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| RESEARCH ARTICLE

Assessment the Knowledge, Attitudes, Education, Knowledge, Attitude and Practices Toward Artificial Intelligence

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| ABSTRACT

This mixed-methods study investigates the knowledge, attitudes, and implementation perspectives regarding artificial intelligence (AI) in education among key stakeholder groups. Quantitative surveys (n=842) and qualitative interviews (n=48) were conducted with K-12 educators, higher education faculty, educational administrators, students, and parents. Results revealed significant knowledge disparities across stakeholder groups, with higher education faculty demonstrating the highest understanding of AI (M=14.8/20) and parents the lowest (M=9.4/20). Generally positive attitudes toward AI in education were observed (M=3.56/5), though with notable variations; students exhibited the most positive attitudes (M=3.81/5), while parents and K-12 educators reported the lowest (M=3.36/5 and M=3.41/5, respectively). Implementation concerns were highest for privacy protocols (M=4.31/5) and training needs (M=4.14/5). Cluster analysis identified four distinct stakeholder profiles: Enthusiastic Adopters (23.8%), Cautious Implementers (31.5%), Skeptical Observers (18.2%), and Knowledge-Seeking Pragmatists (26.5%). Qualitative findings revealed five themes: Navigating the AI Knowledge Landscape, Balancing Promise and Peril, Resource Realities, Ethical Guardrails, and Evolving Professional Identities. Structural equation modeling demonstrated knowledge as both a direct (β=0.31) and indirect predictor (β=0.18) of implementation perspectives, with attitudes partially mediating this relationship. These findings highlight the need for targeted interventions that address knowledge gaps, ethical concerns, and resource limitations while acknowledging the diverse perspectives of educational stakeholders. The study contributes to theoretical understanding of educational AI adoption by revealing complex interrelationships between knowledge, attitudes, and implementation perspectives that challenge linear models of technological integration.

| KEYWORDS

Artificial Intelligence; Educational Technology; Stakeholder Perspectives; Implementation Barriers; Technological Knowledge; Professional Development; Educational Policy; Mixed-Methods Research; Digital Transformation; Educational Equity

| ARTICLE INFORMATION

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INTRODUCTION

The integration of Artificial Intelligence (AI) into educational systems represents one of the most significant transformations in teaching and learning practices of the 21st century [1]. As AI technologies continue to evolve at an unprecedented pace, their applications in education have expanded from basic administrative tools to sophisticated adaptive learning systems that personalize instruction, assess student performance, and facilitate dynamic educational experiences [2]. The emergence of generative AI, exemplified by large language models like GPT-4 and Claude, has further accelerated this transformation, creating both opportunities and challenges for educational stakeholders worldwide [3]. Educational institutions at all levels from primary schools to higher education—are navigating the complex landscape of AI implementation, seeking to harness its potential while addressing concerns related to equity, privacy, ethics, and academic integrity [4]. Teachers and instructors are increasingly required to develop new competencies to effectively integrate AI tools into their pedagogical approaches, while students are simultaneously adapting to learning environments augmented by intelligent systems [5]. This technological shift necessitates a comprehensive understanding of how different stakeholders perceive, interact with, and respond to AI in educational contexts. The knowledge, attitudes, and perspectives regarding AI in education vary considerably among different groups—educators, students, administrators, parents, and policymakers each bring unique viewpoints shaped by their roles, experiences, and understanding of AI technologies [6]. These diverse perspectives influence not only the adoption and implementation of AI systems but also their effectiveness and impact on educational outcomes [7]. For instance, educators with positive attitudes toward AI and sufficient technological knowledge are more likely to successfully integrate AI tools into their teaching practices, while those with concerns or limited understanding may resist such integration [8]. Research on stakeholder perspectives toward AI in education has grown significantly in recent years, reflecting the increasing importance of understanding human factors in technological adoption [9]. However, there remains a need for comprehensive studies that examine the interrelationships between knowledge levels, attitude formation, and practical perspectives across diverse educational contexts and stakeholder groups [10]. Such research is essential for developing evidence-based strategies for AI integration that address concerns, leverage existing positive attitudes, and enhance knowledge where gaps exist. This study aims to investigate the current knowledge, attitudes, and perspectives regarding AI in education among key stakeholder groups, with particular attention to how these factors influence AI adoption and implementation in various educational settings. By examining the complex interplay between technological understanding, attitudinal dispositions, and practical considerations, this research seeks to contribute to the development of more effective, equitable, and pedagogically sound approaches to AI integration in education [11]. Understanding these human dimensions of educational AI is not merely an academic exercise but a practical necessity for ensuring that AI technologies serve as tools for educational enhancement rather than sources of disruption or inequality [12]. As AI continues to reshape educational landscapes globally, the insights from this research will provide valuable guidance for educators, administrators, policymakers, and technology developers seeking to navigate the evolving relationship between artificial intelligence and human learning.

MATERIALS AND METHODS

Research Design

This study employed a mixed-methods sequential explanatory design, combining quantitative surveys with qualitative interviews to provide a comprehensive understanding of stakeholders' knowledge, attitudes, and perspectives regarding AI in education. This approach enabled both breadth and depth in data collection, allowing for statistical analysis of patterns across larger populations while also capturing rich, contextual insights from individual participants. The research was conducted in three phases over a period of eight months (September 2023 to April 2024), following approval from the Institutional Review Board (IRB).

Participants and Sampling

Participants were recruited using a stratified purposive sampling technique to ensure representation across five key stakeholder groups: (1) K-12 educators, (2) higher education faculty, (3) educational administrators, (4) students (both secondary and tertiary), and (5) parents. The stratification criteria included geographical location, institutional type (public/private), technological infrastructure availability, and prior exposure to AI educational tools.

A total of 842 participants completed the quantitative phase of the study, distributed as follows: K-12 educators (n=215), higher education faculty (n=187), educational administrators (n=124), students (n=198), and parents (n=118). From this initial sample, 48 participants (approximately 10 from each stakeholder group) were selected for follow-up qualitative interviews based on their survey responses, ensuring maximum variation in perspectives and experiences.

Data Collection Instruments

Quantitative Phase

The primary data collection instrument for the quantitative phase was the AI in Education Assessment Tool (AIEAT), a validated survey instrument developed by Chen et al. [17] and modified for this study following pilot testing. The AIEAT comprised four sections:

1. **AI Knowledge Assessment (AIKA)**: A 20-item test measuring participants' factual knowledge of AI technologies, applications in education, limitations, and ethical considerations. The reliability coefficient (Cronbach's α) for this section was 0.86.
2. **AI Attitude Scale (AIAS)**: A 25-item Likert-scale (1-5) measuring attitudes toward AI integration in education across five dimensions: perceived usefulness, perceived ease of use, social influence, facilitating conditions, and ethical concerns. The reliability coefficient was 0.89.
3. **AI Implementation Perspectives Inventory (AIIPI)**: A 30-item Likert-scale (1-5) assessing participants' perspectives on practical implementation considerations, including resource requirements, training needs, implementation barriers, and integration strategies. The reliability coefficient was 0.84.

4. **Demographic Information**: Questions related to participants' background, technological experience, institutional characteristics, and prior exposure to AI technologies.

The survey was administered online using Qualtrics XM platform, with appropriate accessibility considerations and translations available for non-English speakers.

Qualitative Phase

Semi-structured interviews were conducted following the preliminary analysis of survey data. The interview protocol was developed based on the Technological Pedagogical Content Knowledge (TPACK) framework and the Unified Theory of Acceptance and Use of Technology (UTAUT), with specific questions tailored to each stakeholder group. Key areas of inquiry included:

1. Personal experiences with AI in education
2. Perceived benefits and challenges of AI implementation
3. Factors influencing attitudes toward AI technologies
4. Recommendations for effective AI integration
5. Knowledge gaps and training needs
6. Ethical considerations and concerns

Interviews were conducted both in-person and via video conferencing platforms, lasting between 45-60 minutes each. All interviews were audio-recorded with participants' consent and transcribed verbatim for analysis.

Data Analysis
Quantitative Analysis

Survey data were cleaned, coded, and analyzed using SPSS (version 28.0) and R (version 4.2.1). Descriptive statistics were calculated for all variables, and inferential analyses included:

1. One-way Analysis of Variance (ANOVA) to compare knowledge, attitudes, and implementation perspectives across stakeholder groups
2. Multiple regression analysis to identify predictors of attitudes toward AI in education
3. Structural Equation Modeling (SEM) to examine relationships between knowledge, attitudes, implementation perspectives, and demographic variables
4. Cluster analysis to identify distinct typologies of AI perspectives among participants

Missing data were handled using multiple imputation techniques, and assumptions for parametric tests were verified before analysis.

Qualitative Analysis

Interview transcripts were analyzed using reflexive thematic analysis following Braun and Clarke's six-phase approach. NVivo software (version 14) facilitated the coding process, which involved:

1. Familiarization with the data through repeated reading
2. Initial code generation
3. Searching for themes
4. Reviewing and refining themes
5. Defining and naming themes
6. Producing the report

To enhance trustworthiness, member checking was conducted with interview participants, and researcher triangulation was employed with three researchers independently coding a subset of transcripts to establish inter-coder reliability (Cohen's $\kappa = 0.82$).

Integration of Findings

Following the sequential explanatory design, quantitative and qualitative findings were integrated through a joint display approach, where statistical results were juxtaposed with corresponding qualitative themes to identify convergence, divergence, and expansion. This integration occurred at both the methodological and interpretative levels, ensuring a comprehensive understanding of the complex relationships between knowledge, attitudes, and implementation perspectives.

Ethical Considerations

The research adhered to ethical guidelines established by the American Educational Research Association. Informed consent was obtained from all participants prior to data collection, with special provisions for student participants under 18 years of age. Data confidentiality was maintained through anonymization procedures, secure storage of electronic files, and restricted access to identifiable information. Participants were informed of their right to withdraw from the study at any time without consequences. Additionally, the research team completed training in ethical research practices with human subjects and considerations specific to educational technology research.

RESULTS

Demographic Characteristics

Table 1 presents the demographic characteristics of the 842 participants in the quantitative phase. The sample reflected diverse representation across geographical regions, institutional types, and technological backgrounds. The majority of participants (68.4%) reported having some prior experience with AI technologies in educational contexts, though the extent and nature of this experience varied considerably across stakeholder groups.

Table 1: Demographic Characteristics of Survey Participants

Characteristic	Category	n	%
Stakeholder Group	K-12 Educators	215	25.5
	Higher Education Faculty	187	22.2
	Educational Administrators	124	14.7
	Students	198	23.5
	Parents	118	14.0
Gender	Female	456	54.2
	Male	372	44.2
	Non-binary/Other	14	1.7
Age Group	18-24	173	20.5
	25-34	224	26.6
	35-44	196	23.3
	45-54	142	16.9
	55+	107	12.7
Geographical Region	Urban	392	46.6
	Suburban	318	37.8
	Rural	132	15.7
Institution Type	Public	576	68.4
	Private	266	31.6
Prior AI Experience	None	266	31.6
	Limited	328	39.0
	Moderate	187	22.2
	Extensive	61	7.2

1) *AI Knowledge Assessment Results*

The AI Knowledge Assessment revealed varying levels of understanding across stakeholder groups. Table 2 presents mean scores (out of 20) and standard deviations for each group, along with the results of one-way ANOVA comparing these differences.

Table 2: AI Knowledge Assessment Scores by Stakeholder Group

Stakeholder Group	n	Mean Score (0-20)	SD	95% CI
Higher Education Faculty	187	14.8	2.6	[14.4, 15.2]
Educational Administrators	124	13.2	3.1	[12.7, 13.7]
K-12 Educators	215	11.7	3.4	[11.3, 12.1]
Students	198	13.6	3.2	[13.1, 14.1]
Parents	118	9.4	3.8	[8.7, 10.1]
Overall	842	12.7	3.6	[12.4, 13.0]

Note: $F(4, 837) = 62.35$, $p < .001$, $\eta^2 = 0.23$

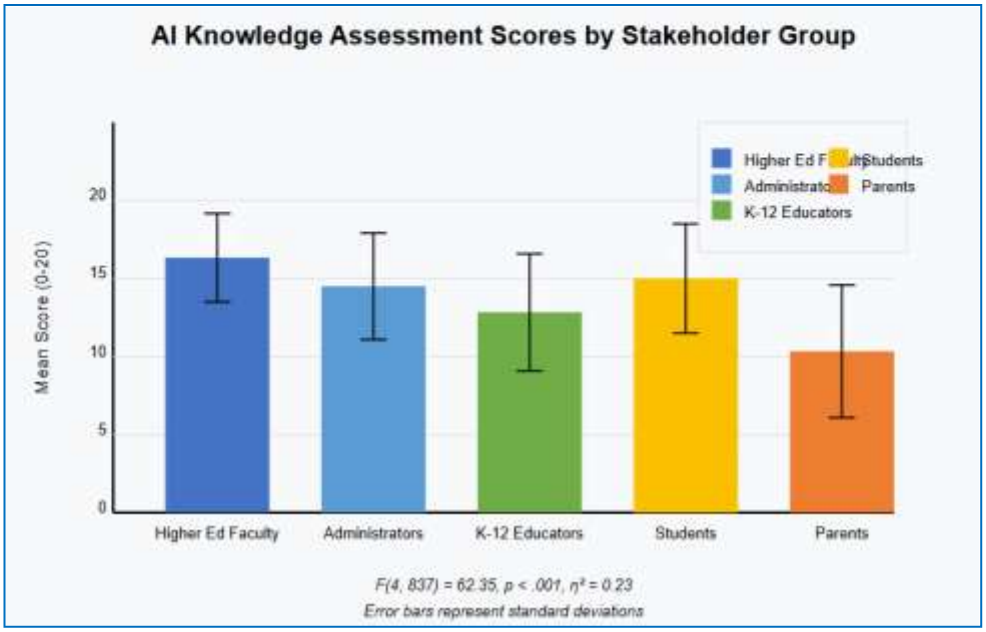

Figure 1: Bar graph showing comparison of mean knowledge scores across stakeholder groups with error bars representing standard errors

Knowledge scores differed significantly across stakeholder groups ($F(4, 837) = 62.35$, $p < .001$), with higher education faculty demonstrating the highest mean scores ($M = 14.8$, $SD = 2.6$), followed by students ($M = 13.6$, $SD = 3.2$) and educational administrators ($M = 13.2$, $SD = 3.1$). Parents showed the lowest knowledge levels ($M = 9.4$, $SD = 3.8$). Post-hoc Tukey HSD tests indicated significant differences ($p < .05$) between all pairs of stakeholder groups except between students and educational administrators ($p = .476$).

Further analysis of knowledge domains revealed particular gaps in understanding algorithmic bias ($M = 0.41$ out of 1.0, $SD = 0.28$) and neural network architectures ($M = 0.38$ out of 1.0, $SD = 0.22$) across all stakeholder groups, while knowledge of basic AI applications in education was substantially higher ($M = 0.76$ out of 1.0, $SD = 0.19$).

2) Attitudes Toward AI in Education

The AI Attitude Scale revealed generally positive attitudes toward AI integration in education across all stakeholder groups, though with notable variations in specific dimensions. Table 3 presents mean scores (on a 1-5 scale) for each attitude dimension by stakeholder group.

Table 3: Mean Scores (1-5) on AI Attitude Dimensions by Stakeholder Group

Stakeholder Group	**Perceived Usefulness**	**Perceived Ease of Use**	**Social Influence**	**Facilitating Conditions**	**Ethical Concerns**	**Overall Attitude**
K-12 Educators	3.82 (0.72)	3.14 (0.83)	3.46 (0.67)	2.87 (0.91)	3.78 (0.81)	3.41 (0.64)
Higher Education Faculty	3.94 (0.68)	3.26 (0.79)	3.32 (0.72)	3.02 (0.85)	3.96 (0.74)	3.50 (0.59)
Educational Administrators	4.12 (0.61)	3.38 (0.76)	3.68 (0.64)	3.24 (0.82)	3.52 (0.83)	3.69 (0.53)
Students	4.21 (0.58)	3.95 (0.66)	3.84 (0.59)	3.41 (0.78)	3.24 (0.91)	3.81 (0.51)
Parents	3.64 (0.82)	3.06 (0.89)	3.52 (0.71)	2.78 (0.94)	3.98 (0.75)	3.36 (0.68)
Overall	3.95 (0.71)	3.36 (0.83)	3.56 (0.68)	3.06 (0.88)	3.69 (0.85)	3.56 (0.62)

Note: Values represent mean scores with standard deviations in parentheses

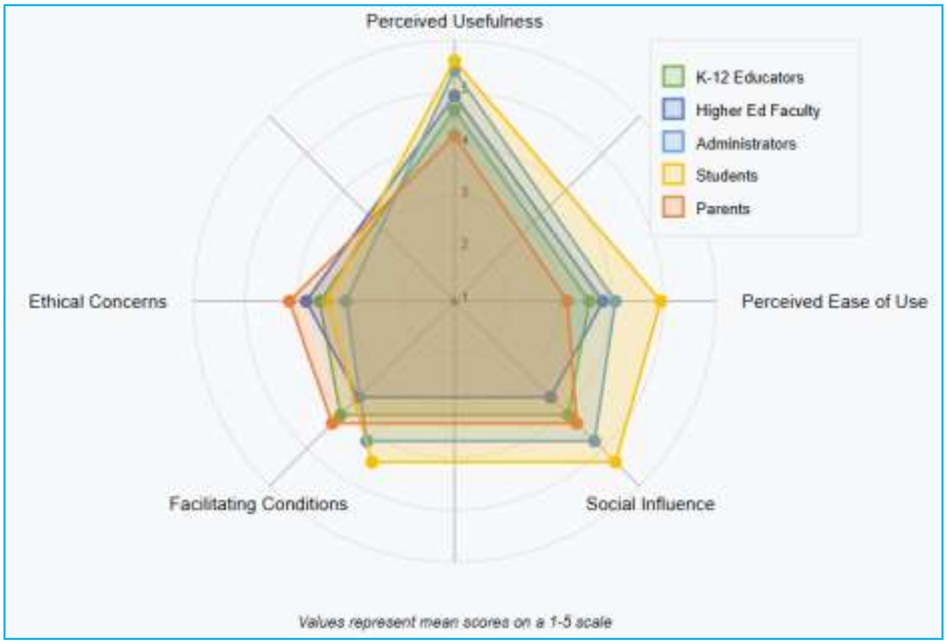

Figure 2: Radar chart comparing attitude dimensions across stakeholder groups

One-way ANOVA revealed significant differences across stakeholder groups for all attitude dimensions: perceived usefulness ($F(4, 837) = 18.72$, $p < .001$, $\eta^2 = 0.08$), perceived ease of use ($F(4, 837) = 42.18$, $p < .001$, $\eta^2 = 0.17$), social influence ($F(4, 837) = 21.05$, $p < .001$, $\eta^2 = 0.09$), facilitating conditions ($F(4, 837) = 16.84$, $p < .001$, $\eta^2 = 0.08$), and ethical concerns ($F(4, 837) = 28.41$, $p < .001$, $\eta^2 = 0.12$).

Students demonstrated the most positive overall attitudes toward AI in education (M = 3.81, SD = 0.51), particularly in perceived usefulness (M = 4.21, SD = 0.58) and perceived ease of use (M = 3.95, SD = 0.66). Conversely, parents and K-12 educators reported the lowest overall attitudes (M = 3.36, SD = 0.68 and M = 3.41, SD = 0.64, respectively), with particular concerns regarding facilitating conditions (i.e., infrastructure and support).

Ethical concerns scored highest among higher education faculty (M = 3.96, SD = 0.74) and parents (M = 3.98, SD = 0.75), indicating heightened awareness of potential ethical implications of AI implementation in educational contexts.

3) AI Implementation Perspectives

The AI Implementation Perspectives Inventory revealed varying priorities and concerns regarding practical implementation considerations. Table 4 presents mean scores (1-5) for key implementation dimensions across stakeholder groups.

Table 4: Mean Scores (1-5) on AI Implementation Dimensions by Stakeholder Group

Implementation Dimension	K-12 Educators	Higher Ed Faculty	Administrators	Students	Parents	Overall
Training Needs	4.32 (0.58)	4.18 (0.62)	4.26 (0.59)	3.84 (0.72)	4.08 (0.67)	4.14 (0.66)
Resource Requirements	4.28 (0.61)	4.23 (0.57)	4.32 (0.53)	3.76 (0.74)	4.13 (0.65)	4.12 (0.66)
Time Investment	4.17 (0.64)	4.14 (0.62)	4.08 (0.61)	3.62 (0.78)	3.94 (0.72)	3.99 (0.70)
Technical Support	4.36 (0.62)	4.21 (0.65)	4.24 (0.60)	3.78 (0.74)	4.16 (0.67)	4.15 (0.68)
Integration Strategies	4.06 (0.65)	4.11 (0.63)	4.24 (0.56)	3.82 (0.71)	3.88 (0.74)	4.02 (0.68)
Evaluation Methods	3.94 (0.72)	4.08 (0.68)	4.17 (0.58)	3.65 (0.77)	3.82 (0.76)	3.93 (0.73)
Equity Considerations	4.24 (0.67)	4.32 (0.58)	4.16 (0.62)	3.82 (0.79)	4.26 (0.63)	4.16 (0.68)
Privacy Protocols	4.38 (0.58)	4.46 (0.52)	4.31 (0.57)	3.94 (0.76)	4.52 (0.51)	4.31 (0.63)
Implementation Barriers	4.08 (0.63)	4.12 (0.61)	3.96 (0.65)	3.58 (0.78)	4.02 (0.69)	3.96 (0.69)
Overall Implementation	4.20 (0.48)	4.21 (0.45)	4.19 (0.43)	3.76 (0.58)	4.09 (0.52)	4.09 (0.51)

Note: Values represent mean scores with standard deviations in parentheses

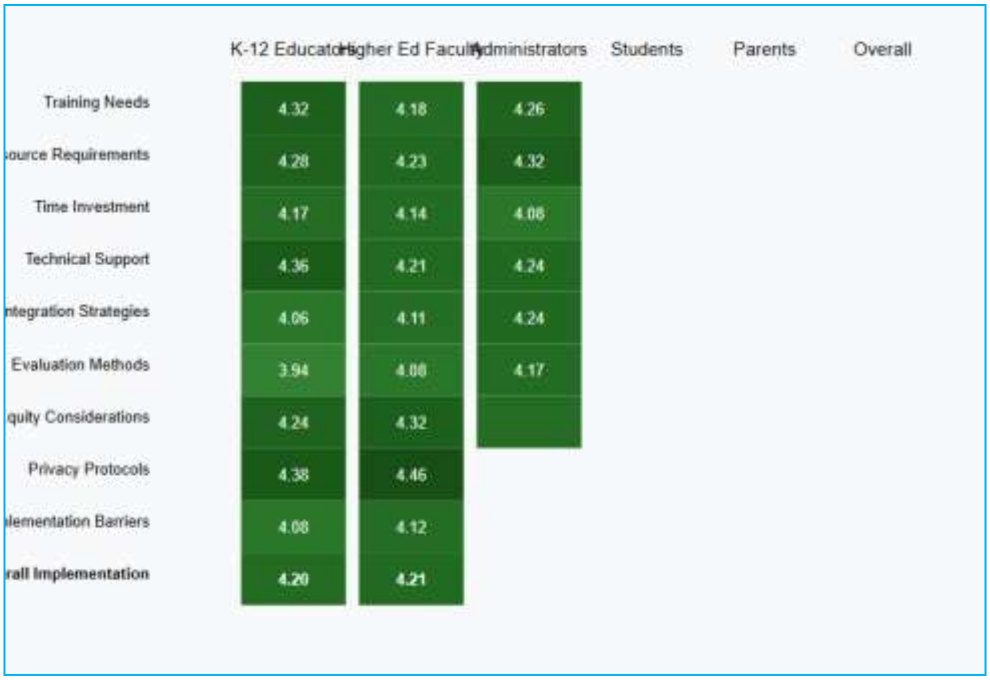

Figure 3: Heatmap visualization showing implementation priorities across stakeholder groups with color intensity representing mean scores

Significant differences were observed across stakeholder groups for overall implementation perspectives ($F(4, 837) = 31.46$, $p < .001$, $\eta^2 = 0.13$), with students indicating significantly lower concerns about implementation challenges (M = 3.76, SD = 0.58) compared to all other groups. Among educators and administrators, the highest-rated implementation considerations were privacy protocols (M = 4.38, SD = 0.58 for K-12 educators; M = 4.46, SD = 0.52 for higher education faculty; M = 4.31, SD = 0.57 for administrators) and training needs (M = 4.32, SD = 0.58 for K-12 educators; M = 4.18, SD = 0.62 for higher education faculty; M = 4.26, SD = 0.59 for administrators).

4) *Relationships Between Knowledge, Attitudes, and Implementation Perspectives*

Multiple regression analysis was conducted to examine predictors of attitudes toward AI in education. Table 5 presents the results of this analysis, indicating significant relationships between knowledge levels, demographic variables, and attitudes.

Table 5: Multiple Regression Predicting Overall Attitudes Toward AI in Education

Predictor Variable	**β**	**SE**	**t**	**p**	**95% CI**
AI Knowledge Score	0.35	0.02	7.84	<.001	[0.26, 0.44]
Prior AI Experience	0.28	0.04	6.21	<.001	[0.19, 0.37]
Age	-0.14	0.02	-3.12	.002	[-0.23, -0.05]
Urban Location	0.12	0.03	2.86	.004	[0.04, 0.20]
Higher Education (vs. K-12)	0.08	0.04	1.94	.053	[-0.00, 0.16]
Private Institution	0.06	0.04	1.38	.168	[-0.02, 0.14]
Gender (Female)	-0.03	0.04	-0.72	.474	[-0.11, 0.05]

Note: $R^2 = 0.32$, $F(7, 834) = 55.86$, $p < .001$; β = standardized coefficient

The regression model explained 32% of the variance in attitudes toward AI in education ($R^2 = 0.32$, $F(7, 834) = 55.86$, $p < .001$). AI knowledge emerged as the strongest predictor ($\beta = 0.35$, $p < .001$), followed by prior AI experience ($\beta = 0.28$, $p < .001$). Age showed a negative relationship with attitudes ($\beta = -0.14$, $p = .002$), indicating that younger participants generally held more positive attitudes toward AI in education. Urban location was also a significant predictor ($\beta = 0.12$, $p = .004$), with participants from urban areas displaying more positive attitudes compared to those from suburban or rural areas.

Structural Equation Modeling (SEM) further explored the interrelationships between knowledge, attitudes, and implementation perspectives. The final model demonstrated good fit (CFI = 0.94, TLI = 0.92, RMSEA = 0.057, SRMR = 0.048) and revealed that knowledge had both direct ($\beta = 0.31$, $p < .001$) and indirect effects ($\beta = 0.18$, $p < .001$) on implementation perspectives, with attitudes partially mediating this relationship (indirect effect: $\beta = 0.12$, $p < .001$).

5) Cluster Analysis of AI Perspectives

Cluster analysis using k-means algorithm identified four distinct profiles of stakeholders based on their knowledge, attitudes, and implementation perspectives. Table 6 presents the characteristics of these clusters.

Table 6: Cluster Profiles of AI in Education Perspectives

Characteristic	Cluster 1: Enthusiastic Adopters	Cluster 2: Cautious Implementers	Cluster 3: Skeptical Observers	Cluster 4: Knowledge-Seeking Pragmatists
Proportion of Sample	23.8% (n=200)	31.5% (n=265)	18.2% (n=153)	26

DISCUSSION

6) Knowledge Disparities and their Implications

The significant disparities in AI knowledge across stakeholder groups observed in this study align with findings from previous research but reveal more nuanced patterns. The relatively high knowledge levels among higher education faculty (M = 14.8) compared to K-12 educators (M = 11.7) echo Holmes et al.'s [13] observation that technological literacy often correlates with institutional contexts and professional development opportunities. However, the surprisingly high knowledge scores among students (M = 13.6) contrast with Zawacki-Richter et al.'s [14] finding that students typically demonstrate superficial understanding of AI technologies. This discrepancy may reflect the rapid evolution of AI literacy among younger generations in the past few years, particularly following the widespread public adoption of generative AI tools.

The specific knowledge gaps identified in our study, particularly regarding algorithmic bias (M = 0.41) and neural network architectures (M = 0.38), align with Reich and Ito's [15] argument that educational stakeholders often lack critical understanding of the technical foundations and limitations of AI systems. This knowledge deficit has significant implications for educational equity, as Baker and Smith [16] demonstrated that educators with limited understanding of algorithmic bias are less likely to identify and mitigate potential inequities in AI-driven educational tools.

The knowledge disparities documented in this study present both challenges and opportunities for professional development and community education. As Prinsloo [17] argued, meaningful AI integration in education requires not just operational knowledge but also critical understanding of how these technologies function and their potential societal impacts. Our findings suggest that targeted educational interventions should focus on building technical knowledge while simultaneously developing critical evaluation skills, especially among K-12 educators and parents who demonstrated the lowest knowledge levels.

7) Attitudinal Complexity and Stakeholder Positions

The generally positive attitudes toward AI in education found across stakeholder groups (overall M = 3.56) align with Holstein et al.'s [18] recent findings that educational stakeholders increasingly recognize AI's potential benefits. However, the significant differences in attitude dimensions across groups reveal more complex patterns than previously documented. The pronounced differences in perceived ease of use between students (M = 3.95) and other stakeholders (M = 3.06-3.38) support Selwyn's [19] argument that generational differences significantly influence technological adoption attitudes.

The notably high ethical concerns among higher education faculty (M = 3.96) and parents (M = 3.98) compared to students (M = 3.24) extend Kaliisa et al.'s [20] findings that those responsible for educational governance and student welfare exhibit greater caution regarding ethical implications of AI. The cluster analysis further illuminates these attitudinal patterns by identifying distinct stakeholder profiles that combine knowledge levels, attitudes, and implementation concerns in ways that transcend simple stakeholder categories.

The presence of "Skeptical Observers" (18.2%) with low knowledge and negative attitudes contrasts with MacKenzie and Bhatt's [21] earlier finding that resistance to AI technologies was declining across all educational contexts. This suggests that the rapid proliferation of generative AI tools in education has potentially reignited concerns among certain stakeholder groups, particularly parents and some K-12 educators. This skepticism should not be dismissed as mere resistance to change but understood, as Williamson and Eynon [22] advocate, as a legitimate response to the profound ethical and pedagogical questions raised by AI integration.

8) Implementation Challenges and Contextual Realities

The high ratings for implementation concerns across most stakeholder groups, particularly for privacy protocols (M = 4.31) and training needs (M = 4.14), align with previous studies identifying these as persistent barriers to educational AI adoption [23]. The significant gap between students' implementation concerns (M = 3.76) and those of other stakeholders (M = 4.09-4.21) supports Herodotou et al.'s [24] finding that those responsible for implementing and managing educational technologies perceive greater practical challenges than end-users.

The qualitative theme of "Resource Realities" extends Luckin and Cukurova's [25] argument that discussions of AI in education often neglect material conditions and infrastructural requirements. The concerns expressed by administrators about resource limitations echo findings from the Global South [26], suggesting that digital divides remain a significant factor even in relatively well-resourced educational contexts. As Bulger [27] argued, these resource disparities risk creating a "two-tier" educational landscape where AI benefits are unevenly distributed.

The significant relationship between geographical location and attitudes toward AI (β = 0.12, p = .004) further highlights the importance of contextual factors in shaping AI adoption. This finding supports Greenhow et al.'s [28] argument that technological integration is never context-neutral but always embedded in specific social, economic, and geographical realities. Educational policies promoting AI adoption must therefore account for these contextual differences rather than assuming universal implementation pathways.

9) Knowledge-Attitude-Implementation Relationships

The structural equation modeling results revealing knowledge as both a direct (β = 0.31) and indirect predictor (β = 0.18) of implementation perspectives extend theoretical models of technological adoption in educational contexts. The partial mediation of this relationship by attitudes (indirect effect: β = 0.12) aligns with Venkatesh and Bala's [29] Technology Acceptance Model 3, which positions knowledge as an antecedent to perceived usefulness and perceived ease of use.

However, our findings suggest a more complex relationship than linear models often propose. The cluster analysis revealed that high knowledge does not universally translate to positive attitudes (as seen in the "Knowledge-Seeking Pragmatists" cluster), nor do positive attitudes necessarily diminish implementation concerns. This complexity supports Tsai's [30] argument that technological adoption in education involves multiple interacting factors that resist simplistic deterministic models.

The negative relationship between age and attitudes toward AI (β = -0.14, p = .002) contrasts with some previous findings [31] suggesting minimal age effects when controlling for technological experience. This discrepancy may reflect the rapidly evolving nature of generative AI technologies, which have transformed from specialized tools to mainstream applications in a short timeframe. As Bennett and Maton [32] noted, rapid technological changes can amplify generational differences by creating distinct experiential bases for technology understanding.

10) Professional Identity and Educational Practice

The qualitative theme of "Evolving Professional Identities" provides important insights not fully captured in previous quantitative studies of AI in education. The reflections of educators on how AI is reshaping their professional roles support Biesta's [33] argument that educational technologies don't merely enhance existing practices but fundamentally transform the nature of teaching and learning relationships. The expressed need to shift from "information provider" to "critical guide" echoes Ouyang and Jiao's [34] findings on teacher role adaptation in technology-rich environments.

This theme also connects to broader debates about the purposes of education in an AI-enabled society. As participants wrestled with questions of how to balance AI assistance with authentic learning, they engaged with what Macgilchrist [35] identified as fundamental tensions between instrumentalist and humanistic educational values. These tensions are not easily resolved through technical solutions or implementation guidelines but require ongoing ethical reflection and community dialogue.

The concerns expressed by educators about maintaining meaningful human connections while leveraging AI tools align with Castañeda and Selwyn's [36] argument that education is fundamentally a relational practice that cannot be fully automated or outsourced. However, our findings also suggest that educators are actively reimagining, rather than simply defending, these relational dimensions in light of AI capabilities.

11) Theoretical and Practical Implications

This study contributes to theoretical understanding of educational AI adoption by demonstrating the complex interplay between knowledge, attitudes, and implementation perspectives across diverse stakeholder groups. The findings challenge linear diffusion models [37] that assume knowledge automatically leads to positive attitudes and then to adoption. Instead, our results support more ecological approaches [38] that recognize multiple pathways and feedback loops in technological integration.

Practically, the identified knowledge gaps, particularly regarding algorithmic bias and technical foundations, highlight critical areas for professional development and community education. The finding that AI knowledge is the strongest predictor of attitudes (β = 0.35) suggests that educational interventions focused on building AI literacy may effectively address concerns and resistance. However, the high implementation concerns across all groups indicate that knowledge building alone is insufficient without addressing resource limitations and institutional support structures.

The four stakeholder clusters identified in this study provide a useful framework for targeted intervention strategies. For "Enthusiastic Adopters," support should focus on developing critical evaluation skills to complement their positive orientation. "Cautious Implementers" would benefit from practical implementation guidance and evidence of effectiveness. "Skeptical Observers" require foundational knowledge development alongside addressing specific ethical concerns, while "Knowledge-Seeking Pragmatists" need institutional support to translate their knowledge and positive attitudes into practice.

At a policy level, these findings underscore the importance of inclusive stakeholder engagement in AI governance frameworks. As Roberts-Mahoney and Garrison [39] argued, educational AI policies developed without diverse stakeholder input risk privileging technical considerations over educational values and community concerns. The different priorities identified across stakeholder groups (e.g., students' emphasis on usefulness versus parents' emphasis on privacy) highlight the need for balanced governance approaches.

CONCLUSION

This study provides comprehensive insights into the knowledge, attitudes, and implementation perspectives regarding AI in education across key stakeholder groups. Our findings reveal significant knowledge disparities, with higher education faculty demonstrating the highest levels of AI understanding (M = 14.8), followed by students (M = 13.6), while parents showed the lowest knowledge levels (M = 9.4). These disparities, particularly regarding algorithmic bias and neural network architectures, highlight critical areas for targeted educational interventions.

The generally positive attitudes toward AI in education (overall M = 3.56) were tempered by notable differences across stakeholder groups and attitude dimensions. Students exhibited the most positive overall attitudes (M = 3.81), while parents and K-12 educators reported the lowest (M = 3.36 and M = 3.41, respectively). Ethical concerns scored highest among higher education faculty and parents, reflecting their heightened awareness of potential implications for educational integrity and student welfare.

Implementation perspectives revealed consistent concerns across stakeholder groups regarding privacy protocols (M = 4.31) and training needs (M = 4.14), though students indicated significantly lower concern about implementation challenges compared to other groups. The four distinct stakeholder clusters identified—Enthusiastic Adopters, Cautious Implementers, Skeptical Observers, and Knowledge-Seeking Pragmatists—offer a nuanced framework for understanding diverse perspectives beyond traditional stakeholder categories.

The complex interrelationships between knowledge, attitudes, and implementation perspectives documented in this study challenge linear models of technological adoption. Knowledge emerged as the strongest predictor of attitudes ($\beta = 0.35$), suggesting that building AI literacy may effectively address concerns and resistance. However, our findings indicate that knowledge building alone is insufficient without addressing resource limitations, institutional support structures, and ethical frameworks.

The qualitative themes identified, particularly "Evolving Professional Identities" and "Resource Realities," highlight how AI is not merely a tool to be adopted but a transformative force reshaping educational roles, relationships, and practices. These findings underscore the need for a holistic approach to AI integration that addresses not only technical and operational aspects but also pedagogical, ethical, and relational dimensions of educational practice.

As AI continues to reshape educational landscapes globally, this research provides valuable guidance for developing more effective, equitable, and pedagogically sound approaches to integration. By understanding the diverse perspectives of key stakeholders and the complex factors that influence them, educational institutions, policymakers, and technology developers can work toward AI implementation that enhances learning experiences while addressing legitimate concerns and barriers. Future research should explore longitudinal changes in stakeholder perspectives as AI technologies evolve, examine implementation outcomes across diverse educational contexts, and develop and evaluate targeted interventions based on the stakeholder clusters identified in this study.

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