care. The R^2 for decision-making is high, which suggests that other variables in the model explain much of it. These could include financial literacy as a direct influence, but this study did not test that. Trust looks like a relevant factor in how employees use generative AI for financial decisions. It is not the only one.

E. Moderating Role of Financial Literacy (Objective 3)

The interaction between trust and financial literacy was negative, very small and not significant (β = −0.026, t = 0.683, p = 0.494; Table IV). The t-value is well below 1.96, so H3 is not supported. In this sample, financial literacy did not change how strongly trust related to financial decision-making. This suggests that trust works in a similar way whatever an employee's level of financial knowledge.

This differs from the study of French investors, where financial literacy moderated reliance on AI insights [5]. The samples and settings are not the same. That study looked at investment tasks among stock investors. Ours covers a broader idea of financial decision-making among employees who are mostly early in their careers. A sample with little variation in experience may also leave less room for literacy to make a visible difference. A more varied sample, or separate measures for specific decision types, could help clarify this.

VI. FINDINGS AND CONTRIBUTIONS

We found four main things. First, usage is high: 84.8% of respondents had used generative AI for financial queries or advice. Second, transparency and usefulness both build trust. Transparency is the stronger of the two. Perceived risk has no significant effect on trust. Third, trust is positively but only modestly related to financial decision-making. Fourth, financial literacy does not significantly moderate that relationship.

The study adds to what we know about how corporate employees use generative AI for financial guidance. It gives evidence from Bengaluru, which adds an Indian corporate setting to a literature dominated by other regions. For providers of AI financial tools, the results suggest a clear priority. Making guidance more useful and more transparent is likely to matter more for trust than addressing risk perception. One way to do this is to show the reasoning or sources behind an answer. Testing financial literacy as a moderator also gave a null result, which is informative for later research.

VII. CONCLUSIONS

This study examined how trust in generative AI financial guidance influences financial decision-making among corporate employees in Bengaluru. It also looked at what shapes that trust. Perceived usefulness and perceived transparency significantly raised trust. Transparency was the stronger predictor. Perceived risk did not matter. Trust was significantly and positively related to financial decision-making, though the effect was small. Financial literacy did not moderate the relationship. AI tools that are clearly useful and open about how they reach their answers appear more important for building trust. They matter more than addressing risk perception or relying on users' financial knowledge.

The study has some limitations. The cross-sectional design captures one moment and cannot show how trust changes over time. The sample is limited to corporate employees in Bengaluru. The model results rest on the 217 respondents who had already used generative AI for financial queries. So the findings may not extend to other cities, to non-users or to other groups. The data are self-reported and may not match exactly what respondents felt or remembered.

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Future studies could follow users over time to see how trust changes with continued use. They could include other Indian cities and compare corporate employees with groups such as students and retail investors. They could also add interviews to the survey, to understand why people trust or distrust AI-generated financial advice.

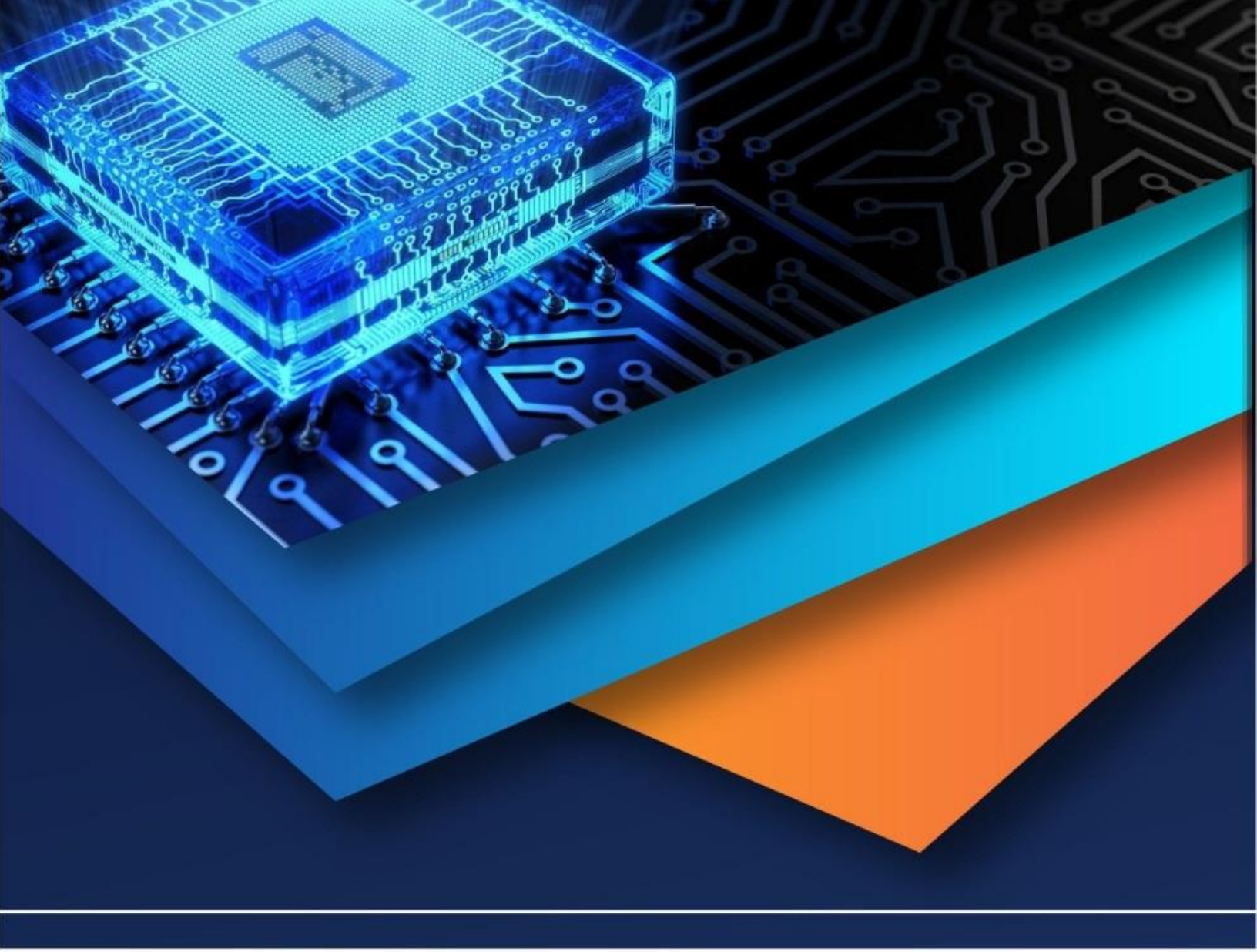
VIII. ACKNOWLEDGMENT

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