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Artificial Intelligence and Human- Cantered Innovation: A Multidisciplinary Study of Diverse Perspectives

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Abstract: *Artificial Intelligence (AI) has rapidly evolved from a specialized computational discipline into a general-purpose technology that is reshaping industry, education, healthcare, commerce, and governance. While the technical capabilities of AI systems continue to expand, growing evidence suggests that the long-term success of AI deployment depends less on algorithmic sophistication and more on the extent to which such systems are designed around human values, needs, and capabilities. This study investigates the determinants of human-centered AI innovation adoption through a multidisciplinary lens, integrating perspectives from information technology, academia, management, healthcare, and student communities. A structured questionnaire based on a five-point Likert scale was administered to 412 respondents selected through stratified random sampling across five stakeholder groups in India. The instrument captured five constructs: perceived usefulness, perceived ease of use, trust in AI, ethical concern, and organizational support. Reliability of the instrument was confirmed using Cronbach's alpha ($\alpha = 0.87$), and the data were analyzed using descriptive statistics, Pearson correlation, multiple regression analysis, and one-way ANOVA. The regression model explained 64.2% of the variance in adoption intention ($R^2 = 0.642$, $F = 145.63$, $p < 0.001$). Perceived usefulness ($\beta = 0.412$) emerged as the strongest positive predictor, followed by trust in AI ($\beta = 0.334$), perceived ease of use ($\beta = 0.287$), and organizational support ($\beta = 0.256$), while ethical concern exerted a significant negative influence ($\beta = -0.198$). ANOVA results revealed statistically significant differences in adoption readiness across stakeholder groups ($F = 18.42$, $p < 0.001$), with IT professionals and students reporting the highest readiness and healthcare professionals the lowest. The findings underscore that human-centered design, transparent governance, and capacity building are essential to converting technological capability into socially beneficial innovation. The paper concludes with managerial, educational, and policy implications, and outlines directions for future longitudinal and cross-cultural research.*

Keywords: Artificial Intelligence; Human-Centered Innovation; Technology Acceptance; Trust in AI; AI Ethics; Multidisciplinary Research; Adoption Intention; Stakeholder Perspectives

I. INTRODUCTION

The twenty-first century has witnessed an unprecedented acceleration in the development and diffusion of Artificial Intelligence. Machine learning models now match or exceed human performance in narrow domains such as image recognition, language translation, medical diagnosis support, and strategic game playing. Generative AI systems have further democratized access to advanced capabilities, enabling individuals and organizations of all sizes to produce text, code, designs, and analyses at a scale that was unimaginable a decade ago. According to multiple industry estimates, AI technologies are projected to contribute trillions of dollars to the global economy over the coming decade, with emerging economies such as India positioned to capture a substantial share of this value through their large digital workforces and rapidly expanding technology sectors.

However, the trajectory of AI development has not been uniformly celebrated. Concerns about algorithmic bias, opacity of decision-making, displacement of human labor, erosion of privacy, and concentration of technological power have generated intense debate among scholars, practitioners, and policymakers. These concerns have given rise to the paradigm of human-centered AI (HCAI), which argues that AI systems should be designed to amplify, augment, and enhance human abilities rather than replace them, and that human control, dignity, and wellbeing must remain central design objectives. Human-centered innovation, in this context, refers to the process of creating and deploying technological solutions whose value is measured not only in efficiency gains but also in their contribution to human flourishing, fairness, and societal trust.

Despite the growing prominence of HCAI in academic and policy discourse, empirical research on how diverse stakeholder groups actually perceive and respond to AI-driven innovation remains fragmented. Much of the existing literature examines single populations, such as software engineers or university students, or single sectors, such as banking or healthcare. Comparatively little is known about how perceptions of usefulness, ease of use, trust, ethics, and organizational support jointly shape adoption intentions across heterogeneous communities, and whether these mechanisms differ systematically between groups. This gap is particularly salient in multidisciplinary environments, where AI systems must serve users with very different technical literacies, professional norms, and value systems.

The present study addresses this gap by pursuing four research objectives. First, it measures the levels of perceived usefulness, perceived ease of use, trust in AI, ethical concern, and organizational support among five stakeholder groups: information technology professionals, academicians, management executives, healthcare professionals, and students. Second, it examines the relationships between these constructs and the intention to adopt human-centered AI innovations. Third, it quantifies the relative predictive power of each construct through multiple regression analysis. Fourth, it tests whether adoption readiness differs significantly across stakeholder groups, thereby revealing where targeted interventions such as training, communication, or governance reform may be most needed.

Accordingly, the study tests the following hypotheses. H1: Perceived usefulness has a significant positive effect on the intention to adopt human-centered AI innovation. H2: Perceived ease of use has a significant positive effect on adoption intention. H3: Trust in AI has a significant positive effect on adoption intention. H4: Ethical concern has a significant negative effect on adoption intention. H5: Organizational support has a significant positive effect on adoption intention. H6: Adoption readiness differs significantly across stakeholder groups.

The significance of this inquiry extends beyond academic interest. India's National Strategy for Artificial Intelligence envisions 'AI for All,' positioning the technology as an instrument of inclusive growth in agriculture, healthcare, education, smart mobility, and financial services. Realizing this vision requires more than computational infrastructure; it requires that millions of professionals, educators, clinicians, managers, and students perceive AI systems as useful, usable, trustworthy, and ethically sound. Empirical evidence on what drives or inhibits these perceptions is therefore an essential input to corporate strategy, curriculum design, and public policy alike. Moreover, because human-centered innovation is fundamentally multidisciplinary, joining computer science with management, ethics, psychology, and domain expertise, research that compares perspectives across disciplines can reveal frictions and synergies that single-discipline studies necessarily miss.

The study makes three contributions. Conceptually, it integrates classical technology acceptance constructs with AI-specific constructs of trust and ethical concern within a single explanatory model of human-centered innovation adoption. Empirically, it provides comparative evidence from five stakeholder groups in an emerging economy, a setting that remains underrepresented in the AI adoption literature despite its global importance. Practically, it translates statistical findings into differentiated recommendations for managers, educators, and policymakers, identifying which levers, namely value demonstration, trust building, usability improvement, ethical assurance, and organizational support, matter most for which audiences.

The remainder of the paper is organized as follows. Section 2 reviews the related literature on AI adoption, human-centered design, and AI ethics. Section 3 describes the research methodology, including the conceptual model, sampling design, measurement instrument, statistical equations, and process flowchart. Section 4 presents the results with supporting tables and charts and discusses their implications. Section 5 concludes the paper, acknowledges limitations, and identifies avenues for future research.

II. RELATED WORK

2.1 Technology Acceptance and AI Adoption

Research on technology adoption has been dominated by the Technology Acceptance Model (TAM) proposed by Davis (1989), which posits that perceived usefulness and perceived ease of use are the primary determinants of an individual's intention to use a new technology. Venkatesh et al. (2003) extended this framework into the Unified Theory of Acceptance and Use of Technology (UTAUT), incorporating social influence and facilitating conditions as additional predictors. Subsequent studies have applied and adapted these models to AI-specific contexts, finding that classical acceptance constructs remain relevant but require augmentation with AI-specific factors such as algorithmic transparency, anthropomorphism, and perceived intelligence. Makridakis (2017) argued that the AI revolution will differ from previous industrial and digital revolutions in both speed and scope, intensifying the need to understand the behavioral mechanisms underlying adoption.

In the Indian context, several studies have documented high enthusiasm for AI adoption among technology professionals and students, coupled with persistent concerns about job security, skill obsolescence, and infrastructure readiness. Dwivedi et al. (2021) synthesized multidisciplinary perspectives on AI and emphasized that successful adoption depends on the interplay of technological, organizational, and environmental factors, a view consistent with the broader information systems literature.

2.2 Human-Centered Artificial Intelligence

The human-centered AI paradigm has been most comprehensively articulated by Shneiderman (2020, 2022), who proposed a two-dimensional framework in which high levels of human control and high levels of computer automation are not mutually exclusive but can be jointly achieved through careful design. HCAI advocates argue that reliable, safe, and trustworthy systems emerge when designers prioritize human oversight, auditability, and the amplification of human capabilities. Xu (2019) similarly called for a transition from technology-centered to human-centered AI engineering practice, noting that user experience professionals must be involved throughout the AI lifecycle rather than only at the interface stage.

Closely related is the literature on augmentation versus automation. Brynjolfsson and McAfee (2014) demonstrated that the greatest economic gains arise when machines complement human strengths rather than substitute for them. Wilson and Daugherty (2018) introduced the notion of collaborative intelligence, documenting how firms that redesign workflows around human-machine teaming outperform those that pursue pure automation. These insights inform the present study's conceptualization of human-centered innovation as a collaborative, augmentation-oriented mode of AI deployment.

2.3 Trust, Ethics, and Governance of AI

Trust has emerged as a central construct in AI research because the opacity of machine learning models complicates the traditional bases of trust formation. Glikson and Woolley (2020) reviewed empirical research on human trust in AI and identified tangibility, transparency, reliability, and immediacy as key antecedents. Studies of algorithm aversion show that users abandon algorithmic advice after observing errors more readily than they abandon human advice, underscoring the fragility of trust in automated systems.

Parallel to the trust literature, a substantial body of work addresses the ethics of AI. Jobin, Ienca, and Vayena (2019) analyzed 84 AI ethics guidelines worldwide and found convergence around five principles: transparency, justice and fairness, non-maleficence, responsibility, and privacy. Floridi et al. (2018) proposed the AI4People framework, mapping ethical principles onto concrete recommendations for a 'good AI society.' Empirical studies suggest that heightened ethical concern can suppress adoption intention, particularly among professionals whose domains involve sensitive personal data, such as healthcare and education. The present study therefore models ethical concern as a potential negative predictor of adoption intention.

A further strand of literature examines explainable AI (XAI) as a bridge between technical opacity and stakeholder trust. Explanation methods that expose feature importance, counterfactual scenarios, or example-based reasoning have been shown to improve users' calibration of trust, helping them rely on algorithmic advice when it is dependable and to question it when it is not. However, scholars caution that explanations can also mislead if they create an illusion of understanding, and that the appropriate form and depth of explanation depend on the audience: a data scientist, a hospital administrator, and a patient require very different accounts of the same model. This audience-sensitivity of trust and transparency reinforces the rationale for studying multiple stakeholder groups within a common framework, as the present study does.

2.4 Multidisciplinary Evidence Across Sectors

Sector-level studies enrich the picture painted by general adoption models. In education, research documents that AI-enabled tutoring, automated assessment, and learning analytics can personalize instruction at scale, yet faculty acceptance hinges on perceived pedagogical value, workload implications, and concerns about academic integrity and student data privacy. In healthcare, clinical decision support systems and diagnostic imaging tools have demonstrated impressive accuracy, but adoption studies consistently report that clinicians demand rigorous validation, clear liability arrangements, and preserved professional autonomy before integrating algorithmic recommendations into care pathways. The healthcare literature thus exemplifies a setting where high potential usefulness coexists with elevated ethical and professional concern.

In management and commerce, AI applications span demand forecasting, customer relationship management, recruitment screening, and financial risk assessment. Studies of managerial adoption highlight the importance of top management support, data infrastructure readiness, and the interpretability of model outputs for accountability purposes. Research on student populations, meanwhile, shows generally high enthusiasm and self-efficacy with AI tools, tempered by anxieties about future employability and the integrity of AI-assisted work. These heterogeneous findings across sectors motivate the comparative, multi-group design of the present study: if the determinants and levels of adoption readiness differ systematically by stakeholder community, then deployment strategies and governance instruments must be correspondingly differentiated.

2.5 Research Gap

Three gaps emerge from the foregoing review. First, most empirical AI adoption studies sample a single occupational group, limiting the comparability of findings across stakeholder communities. Second, the constructs of trust and ethical concern are often studied in isolation from the classical acceptance constructs, preventing an integrated assessment of their relative importance. Third, evidence from emerging economies remains underrepresented relative to North American and European samples. By surveying five distinct stakeholder groups in India with a single integrated instrument, this study contributes a multidisciplinary, comparative, and emerging-market perspective on human-centered AI innovation.

III. RESEARCH METHODOLOGY

3.1 Research Design

The study adopts a quantitative, cross-sectional, descriptive-cum-analytical research design. A survey strategy was selected because the research objectives require the measurement of perceptions and intentions across a large and heterogeneous population, and because survey data permit the application of inferential statistical techniques for hypothesis testing. The conceptual model treats adoption intention toward human-centered AI innovation as the dependent variable and five constructs as independent variables: perceived usefulness (PU), perceived ease of use (PEOU), trust in AI (TR), ethical concern (EC), and organizational support (OS).

The conceptual framework is grounded in three theoretical pillars. The Technology Acceptance Model supplies the instrumental pillar, predicting that usefulness and ease of use drive intention. The human-centered AI literature supplies the relational pillar, positioning trust as the mechanism through which transparency, reliability, and human oversight translate into willingness to depend on automated systems. The AI ethics literature supplies the normative pillar, treating ethical concern as a behavioral inhibitor that operates even when instrumental evaluations are favorable. Organizational support, drawn from the facilitating-conditions construct of UTAUT, represents the institutional environment in which individual judgments are formed. The framework therefore predicts that adoption intention rises with PU, PEOU, TR, and OS, falls with EC, and that the levels of these constructs, though not the structure of their effects, vary across stakeholder groups owing to differences in technical exposure, professional norms, and ethical proximity to affected populations.

3.2 Population, Sample, and Data Collection

The target population comprised five stakeholder groups in India: IT professionals, academicians, management executives, healthcare professionals, and postgraduate students. Stratified random sampling was employed to ensure adequate representation of each group. The minimum sample size was determined using Cochran's formula for large populations:

$$n_0 = Z^2\, p\, q \,/\, e^2 \qquad (1)$$

where Z is the standard normal value at the 95% confidence level (1.96), p is the estimated population proportion (taken as 0.5 to maximize variance), $q = 1 - p$, and e is the desired margin of error (0.05). Substituting these values yields a minimum required sample of approximately 384 respondents. A total of 450 questionnaires were distributed through online and offline channels between January and March 2026, of which 412 complete and usable responses were received, giving an effective response rate of 91.6% and exceeding the minimum requirement.

3.3 Instrument Development and Reliability

The questionnaire contained two parts. Part A captured demographic information, including stakeholder group, age, gender, and years of professional experience. Part B contained 24 statements measuring the six constructs (four items each) on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). Items were adapted from validated scales in the technology acceptance and trust literature and refined through expert review by three faculty members in management and computer science. A pilot study with 40 respondents was conducted, and internal consistency was assessed using Cronbach's alpha:

$$\alpha = (k \,/\, (k - 1)) \times (1 - \Sigma\sigma i^2 \,/\, \sigma t^2) \qquad (2)$$

where k is the number of items, σi^2 is the variance of item i, and σt^2 is the variance of the total score. All constructs exceeded the conventional threshold of 0.70, with alpha values ranging from 0.79 to 0.89 and an overall instrument alpha of 0.87, indicating satisfactory reliability.

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3.4 Statistical Techniques

Data analysis proceeded in four stages. First, descriptive statistics (means, standard deviations, and percentages) summarized the demographic profile and construct scores. Second, Pearson's product-moment correlation examined bivariate associations between constructs:

$$r = \Sigma(x_i - \bar{x})(y_i - \bar{y}) \,/\, \sqrt{[\Sigma(x_i - \bar{x})^2\, \Sigma(y_i - \bar{y})^2]} \qquad (3)$$

Third, multiple linear regression estimated the joint and relative influence of the five predictors on adoption intention (AI_INT):

$$AI\_INT = \beta 0 + \beta 1PU + \beta 2PEOU + \beta 3TR + \beta 4EC + \beta 5OS + \varepsilon \qquad (4)$$

where β0 is the intercept, β1 through β5 are the regression coefficients, and ε is the random error term. The coefficient of determination R^2 quantifies the proportion of variance in adoption intention explained by the model. Fourth, one-way analysis of variance (ANOVA) tested whether mean adoption readiness differed across the five stakeholder groups, using the F statistic:

$$F = MS_{between} \,/\, MS_{within} = (\mathrm{SSB} \,/\, (k - 1)) \,/\, (\mathrm{SSW} \,/\, (N - k)) \qquad (5)$$

where SSB is the between-group sum of squares, SSW is the within-group sum of squares, k is the number of groups, and N is the total sample size. All hypotheses were tested at the 5% significance level using SPSS version 29. Prior to regression, the data were screened for normality (skewness and kurtosis within ±1.5), multicollinearity (variance inflation factors below 2.1), and homoscedasticity, and no serious violations were detected.

3.5 Operational Definitions of Variables

For clarity of measurement, the constructs were operationalized as follows. Perceived usefulness denotes the degree to which a respondent believes that AI-based tools improve the effectiveness and outcomes of their work or study. Perceived ease of use denotes the degree to which interacting with AI tools is perceived as free of effort and easy to learn. Trust in AI captures the respondent's confidence that AI systems behave reliably, competently, and fairly, and that their outputs can be depended upon for consequential tasks. Ethical concern measures apprehension regarding bias and discrimination, privacy and surveillance, accountability for errors, and the broader societal effects of AI, including employment displacement. Organizational support reflects the perceived availability of training, resources, leadership encouragement, and institutional policies that facilitate AI use. Finally, adoption intention, the dependent variable, measures the respondent's stated willingness to use, recommend, and increase reliance on human-centered AI tools in the near future. Each construct was measured with four Likert items, and construct scores were computed as the arithmetic mean of their constituent items.

3.6 Ethical Considerations of the Study

The study adhered to established ethical norms for survey research involving human participants. Respondents were informed of the academic purpose of the study, participation was voluntary, and informed consent was obtained before the questionnaire was administered. No personally identifying information was collected, responses were anonymized at the point of entry, and data were stored on access-controlled systems used solely for the purposes of this research. Respondents were free to withdraw at any stage without consequence. These safeguards align with institutional ethical guidelines and with the broader principle, central to the study's own subject matter, that research on human-centered technology should itself be conducted in a human-centered manner.

3.7 Research Process Flowchart

Figure 1 depicts the sequential research process adopted in this study. The process begins with problem identification and the formulation of research objectives, followed by a structured review of the literature from which the hypotheses were derived. The survey instrument was then designed and subjected to a pilot study to verify reliability through Cronbach's alpha. Upon confirmation of instrument quality, full-scale data collection was undertaken using stratified random sampling. The collected data were screened for completeness, outliers, and distributional assumptions before

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the application of descriptive and inferential statistical techniques. The final stages involve hypothesis testing, interpretation of the empirical findings, and the derivation of conclusions, practical implications, and directions for future research. This staged design ensures methodological transparency and allows each analytical decision to be traced back to the study's objectives.

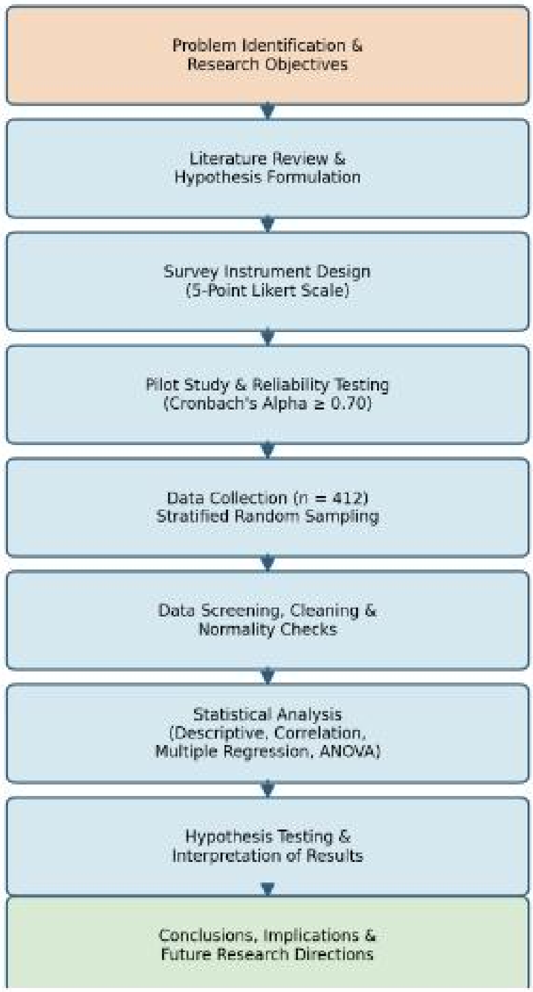

Figure 1. Research methodology flowchart

IV. RESULTS AND DISCUSSION

4.1 Demographic Profile of Respondents

Table 1 summarizes the demographic composition of the 412 respondents. The sample is reasonably balanced across the five stakeholder groups, with IT professionals (24.3%) and students (22.3%) forming the largest strata. Male respondents constitute 56.6% of the sample and female respondents 43.4%. Nearly half of the respondents (47.6%) fall in the 26–40 age bracket, reflecting the working-age concentration of AI exposure, while 31.1% are 25 or younger and 21.3% are above 40.

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Variable	Category	Frequency (n)	Percentage (%)
Stakeholder group	IT professionals	100	24.3
	Academicians	84	20.4
	Management executives	76	18.4
	Healthcare professionals	60	14.6
	Students	92	22.3
Gender	Male	233	56.6
	Female	179	43.4
Age	Up to 25 years	128	31.1
	26–40 years	196	47.6
	Above 40 years	88	21.3
Total		412	100.0

Table 1. Demographic profile of respondents (n = 412)

4.2 Descriptive Statistics and Reliability

Table 2 reports the means, standard deviations, and Cronbach's alpha values for the six constructs. Perceived usefulness records the highest mean ($M = 4.08$, $SD = 0.61$), indicating broad agreement that AI delivers tangible benefits to work and study. Adoption intention ($M = 3.91$) and trust in AI ($M = 3.76$) are also above the scale midpoint, while ethical concern ($M = 3.59$) reveals a non-trivial undercurrent of apprehension about fairness, privacy, and accountability. All alpha coefficients exceed 0.70, confirming the internal consistency of the measurement scales.

Construct	Items	Mean	SD	Cronbach's α
Perceived usefulness (PU)	4	4.08	0.61	0.86
Perceived ease of use (PEOU)	4	3.72	0.68	0.81
Trust in AI (TR)	4	3.76	0.71	0.84
Ethical concern (EC)	4	3.59	0.77	0.79
Organizational support (OS)	4	3.64	0.74	0.83
Adoption intention (AI_INT)	4	3.91	0.66	0.89

Table 2. Descriptive statistics and reliability of constructs

4.3 Correlation Analysis

Table 3 presents the Pearson correlation matrix. Adoption intention correlates positively and significantly with perceived usefulness ($r = 0.71$), trust in AI ($r = 0.66$), perceived ease of use ($r = 0.62$), and organizational support ($r = 0.58$), and negatively with ethical concern ($r = -0.41$), all at $p < 0.01$. The pattern of correlations is consistent with the

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hypothesized model and with prior technology acceptance research, while the moderate magnitudes among predictors (all below 0.60) indicate that multicollinearity is unlikely to distort the regression estimates.

Construct	1	2	3	4	5	6
1. PU	1					
2. PEOU	0.54**	1				
3. TR	0.49**	0.46**	1			
4. EC	−0.28**	−0.22**	−0.37**	1		
5. OS	0.42**	0.39**	0.44**	−0.19**	1	
6. AI_INT	0.71**	0.62**	0.66**	−0.41**	0.58**	1

Table 3. Pearson correlation matrix ($p < 0.01$)**

4.4 Multiple Regression Analysis

Table 4 reports the regression of adoption intention on the five predictors. The model is statistically significant ($F(5, 406) = 145.63$, $p < 0.001$) and explains 64.2% of the variance in adoption intention ($R^2 = 0.642$, adjusted $R^2 = 0.638$). Perceived usefulness is the strongest predictor ($\beta = 0.412$, $t = 9.84$, $p < 0.001$), supporting H1 and confirming the enduring centrality of utility perceptions established in the technology acceptance tradition. Trust in AI ($\beta = 0.334$, $t = 8.12$) supports H3, while perceived ease of use ($\beta = 0.287$, $t = 6.95$) supports H2 and organizational support ($\beta = 0.256$, $t = 6.21$) supports H5. Ethical concern carries a significant negative coefficient ($\beta = -0.198$, $t = -4.87$), supporting H4 and indicating that unresolved ethical apprehensions measurably suppress willingness to adopt. Figure 3 visualizes the standardized coefficients.

Predictor	B	SE	β	t	p-value	VIF
(Constant)	0.482	0.141	—	3.42	0.001	—
Perceived usefulness	0.446	0.045	0.412	9.84	< 0.001	1.92
Perceived ease of use	0.279	0.040	0.287	6.95	< 0.001	1.71
Trust in AI	0.310	0.038	0.334	8.12	< 0.001	1.78
Ethical concern	−0.170	0.035	−0.198	−4.87	< 0.001	1.31
Organizational support	0.228	0.037	0.256	6.21	< 0.001	1.46

Table 4. Multiple regression results (DV: adoption intention; $R^2 = 0.642$; $F = 145.63$; $p < 0.001$)

4.5 Group Differences: ANOVA Results

Figure 2 displays the mean scores of trust, adoption readiness, and ethical concern across the five stakeholder groups, and Table 5 reports the one-way ANOVA for adoption readiness. The F statistic ($F(4, 407) = 18.42$, $p < 0.001$) confirms statistically significant differences among groups, supporting H6. Post-hoc Tukey HSD comparisons indicate that IT professionals ($M = 4.21$) and students ($M = 4.18$) report significantly higher readiness than healthcare professionals ($M = 3.58$) and academicians ($M = 3.74$), with management executives occupying an intermediate position ($M = 4.02$). Conversely, ethical concern is highest among academicians and healthcare professionals, suggesting that proximity to sensitive data and to vulnerable populations sharpens ethical vigilance.

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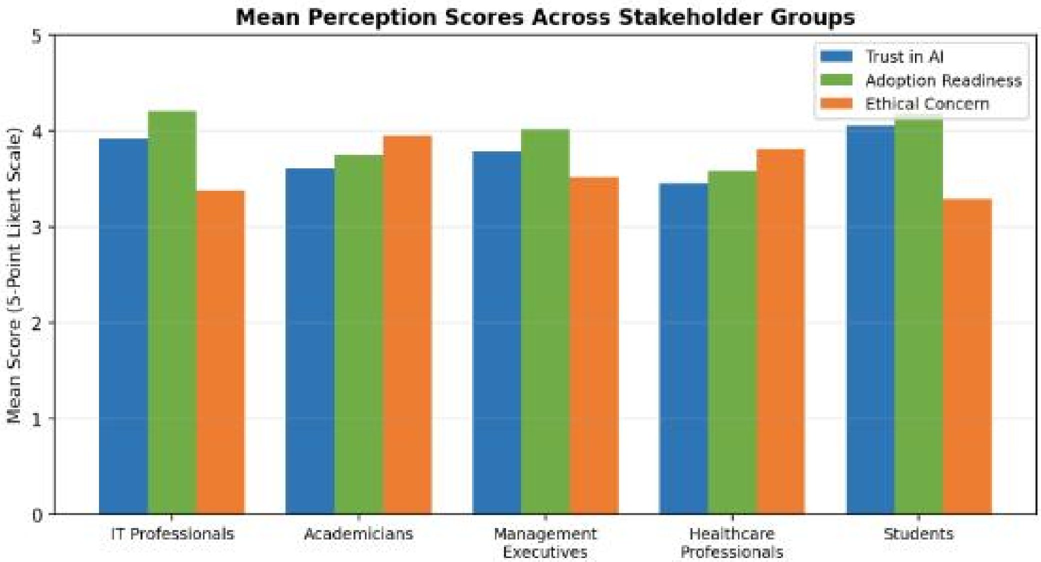

Figure 2. Mean perception scores across stakeholder groups

Source of variation	Sum of squares	df	Mean square	F	p-value
Between groups	26.84	4	6.710	18.42	< 0.001
Within groups	148.27	407	0.364		
Total	175.11	411			

Table 5. One-way ANOVA for adoption readiness across stakeholder groups

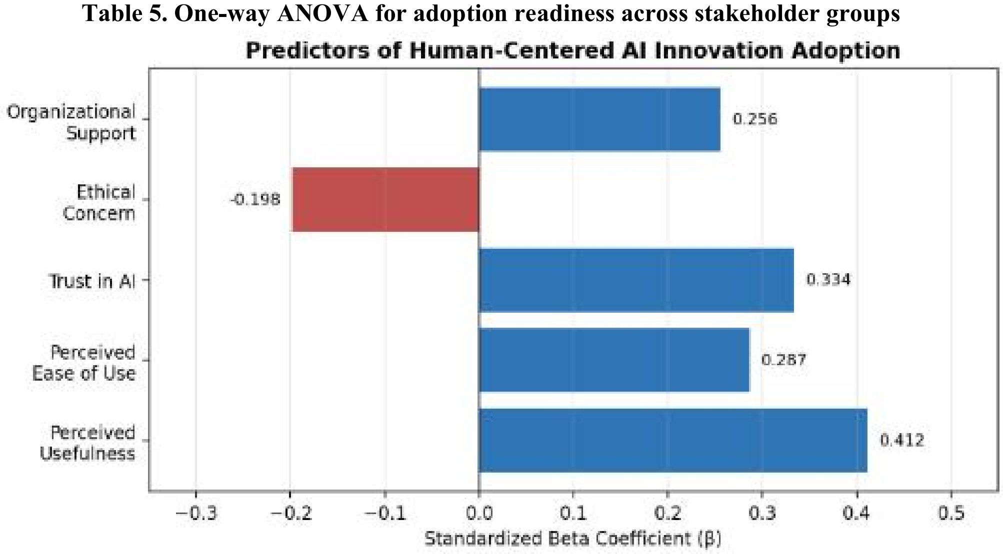

Figure 3. Standardized regression coefficients for predictors of adoption intention

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4.6 Summary of Hypothesis Testing

Table 6 consolidates the outcomes of the six hypotheses. All hypothesized relationships were supported at the 0.1% significance level, providing a coherent empirical validation of the integrated model. The combination of strong positive effects for usefulness, trust, ease of use, and organizational support, alongside the significant negative effect of ethical concern and significant inter-group differences, demonstrates that human-centered AI adoption is shaped simultaneously by instrumental, relational, ethical, and institutional forces.

Hypothesis	Path / Test	Statistic	p-value	Result
H1	PU → AI_INT (+)	$\beta = 0.412$; $t = 9.84$	< 0.001	Supported
H2	PEOU → AI_INT (+)	$\beta = 0.287$; $t = 6.95$	< 0.001	Supported
H3	TR → AI_INT (+)	$\beta = 0.334$; $t = 8.12$	< 0.001	Supported
H4	EC → AI_INT (−)	$\beta = -0.198$; $t = -4.87$	< 0.001	Supported
H5	OS → AI_INT (+)	$\beta = 0.256$; $t = 6.21$	< 0.001	Supported
H6	Group differences (ANOVA)	$F = 18.42$	< 0.001	Supported

Table 6. Summary of hypothesis testing results

4.7 Discussion

Three broad insights emerge from the empirical results. First, the dominance of perceived usefulness and trust as predictors indicates that human-centered AI innovation succeeds when stakeholders can clearly see what the technology does for them and can verify that it behaves reliably and fairly. Organizations should therefore prioritize use cases with demonstrable benefit, communicate performance evidence transparently, and provide explanation facilities that make algorithmic decisions interpretable to non-specialists. The strong role of trust is consistent with the human-centered AI framework, which holds that human oversight and system transparency are preconditions for sustained adoption rather than optional refinements.

Second, the significant negative effect of ethical concern demonstrates that ethics is not merely a compliance topic but a behavioral determinant of adoption. Respondents who worry about bias, surveillance, and accountability are measurably less willing to embrace AI tools, even when they acknowledge their usefulness. This finding strengthens the business case for ethics-by-design: embedding fairness audits, privacy safeguards, and grievance mechanisms into AI systems is likely to pay adoption dividends, particularly in trust-sensitive sectors. The elevated ethical concern observed among healthcare professionals and academicians suggests that sector-specific governance frameworks and professional codes will be more persuasive than generic assurances.

Third, the substantial inter-group differences caution against one-size-fits-all deployment strategies. IT professionals and students, who exhibit high readiness, can serve as early adopters and internal champions, whereas healthcare professionals require longer engagement cycles featuring clinical validation evidence, regulatory clarity, and human-in-the-loop guarantees. Organizational support emerged as a significant predictor across the sample, implying that training programs, leadership endorsement, and resource provision can partially compensate for lower baseline readiness. Taken together, the results portray human-centered innovation as a sociotechnical achievement: algorithmic capability supplies the potential, but perceived value, trust, ethical assurance, and institutional scaffolding convert that potential into adoption.

Fourth, the demographic patterns embedded in the results carry a workforce dimension. The 26–40 age cohort, which constitutes nearly half the sample, sits at the intersection of high AI exposure and high career stakes, and its perceptions will disproportionately shape organizational AI trajectories over the next decade. The strong readiness reported by students signals that incoming cohorts will arrive with expectations of AI-augmented work environments; organizations

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whose tools, policies, and cultures lag those expectations may face recruitment and retention disadvantages. At the same time, the elevated ethical concern among experienced professionals should not be read as resistance to be overcome but as domain expertise to be harnessed: clinicians, educators, and senior academicians possess precisely the contextual judgment needed to identify where AI systems may fail vulnerable users. Human-centered innovation processes should therefore institutionalize channels, such as ethics review panels, participatory design workshops, and incident reporting systems, through which this vigilance can improve system design rather than merely delay deployment.

4.8 Theoretical and Practical Implications

Theoretically, the study extends the technology acceptance tradition in two ways. It demonstrates that AI-specific constructs, trust and ethical concern, add explanatory power beyond the classical usefulness and ease-of-use pair, and it shows that the relative weights of these determinants are stable enough to support an integrated model while their levels vary meaningfully across stakeholder communities. This dual finding suggests that future theorizing should treat acceptance models as structurally general but contextually calibrated: the same mechanism operates everywhere, but its inputs differ by profession, exposure, and ethical proximity to vulnerable populations. The negative coefficient on ethical concern also contributes to an emerging stream that positions ethics as an endogenous behavioral variable in adoption models rather than an exogenous regulatory constraint.

Practically, the results translate into a differentiated playbook. Organizations introducing AI should sequence deployment by readiness, beginning with high-readiness groups to generate internal evidence and champions, while investing earlier and more heavily in trust-building measures, explainability features, and ethical assurance for cautious groups. Communication should foreground concrete usefulness, supported by measurable outcomes, rather than technological novelty. Training and support infrastructure should be treated as adoption investments with quantifiable returns, given the significant coefficient on organizational support. For institutions of higher education, the findings argue for embedding human-centered AI literacy across disciplines, pairing tool proficiency with ethical reasoning so that the next generation of professionals enters the workforce with both high readiness and high vigilance. For policymakers, the evidence supports governance approaches that make ethical compliance visible and verifiable, since reducing ethical concern is empirically equivalent to raising adoption.

V. CONCLUSION

This study set out to examine, through a multidisciplinary lens, the factors that shape the adoption of human-centered AI innovation among five stakeholder groups in India. Drawing on a survey of 412 respondents and a combination of correlation, regression, and ANOVA techniques, the study finds that perceived usefulness, trust in AI, perceived ease of use, and organizational support significantly and positively predict adoption intention, while ethical concern exerts a significant negative influence. The model explains nearly two-thirds of the variance in adoption intention, and significant differences in readiness across stakeholder groups highlight the heterogeneity of the AI adoption landscape.

The findings carry implications for three audiences. For managers, the results recommend investment in demonstrable, well-communicated use cases, transparent and explainable systems, and structured organizational support including training and leadership sponsorship. For educators and curriculum designers, the comparatively high readiness of students represents an opportunity to institutionalize human-centered AI literacy, combining technical skills with ethical reasoning. For policymakers, the suppressive effect of ethical concern underscores the urgency of credible governance frameworks, sectoral standards, and accountability mechanisms that convert abstract ethical principles into verifiable practice.

The study has limitations that frame an agenda for future research. The cross-sectional design captures perceptions at a single point in time and cannot establish causal direction; longitudinal panels could trace how trust and ethical concern evolve with experience. The sample, while diverse, is drawn from one national context, and cross-cultural replication would test the generalizability of the model. Future work could also incorporate additional constructs such as

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algorithmic transparency, perceived job threat, and AI self-efficacy, employ structural equation modeling to examine mediation pathways, and complement survey data with qualitative interviews to capture the lived experience of human–AI collaboration. Notwithstanding these limitations, the study contributes an integrated, comparative, and emerging-market perspective to the growing literature on human-centered artificial intelligence, and reinforces the central proposition that the future of AI will be decided not only by what machines can do, but by how well their design honors the people they serve.

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