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We still have not prepared yet: Indonesian Rural Teacher Perception in Teaching English Using AI

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Abstract

Background: teachers in rural areas, in particular, are at the forefront of this technological revolution, where exposure, institutional support, and connectivity are still uneven. **Objective**: problems of rural teachers deal with slower internet, fewer devices, and less formal training, while urban schools are experimenting with AI-based platforms. Seldom do government efforts to digitize education reach the periphery as deeply. **Methods:** this study used a convergent mixed-methods approach. This research is a mixed design reflects the belief that technological readiness is a human experience influenced by context and meaning rather than just a statistical condition. While qualitative insights were acquired to understand how such preparedness is lived and told in everyday educational life, quantitative data was gathered to measure the structural elements of teachers' readiness. **Results:** The findings ramifications emphasize the necessity of policy frameworks that put fairness and contextual sensitivity ahead of uniform technological advancement. Initiatives pertaining to AI should be adapted to local conditions, especially by guaranteeing long-term access to infrastructure, dependable internet, and reasonably priced digital resources in rural areas. **Conclusion:** rural English teachers remain struggle with the situation of inadequate infrastructure in the area.

Keywords: Rural teacher; artificial intelligence; teaching English

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INTRODUCTION

The need to adjust to AI in education has become more pressing globally (1). Although most teachers still face challenges with access, training, and ethical clarity, reports from around the world characterize it as a revolutionary force capable of rethinking pedagogy (2–4). Though far more slowly than legislators had promised, artificial intelligence has become more prevalent in classrooms than most educators could have predicted. Intelligent technology is frequently presented as a question rather than a tool in Indonesia's rural classrooms. Teachers seldom witness AI in action in their own classrooms, despite hearing about its potential to automate grading and customize instruction (5–7). The gap between discourse and practice has widened to the point where the global debate frequently ignores the fact that systems evolve more quickly than the people who are supposed to carry them, and technology moves more quickly than systems (8).

Teachers in rural areas, in particular, are at the forefront of this technological revolution, where exposure, institutional support, and connectivity are still uneven (9). Their preparedness is based on circumstances rather than opposition. Indonesia provides a clear example of this predicament. While rural teachers deal with slower internet, fewer devices, and less formal training, urban schools are experimenting with AI-based platforms. Seldom do government efforts to digitize education reach the periphery as deeply. The discussion of AI preparation seems aloof, even humorous, to some educators. Instead of rejecting technology, a subtle discussion between capacity and aspiration takes place.

For a long time, academics have maintained that teachers' perceptions, not technology itself, are where educational reform starts (10,11). Engagement, willingness, and creativity are shaped by perception. When educators perceive innovation as beneficial, they incorporate it in a meaningful way; when they perceive it as forced, they quietly oppose it. When it comes to AI, perception becomes even more complicated, encompassing not just technical knowledge but also attitudes on instruction, equity, and the presence of humans in the classroom (12).

By investigating how Indonesian rural instructors view AI's utility, accessibility, and institutional support, this study aims to add to that discussion. It investigates the texture as well as the level of preparedness. the feelings, opinions, and principles associated with the concept of intelligent instruction. By doing this, the study expands theoretical conversations on technological acceptance into an area where acceptance itself needs to be rethought as a kind of adaptation rather than compliance.

According to the study, we must first pay attention to hesitation in order to comprehend preparedness. "We still have not prepared yet" is an expression of concern rather than a declaration of defeat, acknowledging that genuine adoption starts with being open about limitations. The observations of rural instructors serve as a reminder that preparedness is relational and develops via conversation rather than orders. Therefore, the challenge for education in the AI era is not to accelerate more quickly but rather to prepare more thoroughly in order to create systems that respect human learning pace in the face of rapid technology advancement.

METHODS

In order to investigate how Indonesian rural teachers view, understand, and use artificial intelligence (AI) in their teaching practices, this study used a convergent mixed-methods approach. The decision to use a mixed design reflects the belief that technological readiness is a human experience influenced by context and meaning rather than just a statistical condition. While qualitative insights were acquired to understand how such preparedness is lived and told in everyday educational life, quantitative data was gathered to measure the structural elements of teachers' readiness.

The government's renewed push for digital transformation in schools coincided with the data gathering period, which spanned from March to May 2025. In order to reach areas with poor connectivity, surveys were delivered both online and in paper. To guarantee inclusivity, interviews were performed in a variety of modes, with some taking place in person and others using low-bandwidth online platforms. Every participant gave their informed consent, and the study's confidentially was upheld at all times. This study's ethical considerations were crucial since teachers were viewed as partners whose perspectives contribute to a better understanding of technological transition rather than as evaluation subjects.

To investigate proposed links between the UTAUT constructs, quantitative data were analyzed using Structural Equation Modeling with Partial Least Squares (SEM-PLS). Using bootstrapping techniques, the analysis evaluated path significance, validity, and reliability (5,000 resamples). The findings showed that while social influence had little predictive value as a result of the inadequate institutional and peer networks in rural teaching, performance expectancy and conducive conditions had a considerable impact on perceived competence. In accordance with Braun and Clarke's (13) approach, the qualitative data were subjected to thematic analysis with an emphasis on recurrent themes of instructional adaptability, infrastructure, and skill preparedness. This dual analysis made it possible for lived story and empirical measurement to converge, closing the gap between what instructors describe and what they actually experience.

Research Model and Hypothesis

Performance Expectancy (PE)

The degree to which an individual thinks that utilizing technology will enhance work performance is known as performance expectancy. This can be seen by rural educators as the conviction that AI will enhance learning efficacy, expedite the creation of open-ended materials, and creatively and contextually enhance learning content. Perceptions of a technology's usefulness are a significant predictor of user behavioral intentions, according to a number of earlier studies (14–17). Thus, rural teachers are more likely to plan to employ AI if the performance expectations are higher.

Social Influence (SI)

The degree to which people experience social pressure or influence from important people in their surroundings to use technology is known as social influence. Colleagues, principals, government-provided training, and conversations within the teaching professional community can all have an impact on teachers' adoption of AI. Social influence is a major factor in technology adoption decisions in collectivist societies such as Indonesia (18–20). Teachers are more likely to use ChatGPT if the workplace views its use favorably.

Facilitating Conditions (FC)

Individual judgments of the accessibility of resources, training, technical assistance, and sufficient infrastructure for utilizing technology are examples of facilitating conditions. Facilitating environments, like ChatGPT, are crucial in determining the adoption of technology because rural Indonesian teachers still lack access to digital equipment, connectivity, and training. According to the UTAUT paradigm, enabling circumstances can have a direct impact on actual usage behavior in addition to influencing intentions (21).

H1: PE to PC
H2: FC to PC
H3: S1 to PC
H4: SI to FC

Population, samples and sampling

The 123 educators from Indonesia's rural areas took part in the study. In order to ensure a fair understanding of instructors' experiences with AI integration, the sample was purposefully chosen to represent a range of professional and demographic backgrounds. Male and female teachers working in geographically isolated districts at the primary and secondary levels were among the participants. In order to give context for the interpretation of teachers' impressions, demographic information was gathered, especially with regard to their years of teaching experience, exposure to technology, and availability of digital infrastructure. The respondents' demographic profile is shown in the following table.

Table 1. Demographic profile of the participants

		Frequency	**Percentages**
Gender	Male	57	46,3
	Female	66	53,7
Age	22-26	25	20,3
	27-31	36	29,3
	32-36	23	18,7
	36-41	24	19,5
	42-46	11	8,9
	47-51	4	3,3
Experienced (in years)	1-5	58	47,2
	6-10	30	24,4
	11-15	20	16,3
	16-20	10	8,1
	21-25	4	3,3

The gender distribution of the participants was fairly balanced, as Table 1 illustrates, with a little higher percentage of female instructors (53.7%) than male teachers (46.3%). The bulk of responders were between the ages of 27 and 36, suggesting a relatively young teaching workforce that, despite resource and access constraints, is probably more receptive to technological innovation. A significant percentage of the sample consisted of early-career educators, since nearly half of the teachers (47.2%) had between one and five years of teaching experience. This essay offers insightful information about the preparedness and flexibility of younger generations of Indonesian rural instructors when they come across cutting-edge technologies like artificial intelligence. Therefore, in addition to placing the quantitative results in context, the demographic distribution also illustrates the various human realities that underlie the larger discussion of technology integration in education.

RESULTS

study, the measurement model was first evaluated. Each construct's descriptive statistics, such as item means, factor loadings, variance inflation factors (VIF), average variance extracted (AVE), and Cronbach's alpha values, are shown in Table 2. Strong item reliability was indicated by all loading values exceeding the suggested cutoff of 0.70. Convergent validity was also confirmed by the AVE values for every concept being more than 0.60. The range of Cronbach's alpha coefficients, which indicate good internal consistency among items, was 0.860 to 0.893.

The VIF values show that there are no multicollinearity problems because they are all less than 5. Overall, these findings offer strong proof that the measurement tools were valid and reliable in capturing teachers' judgments of perceived competence (PC), social influence (SI), performance expectancy (PE), and facilitating conditions (FC).

Table. 2 Description Statistics Questionnaire, loading factor, VIF, AVE and Cronbach's

Construct	Item Code	Mean	Loading	VIF	AVE	R square	Cronbach's
PE	PE1	3,98	0.819	2.154	0.699		0.892
	PE2	3,93	0.874	2.708			
	PE3	3,93	0.761	1.767			
	PE4	3,87	0.858	2.467			
	PE5	3,98	0.864	2.617			
FC	FC1	2,89	0.800	1.845	0.701		0.893
	FC2	2,74	0.852	2.570			
	FC3	2,87	0.831	2.341			
	FC4	2,79	0.850	2.559			
	FC5	2,76	0.851	2.546			
SI	SI1	3,15	0.838	2.135	0.641		0.860
	SI2	3,13	0.749	1.759			
	SI3	3,07	0.789	1.899			
	SI4	3,12	0.833	2.009			
	SI5	3,15	0.789	1.832			
PC	PC	49,35	1.000	1.000			

The Fornell-Larcker criterion and the Heterotrait-Monotrait (HTMT) ratio were used to further evaluate discriminant validity. Each concept is empirically different from the others because all of the HTMT ratios were below the suggested cut-off of 0.85. Discriminant validity is also confirmed by the Fornell-Larcker results, which demonstrate that the square roots of the AVE values (on the diagonal) are higher than the correlations between constructs. This conclusion was further corroborated by the cross-loading analysis, which showed that every item loaded more strongly on the targeted constructs than on any other dimensions.

Table 3. Heterotrait-monotrait (HTMT) ratio of the constructs in the model

	FC	PC	PE	SI
FC				
PC	0.513			
PE	0.107	0.652		
SI	0.176	0.513	0.144	

Table 4. Fornell

	FC	PC	PE	SI
FC	0.837			
PC	0.486	1.000		
PE	-0.073	0.621	0.836	
SI	-0.144	0.482	-0.006	0.800

Table 5. Cross Loading

	FC	PC	PE	SI
FC1	0.789	0.457	-0.059	0.010
FC2	0.854	0.417	-0.049	-0.125
FC3	0.835	0.372	-0.086	-0.156
FC4	0.855	0.400	-0.033	-0.182
FC5	0.853	0.382	-0.082	-0.152
PC	0.486	1.000	0.621	0.482
PE1	-0.094	0.446	0.819	-0.087
PE2	-0.050	0.517	0.874	-0.058
PE3	-0.174	0.481	0.761	0.108
PE4	0.025	0.601	0.858	0.039
PE5	-0.041	0.528	0.864	-0.036
SI1	-0.182	0.419	0.068	0.842
SI2	-0.072	0.307	-0.149	0.747
SI3	-0.078	0.337	-0.111	0.787
SI4	-0.100	0.442	0.053	0.831
SI5	-0.124	0.398	0.051	0.790

The proposed links between the constructs were then tested by evaluating the structural model. Table 6 provides a summary of the hypothesis testing results. Hypothesis 1 was supported by the path analysis, which showed that performance expectancy (PE) had a substantial positive impact on perceived capability (PC) ($\beta = 0.000$, $t = 17.581$). Additionally, perceived competence was significantly positively impacted by facilitating conditions (FC) ($\beta = 0.000$, $t = 12.758$), supporting Hypothesis 2. However, social influence (SI) had no discernible impact on facilitating circumstances ($p = 0.081$, $t = 1.744$), suggesting that peer or community pressure did not play a substantial role in facilitating access to AI resources.

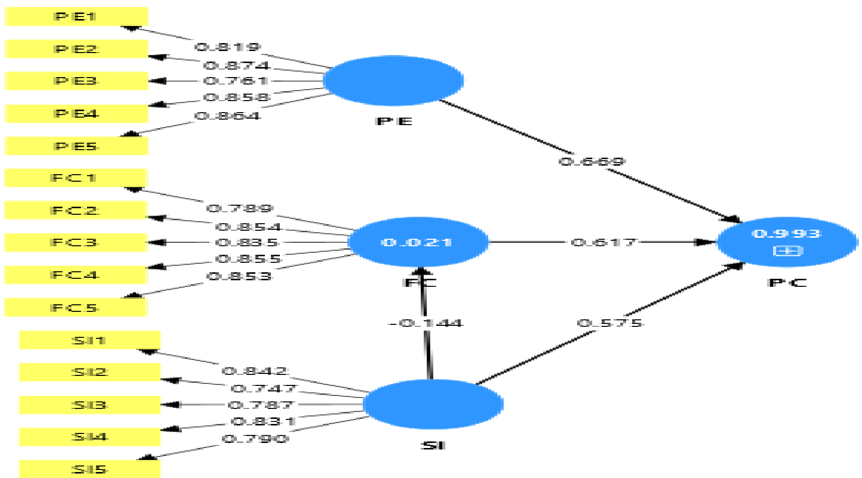
However, SI demonstrated a significant direct correlation with PC ($p = 0.000$, $t = 12.918$), supporting Hypothesis 4. These findings suggest that, rather than being solely influenced by social support, teachers' preparedness for AI integration is mostly determined by how beneficial they believe AI tools to be and the infrastructure resources that are accessible.

Table 6. Summary of Results of Hypothesis Testing

Hypothesis	Path links	t-statistics	p-values	Remarks
H1	PE -> PC	17.581	0.000	Valid
H2	FC -> PC	12.758	0.000	Valid
H3	SI -> FC	1.744	0.081	Not Valid
H4	SI -> PC	12.918	0.000	Valid

Overall, the results show that teachers' perceptions of their abilities to use AI technologies are strongly influenced by two important factors: their confidence in AI's efficacy (performance expectancy) and the availability of adequate institutional and technological support (facilitating conditions). Even if social influence had little indirect effect, when it came directly to perceived aptitude, it nevertheless made a substantial contribution to teachers' confidence. These findings are consistent with earlier research (22) that highlights the importance of environmental facilitation and expectancy beliefs in determining digital preparedness. However, previous research indicates that technological adoption in rural educational settings is more context-driven and self-motivated than socially dictated, which contrasts with the relatively small effect of social influence.

Table Model SEM-PLS for each construct



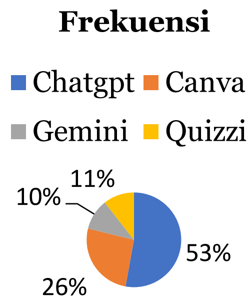


Table 7. Participants' perceptions regarding positive and negative aspects of AI use in education

Thematic Key points	Infrastructures Aspects	Human-Skills Aspects
Challenge	Internet connections, listrik,	
Free platform and trainings of AI needs		Teaching materials, media teaching,

DISCUSSION

The AI Readiness Paradox: Between Awareness and Access

The results of this study show a contradictory trend in Indonesian rural teachers' preparedness for integrating artificial intelligence (AI). a high degree of conceptual knowledge combined with ongoing institutional and infrastructure weakness. Teachers truly feel that AI can improve teaching performance, as evidenced by the performance expectancy (PE) construct's greatest path coefficient toward perceived competence (PC) ($t=17.581$, $p<0.001$). The enabling condition (FC) construct, on the other hand, showed lower mean scores ($M=2.74–2.89$), even though it was similarly significant ($t=12.758$, $p<0.001$). This suggests that a setting that seldom encourages prolonged technology usage undermines teachers' enthusiasm. What can be called cognitive preparedness without infrastructural readiness is reflected in this contradiction between conviction and feasibility.

From a theoretical perspective, these findings improve the UTAUT in this study. The model's emphasis on perceived usefulness is supported by the significant correlation between PE and PC, but the diminished influence of social influence (SI) on facilitating conditions (FC) ($t=1.744$, $p>0.05$) indicates that collective adoption mechanisms are still underdeveloped in rural teaching. To put it another way, teachers are more motivated to use AI because of their own beliefs than because of institutional or societal support. This contrasts with the findings of Kim et al. (23), who found that teachers' usage of technology was significantly influenced by institutional support and collective culture.

The experience of rural teachers essentially reframes preparation as a continuum of adaptation rather than a binary (ready/not ready). Teachers are aware of what AI has the potential to accomplish, but they are also aware of what their classrooms are currently unable to support. As a result, their voices represent a complex balancing act between hope and limitation. By emphasizing the emotive and contextual burdens that define the true dimensions of ready, this dual awareness expands our understanding of educational technology adoption beyond behavioral intention (24,25). Adoption of AI is not hampered by a lack of willingness, but rather by the silence surrounding that willingness in the infrastructure.

Human Bargaining in the Transition to Technology

The qualitative results of this study reveal the human depth of teachers' interactions with artificial intelligence as a place where optimism meets tiredness and innovation becomes an act of resilience rather than privilege, going beyond the numerical evidence of preparation. Teachers in rural Indonesia work in a digital frontier characterized more by emotional negotiation than by technological expertise. Teachers are expressing a lived type of reflection that addresses the human cost of technology transformation when they talk about their interaction with AI but how connectivity and electricity fail us.

According to the interviews, the majority of teachers have tried with AI tools, especially ChatGPT, Canva, and Gemini, but their involvement is still irregular and dependent (26,27). While some educators reported using ChatGPT to create tests, write lesson plans, or translate literature, nearly all of them brought up the issue of unstable infrastructure. Despite these obstacles, the majority of instructors said that they would be eager to take part in AI training and preferred accessible, free platforms

(28–30). These answers indicate that the limitations imposed on instructors are external rather than attitudinal.

This is consistent with Mustafa et al. (31), who highlighted that ecological support is more important for instructors' digital confidence than personal motivation. Motivation on its own becomes emotionally taxing in the absence of such support. In spite of systematic indifference, the teachers' adaptive behaviors—such as depending on mobile data, self-learning, or sharing devices—reflect a collective improvisation that maintains instructional continuity. In her practice-based theory of technology, Baram & Uygun (32) contend that technology in organizations is constantly performed through regular improvisations molded by creativity and constraint rather than just being adopted. Accordingly, rural educators actively modify the meaning of AI to suit their own schedules rather than passively accepting it.

The results of this study indicate that rural educators are at the vanguard of negotiating what meaningful technology use actually looks like, in contrast to deficit narratives that portray them as falling behind. They want to safeguard the pedagogical integrity of human connection while carefully interacting with algorithmic systems, and their preparedness is performative, relational, and moral. This dual consciousness is consistent with the findings of Rulyansah et al. (33), who noted that the capacity to perceive innovation in culturally situated ways is the source of teacher agency in technology use. This notion that teachers' agency is demonstrated by moral discernment, reflective skepticism, and selective adoption rather than heedless enthusiasm is extended by the Indonesian situation.

Teachers are thus positioned within the socio-technical lens as co-constructors of preparation rather than passive recipients of technology. In order for teachers to understand, filter, and repurpose AI technology in a way that is consistent with their professional principles, readiness itself arises as a negotiated construct and an emotive, social, and cultural process. Teachers rely on their own meaning-making to sustain innovation in the absence of institutional culture, as evidenced by the finding that social influence (SI) did not substantially predict enabling conditions (FC) ($t=1.744$, $p>0.05$). observation that "communities of practice" and interpersonal improvisation, rather than rigid institutions, sustain adaptation.

Reevaluating Preparedness: Human Pace, Equity, and Policy

The results of this study force us to reconsider what it really means to be prepared for artificial intelligence in the classroom. Global frameworks like the OECD (4) and UNESCO (34) Guidance for Generative AI in Education dominate the traditional policy discourse. Infrastructure, digital literacy, and innovation speed are frequently equated with preparedness in education at a glance.

Teachers' cognitive willingness is already present, as demonstrated quantitatively by the significant relationship between performance expectancy (PE), facilitating conditions (FC), and perceived competence (PC). But teachers' qualitative accounts of "sinyal tidak stabil, listrik mati, kuota mahal" and the persistently low mean in FC (2.74–2.89) highlight a structural injustice that policy optimism frequently ignores. Therefore, equity-centered ecosystems that align resources, training, and empathy are necessary to create AI preparedness, which cannot be expedited by digital mandates alone. They cautioned that if AI adoption continues unchecked, educational disparities may worsen, especially between institutions with varying degrees of connectedness. The current study provides a clear illustration of this caution. Teachers in rural Indonesia are trapped in a bureaucratic and infrastructure lag rather than refusing to interact with AI. Their recurrent requests for contextual training indicate a desire for fairness to be prepared on their terms and with their reality in mind, rather than a symptom of reliance. This implies that readiness is a collective state shaped by the ways in which systems facilitate participation rather than an individual characteristic.

A structural paradox is revealed by the socio-technical interaction at play here. Rural teachers' voices reveal the dark side of digital optimism as the unacknowledged labor of adapting to tools that were not designed for their constraints, even though national policies promote AI for everyone. This leads to "digital stratification disguised as innovation" (35,36). According to one participant, policymakers should pay attention to ready measures as well as preparedness emotions, such as the weariness of self-teaching, the fear of obsolescence, and the unwavering desire to remain relevant.

Policy must shift from acceleration to accompaniment in order to reframe preparedness through the lens of human pace. Governments and institutions should promote delayed readiness—a gradual, context-sensitive approach that prioritizes understanding over compliance—instead than enforcing hasty integration. In order to integrate AI in a meaningful way, educators must be able to think critically and morally about technology in addition to using it (37). This entails establishing areas where educators can try new things, make mistakes, and reflect without worrying about failing or becoming irrelevant in Indonesia's rural setting.

In practical terms, the results support three reform avenues. First, infrastructure needs to be fair rather than uniform. Continuity of access should take precedence over symbolic inclusion in connectivity initiatives. A high-speed fiber optic network that never reaches the village might not be as revolutionary as a consistent 4G connection in a rural school. Second, the focus of AI training needs to change from tools to meaning. Teachers require introspective sessions that connect AI with their educational beliefs, cultural settings, and ethical obligations rather than generic courses. Third, qualitative evidence must be incorporated into policy evaluation. Iterative policy changes that respect lived realities should be informed by the testimony of teachers, which are frequently disregarded in top-down evaluations.

This study concludes by advocating for an epistemological change that views readiness as a cultural and ethical condition rather than a set of competencies. Indonesian rural educators' show that being ready involves more than just having tools; it also entails having faith in training, systems, and oneself. Their unassuming perseverance reframes preparedness as caring as a profoundly human demand that technology advance at the rate of learning rather than the other way around.

CONCLUSIONS

According to the study's findings, rural Indonesian teachers' willingness to include artificial intelligence (AI) into their lesson plans is a reflection of the structural and contextual factors that surround them rather than their opposition to innovation. Quantitative results show that teachers' perceived capacity is strongly influenced by performance expectancy and conducive settings, indicating that institutional support and conviction in the use of AI are important factors that determine participation. Qualitative insights also show that despite infrastructure constraints, erratic connectivity, and a lack of regular training, teachers demonstrate a remarkable willingness to adapt. This paradox is summed up in the sentence, "We still have not prepared yet." It is a reflective understanding of the gap between aspiration and access rather than a sign of failure. In this perspective, readiness should be viewed as a slow, thoughtful process that honors the human rhythm of adaption rather than just a technical adoption. When technological integration is driven by comprehension, equity, and trust rather than just speed, true preparedness arises.

These findings' ramifications emphasize the necessity of policy frameworks that put fairness and contextual sensitivity ahead of uniform technological advancement. Initiatives pertaining to AI should be adapted to local conditions, especially by guaranteeing long-term access to infrastructure, dependable internet, and reasonably priced digital resources in rural areas. In order to help educators comprehend both the pedagogical and moral aspects of intelligent technology, teacher training programs should shift from concentrating only on operational abilities to fostering interpretive and ethical AI literacy.

The cross-sectional methodology and sample size limitations of this study may prevent it from accurately capturing how readiness changes over time. In order to investigate how social, cultural, and institutional aspects synergistically influence teachers' adaption to AI, future research should use mixed-method and longitudinal methodologies. Our comprehension of how readiness is created as a systemic and human process might be strengthened by additional research into digital ethics, collaborative learning communities, and locally based policy initiatives. In order to ensure that educational transformation unfolds at a speed congruent with the values and reality of individuals who bring learning to life, preparing teachers for AI integration ultimately involves not only tools and training but also empathy and introspection.

CONFLICT OF INTEREST

This research was conducted in the absence of any commercial or financial relationships that could be constructed as a potential conflict of interest.

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DECLARATION OF ARTIFICIAL INTELLIGENCE USE

Our research was constructed from the assistance of AI, however, we do some revision, paraphrasing and synthesis of ideas from different research.

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