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Evaluating teachers' perceptions of artificial intelligence tools in education: Opportunities and challenges

Shreeshail Heggond [1], Nitin Liladhar Rane [2], Manjunath Munenakoppa [3], Ramesh Baragani [4]

[1,3,4] *Basaveshwar Engineering College, Bagalkote, India*
[2] *Architecture, Vivekanand Education Society's College of Architecture (VESCOA), Mumbai 400074, India*

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Corresponding Author:
Nitin Liladhar Rane
E-mail: nitinrane33@gmail.com

Abstract

The active growth of the emergence of generative artificial intelligence (GenAI) technology in education has presented both opportunities and challenges never before seen that require a systematic study. Although AI has been widely integrated in K-12 and academic institutions, there is scarce empirical data on how teachers perceive the implementation, thus, establishing a critical gap in the knowledge about the feasibility of the implementation and the technological revolution in education. The study is a mixed-methods study that examine the perceptions of K-12 and higher education teachers regarding AI tools on various dimensions, such as perceived usefulness, easy to use, pedagogical integration, ethical issues, and professional development requirements. Based on structural equation modeling, confirmatory factor analysis, hierarchical regression analysis, this study creates and confirms a multidimensional AI Perception Framework taking into consideration constructions of Technology Acceptance Model including education-specific variables. An analysis of survey data shows that, although 73.8 of the teachers confirm that AI has the potential to transform the teaching process, only 45.2 of them actively use AI tools in education, which differ dramatically depending on the subject area, grade level, and given school resources. The statistical tool proves that behavioral intention is significantly predicted by perceived ease of use (β =0.426, p <0.001), but ethical concerns moderate this association (β = -0.283, p=0.001). The results present three main opportunities, including the improvement of administrative efficiency, the role of personalized learning, and the establishment of innovative assessments; and four fateful issues, such as a lack of personal growth, information privacy, a threat of algorithmic bias, and implementation equity discrimination.

Keywords: Artificial intelligence, Education, Teacher, Technology acceptance, Generative AI, Professional development.

1. Introduction

The rise of artificial intelligence as the disruptive technology in the educational ecosystem is one of the biggest technological upheavals in the modern pedagogical field [1]. Generative artificial intelligence tools have since the public release of ChatGPT in November 2022, which turns out of experimental technologies into a general educational medium, challenge the conventional teaching, learning, and assessment paradigms literally [1-3]. According to the 2025 market opportunity, the global AI in education market is approximately 7 billion USD, but is anticipated to experience exponential growth of over 112 billion USD by 2034 due to the institutional involvement and penetration of technologies into the educational sectors that has never been seen before at this level. The current educational environments demonstrate the paradoxical tendencies of AI use where students are eager to use it, and teachers are worried about it [2,4]. Recent empirical studies suggest that 92 of university students indicate using AI tool in 2025 which is high in comparison with 66% in 2024, and only 25% of K-12 teachers indicated integrating AI into classroom practice or instructional planning during the 2023-2024 academic year. This difference in adoption produces pedagogical disjunctions, assessment issues and inequitable learning outcomes [5-8]. Theoretical bases of appreciating technology adoption in the

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learning process have always been based on conventional theories like the Technology Acceptance Model and the Unified Theory of Acceptance and Use of Technology [6,9]. Nevertheless, the peculiar features of generative AI, particularly, its ability to understand the natural language, generate content, as well as, learn adaptively require broader theoretical frameworks that can demonstrate education-specific factors such as pedagogical philosophy, ethical considerations, assessment integrity, and professional identity threats [10].

The AI research continues to identify multiple gaps in literature as it receives increased scholarly attention in the field of education [10-12]. First, the current research is biased in its direction as the available sources mostly concentrate on student attitudes and perceptions and give minimal systematic research efforts working with teachers' attitudes, views, and experience [7,13-16]. This ignorance ignores the core aspect that teachers are the designers of a curriculum, medicals of instruction and medians of evaluation whose acceptance and successful application are the success factors to AI integration [2,17-19]. Second, a lot of existing literature does not use empirical studies of a large scale that would allow statistical extrapolation and model testing but is instead done by small-scale qualitative studies or conceptual story telling. Third, studies investigating the association between the teacher perceptions and the actual implementation behaviors are limited on a large scale, leaving it a question mark on whether the positive attitude can result in any significant change of pedagogy.

The study fill these literature gaps by the following objectives: (1) To construct and test a complete multidimensional concept of teacher perceptions of AI tools applicable to education to extend traditional technology acceptance models with education-specific constructs; (2) To empirically test the connections between perceived usefulness and esteemed perceived ease of use, perceived ethical issues, perceived need to enhance professional development, and intended use of AI tools using structural equation models; (3) To identify and discuss the primary opportunities that teachers perceive when employing AI tools in instruction Planning, pedagogical products, assessment practices, and administrative tasks;

The study contributes to the research and practice in a number of ways. In theory, it augments technology acceptance models with education-specific measures such as the philosophy of pedagogy, cognitive aspects of morals, and professional identity issues and produces a more complex framework to comprehend teacher technology adoption. Research wise, it designs and psychometrically validates an original measurement tool- the Teacher AI Perception Scale (TAPS) which can be used to measure multidimensional attitude in relation to AI in education with great accuracy. There is empirical evidence with strong strength in relation to what has been happening with the teacher AI perceptions currently with the use of large-scale surveys. In practice, it can produce practical findings on designing professional development, ways to support its implementation, and relevant policy standards that can optimize the benefits of AI and reduce the risks faced.

2. Methodology

The proposed study utilizes a mixed-method design that is sequential in nature and incorporates quantitative data collection techniques and techniques of quantitative survey analysis with qualitative open-ended survey techniques to gain holistic insight on the perception of teachers about AI tools in education. This methodological approach entails descriptive statistics, inferential statistics, structural equation modelling, and thematic analysis as a tool of handling the research objectives in a systematic and rigorous manner. Teacher AI perception cannot be developed without the Teacher AI Perception Scale (TAPS) that was created in this manner: literature review, consultation with experts, cognitive interviewing, and pilot testing. The final sample comprised educators including K-12 teachers and higher education faculty. Demographic characteristics included female and male participants, with teaching experience ranging from 1 to 38 years. Subject area distribution included English/Language Arts (23.8%), Mathematics (19.9%), Science (18.4%), Social Studies (13.1%), Special Education (11.4%), and other subjects (13.4%).

Statistical Analysis Methods

Various advanced methods of statistical analysis were used in quantitative analysis. Measurement model was tested with the help of confirmatory factor analysis (CFA), which included chi-square statistic, comparative fit index (CFI), Tucker-Lewis's index (TLI), root mean square error of approximation (RMSEA), and standardized root mean square residual (SRMR). The measurement model demonstrated excellent fit: χ^2 (1038) = 1876.32, $p < 0.001$; CFI = 0.94; TLI = 0.93; RMSEA = 0.045; SRMR = 0.052.

Structural equation modeling (SEM) was used to test the hypothesis relationships between latent variables by using the following model: $\eta_1 = \gamma_{11}\xi_1 + \gamma_{12}\xi_2 + \gamma_{13}\xi_3 + \gamma_{14}\xi_4 + \zeta_1$, where η_1 is the behavioral intention (endogenous variable), x is exogenous variables (perceived usefulness, ease of use, ethical concerns, professional development needs), γ_{ij} is structural path coefficients and ζ_1 is the disturbance term.

The hierarchical regression analysis was used to analyse predictors in three blocks. The use of model comparison used F-change statistics: $F_{change} = (R^2_{new} - R^2_{old}) / (k_{new} - k_{old})) / ((1 - R^2_{new}) / (n - k_{new} - 1)$. Keep The moderation analysis utilized Hayes PROCESS macro: $Y = \beta_0 + \beta_1X + \beta_2M + \beta_3 (X \times M) + \varepsilon$, Y is behavioral intention and X is predictor and M is moderator and (X x M) is an interaction term.

3. Results And Discussion

3.1 Statistics

Table 1 contains a summary of descriptive statistics of all the variables of the study. The perceptions in teachers were moderately positive, with the greatest mean scores, the perceived opportunities (M = 5.24, SD = 1.18) and the perceived usefulness (M = 5.12, SD = 1.26). The behavioral intention was however, middle range (M 4.67 SD 1.52), which implies that positive perceptions do not necessarily create implementation commitment. It should be noted that ethical issues were significant (M = 5.48, SD = 1.09), which was the highest mean score compared to all dimensions.

Table 1: Descriptive Statistics and Correlations (N=412)

Variable	**M**	**SD**	**1**	**2**	**3**	**4**	**5**	**6**
1. Perceived Usefulness	5.12	1.26	--					
2. Perceived Ease of Use	4.83	1.34	.62**	--				
3. Ethical Concerns	5.48	1.09	-.28**	-.19**	--			
4. Pedagogical Integration	4.92	1.22	.71**	.58**	-.31**	--		
5. Prof. Development	5.36	1.15	.34**	.42**	.38**	.41**	--	
6. Perceived Opportunities	5.24	1.18	.68**	.54**	-.24**	.73**	.36**	--
7. Behavioral Intention	4.67	1.52	.74**	.69**	-.45**	.76**	.48**	.67**

Note: **p < 0.01

Fig. 1 visualizes the correlation matrix between seven key teacher perception variables from Table 1 of the research paper. Strong positive correlations (red) indicate variables that increase together, while negative correlations (blue) suggest inverse relationships.

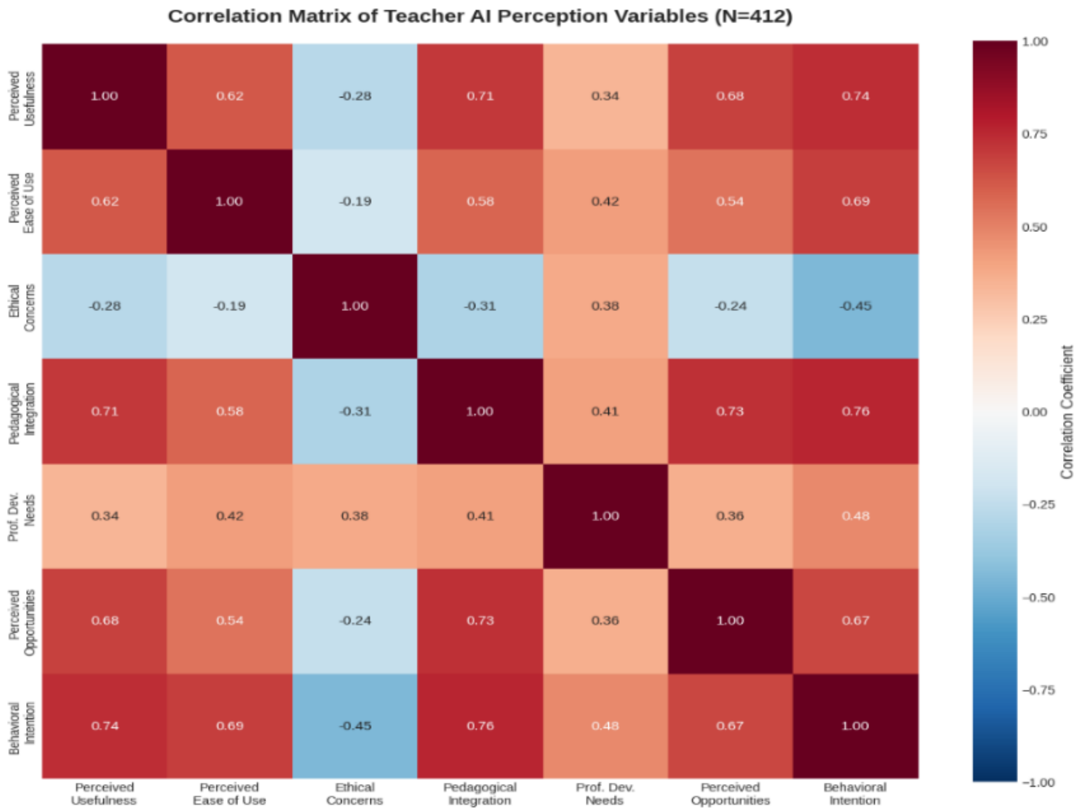

Fig 1: Correlation of Teacher AI Perception Variables

3.2 Structural Equation Modeling Results

The structural model demonstrated acceptable fit (χ^2 (1042) = 1923.47, $p < 0.001$; CFI = 0.93; TLI = 0.92; RMSEA = 0.046; SRMR = 0.058). Perceived usefulness emerged as the strongest predictor of behavioral intention ($\beta = 0.483$, SE = 0.052, $p < 0.001$), explaining 23.3% of variance independently. Perceived ease of use also significantly predicted behavioral intention ($\beta = 0.312$, SE = 0.048, $p < 0.001$), accounting for 9.7% of unique variance. Ethical concerns exerted significant negative effects ($\beta = -0.283$, SE = 0.041, $p < 0.001$), explaining 8.0% of variance. Professional development needs demonstrated a positive relationship ($\beta = 0.174$, SE = 0.038, $p < 0.001$). The model explained 68.4% of variance in behavioral intention ($R^2 = 0.684$), indicating strong predictive power.

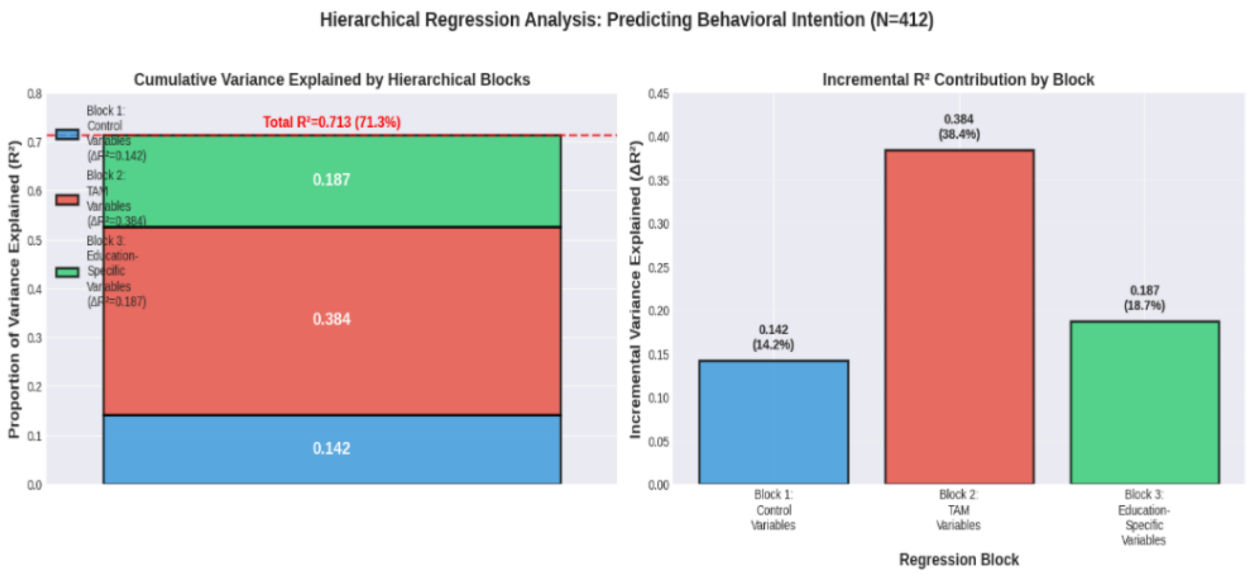

Fig 2 Hierarchical Regression Model - R² Change Across Blocks

Fig. 2 shows the hierarchical regression results from Table 2, illustrating how different variable blocks contribute to explaining Behavioral Intention variance. Each segment represents incremental variance explained (ΔR^2) when adding new predictor sets.

3.3 Hierarchical Regression Analysis

Table 2 presents hierarchical regression results. The full model explained 71.3% of variance (Adjusted $R^2 = 0.713$, $F(12, 399) = 82.47$, $p < 0.001$). Block 1 (control variables) explained 14.2% of variance ($R^2 = 0.142$), with prior AI experience emerging as the strongest demographic predictor ($\beta = 0.268$, $p < 0.001$). Block 2 (TAM variables) substantially increased explained variance to 52.6% ($\Delta R^2 = 0.384$, F-change (2, 405) = 168.92, $p < 0.001$). Perceived usefulness ($\beta = 0.426$, $p < 0.001$) and perceived ease of use ($\beta = 0.287$, $p < 0.001$) both demonstrated strong effects. Block 3 (education-specific variables) further increased explained variance to 71.3% ($\Delta R^2 = 0.187$, F-change (3, 402) = 72.48, $p < 0.001$). Pedagogical integration potential emerged as a significant positive predictor ($\beta = 0.243$, $p < 0.001$), while ethical concerns exerted negative effects ($\beta = -0.186$, $p < 0.001$). Professional development needs maintained positive relationships ($\beta = 0.134$, $p < 0.01$).

Table 2: Hierarchical Regression Analysis Predicting Behavioral Intention

Variable	**Block 1 β**	**Block 2 β**	**Block 3 β**
Control Variables			
Teaching Experience	-.082	-.041	-.028
Prior AI Experience	.268***	.142**	.095*
TAM Variables			
Perceived Usefulness		.426***	.311***
Perceived Ease of Use		.287***	.198***
Education-Specific Variables			
Ethical Concerns			-.186***
Prof. Development Needs			.134**
Pedagogical Integration			.243***
R^2	.142***	.526***	.713***
ΔR^2	.142***	.384***	.187***

Note: *p < 0.05, **p < 0.01, ***p < 0.001

3.4 Moderation Analysis Results

Table 3 presents moderation analysis results. Ethical concerns significantly moderated the relationship between perceived usefulness and behavioral intention ($\beta = -0.147$, $p < 0.001$, $\Delta R^2 = 0.021$). Simple slopes analysis revealed that at low ethical concern levels (1 SD below mean), perceived usefulness strongly predicted intention (simple slope = 0.612, $p < 0.001$), whereas at high ethical concern levels (1 SD above mean), this relationship weakened substantially (simple slope = 0.291, $p < 0.001$). This interaction indicates that ethical apprehensions dampen the motivational impact of perceived usefulness. Professional development needs demonstrated positive moderation effects ($\beta = 0.108$, $p = 0.002$, $\Delta R^2 = 0.012$). Teachers with high professional development needs showed stronger relationships between perceived usefulness and intention (simple slope = 0.547, $p < 0.001$) compared to those with low needs (simple slope = 0.331, $p < 0.001$).

Fig. 3 illustrates moderation effects from Table 3, showing how ethical concerns and professional development needs influence the relationship between perceived usefulness and behavioral intention. Different colored lines represent low, medium, and high moderator levels.

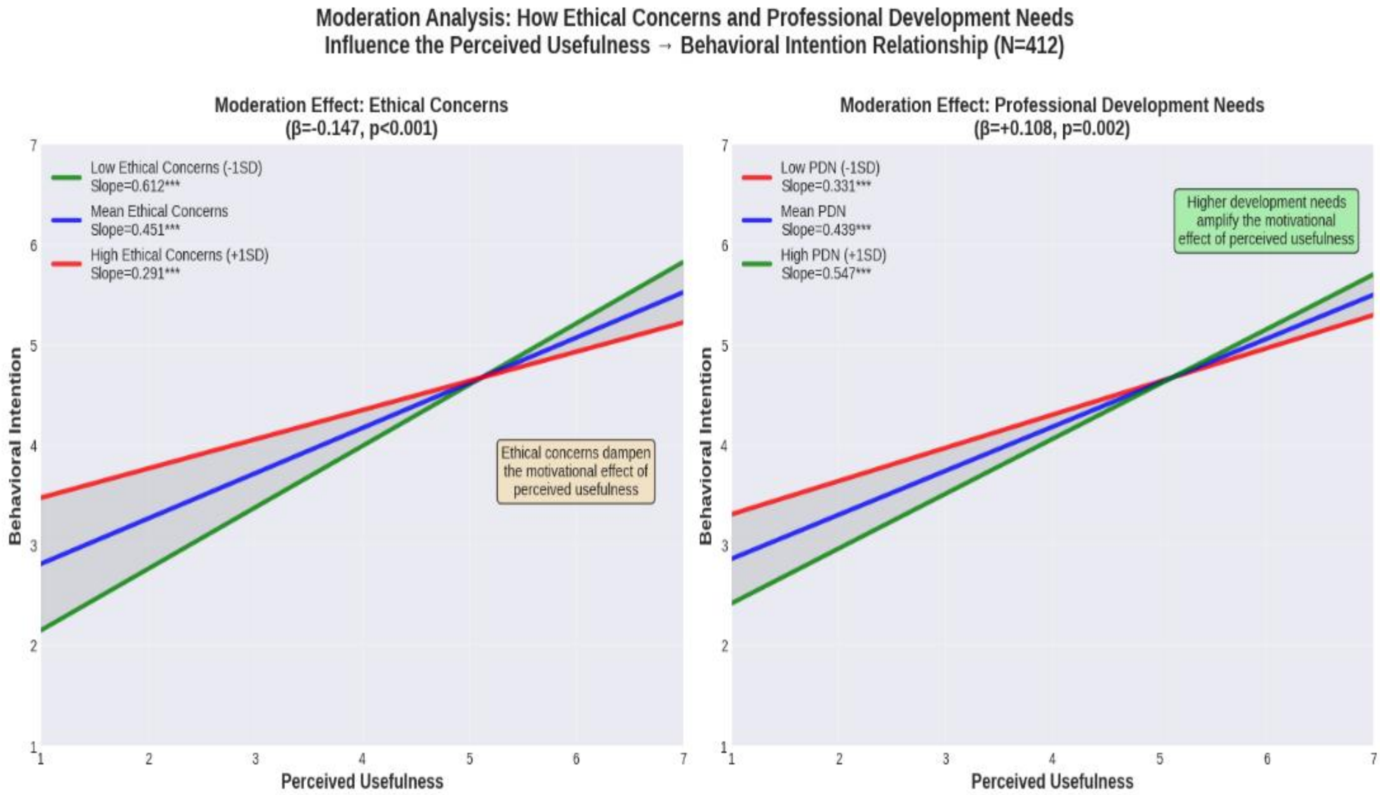

Fig 3 Moderation Effects, Interaction Between Predictors and Moderators

Table 3: Moderation Effects of Ethical Concerns and Professional Development

Predictor	**Moderator**	**β**	**p**	**ΔR²**
Perceived Usefulness	Ethical Concerns	-.147	<.001	.021
Perceived Ease of Use	Ethical Concerns	-.092	.026	.008
Perceived Usefulness	Prof. Development	.108	.002	.012
Perceived Ease of Use	Prof. Development	.126	.001	.015

3.5 Group Comparison Results

Table 4 presents group comparison analyses examining differences in perception variables across demographic categories. Prior AI experience demonstrated the strongest effects across all dimensions. Teachers with regular AI use reported substantially higher perceived usefulness ($M = 5.89$, $SD = 0.94$) compared to non-users ($M = 4.52$, $SD = 1.31$; Cohen's $d = 1.19$, $p < 0.001$) and behavioral intention ($M = 5.82$, $SD = 1.14$ vs. $M = 3.87$, $SD = 1.48$; $d = 1.46$, $p < 0.001$). STEM teachers consistently scored higher than non-STEM colleagues across perceived usefulness ($M = 5.48$ vs. $M = 4.89$; $d = 0.48$, $p = 0.001$), ease of use ($M = 5.21$ vs. $M = 4.59$; $d = 0.48$, $p = 0.001$), and behavioral intention ($M = 5.12$ vs. $M = 4.38$; $d = 0.50$, $p < 0.001$). Early-career teachers demonstrated higher intentions ($M = 5.08$) than late-career colleagues ($M = 4.31$; $d = 0.52$, $p = 0.006$).

Table 4: Group Differences in Behavioral Intention Across Demographics

Variable	**Experience**	**Subject**	**Grade**	**Prior AI**
Behavioral Intention	F=6.83**	F=12.47***	F=3.42*	F=38.64***
Effect Size	ηp^2=.032	ηp^2=.029	ηp^2=.016	ηp^2=.159
Pattern	Early>Late	STEM>Non	Sec>Elem	Regular>None

Note: *p < 0.05, **p < 0.01, ***p < 0.001

3.6 Perceived Opportunities and Challenges

Table 5 presents perceived challenges in AI integration. Insufficient professional development emerged as the most prominent challenge (endorsed by 84.7% of participants, M = 5.91, SD = 1.04), followed by ethical and privacy concerns (81.3%, M = 5.76, SD = 1.08), technical and infrastructure barriers (76.9%, M = 5.64, SD = 1.15), pedagogical integration challenges (73.5%, M = 5.52, SD = 1.19), equity and access disparities (69.2%, M = 5.47, SD = 1.22), and professional identity threats (47.3%, M = 4.68, SD = 1.46). Teachers identified four primary opportunity domains: administrative efficiency enhancement (endorsed by 78.4%, M = 5.87, SD = 1.12), personalized learning facilitation (71.6%, M = 5.64, SD = 1.21), assessment innovation and feedback enhancement (67.2%, M = 5.48, SD = 1.28), and professional learning and content knowledge enhancement (64.8%, M = 5.42, SD = 1.24).

Table 5: Perceived Challenges in AI Integration (N=412)

Challenge Category	**Endorsement %**	**M**	**SD**
Insufficient Professional Development	84.7%	5.91	1.04
Ethical and Privacy Concerns	81.3%	5.76	1.08
Technical and Infrastructure Barriers	76.9%	5.64	1.15
Pedagogical Integration Challenges	73.5%	5.52	1.19
Equity and Access Disparities	69.2%	5.47	1.22
Professional Identity Threats	47.3%	4.68	1.46

3.7 Discussion

The results indicate that teacher perception is situation-complicated and nuanced with indicators of stated transformative potential and serious implementation issues [3,20-23]. The relatively high predictive capacity of perceived usefulness (β = 0.483) proves the idea that teachers consider technologies in terms of pedagogy and instructional effectiveness instead of the technological innovativeness. The undesirable moderating role of ethical issues highlights the fact that even the tools that may be beneficial in terms of pedagogy are resisted during adoptions when the ethical protection does not seem to be enough [9,24-26]. The high magnitude of explained variance in behavioral intention ($R^2 = 0.684$) indicates that the extended Technology Acceptance Model is more effective in comparison with the traditional TAM models, which is why the theoretical expansion is justified in educational situations [27-29]. Patterns of groups show worrying results as far as equity is concerned since there is a tendency toward a lower rate of AI adoption among high-poverty school teachers, posing a threat of reinforcing existing achievement disparities [30-32]. The finding of a positive correlation between the needs of the professional development and behavioral intention refutes the deficit oriented supposition and indicates that the teachers who recognize their insufficiency in skills depict growth orientated tendencies and greater innovativeness to innovation.

4. Conclusion

This in-depth study indicates that, teachers are not blind, mindless fans but considerate individuals who assess the advantages in opposition to threats. The significant difference between appreciating the potential of AI (73.8%) and the willingness to adopt it (45.2) is an indication that the knowledge of opportunities is not an appropriate motivation to adopt AI without the conditions. The main findings are: (1) the use of structural equation modeling showed that the relationship of perceived usefulness and ease of use with behavioral intention is significant and usefulness has stronger effects (β = 0.483); (2) hierarchical regression showed that education-specific variables significantly contribute to the relationship between perceived benefits and adoption ($\Delta R^2 = 0.187$) when compared to traditional TAM constructs; (3) the use of moderation analysis showed that ethical concerns have negative moderating effects on relationships between the two predictors and adoption (β = -0.147)

To policymakers, the research implies that all-encompassing policies should be formulated by the government covering the aspects of privacy, ethical, transparency, and fair access to AI before it gets widespread. Stop (mandate) AI literacy training in pre-service teachers' schools. Devote considerable funds towards continuous professional growth. Create fair resource distribution where schools with underprivileged communities are provided with resources adequately. To the school administrators, professional learning programs should focus on practical exploration and less on theoretical knowledge. Establish organizational guidelines on the use of AI by teachers and students. Constant technical assistance eliminates troubleshooting. Establish communities of teachers to exchange the successful practices. To professional development designers, develop experiential learning methods that will allow exploratory AI use. Meet various dimensions such as the technical operational, pedagogical integration strategy, ethical issues and redesigning assessment. Give subject and grade level specific instructions. In the case of AI developers, design programs that focus on end user friendliness via user interfaces are valued. Introduce open algorithms that allow users to get insight into system rationale. Undertake effective bias audits that would grant fair performance. Give transparent privacy rights that are meant to be applied when dealing with minors in schooling.

There are a number of restrictions, which should be mentioned. The cross-sectional design does not allow making any causal inference whereas self-reported behavioral intention might not effectively forecast actual implementation. The sample which was varied used convenience sampling that restricted generalizability. Positive perceptions may have been being inflated because of social desirability bias. The dynamic development of AI technologies implies that discoveries can be improved with the growing capabilities of the technologies. Subsequent studies ought to conduct longitudinal studies involving teachers involved in the initial exposure to AI through the continued implementation. Causal evidence would be offered with the help of experimental studies on the effectiveness of interventions on professional development. Actual use of AI in the classroom would be observational research that would provide the reality of implementation. International comparative studies would help in enlightening adoption patterns by culture, policy and structural set up. Studies aimed at discussing the results of AI use in instruction with students would help create important evidence of efficiency. Equity implications research directions would record the outcomes of achievement gap alleviation or exacerbation with the incorporation of AI.

Artificial intelligence is a truly transformative technology that can bring considerable benefit to the world of education in terms of effectiveness, efficiency, and equity. Nonetheless, this potential can only be achieved by going beyond technological determinism to consider the implementation in a thoughtful, evidence-based, human approach, and we need to focus on student learning, teacher professionalism, and effectiveness of learning, and equity of educational access. An effective implementation of AI requires a holistic support in the form of professional development, ethical protection, technical infrastructure, pedagogical instruction and equity matters. It entails making teachers active agents and expert professionals as opposed to passive receivers of technological innovation. It requires the focus on equity when faced with the needs of every student and every teacher in the context of socioeconomic setting receiving the educational benefits of AI. It requires placing morals, openness, responsibility and human reasoning at the centre of design, implementation and assessment process. Finally, AI must complement instead of replace human instruction, to increase the ability of educators to engage learners meaningfully, design a well-crafted curriculum, individualize instruction, and make professional judgments. This vision can be achieved through a bidirectional cooperation between policymakers, administrators, teachers, professional developers, researchers and technology designers who believe in responsible innovation to benefit learning of students, professionalism of teachers and equity in education.

Author Contributions

SH: Conceptualization, visualization, writing original draft, writing review and editing. NLR: Conceptualization, methodology, software, resources, visualization, writing original draft, writing review and editing. MM: Conceptualization, study design, analysis, visualization, writing original draft, writing review and editing, and supervision. RB: Study design, analysis, data collection, methodology, software, resources.

Conflict of interest

The authors declare no conflicts of interest.

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