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Exploring Teacher Perceptions of Deep Learning for Professional Development: A Technology Acceptance Model Approach

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ABSTRACT

Teacher professional development is a critical component for enhancing educational quality, and the integration of deep learning technologies has emerged as a transformative tool, although its implementation presents challenges. This study aimed to analyze the acceptance and usage of deep learning technologies in professional development programs using the Technology Acceptance Model (TAM) by investigating associated challenges and opportunities. Adopting a convergent parallel mixed-methods research design, data were collected through semi-structured interviews, focus group discussions (FGDs), and surveys measuring Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) from 30 participants comprising teachers, school administrators, and policymakers. Qualitative data underwent thematic analysis, while quantitative survey data were analyzed descriptively. Key findings reveal significant challenges such as technological infrastructure gaps (including internet access issues and inadequate hardware), limited digital literacy (compounded by training complexity), and resistance to change (including fear of being replaced by AI). Conversely, opportunities include personalized learning paths (such as personalized training recommendations), enhanced pedagogical insights, and scalable training programs. Although stakeholders perceived deep learning platforms as generally useful and easy to use, concerns about practical usability among policymakers and the impact of external barriers persist. The study concludes that deep learning offers substantial potential, but its successful integration necessitates addressing these structural, systemic, and human-centric barriers. It also offers actionable insights for educators, policymakers, and technology developers to foster more effective and inclusive deep learning-enhanced professional development.

I. Introduction

The rapid evolution of educational technology has significantly impacted teacher professional development, reshaping traditional paradigms and introducing innovative approaches to training and capacity building (Gyawali & Mehndroo, 2024; Khulbe & Tammets, 2021; Waldia et al., 2023; W. Zhang, 2022). Digital tools, powered by artificial intelligence and machine learning, have paved the way for more interactive, adaptive, and effective professional development programs. Among these technological advancements, deep learning, a subset of AI focused on mimicking the human brain's neural networks (Mucha et al., 2023; Sharma et al., 2024; Q. Zhang, 2025), stands out for its potential to analyze complex data sets and generate insights that can personalize and optimize learning processes.

Deep learning technologies can transform teacher professional development by offering real-time feedback, designing adaptive learning pathways, and supporting data-driven decision-making in training modules (Duan & Zhao, 2024; J. Li, 2025; Rajput & Sharma, 2025). For instance, deep learning models can analyze patterns in teacher performance, identify specific skill gaps, and recommend targeted interventions (Y. Gao, 2025; Zhu, 2023). This level of personalization can empower teachers to engage in self-directed learning that aligns with their professional goals and classroom needs.

However, the adoption of deep learning technologies in teacher training programs is not without its challenges. Issues such as technological infrastructure limitations, a digital divide between urban and rural regions, and resistance to change among educators hinder the effective integration of these tools (Esakkiammal & Kasturi, 2024; Jacka, 2023; Murari & Parmar, 2025; Zhu, 2023). Moreover, ethical concerns about data privacy and security present additional complexities in leveraging AI-driven solutions. In contexts where technological readiness varies significantly, these challenges are

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amplified, creating disparities in access to innovative training resources.

Although deep learning technology holds great potential to transform teacher professional development programs, few studies have explored how this technology is perceived, accepted, and utilized within such programs, particularly through structured theoretical frameworks like the Technology Acceptance Model (TAM) (Tan et al., 2025). TAM emphasizes two core constructs, perceived usefulness (PU) and perceived ease of use (PEOU), which have significantly influenced teachers' acceptance of technology. In addition, external factors such as technology self-efficacy, subjective norms, and institutional support and training play crucial roles in shaping teachers' attitudes and behavioral intentions toward technology use (Sundararasan, 2024). Recent studies have extended TAM by incorporating additional constructs such as peer influence, perceived teaching quality, and technological pedagogical content knowledge (TPACK) to capture the broader educational context better (Sundararasan, 2024). However, adopting advanced technologies such as AI and deep learning still faces internal barriers, including limited infrastructure, inadequate training, and resistance to change (Okur & Hamutoğlu, 2023). Digital divides and technological accessibility also present significant challenges that have not been sufficiently addressed in the current literature (Tan et al., 2025; Yadav, 2025). Therefore, this study must address fundamental questions regarding how teachers perceive, accept, and utilize deep learning technologies in their professional development, using TAM as its main analytical framework.

The potential of deep learning technologies to address pressing issues in teacher professional development makes them an area of great interest. Yet, despite their promise, their implementation remains underexplored in educational research (Ji et al., 2025; Tan et al., 2025). There is a need to better understand how educators perceive and interact with deep learning technologies and the factors influencing their acceptance and practical use.

To address this gap, this study investigates the challenges and opportunities associated with implementing deep learning technologies in teacher professional development programs. The study employs the Technology Acceptance Model (TAM) as its theoretical framework, which provides a structured approach to analyzing the factors influencing the acceptance of new technologies (Armouti et al., 2023; Caldarelli et al., 2019). TAM emphasizes two critical determinants of technology adoption: perceived usefulness (PU) and perceived ease of use (PEOU) (B. Gao et al., 2024; C.-J. Li et al., 2025; Malatji et al., 2020). These determinants and external factors, such as technological infrastructure, training quality, and organizational support, influence an individual's behavioral intention to adopt a technology and their actual usage behavior.

By applying TAM, this study aims to generate actionable insights into the conditions that facilitate or hinder the adoption of deep learning in teacher training. The findings contribute to a nuanced understanding of the interplay between technology, pedagogy, and organizational dynamics in professional development (Mustofa et al., 2025). Moreover, the study offers practical recommendations for educators, policymakers, and technology developers to design and implement more effective and inclusive training programs.

II. Method

This study adopts a mixed-methods research design to explore the implementation of deep learning in teacher professional development, leveraging the Technology Acceptance Model (TAM) as its guiding theoretical framework. This approach was chosen to gain comprehensive insights by triangulating an in-depth qualitative understanding of stakeholder experiences and perceptions with quantitative technology acceptance measures. The qualitative component aimed to uncover nuanced perspectives on challenges and opportunities, while the quantitative component sought to measure key TAM constructs. The TAM framework, as outlined by Davis (1989), focuses on perceived usefulness (PU), perceived ease of use (PEOU), and external variables influencing technology adoption.

A. Research Design

This study employed a convergent parallel mixed-methods design, allowing for a comprehensive understanding by simultaneously integrating qualitative and quantitative data. In the qualitative phase, semi-structured interviews and focus group discussions (FGDs) were conducted to explore participants' in-depth experiences and perceptions regarding AI-based learning platforms. A purposive sampling approach was used to ensure the inclusion of diverse viewpoints, involving 30 participants comprising 15 teachers, 10 school administrators, and 5 policymakers. These participants were selected based on their roles and relevance to the implementation and policy of educational technology. The total of 30 participants was deemed sufficient based on the principle of data saturation for qualitative inquiry and the manageable sample size typically acceptable for preliminary explanatory analysis in small-scale mixed-methods research. In parallel, the quantitative phase involved administering a structured survey to the same group of participants. The survey measured perceptions of Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) using a Likert-scale instrument (ranging from 1 = Strongly Disagree to 5 = Strongly Agree). The items were adapted from previously validated Technology Acceptance Model (TAM) instruments to ensure reliability and consistency with established theoretical constructs. Integrating both data types provided a robust and well-rounded analysis of stakeholders' experiences and acceptance of AI-driven learning technologies.

B. Research subject

Participants were purposefully selected from three key stakeholder groups: teachers, school administrators, and policymakers, to ensure a comprehensive understanding of perspectives related to the use of AI-based learning platforms. These groups represent different levels of involvement in the educational ecosystem, from classroom implementation to institutional decision-making and policy development. The rationale for selecting 30 participants across these groups was to ensure data adequacy, diversity of perspectives, and the feasibility of conducting simultaneous qualitative and quantitative analyses without compromising depth or breadth. The demographic characteristics of the participants are presented in Table 1.

Table 1. The demographic profile of participants

Participant Group	Number of Participants	Gender Breakdown (M/F)	Experience (Years)
Teachers	15	7/8	5–20
School Administrators	10	6/4	10–25
Policymakers	5	3/2	15–30

Table 1 shows that the study included a total of 30 participants. The teacher group, with a balanced gender distribution (7 males and 8 females), had a range of teaching experience from 5 to 20 years. School administrators had slightly more males (6) than females (4) and had between 10 and 25 years of leadership experience. Although the smallest group, policymakers were highly experienced, with 15 to 30 years in education policy development, and a gender distribution of 3 males and 2 females. This distribution of participants provided a well-rounded perspective on the research topic, combining practical insights from educators with strategic viewpoints from decision-makers and policy influencers.

C. Research Instruments and Data Collection Techniques

The data collection process was carried out in four sequential and complementary phases to ensure the findings' depth, reliability, and contextual accuracy. First, semi-structured interviews with individual participants lasted 45 to 60 minutes. These interviews were guided by open-ended questions aligned with the core dimensions of the Technology Acceptance Model (TAM), specifically Perceived Usefulness (PU) and Perceived Ease of Use (PEOU). This approach enabled participants to elaborate on their experiences, perceptions, and challenges in adopting AI-based learning platforms.

To enhance the credibility of the findings and encourage collaborative reflection, focus group discussions (FGDs) were subsequently organized. Each FGD consisted of five to seven participants from similar stakeholder groups (teachers, school leaders, or policymakers). These discussions served to triangulate the interview data and uncover shared themes, contrasting viewpoints, or group dynamics that may not surface in one-on-one interviews. Following the qualitative phases, a structured survey was administered to all participants. The survey consisted of standardized items measuring PU and PEOU and was designed to assess participants' acceptance levels of the AI platform quantitatively. Integrating survey data provided a broader response pattern that complemented the earlier stages' in-depth narratives. Finally, document analysis was undertaken to contextualize and support participants' responses. Relevant policy documents, training guidelines, and implementation manuals were reviewed to identify potential alignment or misalignment between institutional frameworks and users' experiences. This phase offered valuable background information and reinforced qualitative and quantitative data interpretation. Together, these four phases formed a comprehensive and integrated data collection strategy that ensured both rigor and relevance in exploring the adoption of AI-based learning platforms across educational stakeholders.

D. Data Analysis Techniques

Qualitative data were analyzed using thematic analysis on interview transcripts and focus group discussion (FGD) notes to identify patterns related to Perceived Usefulness (PU), Perceived Ease of Use (PEOU), and other external variables. This process involved three main stages: first, coding, where transcripts were systematically reviewed and assigned codes; second, theme identification, which grouped these codes into broader themes; and third, validation through member-checking to ensure the credibility of the findings. Additionally, the frequency of specific emergent themes, such as barriers, was counted to indicate their prominence among participants. Meanwhile, quantitative data from surveys on PU and PEOU were analyzed descriptively to produce mean scores and percentages, which were then visualized using heatmaps and pie charts. This quantitative data served to complement and contextualize the qualitative findings. Finally, qualitative and quantitative results were integrated during the interpretation phase to understand the research questions comprehensively. This approach combined the strengths of both data types, resulting in richer and more meaningful insights.

III. Results and Discussion

This study aims to identify the factors that influence the adoption of AI-based learning platforms among key stakeholders in the education sector, namely teachers, school principals, and policymakers. Data were collected using a mixed-methods approach, which included in-depth interviews, focus group discussions (FGDs), and document analysis. A total of 30 participants representing the three stakeholder groups contributed to the study. This combination of quantitative and qualitative data provides a comprehensive understanding of stakeholders' perceptions, challenges, and expectations regarding integrating AI technologies in education. The following section outlines three significant findings that reveal how user perceptions, external barriers, and differing stakeholder priorities collectively shape the dynamics of AI-based learning platform implementation.

A. Perceived Usefulness and Ease of Use of the AI-Based Learning Platform

The findings indicate that stakeholders have relatively high perceptions of the AI-based learning platform's usefulness (Perceived Usefulness/PU) and ease of use (Perceived Ease of Use/PEOU).

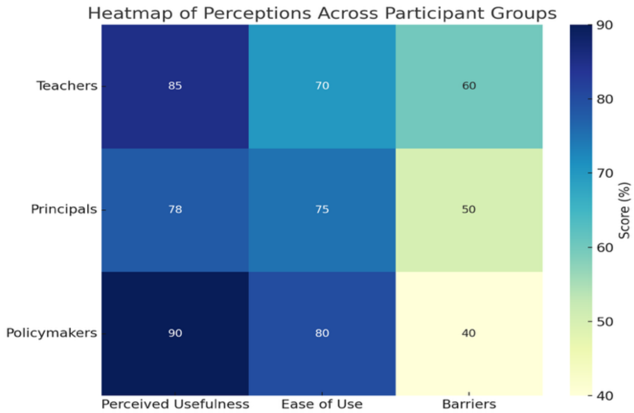

Fig. 1. Heatmap of PU and PEOU Perceptions by Stakeholder Groups

Figure 1 presents a heatmap illustrating the perceptions of three key stakeholder groups, teachers, principals, and policymakers, regarding deep learning technology across three dimensions: perceived usefulness, ease of use, and barriers. Overall, perceived usefulness received the highest ratings across all groups, with policymakers assigning the highest score (90%), followed by teachers (85%) and principals (78%). This trend indicates a strong consensus that deep learning technology benefits educational improvement, particularly among policymakers who likely focus on its strategic and systemic value.

Regarding ease of use, perceptions were moderately positive, with policymakers again giving the highest rating (80%), while principals and teachers followed closely at 75% and 70%, respectively. These results suggest that while the technology is generally perceived as user-friendly, its practical implementation may still be challenging, especially for end-users like teachers.

The most notable variation appears in the barriers dimension. Here, scores were substantially lower across all groups, reflecting recognized challenges in adopting deep learning technology. Policymakers reported the lowest perceived barriers (40%), possibly indicating a disconnect between policy-level assumptions and ground-level realities. Teachers and principals, who are more directly involved in implementation, reported higher barrier perceptions at 60% and 50%, respectively. This disparity underscores the need for improved alignment between policy design and institutional or classroom-level support.

The heatmap highlights a generally positive perception of deep learning's usefulness and ease of use. However, it also brings attention to the significant barriers those directly involved in educational practice perceive. Addressing these barriers, particularly those that teachers encounter, will be essential to successfully and equitably integrating deep learning technologies in education systems.

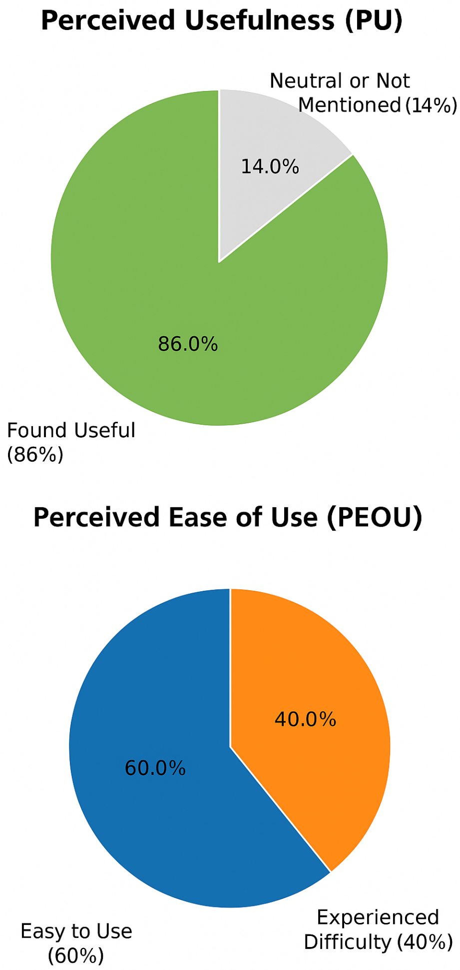

Fig. 2. Average PU and PEOU Scores by Stakeholder Group

Figure 2 provides two pie charts illustrating stakeholder perceptions regarding key constructs: Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) in adopting deep learning technologies in education. The first chart indicates that most participants (86%) found the helpful technology, affirming its relevance and alignment with educational goals. A smaller portion (14%) either expressed neutral views or did not explicitly mention usefulness, suggesting minimal resistance in recognizing the potential value of the technology. This strong consensus on usefulness aligns well with the earlier heatmap results, where all participant groups, teachers, principals, and policymakers rated perceived usefulness highly. The second pie chart addresses perceived ease of use, with 60% of respondents indicating the platform was easy to use, while 40% reported experiencing some difficulty. These findings suggest that while the interface and functionality are generally accessible, many users still face practical challenges, likely related to technological integration, digital fluency, or limited support infrastructure. This chart reinforces the heatmap results, showing average PU scores ranging from 4.1 to 4.5 (on a scale of 1 to 5), and PEOU scores from 3.7 to 4.3. A noticeable gap between PU and PEOU is observed among policymakers, indicating a difference in perception between long-term benefits and day-to-day usability. Teachers find the platform relatively easy to use but acknowledge the need for time and support to fully utilize its AI-driven features in classroom settings.

The charts underscore a critical insight: while stakeholders largely agree on the promise and value of deep learning technologies, practical barriers related to ease of use and technical readiness still require targeted interventions. Training, user-centered design improvements, and ongoing institutional support ensure that perceived usefulness translates into sustained, practical use.

B. External Factors Affecting Technology Adoption

External factors play a significant role in determining the success of technology adoption. Interviews and focus group discussions identified several challenges.

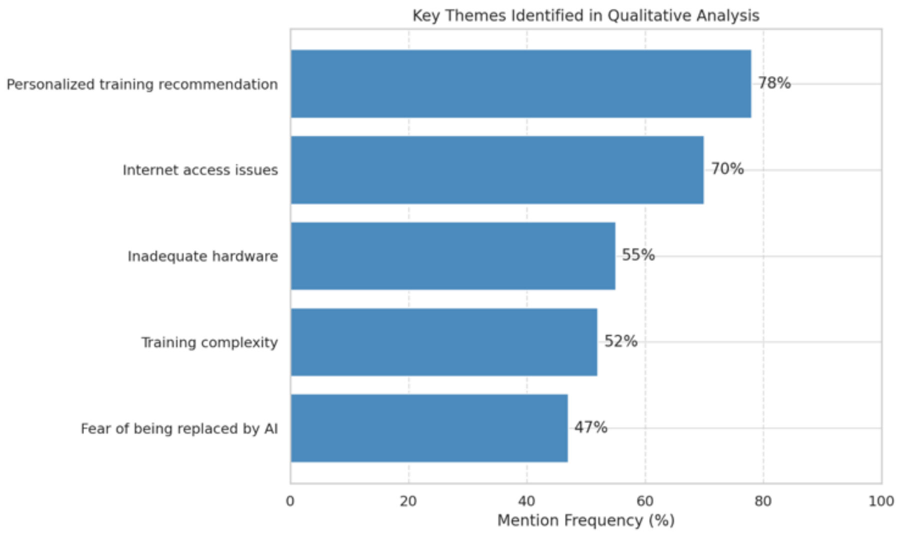

Fig. 3. Thematic Map of External Barriers to AI-Based Learning Implementation.

Figure 3 illustrates the key themes emerging from the qualitative analysis, highlighting major concerns and expectations related to adopting AI-based educational technologies among stakeholders. The bar chart displays the frequency of mention for each theme, offering insight into the area's most frequently raised during interviews, focus groups, and open-ended survey responses.

The most commonly cited theme was the need for personalized training recommendations (78%), underscoring the demand for adaptive, user-centered professional development tailored to individual skill levels and teaching contexts. This reflects a broader trend in educational technology, where generic training is often viewed as insufficient for enabling meaningful engagement with advanced tools such as deep learning platforms. The second most mentioned theme was internet access issues (70%), a persistent infrastructural challenge, particularly in under-resourced or rural areas. Limited bandwidth, unstable connections, and inconsistent access to digital infrastructure were repeatedly highlighted as barriers that hindered smooth adoption and usage. Inadequate hardware was also a prominent concern (55%), suggesting that even when connectivity is available, outdated or underpowered devices can restrict the effective use of AI-based systems. This was often mentioned alongside training complexity (52%), reflecting stakeholders' concerns over the steep learning curve of integrating complex technologies into existing pedagogical routines.

Notably, fear of being replaced by AI was raised by nearly half of the respondents (47%). This reflects more profound anxieties around the implications of automation and artificial intelligence in education, especially among teachers who worry that their roles may be diminished or rendered obsolete. Such concerns point to the need for reassurance through policy, transparency, and human-centered AI design that emphasizes augmentation rather than replacement. Overall, the findings in this figure deepen the understanding of the barriers and support needs identified in Figures 1 and 2. While stakeholders see value and potential in deep learning applications, systemic technical and psychological challenges must be addressed through holistic implementation strategies. These should include targeted professional development, infrastructure investments, and strategic communication to mitigate fear and foster trust in AI-enabled education.

C. Stakeholder Perspectives: Divergent Priorities and Shared Concerns

Each stakeholder group brings different perspectives and priorities when assessing and planning the implementation of the AI platform.

Table 2. Comparison of Stakeholder Perspectives on the AI-Based Learning Platform

Stakeholder	Main Focus	Primary Concerns	Expectations for the AI Platform
Teachers	Ease of use	Limited time and training	Technical support and regular training
School Principals	Curriculum and management integration	School infrastructure	Curriculum alignment and improved quality
Policymakers	Scalability and sustainability	Digital divide and school readiness	National standardization and policy roadmap

Table 2 illustrates that despite differing focuses, all stakeholders emphasize the need for training and inclusive implementation strategies. Teachers desire a user-friendly system and hands-on assistance. Principals seek alignment between the platform and internal school policies. Policymakers focus on aligning the platform with long-term national education goals. Shared infrastructure and human resource readiness concerns emerge as key common ground that must be addressed in future implementation plans.

This study confirms that *perceived usefulness* (PU) and *perceived ease of use* (PEOU) are key determinants in teachers' acceptance of deep learning technologies for professional development. PU refers to the belief that using technology will enhance job performance, while PEOU reflects the perception that the technology is easy to operate without excessive effort (Wangdi et al., 2023). The teachers in this study indicated that deep learning technologies offer tangible benefits, particularly in facilitating personalized training, providing data-driven feedback, and improving instructional quality (Siyam, 2019). However, despite the relatively high perceived benefits, technical complexity and non-intuitive user interfaces emerged as barriers to adoption (Guo et al., 2024). Furthermore, external factors such as gaps in digital infrastructure, inadequate organizational support, and educational policies that do not yet accommodate systematic technology integration also hinder successful implementation (Guo et al., 2024; Maré & Mihai, 2018; Siyam et al., 2022). This study aligns with previous findings, emphasizing that the success of educational technology adoption depends on individual perceptions, systemic readiness, and sustained institutional support (Huang et al., 2022; Sinatra et al., 2017).

This research identifies three significant challenges that impede the widespread and equitable adoption of deep learning technologies in teacher professional development: limited digital infrastructure, low teacher digital literacy, and resistance to change. First, the lack of digital infrastructure, particularly in rural areas, poses a significant barrier due to limited access to stable internet connections and adequate technological devices (Salemink et al., 2017; Shukla et al., 2025; Wang & Yin, 2023). Geographical conditions and high investment costs further exacerbate the digital divide between urban and rural regions (Naik et al., 2020). Second, low levels of teacher digital literacy stem from the lack of comprehensive training and the pressing need for ongoing professional development to enable effective technology integration in classroom practices (Dalelo et al., 2023; Spiteri & Chang Rundgren, 2020; White, 2019). Senior teachers also tend to have lower digital proficiency than their younger counterparts, which affects their readiness to adopt new technologies (Portela & Juste, 2020; Saripudin et al., 2021). Third, resistance to change arises from concerns that artificial intelligence (AI) may replace teachers' roles, sparking discomfort and fears of professional obsolescence (Ilhan, 2025; Jabali et al., 2025; Singh, 2024). The rapid transformation of the education system is often perceived as a threat to job security, especially when not accompanied by emotional and professional support from institutions (Córica, 2020; Lomba-Portela et al., 2022). Therefore, these three challenges must be addressed holistically, involving infrastructure investment, capacity-building initiatives, and inclusive and collaborative change management strategies.

Deep learning technology presents strategic opportunities to reform teacher professional development through adaptive, data-driven, intuitive, and highly scalable training systems. Adaptive training systems enable comprehensive analysis of teacher performance data, such as academic outcomes, student feedback, and teaching experiences, to develop personalized and relevant professional development programs (Liu et al., 2022; Q. Zhang, 2025). This approach has proven effective in enhancing pedagogical competence and student engagement (Naseer et al., 2024; Yu, 2024). Furthermore, integrating intelligent interfaces, such as virtual tutors and chatbots, allows teachers to receive real-time feedback, accelerating self-directed learning and improving work efficiency (Rizvi et al., 2025). In terms of scalability, these technologies facilitate the delivery of high-quality training to educators in diverse regions, including remote areas, via online platforms and adaptive learning systems (Tang et al., 2024). The personalization feature is a significant advantage, enabling teachers to follow a development path tailored to their specific needs, experiences, and preferences (Yanjin et al., 2023). Additionally, AI systems support teachers in understanding classroom dynamics, designing lesson plans based on behavioural analytics, and developing evidence-based instructional strategies (Lu et al., 2024). Nevertheless, implementing such technologies still faces technical challenges, such as teachers' limited understanding of advanced

technologies and persistent concerns over data privacy and security. Addressing these concerns through clear guidelines, ethical standards, and data protection protocols is crucial to building trust in technology use among educators. Thus, the utilization of deep learning not only promises to enhance teacher quality but also catalyzes educational transformation in the 21st century. To realize these potentials, policymakers must take concrete steps by investing in digital infrastructure, designing differentiated digital literacy programs, institutionalizing continuous support mechanisms, and developing ethical regulatory frameworks. Engaging teachers as co-designers of technological change is equally important to reduce resistance and ensure inclusive implementation. These policy directions will strengthen systemic readiness and ensure that deep learning technologies act as empowering tools in teacher professional development, rather than alienating them.

IV. Conclusion

This study found that while Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) are key determinants in teachers' acceptance of deep learning for professional development, with educators recognizing benefits such as personalized training and data-driven feedback, adoption is significantly hindered by technical complexities impacting PEOU. Prevalent external barriers include infrastructure gaps, limited digital literacy (particularly AI-specific data literacy), and resistance to change, often stemming from fears of job displacement. Divergent priorities among stakeholders were noted, although shared concerns regarding infrastructure and human resource readiness emerged as common ground. Opportunities lie in deep learning's capacity for adaptive, data-driven, and scalable training. As the provided text does not explicitly detail the study's limitations, it is acknowledged that factors such as the specific AI platforms examined and the generalizability of findings from a sample of 30 participants could be considered limitations in broader application. Recommendations include collaborative efforts among governments, educational institutions, and technology providers to invest in robust infrastructure; deliver comprehensive training programs focused on enhancing digital and AI data literacy; foster an innovation-friendly culture to reduce resistance; and establish clear operational guidelines and adequate funding. These strategies should be holistic, addressing technical, human-centric, and policy factors to ensure ethical and sustainable implementation of deep learning in teacher professional development.

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