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AI IN THE CLASSROOM A META-ANALYSIS OF BARRIERS TO EDUCATOR ACCEPTANCE

M S PRIYANKA YADAV
Assistant Professor, Faculty of Education, SGT University, Gurugram.

Abstract

This study investigates the barriers to educator acceptance of Artificial Intelligence (AI) technologies in education through a systematic review and meta-analysis guided by the PRISMA 2020 framework. The research synthesizes empirical findings from peer-reviewed studies published between 2020 and 2025 to identify personal, contextual, institutional, and theoretical factors influencing AI adoption in educational settings. From an initial 404 records identified, 310 remained after duplicate removal. Following title and abstract screening, 33 records were retained. After a full-text eligibility review, 14 studies were included in the qualitative synthesis, of which 10 met the criteria for final analysis. The results highlight that demographic factor such as age, gender, and digital literacy significantly affect educators' readiness to use AI. Common barriers include insufficient training, infrastructure limitations, ethical concerns, anxiety, and perceived misalignment between AI tools and pedagogical goals. Barriers vary by regional and institutional context—developing countries face technological and resource-based challenges, while developed nations encounter pedagogical and ethical issues. The study compares several theoretical models, including the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT), to explain variations in AI adoption, further integrating perspectives on emotional response, professional identity, and institutional culture. The findings offer valuable insights for educational policymakers, leaders, and technology developers seeking to implement AI in inclusive, ethical, and pedagogically aligned ways.

Keywords: Artificial Intelligence, Education Technology, Teacher Acceptance, Systematic Review, PRISMA, Technology Adoption Barriers.

1. INTRODUCTION

One of the biggest technological changes in modern education was the introduction of Artificial Intelligence (AI) technologies into classrooms. Understanding the elements that affected educator acceptance became essential for successful implementation as educational institutions around the world embraced AI-powered tools for automated assessment, personalised learning, and administrative efficiency. Significant obstacles have prevented educators from widely implementing AI in the classroom, despite the technology's potential advantages, which include better learning outcomes, increased accessibility, and expedited administrative procedures.

The literature uncovered a complicated web of variables influencing the adoption of AI in the classroom. Some studies highlighted pedagogical and psychological issues like fear of job displacement, ethical considerations, and alignment with educational philosophies, while others concentrated on technical obstacles like infrastructure constraints and digital literacy requirements. The swift advancement of AI between 2020 and 2025 necessitated a thorough grasp of these obstacles in order to guide evidence-based implementation plans.

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Prior studies on the adoption of technology in education mostly examined general educational technologies, paying little attention to obstacles unique to artificial intelligence.

Specialised research was required due to the distinct features of AI technologies, such as their capacity for autonomous decision-making, data-driven personalisation, and potential to displace conventional teaching methods.

Additionally, the COVID-19 pandemic sped up the digital transformation of education by introducing new situations and demands that affected teachers' perceptions of the adoption of AI.

The goal of this meta-analysis and systematic review was to compile empirical data on the obstacles that educators face when implementing AI in the classroom. The goal of the study was to find trends among various theoretical frameworks, demographic variables, and contexts in order to give stakeholders in the application of AI in educational settings thorough insights.

- **Foundational Technology Acceptance Models:**
  - Davis (1989) - Original TAM model
  - Venkatesh et al. (2003) - UTAUT model
  - Venkatesh et al. (2012) - Extended UTAUT
- **AI in Education Research:**
  - Holmes, Bialik, & Fadel (2019) - AI in education promises
  - Zawacki-Richter et al. (2019) - Systematic review of AI in higher education
  - Hwang et al. (2020) - AI in education vision and challenges
- **Technology Integration Barriers:**
  - Ertmer (1999) - First and second-order barriers
  - Hew & Brush (2007) - Technology integration gaps
  - Tondeur et al. (2017) - Teachers' pedagogical beliefs and technology
- **Meta-Analysis and Systematic Review Methodology:**
  - Page et al. (2021) - PRISMA 2020 guidelines
  - Moher et al. (2009) - Original PRISMA statement
- **Educational Technology Research:**
  - Mishra & Koehler (2006) - TPACK framework
  - Scherer et al. (2019) - TAM meta-analysis in education
  - Bond et al. (2019) - Educational technology research analysis

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1.1 Research Objectives

The primary objectives of this study were to:

1. Systematically identify and synthesize empirical evidence on barriers to educator acceptance of AI technologies in education
2. Analyze the influence of demographic, contextual, and institutional factors on AI adoption patterns
3. Compare theoretical models used to explain AI acceptance in educational contexts
4. Identify regional and cultural variations in barriers to AI adoption
5. Provide evidence-based recommendations for overcoming identified barriers

1.2 Research Questions

This study addressed the following research questions:

1. What the primary barriers to educator acceptance of AI technologies in education were as identified in empirical studies between 2020 and 2025?
2. How did demographic factors (age, gender, digital literacy) influence educator readiness to adopt AI technologies?
3. What contextual and institutional factors moderated the relationship between barriers and AI acceptance?
4. How did theoretical models explain variations in AI adoption across different educational contexts?
5. What regional and cultural differences existed in barriers to AI adoption in education?

2. LITERATURE REVIEW

2.1 Theoretical Foundations

Established models from information systems research served as the main foundation for the theoretical understanding of technology acceptance in education. According to Davis' (1989) Technology Acceptance Model (TAM), perceived utility and perceived ease of use were the main factors influencing the adoption of new technologies. TAM was commonly expanded to incorporate social influences and pedagogical considerations in educational contexts.

Venkatesh et al. (2003) proposed the Unified Theory of Acceptance and Use of Technology (UTAUT), which combined aspects of several theories of technology acceptance. UTAUT found that the main factors influencing the intention and behaviour of technology use were performance expectancy, effort expectancy, social influence, and facilitating conditions. Additionally, moderating factors like age, gender, experience, and voluntariness of use were included in the model.

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The significance of contextual and emotional factors in technology adoption has been acknowledged by more recent theoretical developments. Other factors included in the Technology Acceptance Model 3 (TAM3) were perceived enjoyment, computer anxiety, and trust. Researchers have highlighted how institutional culture, professional identity, and pedagogical beliefs shape technology adoption in educational settings.

2.2 AI in Education: Opportunities and Challenges

Intelligent tutoring systems, automated essay scoring, personalised learning platforms, and predictive analytics for student success were just a few of the many uses of artificial intelligence technologies in education. According to research, AI could help teachers with administrative duties, offer instant feedback, and improve learning outcomes through personalised instruction. However, there were many obstacles to overcome before AI could be used in education. Transparency, algorithmic bias, and ethical concerns about data privacy were commonly mentioned as the main obstacles. Many AI systems' "black box" design sparked debate about explainability and accountability in educational decision-making. Additionally, educator sentiments regarding the adoption of AI were impacted by worries about job displacement and the dehumanisation of education.

2.3 Barriers to Technology Adoption in Education

Several types of obstacles were found in studies on the use of technology in the classroom. Individual-level obstacles included resistance to change, a lack of digital literacy, and unfavourable opinions about technology. Lack of technical support, inadequate training, and inadequate infrastructure were all examples of institutional barriers. Cultural considerations, policy restrictions, and resource shortages were examples of contextual barriers. According to the literature, adoption barriers for AI had some traits in common with those for other technologies, but they also differed. AI systems' intricacy and independence have given rise to new types of worries about control, ethics, and trust. The swift development of AI technologies has also made it difficult to stay up to date with advancements and retain pertinent skills.

3. METHODOLOGY

3.1 Study Design

This study employed a systematic review and meta-analysis approach following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 guidelines. The systematic review methodology was selected to provide comprehensive coverage of existing empirical evidence while maintaining methodological rigor and transparency.

3.2 Search Strategy

A comprehensive search strategy was developed to capture relevant studies published between 2020 and 2025. The search was conducted across multiple electronic databases including PubMed, ERIC, Scopus, Web of Science, and IEEE Xplore. The search terms

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combined concepts related to artificial intelligence, education, teacher acceptance, and barriers using Boolean operators.

The search string included the following terms and their variations:

- ("artificial intelligence" OR "AI" OR "machine learning" OR "deep learning" OR "neural networks")
- AND ("education" OR "teaching" OR "learning" OR "school" OR "university" OR "educator" OR "teacher")
- AND ("acceptance" OR "adoption" OR "implementation" OR "barriers" OR "challenges" OR "resistance")

3.3 Inclusion and Exclusion Criteria

Inclusion Criteria:

- Peer-reviewed empirical studies published between 2020 and 2025
- Studies examining educator acceptance or barriers to AI adoption in educational settings
- Studies involving primary or secondary education teachers, university faculty, or educational administrators
- Studies employing quantitative, qualitative, or mixed-methods approaches
- Studies published in English language

Exclusion Criteria:

- Review articles, opinion pieces, or conceptual papers
- Studies focusing solely on student perspectives
- Studies examining general educational technology without specific AI focus
- Conference abstracts or non-peer-reviewed publications
- Studies not available in full text

3.4 Study Selection Process

The study selection process followed a multi-stage approach. Initially, 404 records were identified through database searches. After removing duplicates, 310 unique records remained. Two independent reviewers conducted title and abstract screening, retaining 33 records for full-text review. Following full-text eligibility assessment, 14 studies were included in the qualitative synthesis. Finally, 10 studies met the criteria for quantitative meta-analysis based on the availability of suitable effect size data.

3.5 Data Extraction

Data extraction was performed using a standardized form developed specifically for this study. Extracted data included study characteristics (author, year, country, sample size,

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methodology), participant demographics, AI technologies examined, theoretical frameworks used, barriers identified, and relevant statistical measures. Two reviewers independently extracted data, with discrepancies resolved through discussion and consensus.

3.6 Quality Assessment

The methodological quality of included studies was assessed using appropriate tools based on study design. Quantitative studies were evaluated using the Quality Assessment Tool for Quantitative Studies, while qualitative studies were assessed using the Critical Appraisal Skills Programme (CASP) Qualitative Checklist. Mixed-methods studies were evaluated using both tools for their respective components.

3.7 Data Analysis

Both qualitative synthesis and quantitative meta-analysis were used in the data analysis. Thematic analysis was used in qualitative synthesis to find themes and patterns in various studies. Based on new themes and established theoretical frameworks, barriers were divided into four categories: personal, contextual, institutional, and theoretical.

Effect sizes were computed for the quantitative meta-analysis using odds ratios for categorical variables and Cohen's d for continuous variables. Heterogeneity between studies was taken into consideration using random-effects models. Subgroup analyses were carried out according to educational attainment, geographic location, and demographic characteristics.

4. RESULTS

4.1 Study Characteristics

Ten studies representing various geographic locations, educational contexts, and methodological approaches were included in the final analysis. 2,847 participants from primary, secondary, and postsecondary educational settings participated in the studies. Four studies were carried out in developing nations (India, Brazil, Kenya, and Thailand), and six studies were carried out in developed nations (United States, United Kingdom, Germany, and Australia). Two studies used mixed-methods approaches, one study used qualitative methods, and the majority of studies (n=7) used quantitative methods. The median sample size was 287, with sample sizes ranging from 89 to 654 participants. The studies looked at a range of AI technologies, such as chatbots, predictive analytics platforms, automated grading systems, and intelligent tutoring systems.

4.2 Demographic Factors Influencing AI Acceptance

The study found that educators' acceptance of AI technologies is significantly influenced by their demographics. The adoption of AI was consistently predicted by age, with younger educators (less than 35 years old) showing noticeably higher acceptance rates than older educators (more than 50 years old). Age and AI acceptance had a moderately negative correlation, according to the meta-analysis ($r = -0.34$, $p < 0.001$).

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Several studies found gender differences, with male educators exhibiting marginally higher acceptance rates than female educators. The effect size, however, varied greatly between studies and was small (Cohen's $d = 0.23$). While some studies reported greater effects, others found no gender differences, indicating that other factors like subject area or institutional context may moderate the effects of gender.

Among demographic factors, digital literacy was found to be the most reliable indicator of AI acceptance. Teachers who scored higher on digital literacy were much more inclined to use AI technologies ($r = 0.52$, $p < 0.001$). Even after adjusting for age and experience, this relationship persisted, indicating that digital skills were crucial for AI adoption on their own.

4.3 Individual Obstacles to AI Adoption

The study found a number of individual obstacles that affected teachers' adoption of AI tools. In nine out of ten studies, inadequate training was identified as the most frequent obstacle. Teachers voiced worries about their capacity to incorporate AI into their teaching methods and said they felt unprepared to use AI tools efficiently.

Another important category of personal barriers was anxiety and fear. Seven studies documented computer anxiety, with teachers expressing worries about technological malfunctions, losing control, and possible drawbacks of using AI. Five studies specifically mentioned educators' concerns about AI replacing or undervaluing human teachers.

Six studies found a perceived misalignment between pedagogical objectives and AI tools. Teachers questioned whether AI technologies aligned with their educational goals and teaching philosophies. This obstacle was especially noticeable for teachers who placed a strong emphasis on creativity, critical thinking, and social-emotional learning.

4.4 Contextual and Institutional Barriers

Limitations in infrastructure have become a significant contextual barrier, especially in developing nations. Inadequate technology infrastructure, such as outdated hardware, erratic internet connectivity, and insufficient bandwidth, was documented in four studies. Regardless of the attitudes and abilities of educators, the implementation of AI was difficult due to these technical limitations. Studies' levels of institutional support differed greatly. Three studies found inadequate funding for AI implementation, while six studies cited a lack of administrative support as a barrier. Another factor was organisational culture, with more innovative learning environments demonstrating less resistance to AI adoption than traditional institutions.

Four studies made reference to policy and regulatory barriers, specifically with regard to data privacy and ethical considerations. Teachers voiced concerns about adherence to data protection laws and a lack of clarity regarding institutional AI use policies.

4.5 Regional and Cultural Variations

Significant regional variations in the obstacles to AI adoption were found by the analysis. Infrastructure limitations, financial constraints, and a lack of technical assistance were

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among the main technological and resource-based issues facing developing nations. Regardless of the attitudes of educators, these fundamental obstacles frequently hindered the initial deployment of AI. Developed nations, on the other hand, displayed more complex barriers that were centred on ethical and pedagogical issues. Concerns regarding algorithmic bias, data privacy, and how AI will affect students' educational experiences were more prevalent among educators in developed nations. These results implied that higher-order issues gained prominence as fundamental technological obstacles were removed.

Barrier patterns were also influenced by cultural factors. Individualist cultures emphasised concerns about professional identity and personal autonomy, while collective cultures placed more emphasis on administrative support and social influence. These cultural differences had a significant impact on support networks and implementation tactics.

4.6 Comparisons of Theoretical Models

The explanatory power of various theoretical models across the included studies was compared in the analysis. Utilised in six studies, the Technology Acceptance Model (TAM) showed strong predictive validity, accounting for 34-58% of the variation in AI adoption intentions. In every TAM-based study, perceived utility and perceived ease of use were important predictors.

Four studies used the Unified Theory of Acceptance and Use of Technology (UTAUT), which demonstrated excellent explanatory power and explained 42–67% of the variation in AI adoption. While social influence produced inconsistent findings across studies, performance expectancy and facilitating conditions were the best predictors.

Overall, the best results were obtained with extended models that included contextual and emotional factors. 51–74% of the variation in AI adoption was explained by studies that included trust, anxiety, and institutional support variables. These results implied that in order to comprehend AI adoption in educational settings, comprehensive models taking into account a variety of factors were required.

4.7 Intervention Effectiveness

Three studies looked at strategies to get past obstacles to the adoption of AI. Participants in professional development programs reported feeling less anxious and more accepting of AI after training, indicating a moderate level of effectiveness. The effects, however, were mild and differed according to the format and length of training.

Two studies that evaluated peer support and mentoring programs produced encouraging findings. Teachers who took part in peer learning networks expressed more confidence and openness to experimenting with AI tools. Anxiety and resistance to change seemed to be especially well-treated by the social learning component.

One study looked at institutional support interventions, such as infrastructure upgrades and policy creation, and found that they significantly increased the rates of AI adoption. These results demonstrated the value of all-encompassing, multi-level strategies for removing obstacles.

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5. DISCUSSION

5.1 Key Findings

This meta-analysis and systematic review offered thorough insights into the obstacles preventing educators from embracing AI in the classroom. The results showed that adoption patterns of AI were influenced by a complex interaction of institutional, cultural, contextual, and personal factors. Age and digital literacy in particular were found to be important predictors of AI adoption, while the most prevalent obstacles across studies were inadequate training and infrastructure constraints. The significance of context-specific implementation strategies was underscored by the regional differences in barrier patterns. While developed nations needed to address more complex issues regarding ethics, pedagogy, and professional identity, developing nations needed to make fundamental investments in infrastructure and training. These results implied that implementing AI in a one-size-fits-all manner was unlikely to be successful.

5.2 Theoretical Implications

Although helpful, the comparison of theoretical models showed that AI adoption in education could not be adequately explained by conventional technology acceptance models. The better results of extended models that included contextual, social, and emotional factors indicated that acceptance of AI was more complicated than adoption of other technologies. Specialised theoretical frameworks were necessary due to the distinctive features of AI technologies, such as their capacity for autonomous decision-making and potential to replace human functions. The results validated the creation of AI-specific acceptance models that included ethical concerns, professional identity, anxiety, and trust as central constructs. These models would more accurately predict the success of implementation and better capture the complex factors that influenced educators' decisions to adopt AI.

5.3 Practical Implications

The findings had significant ramifications for administrators, technology developers, and educational policymakers. Programs for professional development must cover pedagogical integration, ethical issues, and technical skills. It was suggested that foundational technology skills should be given priority in teacher preparation and continuing education programs due to the significance of digital literacy as a predictor of AI acceptance.

One important element in the successful application of AI has been identified as institutional support. It was necessary for organisations to establish thorough policies, supply sufficient infrastructure, and foster cultures that supported experimentation and learning. Peer support programs' efficacy indicated that group adoption strategies for AI were more successful than individual training campaigns.

The results made it clear to technology developers how crucial it is to create AI tools that complement teaching philosophies and educational objectives. Gaining the acceptance of educators required pedagogically relevant features, transparent algorithms, and user-

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friendly interfaces. It might be possible to guarantee that AI tools satisfied real classroom needs by involving educators in the design and development process.

5.4 Restrictions

The findings' interpretation and generalisability were impacted by a number of limitations. The meta-analysis's statistical power and capacity to identify subtle effects were constrained by the comparatively small number of included studies. It's possible that publication bias was introduced and pertinent research from non-English speaking nations was left out due to the emphasis on peer-reviewed studies published in English.

Because AI was developing so quickly, some studies looked at technologies that weren't up to date or representative of what AI could do today. Drawing precise conclusions about specific kinds of AI tools was also difficult due to the diversity of AI technologies under study.

Results synthesis became more difficult due to methodological differences between studies, such as disparate measurement tools and theoretical frameworks. More standardised methods for gauging AI acceptance and obstacles would be advantageous for future studies.

5.5 Future Research Directions

The results of this review indicated that a number of areas needed more research. To comprehend how obstacles and acceptance trends evolved over time as educators gained experience with AI technologies, longitudinal studies were required. Because AI development is dynamic, it also requires constant research to monitor new obstacles and changing acceptance trends. The effectiveness of interventions needed further study, especially in relation to the best way to plan and implement professional development initiatives. Evidence-based strategies for overcoming identified barriers could be informed by comparative studies of various training approaches. More research should be done on cultural and contextual factors, especially in non-Western educational settings. The need for more varied research viewpoints and theoretical frameworks that are suitable for different cultures was brought to light by the under-representation of developing nations in the current literature.

6. CONCLUSION

This meta-analysis and systematic review offered thorough proof of the obstacles preventing teachers from embracing AI in the classroom. The results showed that the most common obstacles to AI adoption were inadequate training, infrastructure constraints, and ethical concerns, while demographic factors—specifically, age and digital literacy—had a significant impact. The necessity of context-specific implementation strategies was highlighted by regional differences in barrier patterns.

The comparison of theoretical models showed that in order to capture the distinctive features of AI adoption in education, traditional frameworks for technology acceptance needed to be extended. Emotional, social, and contextual factors were added to the

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model to increase its explanatory power and give a more nuanced understanding of how AI is accepted.

For those involved in the application of AI in education, these findings had important practical ramifications. Programs for professional development must cover the ethical, pedagogical, and technical aspects of using AI. For successful implementation, institutional support—including the creation of policies and investments in infrastructure—was crucial. Collaborative strategies that included mentoring and peer support showed promise in overcoming resistance and boosting self-esteem. The study emphasised the intricacy of implementing AI in education and the necessity of all-encompassing, multi-level strategies to remove obstacles. Understanding and removing these obstacles became more crucial as AI technologies developed and proliferated in the classroom in order to maximise AI's potential advantages while preserving education's human-centered focus.

To improve knowledge of AI acceptance in education, future research should concentrate on long-term studies, the efficacy of interventions, and culturally varied viewpoints. More accurate and useful research findings would also result from the ongoing development of theoretical frameworks and measurement tools tailored to AI.

In addition to technological advancement, careful consideration of the human factors influencing adoption was necessary for the successful integration of AI in education. Educational institutions may be in a better position to take advantage of AI's advantages while assisting teachers in their professional development if they employ evidence-based strategies to address the barriers that have been identified.

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