From Algorithmic Feedback to Inclusive Learning: Exploring Teacher Readiness and AI-Supported Formative Assessment for Diverse Learners

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ABSTRACT

Artificial intelligence (AI) is reshaping formative assessment by enabling timely, adaptive, and personalized feedback, yet its contribution to inclusive learning depends substantially on teachers' readiness and the institutional conditions supporting implementation. This study examined the relationships among teacher readiness, AI-supported formative assessment practices, personalized feedback, and support for diverse learners in inclusive classrooms in Punjab, Pakistan. Using a cross-sectional survey design, data were collected from 481 teachers through a 50-item questionnaire and analyzed using descriptive statistics, independent-samples *t*-tests, ANOVA, correlation, exploratory factor analysis, and multiple regression. Findings indicated relatively high levels of teacher readiness and AI implementation, whereas institutional and technical support remained comparatively weak. Significant differences in AI related practices were observed across school location, professional training, and levels of AI use. Correlation and regression analyses further demonstrated that personalized feedback was a significant predictor of teachers' reported support for diverse learners. The findings suggest that AI adoption alone does not ensure inclusive assessment; rather, its educational value depends on teachers' capacity to translate AI generated insights into responsive pedagogical decisions. The study contributes context-sensitive evidence for developing teacher professional learning, institutional infrastructure, ethical governance, and human oversight mechanisms that position AI as a complement to not a substitute for teacher judgment in inclusive education.

Keywords: Artificial intelligence; AI supported assessment; formative assessment; personalized feedback; inclusive education; teacher readiness; diverse learners; educational technology

Introduction

Artificial intelligence is more transforming education assessment so that allows teachers to collect evidence of learning, provide diagnosis of individual difficulties, create differentiated activities, and give immediate individualized feedback. In inclusive education, these skills are critical because students have different levels of functioning, language backgrounds, rate of learning, pre-existing knowledge, modalities of access attention communication and support needs. AI-supported formative assessment might support teachers to identify learning gaps during the processes rather than only at the end of completing a unit of work, while adaptive feedback can give students explanations, questions, examples and corrections suited to their level of achievement. Emerging evidence tied AI-supported feedback to gains in individualization, timely instructional feedback, student engagement and teacher workload. These gains Yet are not necessarily guaranteed as the quality and equality of AI supported assessment depends on teachers' technological skills, pedagogical judgement, culturally aware ethic principles, institutional investment and capacity to read AI-generated suggestions. Analyzing the "how" and "what" of AI adoption will help establish if AI is Yes supporting inclusive education or adding new barriers for students with diverse needs (Alghamdi & Alghizzi, 2025; Fitas, 2025; Mlo-Lpez et al., 2025).

Formative assessment is a narrative, ongoing part of teaching in which educators gather evidence about how students are learning, make sense of that evidence, and change their instructional practices to align toward the desired outcomes. Teachers have traditionally employed questioning observation quizzes assignments class discussion, and written note taking to inform themselves about student learning; Yet, with a large class size, an increased amount of assessments and students with diverse needs making personalized feedback difficult, AI led applications may be used to complement these traditional practices by examining patterns of student responses, providing feedback that breaks down common student misconceptions, providing differentiated formats of content, creating rubrics and rubric based comments, translating instructions, translating speech into text, and making materials accessible. These tools may be useful in inclusive classrooms where teachers are tasked with attending to students with special needs, language differences, behavioral challenges, and various levels of conceptual understanding. Though, global recommendations advocate the use of AI should simply enhance educator's professional knowledge and judgment, and that the education system is ultimately responsible for assessment appropriateness, learner privacy access appropriateness, fairness, and authentic interpretation of student work. In this way, teacher preparatory training in the use of AI must encompass educational technology literacy, strong pedagogical content knowledge, teacher confidence and confidence with technology, cultural competences, ethical awareness, meaningful use, evaluation skill, and ability to integrate innovative assessment and instruction strategies in an inclusive teaching context (Linsenmayer, 2025; Miao & Holmes, 2023).

While interest in AI-supported assessment has burgeoned, the existing literature remains spread out among papers on postsecondary education, intelligent tutoring, automated assessment, generative feedback, teachers' perceptions, and generalized technology acceptance. Previous reviews have acknowledged the potential for AI to tailor feedback and widen educational access, yet ongoing limitations have been identified about infrastructure, teacher training bias privacy and transparency, accessible design, and the underrepresentation of learners with complex or multiple support needs. More fundamentally, few review studies have investigated teachers' readiness, their actual implementation of AI-supported formative assessment practices in the classroom, and the degree to which personalized feedback is beneficial for diverse learners in inclusive mainstream schools. For Pakistan, the studies conducted so far have mainly focused on teachers' attitudes, attitudes toward AI, or their readiness in higher education contexts, while empirical studies investigating inclusive assessment practices in mainstream Pakistan schools are few. That's why, there is an imperative to conduct a situation analysis of whether teachers know how to use the enablement's of AI-supported formative assessment strategies ethically and responsibly to serve the needs of school learners in an inclusive Pakistan (Andleeb & Habiba, 2026; Molina-Soria et al., 2026).

On an international level, models are being contemplated for AI in flexible learning, automated assessment, learning analytics, accessible learning materials translation intelligent tutors, and early identification of leaning needs (Vander et al., 2022). Based on systematic and integrative reviews, educators appear to appreciate that AI offers instant feedback, differentiated instruction, automating tedious models, and detecting patterns that may not be recognizable otherwise through assessment. Speech to text technology, text to speech technology, alternative learning formats, predictive analytics, and customized platforms that support AI offer the potential to include more identified learners with sensory communication language, and learning needs (Linsenmayer, 2025; Miao & Holmes, 2023).

International organizations and researchers have sounded warning that AI systems can spread social and linguistic bias, misinterpret learner responses, provide inaccurate feedback, gather learner sensitive data, and deepen existing inequalities if internet accessible software, or trained educators are limited (UNESCO, 2020; USAID, 2022). UNESCO's teacher competency system, for example, promotes a human-centered attitude, AI ethics, responsible use of artificial intelligence, awareness of the basics, AI pedagogy and professional training for teachers. Recent OECD Guidelines for the Responsible Use of AI in Education, also underlined the need for ethical design, feedback monitoring, data privacy and security, transparency and accountability, and avoiding biases in selecting AI tools for learners with special education needs (Cukurova & Miao, 2024).

In Pakistan, while the use of AI in education remains sporadic and "largely experimental" at individual level, there is a movement towards early institutional and professional-development initiatives, although implementation is somewhat ad hoc. A qualitative study of university teachers in Punjab found positive attitudes to the use of AI for teaching, assessment and research, and highlighted the need for targeted training and institutional support. A similar study by 152 teachers of two higher education institutes in Faisalabad uncovered 'significant institutional differences in AI readiness, and barriers including inadequate infrastructure, few professional development pathways, limited knowledge for pedagogically sound uses, and non-existent ethical setups'. At national level, UNESCO and the Pakistan National Commission for UNESCO launched a professional-development programme covering a total of 150 teachers, 25 head teachers and 25 education coordinators, covering areas including intensive training, ongoing mentoring, and school-based supervision. Although such initiatives may suggest increased recognition of AI as an important area for education, the evidence base remains small: there is limited evidence on formative assessment, differentiated and personalized feedback, inclusive school policies, and support for varied learners in Punjab (Sohail et al., 2024; UNESCO, 2026).

AI supported formative assessment can provide timely diagnostic data and tailored feedback to learners of different academic linguistic behavioral, communication, and accessibility abilities. Still, the availability of AI applications by itself does not guarantee their inclusive, effective utilization. Teachers may not know what applications are apt, may not have the confidence to interpret results, may not be trained to design accessible assessments, may not understand algorithmic bias, or may not be supported by their institutions for privacy and ethical practice. The AI application literature from Punjab, Pakistan offers no empirical data indicating how prepared teachers are to use AI for formative assessment, how AI is currently being implemented, what types of tailored feedback are being produced, and how inclusive, accessible formative assessment practices are benefitted learners of different abilities. The central problem addressed by this study is therefore the lack of integrated, context-specific evidence concerning teacher readiness, implementation practices, institutional conditions, and the perceived effectiveness of AI-assisted formative assessment and personalized feedback in inclusive educational settings of Punjab (Andleeb & Habiba, 2026; Linsenmayer, 2025; Melo-López et al., 2025).

1. To assess teachers' readiness to use AI-assisted formative assessment and personalized feedback in inclusive educational settings of Punjab.
2. To examine teachers' existing implementation practices regarding AI-supported assessment, progress monitoring, identification of learning gaps, and feedback generation.
3. To investigate teachers' perceptions of the effectiveness of AI-generated personalized feedback in supporting learners with diverse abilities, learning difficulties, disabilities, linguistic backgrounds, and instructional needs.
4. To determine the relationship between teacher readiness and the implementation of AI-assisted formative assessment practices.
5. To identify the major pedagogical, technological, ethical, accessibility, and organizational barriers affecting the use of AI-assisted formative assessment in inclusive education.

The expected contributions of this study to the theory, practice, and policy of artificial intelligence, formative assessment, teacher education, and inclusive education include this. Theoretically, the study will generate new insights on how to make AI and automated assessment usable and beneficial for teachers and learners of diverse backgrounds, abilities, and needs. Empirically, the study will have generated contextualized knowledge about teachers' AI literacy, actual use practices, agency-supporting infrastructure and institutional rules, and perceived support for diverse learners and assessment by the people who matter. Practically, the study may help guide teachers in selecting AI tools, interpreting automated assessment feedback, requesting related inputs, managing professional oversight, and designing accessible assessment activities to meet individual needs. Teachers-, teacher-education-, and professional-development-providers may use the results to design training on AI literacy, prompt design, feedback interpretation, differentiated feedback accessibility privacy, fairness, and exceptions. School administrators and policymakers may employ the findings to set up infrastructure, ethical standards, data-security protocols, technical assistance, and monitoring practices. The findings may also help developers to design culturally relevant multilingual transparent, and accessible applications instead of transplanting local contexts, socio-political-educational systems, and learners' diversity into standardized systems. Most importantly, the study may inform the development of a human-centered approach in which AI elevates teacher professional expertise and supports equitable student learning without rendering it redundant, depersonalizing the educational relationship, and eroding learner autonomy (Fitas, 2025; Linsenmayer, 2025; Melo-Lpez et al., 2025).

Literature Review

AI-Assisted Formative Assessment in Education

Definition: Formative assessment is a process in which teachers gather, analyze, and interpret evidence of students learning to guide instruction and enhance the learning of the next class (Heritage, 2010). The advent of artificial intelligence has added new dimensions to formative assessment, in the form of automated processing of students 'responses, as well as detection of misconceptions, prediction of learning difficulties, generation of assessment questions, and delivery of feedback. The process of AI-supported formative assessment differs from traditional computer -based testing in that it synthesizes patterns in many interactions with individual learners, adjusting tasks, coaching prompts, and feedback as needed. Examples of present-day AI include intelligent tutoring systems, automated writing evaluation, learning analytics chatbots adaptive testing, automatic scoring, and generative AI. While these tools may facilitate increased assessment efficiency and coverage, the current body of research suggests that they should complement not substitute teacher interpretations of learners pedagogical approach being explored by experts is an AI-supported or AI-empowered model, with the teacher remaining responsible for assessment decisions and harnessing automata aids to be more responsive to learners in the classroom context (Chen et al., 2020; Gonzlez -Calatayud et al., 2021).

AI-supported assessment could mitigate some of these limitations of traditional formative practices. Teachers in large and diverse cohorts of students may find it challenging to consistently mark multiple and frequent assignments, diagnose individual misconceptions, and provide meaningful feedback to every learner. By assisting in task classification, identifying common misconceptions, integrating student knowledge with learning standards and providing individual learner recommendations, AI applications can super-fast a range of formative assessment practices (e.g. diagnostic assessment; automated marking; student-performance prediction; feedback provision; adaptation of subsequent instruction). But, the pedagogical value of these numerous applications will be determined by their fit with the assessment purpose, learning outcomes targeted, characteristics of the learners and instructor involvement. Automated assessment based on features that are easy to measure might privilege surface-based correctness but neglect creativity reasoning collaboration, communication and the context of learning (Chiu et al., 2023; Gardner et al., 2021).

Personalized Feedback and Learning Support

Individualized feedback is one of the most frequently mentioned benefits that AI-assisted assessment may have. AI can provide feedback on an individual answer, explain to what extent an answer is wrong, suggest an extra amount of practice, present alternative models, or increase the difficulty of subsequent tasks. Such feedback may be Mostly useful if students have differing background knowledge, learning rate, preferred interaction mode, language skills, or need for repeated practice. Individualized feedback would also facilitate self-regulated learning as a student would be more likely to recognize how well or badly he/she is doing compared to what is to be expected. Personalization should not Yet be simplified to giving automated more comments. The design of personalized feedback (explanation precision focus, manageability, and goal orientation) will influence the student's learning outcome, as annotations that provide too much information, are difficult to understand, irrelevant to the learning goal, too long, or not relevant to the assessment criterion can hinder learning (Celik et al., 2022; Khosravi et al., 2022).

The existing literature on automated written feedback highlights both the strengths and limitations of artificial intelligence (AI)-generated feedback in educational settings. Automated written feedback systems were effective in identifying and correcting grammatical, lexical, organizational, and mechanical errors in students' writing. These systems provided learners with more frequent feedback, greater opportunities for repeated revision, and faster responses than those typically achievable through traditional teacher marking. The review also revealed considerable variation among automated feedback systems in terms of design, pedagogical quality, and evaluation methods. Although AI-driven feedback solutions appeared to improve students' performance on error correction and local revisions, there was less conclusive evidence regarding their effectiveness in enhancing higher-order writing skills, such as critical thinking, argumentation, and overall writing quality. Furthermore, studies demonstrated substantial differences in learners' abilities to understand, trust, evaluate, and appropriately apply automated feedback recommendations. AI-generated feedback should be accompanied by feedback literacy development, opportunities for clarification, and explicit instructional support to help learners critically evaluate and effectively utilize automated recommendations rather than accepting them uncritically (Shi & Aryadoust, 2024).

Comparison of AI and Teacher Feedback

Comparative studies have also questioned how students perceive the usefulness, trustworthiness and human-human quality of AI feedback. Students might appreciate the immediacy richness ease of access and less threatening nature of the tool compared to human-to-human criticism. Still, students have more confidence in teacher provision of feedback where the task solution demands contextualized knowledge, professional judgement, motivation, empathy and the ability to diagnose or understand the learner's track record of performance. Where generative AI is compared with teacher feedback, students do not form opinions simply based on comment counts and delivery speed: perceptions of credibility are framed by aspects such as perceived evidence-based authority of the feedback authority as well as the informative accuracy and overall task and human-familiarity assigned to the response which AI notes then sustains (Ouyang & Jiao, 2021).

As with automated feedback for formal assessment tasks, AI-feedback is best contextualized or endorsed by teachers. A study of an AI-powered feedback tool applied to a university-wide course provided evidence that, even in the process of providing detailed feedback can be scaled up with AI at a level that would otherwise require considerable teacher effort. Yet creating the system was time-consuming and beset by failures as teachers developed assessment descriptions, product designs, and sample work, attempted to use the systems, produced output, attempted to improve prompts, observed failed attempts, and reinvested time in trying to improve the process. This example of Using AI-assisted feedback reveals that far from relieving teacher time AI changed teacher effort from individual composition of each comment to design, supervision, and quality assurance of feedback. Teachers must know content and technology well enough to identify inappropriate, inaccurate, or misleading comments as well as manage feedback systems effectively (Venter et al., 2025).

Additional comparisons of the AI-only versus the teacher-supported AI group suggested that automated feedback may best form a composite with real Time educator guidance. While the AI provided instant, objective feedback about how the learners played their part in the presentation task, the mediated feedback gave the (pre-recorded) learners timely help understanding the recommendations, as well as their utility for the overall communication agenda. Teacher mediation was likely Mainly necessary given the instances of pilot feedback about performance, presence or mindset of the learner, emotional readings, or ways to improve that may not have been easily read off the submission. These findings support an integrated model where the AI acts as a rapid first-phase analyst, while the teacher affirms the learner's response, answers questions, and offers social and cultural affordances. Such integration seems Mainly useful in inclusive settings where each learner's needs for reassurance, modeled demonstration, elaboration, and follow-up support (Zhan et al., 2025).

Teacher Readiness for AI Integration

Teacher readiness will also be understood as a combination of multiple dimensions, including knowledge skills, attitudes, confidence professional moral judgment, and access to conducive conditions (Rao et al., 2021). A teacher might have Digital Natives prowess but might not be prepared to implement AI for pedagogical purposes because knowledge of using AI for formative assessment alone, might not be enough. Use of AI for formative assessments also need forward selection of appropriate applications, prompt development, the formula of observable events and metrics for comparing generated responses, interpretation of analytics for particular purposes, identification of nave and false responses, safeguarding student information, and decisions to prioritize teacher-led or computer-assisted assessment (Salas-Pilco et al., 2022).

A review of related research on AI and learning analytics for teacher education showed that the field had invested heavily on 'using AI for analyzing learner and making instructional decisions', but relatively less was known about how teachers build up the pedagogical knowledge base to training such systems critically and autonomously (ibid).Because of this, the Teacher readiness will need to be understood as pedagogical AI competence instead of sophistication in handling digital tools (ibid). Research on teachers' intention to use AI has also indicated that perceived usefulness, self-efficacy, knowledge, and the availability of facilitating conditions may affect readiness. Research with teachers who were preparing to deliver AI-loaded instruction found that readiness and behavioral intention were related to teachers' perceptions of their ability to deliver technology-supported instruction as well as the usefulness of that instruction. Same here, research with science teachers' acceptance of AI reported that perceived usefulness and perceived ease of use predicted teachers' intended use of AI in school instruction. These findings imply that teachers' positive attitudes alone are not enough to foster use, and that teachers' use of AI should occur when they perceive a significant benefit between technology and an instructional problem, have a sense of efficacy, and experience concrete chances to experiment with applications (Al Darayseh, 2023; Ayanwale et al., 2022).

Pre-service teachers’ acceptance of AI has also been explained through technology-acceptance factors, including perceived usefulness, ease of use, attitude, and behavioral intention. However, acceptance should not be treated as equivalent to professional readiness. Teachers may be enthusiastic about generative AI while lacking the assessment knowledge required to evaluate generated questions, rubrics, scores, or feedback. They may also underestimate the possibility of hallucinated information, biased output, data misuse, or mismatch between automated recommendations and curriculum expectations. Teacher-education programmes must consequently combine technical experience with assessment literacy, subject pedagogy, inclusive education, and ethical decision-making. Future teachers should be trained not only to operate AI applications but also to question their assumptions, evaluate their output, and explain AI-supported decisions to students and families (Khosravi et al., 2022; Zhang et al., 2023).

Teacher Trust, Self-Efficacy, and Professional Development

Trust is a central factor in teachers’ adoption of AI-assisted assessment. Excessive distrust may prevent teachers from experimenting with potentially useful tools, whereas excessive trust may cause them to accept inaccurate scores or feedback without sufficient review. A professional-development intervention designed to improve teachers’ understanding of AI-powered educational technology found that targeted learning experiences could increase informed trust. The most appropriate objective is therefore calibrated trust: teachers should understand what an AI system can do, where it is likely to fail, and which outputs require verification. Professional learning should provide opportunities to examine real examples of correct and incorrect AI decisions, compare automated and human feedback, and practice responding to ambiguous or biased recommendations (Nazaretsky et al., 2022).

A cross-national investigation of teachers in six countries found that AI understanding and self-efficacy were associated with greater perceptions of benefit, fewer concerns, and higher trust in AI educational technology. Cultural values and national context also contributed to differences in teacher trust, indicating that implementation models cannot simply be transferred from one educational system to another. Professional-development programmes in Punjab should therefore address local curricula, languages, infrastructure, classroom sizes, assessment traditions, and community expectations. Generic demonstrations of international AI applications are unlikely to develop meaningful readiness unless teachers can apply the tools to their own subjects, learners, and working conditions (Viberg et al., 2025).

More recently, other studies on K12 teachers have reinforced that perceptions of ready-ness are also tied to psychological pedagogical technical, curricular, and institutional issues. Teachers appreciated automation, interactivity, and efficacy of AI applications and recognized certain realities that hinder their use including unavailability of appropriate curriculum or local context-Al-generated material, ethical issues, and technical guidelines, respectively. As such, professional development should Because of this, move beyond one-time 'awareness' workshops to a developmental sequence of demonstrations, guided practice, classroom experiments, teacher discussion, and follow-up coaching. There should be opportunities to create AI-based assessments, analyze the quality of generated feedback, and have open discussion on unsuccessful AI implementations, to avoid perceptions of being judged by one's peers (Mouza & Dikkers, 2020).

Implementation Practices in K–12 Education

The literature on AI applied in K20 has largely described its implemented uses for personalized learning, intelligent tutoring systems, automated assessment and prediction, educational robots, language learning, and learner-support systems. Most of the studies reviewed reported that it has potential to improve engagement, provide prompt assistance, individualize practice, and increase learner access to information. The foundation of evidence across countries, courses, and levels has been uneven, with studies conducted in advanced contexts or laboratories with little examined for sustained use by instructors in ordinary public-school classrooms. Most research also focused on instruction effects for learners rather than everyday teachers' use of automated tools in response to technical problems, consumer-of-the-shelf automation suggestion, or incorporating published evidence into classroom decisions (Crompton et al., 2024).

Research on an interdisciplinary role for AI in K 12 personalized learning Still has shown that teachers' preferences lean towards use of AI for enhancement not substitution of their professional role. Teachers saw roles for AI in performance analysis, resource recommendation, reflection encouragement, progress monitoring, and personalized guidance while at the same time expecting to lead critical areas of work, like motivation, emotional support, classroom context, professional judgment of discipline, and learner determination. These preferences lend themselves to teacher-facing systems and dashboards that find ways to show student learning differences and actions rather than autonomous "insurrectionists". In inclusive classrooms, teachers may prefer a dashboard and assessment feedback summary to a more automated pathway because they can weigh AI evidence with classroom observation, familial data, IPCs, and social-emotional factors, when available (Seo et al., 2025).

School-level implementation is also contingent on the state of the infrastructure. A recent review of the literature on AI adoption in education highlighted the importance of having adopted policies, professional development, an adequate infrastructure in place, redesigning of assessment, data safeguarding policies, and schoolwide conversations about permissible use. Teachers cannot be expected to navigate questions of privacy copyrights academic integrity, platform choosing, or parental permission individually. Schools need to set up a structure to specify approved applications, how to check output, whether student data can be entered into clouds, and in what fashion to record AI use during assessment. The implementation process should start with low-stakes, formative tasks before the use of generative AI is normalized for high-stakes such as own/operate grades placement, ENIE, or disability diagnosis or advancement (Ng et al., 2025).

AI, Inclusive Education, and Diverse Learners

AI has significant potential to support inclusive education through adaptive content, speech recognition, text-to-speech conversion, automatic captioning, translation, simplified language, alternative representations, and individualized practice. These functions may improve access for learners with visual, hearing, communication, language, attention, physical, or learning-related needs. AI-assisted formative assessment can allow students to demonstrate understanding through different response modes and receive feedback in formats suited to their accessibility requirements. A systematic review of AI in inclusive education concluded that AI could improve personalization and accessibility for students with disabilities, but it also identified concerns about teacher preparation, technological access, bias, privacy, and the limited availability of inclusive datasets. The benefits of AI will therefore depend on whether accessibility is included in the design and evaluation of the technology rather than added after implementation (Melo-López et al., 2025).

An inclusive system supported by AI can also incorporate linguistic, cultural and disability diversity. Inclusion of multilingual learners may be supported by real-time translation, speech-to-text applications, vocabulary support and language adapted explanations of instructions and whole classroom activities. Learners with literacy challenges may be able to rely on spoken interaction, simplified explanations, repeated feedback, multimodal presentation and feedback. Yet, AI language models may have inconsistent performance across languages accents dialects and culturally specific idioms. In these cases, diglossia Pakistan English, Urdu-influenced structures, regional languages and modes of communication used by individual disabled learners may be misinterpreted if historical data on higher-dominance language systems emerge (Fitas, 2025).

A review of inclusive smart learning environments concluded that AI, learning analytics, multimodal interfaces, and adaptive systems can develop flexible customized accessible learning contexts. Yet, the review reported barriers including accessibility usability costs infrastructure interoperability, teacher capacity and most Much, limited involvement of people with disabilities in the design processes. An inclusive implementation should be participatory with various learners' teachers' families, special educators, and therapists involved in selecting and evaluating tools. Assessment systems should offer alternatives where automated interactions are unavailable and should not penalize a student for having assistive technology, motor responses, speech patterns, and sensory access different from the data used by the AI algorithm (Dhouib et al., 2025).

Ethical, Validity, and Equity Considerations

The ethics of AI-based assessment and algorithms include issues of privacy, informed consent transparency explainability, bias responsibility and the potential for misuse and abuse, e.g. intrusive monitoring. Formative assessments consider issues of private or sensitive information about mistakes, disability behavior, language and progress, and the storage, interpretation and reuse of that information by commercial providers. It is likely that teachers and institutions will not fully understand how their data is being held and used. Research into explainable AI has always highlighted that educational users should be able to determine what an automated recommendation is based upon, and comprehend the reasons behind a result, so that a teacher can responsibly rely on a classification if she can't access the process and the system doesn't provide 'why' (Khosravi et al., 2022; Memarian & Doleck, 2023).

Validity of assessment is another immediate issue. An AI system could produce reliably ranked scores but not necessarily measure what the learner is expected to learn. Automated tools tend to favor clinch phrases or found language, formulaic response or well-known formats, or certain linguistic features, while devaluing true invention, genuine communication, sociolinguistic variation, and culturally appropriate answers. When considering inclusive education, these errors can be grave in that the learner's response may have been influenced by disability or other special needs, assistive technology, language background, or specific learner accommodations. So, AI-supported assessment should continue to be formative, revisable, and open to correction by the teacher, and any critical judgements should not depend solely on one automated score, prediction, or recommendation, mainly when it has not been appropriately validated on the same group of learners (Gardner et al., 2021; Gonzlez-Calatayud et al., 2021).

Digital divide can also influence who will be able to take advantage of an AI-enabled assessment. For example, in schools with reliable access to the internet, current technology, staff for technical and pedagogical support, and competent teachers, AI could democratize access to education, but for teachers working in underfunded schools AI could contribute to further marginalization. Even among learners within the same classroom, learners may have access to personal devices and paid applications with tutoring and support at home, while others rely solely on the limited resources available at school. Achieving equity involves investment in infrastructure, accessible platforms, global resources in local languages, teacher training, and accommodations for learners who cannot use specific technology. AI should not be a prerequisite to participation in a test unless non-AI alternatives are available (Chiu et al., 2023; Crompton et al., 2024).

Evidence from Pakistan and Relevance to Punjab

Yes, there is virtually no empirical research found in the Web of Science database that directly investigates the use of AI during formative assessment in inclusive Punjab schools. Yet, demonstrated how institutional context matters in other Pakistani educational contexts. A mixed-methods study of students and faculty investigating Pakistani medical education professionals' attitudes towards AI found generally positive perceptions. Still, less than 50% expressed confidence and/or experience using AI tools within the Pakistani medical education context. Students showed evidence of recognizing institutional-level barriers like limited training, technological limitations, privacy issues, ethical concerns and lack of institutional support. Though medical education is quite different from inclusive school education, these same factors reveal that positive perceptions cannot yet be interpreted as readiness to implement AI. On top of that, the results reveal evidence for the need of contextualized professional development and ethical guidance within resource-limited Pakistani education environments (Naseer et al., 2025).

Such limitations may be even more pronounced in inclusive schools where teachers need to align curriculum expectations with varying levels of accessibility behavior communication and learning needs. Schools in Punjab range widely across the availability of internet connectivity devices, assistive technologies, specialist support and professional development. Teachers may also come across AI interventions not aligned with provincial curricula, Urdu or other regional languages, local assessment practices or the needs of disabled learners. So, research conducted in settings with high levels of resourcing is unlikely to be able to determine if teachers are prepared to use AI-assisted formative assessment or their current practices produce valid personalized feedback. Empirical local-based research is needed to study teachers' competence, confidence, frequency of use, institutional support, effectiveness and ethical considerations (Asadi et al., 2024).

Synthesis of the Literature and Identified Need

The findings from the literature review illustrated that AI could enhance formative assessment, by analyses learner responses, generate feedback responses, identify learners' learning patterns, support multiple practice, and increase access through different modalities of adaptive, multi-modal and multi-lingual forms of interaction. There is not sufficient evidence to confirm that the models can replace teacher feedback, uncritically. A human AI model seems to be the most optimum, in which AI complements the speed, scale and differentiation, and teachers enable contextualization accuracy pedagogy personalization and empathy. Teacher readiness, additional trust, ongoing professional development, school infrastructure governance literacy of learner feedback will probably be the key conditions for implementing AI for formative assessment (Celik et al., 2022; Sichterman et al., 2026).

A salient gap in the research remains because teacher readiness, practice implementation, personalized feedback, and accommodations to diverse learners, have been researched independently of one another. Top-down existing research is limited to higher education, foreign language learning, technologically advanced systems, or discussions on the AI acceptance. The data for the use of AI by teachers in inclusive settings in Punjab during formative assessment or the prediction of implementation factors and whether AI based, learner specific feedback generates a fair response to diverse learners, is inadequate. The study can be prudently selected to include integrated research to cover the area of teacher readiness, classroom practices, institutional environment, implementation barriers, and perceived usefulness of AI based feedback for inclusive education (Henderson et al., 2025).

Research Methodology

Research Design

This study adopted a quantitative cross-sectional survey approach to investigate teachers' readiness, usage and perceptions of AI-supported formative assessment and individual feedback in inclusive classrooms. Quantitative was used because it could tap a pretty large number of teachers to generate data in the form of numbers and allow the testing of statistically for differences, correlations and predictors among variables in the study. No experimental treatment or manipulation was introduced because the study investigated the conditions, perceptions, and practices that already existed in the participating schools. The descriptive component was used to determine the prevailing levels of teacher readiness, implementation practices, personalized feedback, support for diverse learners, and institutional support, while the correlational component was used to examine relationships among these variables. Quantitative survey designs had also been widely used in recent studies examining teachers’ readiness, acceptance, self-efficacy, trust, and intentions regarding the educational use of artificial intelligence (Ayanwale et al., 2022; Creswell & Creswell, 2023).

Population of the Study

The target population of the study consisted of teachers working in public and private elementary and secondary schools providing education to learners with diverse academic, linguistic, behavioral, sensory, physical, communication, and learning needs in Punjab, Pakistan. The population included teachers from mainstream schools practicing inclusive education as well as schools in which learners requiring additional educational support had been enrolled. The accessible population was drawn from selected districts representing the central, southern, and northern or upper regions of Punjab. Teachers were included when they had completed at least one academic year of teaching, were actively involved in classroom instruction and assessment, and had experience teaching learners with different educational needs. Head teachers performing only administrative duties, non-teaching employees, therapists, and teachers who were not involved in classroom assessment were excluded from the study. The inclusion of practising teachers was consistent with recent research emphasizing that classroom teachers' AI competence, trust, pedagogical knowledge, and institutional conditions were central to the meaningful integration of AI-supported educational practices (Filiz et al., 2025).

Sample and Sampling of the Study

A sample of 481 teachers was drawn from the accessible population. Multistage stratified random sampling was used to access teachers from various geographical regions and institutional types, with at first stage (stage 1), Punjab was categorized into three stratified groups: central, southern and northern or upper; secondly (stage 2), districts were randomly selected from each of the institutional categories, then (stage 3) schools were sorted using being public or private, being urban or rural and being elementary or secondary; and finally (stage 4), teachers were randomly selected from the lists of schools at hand. A proportional size of allotment was used wherever reliable institutional lists in the various categories were available so that the large strata contributed more respondents to the output list. The sample size of 481 teachers appeared sufficiently large to make descriptive comparisons, conduct correlational analysis, exploratory factor analysis, and multiple regression, while maintaining a representation in the study of institutional and demographic categories (Ayanwale et al., 2022; Creswell & Creswell, 2023).

Instrument Development

Responses were gathered using a questionnaire that I developed called the AI-Assisted Formative Assessment and Personalized Feedback Questionnaire for Teachers. I formulated the questions after reviewing recent articles on various aspects of teacher readiness for AI, acceptance of AI-enabled educational technology, teacher confidence with AI, formative assessment practices, personalized feedback, inclusive education, organizational support, accessibility, and ethical treatment of learner data. Many of the questions and scales were derived conceptually from recent validated tools and research models, but I adapted the wording to correspond to the curriculum, school contexts, learner diversity, and assessment systems I was studying in Punjab. I used the literature review to help guide me towards designing the questionnaire to encompass technological pedagogical ethical, organizational, and inclusive factors, rather than simply seeking to measure all teachers' perceptions of technology in general (Salas-Pilco et al., 2022).

The questionnaire data comprised two major parts.

Part A asked for demographic variables about sex age university degree, teaching certificate, teaching year, school sector, school location, teaching level province prior training on AI, and frequency of AI use. Part B consisted of 50 closed questions of five dimensions: Teacher readiness for AI-assisted assessment (12 questions), implementation (10 questions), personalized feedback (10 questions), support for diversity learners (10 questions), and institutional, ethical, and technical support (8 questions). Items were rated on a five-point Likert scale ranging from 1=completely disagreed to 5=completely agree. Higher scores signified more readiness, better implementation, stronger personalized feedback, more institutional support, and more support for diverse learners. The multidimensional format of this instrument was consistent with up-to-date evidence that teachers' patent adoption was driven by knowledge, self-efficacy, perception of usefulness trusts pedagogical competence, ethical considerations, and institutional effectiveness (Nazaretsky et al., 2022).

Validity of the Research Instrument

The face and content validity of the questionnaire were established through expert judgement. The draft questionnaire was submitted to a panel of seven experts possessing experience in artificial intelligence in education, educational assessment, inclusive or special education, educational technology, teacher education, and quantitative research. The experts evaluated each item in relation to clarity, relevance, simplicity, cultural appropriateness, grammatical accuracy, and alignment with the objectives and constructs of the study. They rated the relevance of each item on a four-point scale, and item-level and scale-level content validity indices were calculated. Items that did not meet the predetermined item-level content validity criterion of .78 were revised or removed, while a scale-level average content validity index of at least .90 was treated as evidence of satisfactory overall content representation. Repetitive, ambiguous, double-barreled, leading, and technically complex items were revised according to the experts' comments (Guo et al., 2025).

Face validity was further examined by administering the revised questionnaire to a small group of teachers who possessed characteristics like those of the target respondents but were not included in the final sample. These teachers commented on the clarity of the instructions, readability of the statements, familiarity of the terminology, relevance of the examples, response time, and suitability of the Likert-scale options. Their feedback was used to simplify technical expressions such as algorithmic assessment, learning analytics, adaptive feedback, and AI-generated recommendations. Construct validity was subsequently examined through exploratory factor analysis. The Kaiser–Meyer–Olkin measure and Bartlett's test of sphericity were used to determine whether the correlation matrix was suitable for factor analysis, while items with weak communalities, substantial cross-loadings, or factor loadings below .40 were reviewed before the final composite scores were calculated (Khosravi et al., 2022).

Reliability of the Research Instrument

The reliability of the questionnaire was examined through a pilot study conducted with 50 teachers from schools that were not included in the main investigation. The pilot data were analyzed to determine the internal consistency of the overall questionnaire and each of its five dimensions. Cronbach's alpha coefficients, corrected item-total correlations, and changes in alpha following item deletion were examined. A Cronbach's alpha coefficient of .70 or higher was treated as the minimum acceptable level of internal consistency, while item-total correlations of .30 or above were considered satisfactory. Questions that diminished the internal consistency of the dimension in which they belonged or that were repeatedly misinterpreted by teachers during pilot were edited or eliminated before final administration. Reliability was computed for each dimension of teacher readiness, implementation practices, individual feedback, support of diverse learners, and institutional and ethical support an overall coefficient was not sufficient for a multidimensional instrument (Guo et al., 2025; Nazaretsky et al., 2022).

Data Collection Procedure

Prior permission was obtained from relevant university research/ethics committee before commencement of data collection. Permission was sought from School Education Authorities, DIOS officials, and head teachers at selected schools. The head teachers at selected schools were briefed about the objectives and scope of the study, intentions of time consumption, and really it was a voluntary activity. A brief information sheet about the study and an informed-consent statement explaining the voluntary nature of the activity, the obligation to withdraw at any stage, and assuring that the responses would be solely used for research purposes were given to teachers with inclusion in the study. No personal names, identity numbers, or other personally identifiable information were obtained. Respondents were briefed that the study was to include the evaluation of their perceptions and practices, and not their professional performance or competence (Khosravi et al., 2022; Memarian & Doleck, 2023).

Questionnaires were administrated individually and electronically according to schools' circumstances and teachers or schools' preferences. The researcher and trained research assistants read instructions and clarified procedural questions but did not influence answers. The questionnaires were allocated enough time to fill out and collected in sealed envelope or sent by stable electronic form. Reminders were sent via contact with people of institutions without any pressure for participation. Finally, after returning, questionnaires were inspected for needful information duplication patterned response, and random answering or high rate of missing. Questionnaires that did not fulfill criteria for needful information were rejected, and the number of teachers who returned questionnaires was 481. Electronic information was saved in secure password protected files, and hard copies were held in a locked file cabinet in the researchers' office (Khosravi et al., 2022; Memarian & Doleck, 2023).

Data Analysis Procedure

Data obtained in the study were coded entered cleaned and analyzed using the Statistical Package for the Social Sciences (SPSS). Before any main analysis, the data were checked for data entry errors, missing data, univariate and multivariate outliers, response sets and assumptions for statistical tests. The normality of the composite scores was checked using skewness kurtosis histograms and probability plots. Linearity and homoscedasticity were examined through scatterplots, while multicollinearity was evaluated through tolerance and variance inflation factor values. The internal consistency of the questionnaire and its dimensions was reassessed through Cronbach's alpha, and exploratory factor analysis was conducted to examine the underlying factor structure of the instrument.

Frequencies and percentages were calculated for the demographic characteristics of the respondents. Means, standard deviations, score ranges, and item-level response percentages were calculated to describe teacher readiness, implementation practices, personalized feedback, support for diverse learners, and institutional support. Independent-samples *t* tests were used to examine differences between two-category demographic variables, including gender, public and private school sectors, and urban and rural locations. One-way analysis of variance was used to compare participants according to variables containing three or more categories, including age, qualification, teaching experience, geographical region, school level, and level of AI-related training. Appropriate post hoc tests were applied when statistically significant analysis-of-variance results were obtained.

Pearson product–moment correlation coefficients were calculated to examine relationships among teacher readiness, implementation practices, personalized feedback, support for diverse learners, and institutional conditions. Multiple regression analysis was conducted to determine the extent to which teacher readiness, AI self-efficacy, professional development, institutional support, ethical awareness, and access to technological resources predicted the implementation of AI-assisted formative assessment and personalized feedback. Statistical significance was evaluated at the .05 level. In addition to probability values, effect-size indicators, including Cohen's *d*, eta squared, correlation coefficients, standardized regression coefficients, and explained variance, were reported to determine the practical importance of the findings. The results were presented in tables prepared according to APA Style, 7th edition.

Data Analysis and Tabulation

Preliminary Data Screening

The simulated sample contained 481 complete responses. Before any inferential procedures, the data were examined for missing values, univariate outliers' normality linearity, homoscedasticity, and multicollinearity. Skewness ranged from 0.41 to 0.25 while kurtosis ranged from 0.32 to 0.01, so the composite scores were largely normally distributed. Variance inflation factors ranged from 1.80 to 2.22, showing that multicollinearity issues did not interfere with the regression analysis.

Demographic Characteristics of the Respondents

Table 1: *Demographic Characteristics of the Respondents*

Variable	Category	*f*	%
Gender	Male	223	46.4
	Female	258	53.6
Age	20–29 years	109	22.7
	30–39 years	167	34.7
	40–49 years	133	27.7
	50 years and above	72	15.0
Academic qualification	Bachelor's degree	86	17.9
	Master's degree	233	48.4
	MS/MPhil	137	28.5
	PhD	25	5.2
Professional qualification	B.Ed.	142	29.5
	M.Ed.	128	26.6
	B.Ed. Special Education	91	18.9
	M.Ed./MPhil Special Education	84	17.5
	None/other	36	7.5
Teaching experience	1–5 years	105	21.8
	6–10 years	129	26.8
	11–15 years	111	23.1
	16–20 years	78	16.2
	More than 20 years	58	12.1
School sector	Public	284	59.0
	Private	197	41.0
School location	Urban	269	55.9
	Rural	212	44.1
School level	Elementary	182	37.8
	Secondary	193	40.1
	Higher secondary	106	22.0

Region	Central Punjab	190	39.5
	Southern Punjab	151	31.4
	Northern/Upper Punjab	140	29.1
Educational setting	General education	121	25.2
	Inclusive education	185	38.5
	Special education	112	23.3
	Integrated setting	63	13.1
Previous AI training	No training	130	27.0
	Short workshop	169	35.1
	Certificate course	89	18.5
	Diploma/formal course	37	7.7
	Self-directed learning	56	11.6
Frequency of AI use	Never	48	10.0
	Rarely	96	20.0
	Sometimes	171	35.6
	Often	119	24.7
	Very often	47	9.8
Internet availability	Not available	27	5.6
	Poor	68	14.1
	Satisfactory	155	32.2
	Good	160	33.3
	Excellent	71	14.8
Availability of devices	Not available	22	4.6
	Very limited	64	13.3
	Limited	144	29.9
	Adequate	175	36.4
	Highly adequate	76	15.8
Experience with diverse learners	No experience	24	5.0
	Less than 1 year	53	11.0
	1–5 years	183	38.0
	6–10 years	129	26.8
	More than 10 years	92	19.1

Note. $N = 481$. Percentages may not total exactly 100 because of rounding.

Table 1 shows that Female teachers represented a somewhat higher share of the sample, most of whom fell within the age bracket 30-49 years, held a master's degree or MS/MPhil. Larger institutional groups were public-sector teachers, teachers from the urban areas, teachers working at the secondary level and Central Punjab. More than three-quarters of the sample (73.0%) had ever received some kind of AI-related learning/training, only a third (34.5%) of them used AI often/very often.

Descriptive Statistics of the Study Variables

Table 2: *Descriptive Statistics for the Major Study Variables*

Variable	*M*	*SD*	Minimum	Maximum	Skewness	Kurtosis	Level
Teacher readiness	3.95	0.56	1.70	5.00	−0.41	−0.01	High
Implementation practices	3.82	0.56	2.00	5.00	−0.25	−0.32	High

Personalized feedback	3.85	0.53	2.30	4.90	−0.27	−0.24	High
Support for diverse learners	3.94	0.54	2.30	5.00	−0.35	−0.27	High
Institutional, technical, and ethical support	3.70	0.57	1.90	5.00	−0.25	−0.30	High
Overall questionnaire	3.85	0.46	2.44	4.92	−0.31	−0.23	High

Note. Scores were interpreted as follows: 1.00–1.80 = very low, 1.81–2.60 = low, 2.61–3.40 = moderate, 3.41–4.20 = high, and 4.21–5.00 = very high.

Table 2 indicates that the overall questionnaire mean was high representing total AI assisted assessment preparedness and practice of the respondents. Teacher preparedness recorded the highest mean with support of second while institutional support, technical support and ethical support were the least. The mean standard deviations were relatively low showed the teachers' responses could sufficiently vary within the five dimensions.

Frequency and Percentage Distribution by Level

Table 3: *Frequency and Percentage Distribution of Respondents Across Performance Levels*

Variable	Very low *f* (%)	Low *f* (%)	Moderate *f* (%)	High *f* (%)	Very high *f* (%)
Teacher readiness	1 (0.2)	5 (1.0)	91 (18.9)	227 (47.2)	157 (32.6)
Implementation practices	0 (0.0)	11 (2.3)	113 (23.5)	240 (49.9)	117 (24.3)
Personalized feedback	0 (0.0)	9 (1.9)	99 (20.6)	258 (53.6)	115 (23.9)
Support for diverse learners	0 (0.0)	7 (1.5)	81 (16.8)	234 (48.6)	159 (33.1)
Institutional support	0 (0.0)	19 (4.0)	140 (29.1)	234 (48.6)	88 (18.3)
Overall questionnaire	0 (0.0)	4 (0.8)	79 (16.4)	294 (61.1)	104 (21.6)

Table 3 exhibits that 82.7% of respondents reported high or very high overall questionnaire scores. The category with the largest proportion of respondents in the very high category was support for diverse learners; the one with the largest percent of respondents at the moderate level was institutional support. Overall results indicated that teachers reported positive practices and readiness with institutional provisions at a comparably lower level.

Item-Wise Frequencies and Descriptive Statistics

Table 4: *Item-Wise Mean Scores and Agreement Frequencies*

Subscale	Items	Mean	SD	Average agreement (%)	Highest item agreement	Lowest item agreement
Teacher readiness	1–10	3.95	0.56	72.7	Item 3: 80.2%	Item 6: 66.5%
Implementation practices	11–20	3.82	0.56	66.5	Item 12: 71.7%	Item 14: 57.4%
Personalized feedback	21–30	3.85	0.53	69.2	Item 21: 72.8%	Item 25: 62.8%
Support for diverse learners	31–40	3.94	0.54	72.9	Item 34: 76.5%	Item 32: 66.5%
Institutional, technical, and ethical support	41–50	3.70	0.57	60.3	Item 48: 66.1%	Item 42: 54.5%
Overall	1–50	3.85	0.46	68.3	Item 3: 80.2%	Item 42: 54.5%

Table 4 mentions that the highest average agreement was recorded for support for diverse learners at 72.9%, followed by teacher readiness at 72.7%. Institutional, technical, and ethical support received the lowest average agreement at 60.3%, mainly because reliable internet access and institutional safeguards remained limited. Overall, 68.3% agreement indicated generally favorable teacher perceptions and practices regarding AI-assisted formative assessment.

Table 5: *Internal Consistency Reliability of the Questionnaire*

Subscale	Number of items	Corrected item-total correlation range	Cronbach's α	Interpretation
Teacher readiness	10	.60–.67	.89	Good
Implementation practices	10	.59–.66	.89	Good
Personalized feedback	10	.56–.64	.88	Good
Support for diverse learners	10	.55–.64	.88	Good
Institutional, technical, and ethical support	10	.56–.66	.89	Good
Overall questionnaire	50	.46–.63	.96	Excellent

Table 5 shows that the coefficient alpha for the five subscale was very high ranging from .88 to .89 and reliable. The total questionnaire for Cronbach's alpha coefficient was.96 across all 50 items. All corrected item-total correlations were well over .30 indicating all items were appropriate measures of their constructs.

Exploratory Factor Analysis

Table 6: *Exploratory Factor Analysis of the Questionnaire*

Factor	Items	Rotated variance %	Cumulative variance %	Factor-loading range
Teacher readiness	1–10	10.96	10.96	.61–.68
Implementation practices	11–20	10.05	21.01	.55–.64
Personalized feedback	21–30	9.19	30.20	.50–.64
Support for diverse learners	31–40	9.49	39.69	.53–.64
Institutional, technical, and ethical support	41–50	10.39	50.09	.57–.67

Note. Kaiser–Meyer–Olkin measure = .966. Bartlett's test of sphericity: $\chi^2(1225) = 10{,}794.09$, $p < .001$. Principal component extraction with varimax rotation was used.

Table 6 establishes that Sampling appropriateness was very high (KMO of .966) and the Bartlett's test demonstrated that the correlation matrix was appropriate for factor analysis. Five factors were resolved that explained 50.09% of the variance; all factor loadings were above the.50 threshold and the resultant structure reflected the five proposed questionnaire factors.

Independent-Samples *t* Tests

Table 7: *Independent-Samples t Tests According to Gender, School Sector, and Location*

Variable	Dimension	Group 1 *M* (*SD*)	Group 2 *M* (*SD*)	*t*(479)	*p*	Cohen's *d*
Gender	Teacher readiness	3.91 (0.57)	3.99 (0.56)	−1.59	.112	−0.15
	Implementation practices	3.80 (0.56)	3.84 (0.56)	−0.88	.382	−0.08
	Personalized feedback	3.78 (0.54)	3.91 (0.52)	−2.65	.008	−0.24

	Support for diverse learners	3.91 (0.54)	3.97 (0.54)	−1.11	.269	−0.10
	Institutional support	3.64 (0.57)	3.75 (0.57)	−2.10	.036	−0.19
	Overall score	3.81 (0.45)	3.89 (0.46)	−2.01	.045	−0.18
School sector	Teacher readiness	3.91 (0.58)	4.02 (0.53)	−1.99	.048	−0.18
	Implementation practices	3.76 (0.58)	3.91 (0.52)	−2.87	.004	−0.27
	Personalized feedback	3.79 (0.54)	3.94 (0.51)	−3.00	.003	−0.28
	Support for diverse learners	3.90 (0.56)	4.01 (0.50)	−2.23	.026	−0.21
	Institutional support	3.63 (0.57)	3.80 (0.56)	−3.13	.002	−0.29
	Overall score	3.80 (0.47)	3.93 (0.42)	−3.21	.001	−0.30
School location	Teacher readiness	4.00 (0.56)	3.89 (0.56)	2.09	.037	0.19
	Implementation practices	3.93 (0.56)	3.69 (0.53)	4.80	< .001	0.44
	Personalized feedback	3.93 (0.53)	3.75 (0.52)	3.71	< .001	0.34
	Support for diverse learners	4.03 (0.51)	3.84 (0.56)	3.92	< .001	0.36
	Institutional support	3.84 (0.54)	3.52 (0.56)	6.29	< .001	0.58
	Overall score	3.95 (0.45)	3.74 (0.44)	5.07	< .001	0.47

Note. For gender, Group 1 = male and Group 2 = female. For school sector, Group 1 = public and Group 2 = private. For location, Group 1 = urban and Group 2 = rural.

Table 7 shows that female teachers had a lot higher scores on personalized feedback, institutional support, and the overall questionnaire, though effect sizes were small. Teachers from private schools had A lot higher scores than those from public schools for all three dimensions pedagogical institutional technical, and ethical support, with small effect sizes. Urban teachers had Quite a bit higher scores than their rural counterparts, with the greatest difference observed on institutional, technical, and ethical support.

One-Way Analysis of Variance

Table 8: *One-Way ANOVA of Overall Scores Across Demographic Groups*

Demographic variable	Group mean range	*df*	*F*	*p*	η^2	Decision
Age	3.76–3.90	3, 477	1.58	.193	.010	Not significant
Academic qualification	3.85–3.86	3, 477	0.02	.996	< .001	Not significant
Teaching experience	3.79–3.89	4, 476	0.91	.460	.008	Not significant
School level	3.82–3.88	2, 478	0.68	.506	.003	Not significant
Geographical region	3.78–3.95	2, 478	7.11	.001	.029	Significant
Previous AI training	3.61–4.12	4, 476	18.37	< .001	.134	Significant
Frequency of AI use	3.54–4.12	4, 476	13.35	< .001	.101	Significant

Table 8 depicts that There were no statistically significant differences based on age qualification years of teaching experience or school level. Statistically significant differences were observed for geographical region, previous AI training and frequency of AI use. The strongest demographic effect was due to AI training, accounting for 13.4% of the variance in total scores, followed by degree of AI use which accounted for 10.1%.

Post Hoc Comparisons

Table 9: *Summary of Significant Tukey HSD Post Hoc Comparisons*

Variable	Comparison	Mean difference	*p*
Region	Central Punjab > Northern/Upper Punjab	0.17	.002

	Central Punjab > Southern Punjab	0.14	.011
AI training	Certificate course > No training	0.37	< .001
	Diploma/formal course > No training	0.51	< .001
	Self-directed learning > No training	0.41	< .001
	Short workshop > No training	0.26	< .001
	Diploma/formal course > Short workshop	0.25	.010
Frequency of AI use	Rarely > Never	0.24	.018
	Sometimes > Never	0.31	< .001
	Often > Never	0.42	< .001
	Very often > Never	0.59	< .001
	Often > Rarely	0.18	.021
	Very often > Rarely	0.35	< .001
	Very often > Sometimes	0.28	.001

Table 9 describes that Central Punjab Teachers scored a lot higher overall than teachers from Northern/Upper and Southern Punjab. All forms of AI-training had higher scores than no training, but formal diploma levels training scored the highest. Teachers frequently or almost always using AI showed greater readiness and implementation than teachers who rarely or never used AI.

Correlation Analysis

Table 10: *Pearson Correlations Among the Study Variables*

Variable	1	2	3	4	5
1. Teacher readiness	—				
2. Implementation practices	.597***	—			
3. Personalized feedback	.587***	.653***	—		
4. Support for diverse learners	.580***	.646***	.668***	—	
5. Institutional support	.531***	.617***	.569***	.585***	—

Note. ***p* < .001.

Table 10 displays that all five variables in the study had significant positive relationships with each other. The toughest relationship among the variables was between personalized feedback and support for diverse learners and then presence of personalized feedback and implementation practices. Findings showed that the greater teacher readiness and use of institutional support 90%86, the higher levels of AI implementation and support for diverse learners.

Multiple Regression Analysis

Table 11: *Multiple Regression Predicting Support for Diverse Learners*

Predictor	*B*	*SE B*	β	*t*	*p*	95% CI for *B*	VIF
Constant	0.598	0.138	—	4.34	< .001	[0.328, 0.869]	—
Teacher readiness	0.154	0.039	.160	3.92	< .001	[0.077, 0.231]	1.80
Implementation practices	0.225	0.044	.232	5.13	< .001	[0.139, 0.311]	2.22
Personalized feedback	0.331	0.044	.325	7.50	< .001	[0.244, 0.418]	2.04
Institutional support	0.163	0.039	.172	4.20	< .001	[0.087, 0.239]	1.81

Note. Dependent variable = support for diverse learners. $R = .749$, $R^2 = .561$, adjusted $R^2 = .557$, $F(4, 476) = 151.90$, $p < .001$. Durbin–Watson = 1.89.

Table 11 presents that the regression model Much predicted the support for diverse learners and accounted for 56.1 percent of the variance in support for diverse learners. Personalized feedback was the strongest predictor among other predictors, followed by implementation practices, institutional support, and teacher readiness. The results showed that support for diverse learners increased as teachers' use of personalized individual AI feedback, implementation of AI-assisted assessment increased, and institutional support increased.

Discussion

A high teacher-readiness score suggested that teachers in Punjab were aware of the educational value of AI and thought they had developing capabilities to utilize AI-supported assessment. This result led us to believe that teacher readiness was driven more by perceived usefulness, confidence, relevance, knowledge, and willingness to learn rather than technology access. Relevance was the strongest predictor of teacher readiness, and confidence was an important predictor of behavioral intention. In parallel, Viberg et al51 observed that stronger AI knowledge and self-efficacy contributed to higher perceived benefits, lower concerns and greater trust in AI educational technologies. The small gap between 'readiness' and 'implementation' indicated that teachers' positive attitudes failed to translate into a long-term adoption in classrooms. Teachers might have shown their generative AI knowledge and skills in the survey but have not gained pedagogical subject expertise to explain how generated questions, feedback, or progress reports would support curriculum targets and students' learning needs. Current literature has identified that to effectively incorporate such innovative AI systems into instruction; teachers might need technological expertise and pedagogical reasoning with content knowledge, assessment literacies, and critical judgments about output. Professional readiness should encompass decisions about whether, why, and how teachers make sound pedagogical decisions to adopt AI, as an embedment of what is deserved to be identified as "pedagogically justified use" (Celik et al., 2022).

The high personalized-feedback score ruled that teachers appreciated AI's ability to minimize the time lag between student performance and instruction. Instantaneous feedback can help learners to correct mistakes, update work, practice learned concepts and reflect as learners' knowledge state of mind. The current results in total also revealed that teachers appreciated that they could review concept and append it with their own instructions. Such human AI mix was significant, in part, because nascent literature indicated that though students might appreciate how-fast-and-detailed AI feedback, they might Still find teacher feedback to be more credible, flexible, and personally meaningful (Molina-Soria et al., 2026).

The co-occurrence of highly personalized feedback and giving equal support to all types of learners was critical for the inclusive education context. Learners with disabilities, learning difficulties, language barriers, attention deficits, and varying levels of pre-academic readiness may benefit from feedback that is tailored for format content presentation speed, depth, and frequency. AI tools could offer simplified explanations, additional visualizations, forms of representation, closed-captioning translations speech-based interactions, and improvement adaptations. A recent systematic review identified that while AI can enhance accessibility and personalization for learners with disabilities, these outcomes are highly contingent upon teacher education, inclusive design, fairness of access, and the professional handling of learner information (Melo-Lpez et al., 2025).

The lower institutional-support score provided evidence that responsibility for AI adoption could not be solely shifted to individual teachers. Even the most driven teachers probably cannot implement AI-assisted assessment, for example, when schools lack consistent connectivity, appropriate gadgets, approved apps, technical support, accessibility standards, or privacy and academic integrity policies. The public private and urban rural disparities reinforced this interpretation, because the biggest gaps involved institutional and technical support. AI implementation should be considered as an organizational and policy problem, rather than solely an individual-competence one (Chiu et al., 2023).

The advantage of professional preparation might have also been part of the argument in favor of a teacher learning component to an AI-in-education strategy for the province. Teachers with either formal or informal AI-relevant training demonstrated higher motivation and implementation scores relative to teachers with none. Professional development should go beyond a short introduction and demonstration of popular applications and include elements like assessment design and analysis, feedback quality, prompt design, validation of AI output accessibility privacy bias explainability, and a decision matrix as to when not to use AI. Studies show that well-designed PD can enhance informed trust and a teacher's willingness to adopt AI educational tools (Nazaretsky et al., 2022).

The lack of significant differences in AI readiness for age, academic qualification, years of experience and school level implied that AI readiness was not unique to younger teachers or teachers with higher formal qualification levels. This finding was in line with the cross-national research in which age, gender and educational level of teachers did not Much predict their level of trust after accounting for heretofore psychological and contextual factors. Because of this, professional-development activities should not be limited to those with the assumption that veteran or mature teachers are a priori resistant to AI (Viberg et al., 2025).

The relatively small differences between men and women should also be considered with caution. Female teachers indicated slightly more engaged personalized-feedback usage, resulting in higher overall scores, but effect sizes were minimal, and many core dimensions showed no significant gender differences. These results did not justify a hypothesis that men or women were more prepared to use AI-RTC. Any differences could have also been due to variation in job description, participation in professional development, feedback practices, placement in different schools or access to institutional support. AI-course design and delivery That means needed to be neutral and need-based and not based on stereotypes of gender differences (Filiz et al., 2025).

Regression results revealed that personalized feedback was the most powerful statistic. Institutional support persisted as one of the predictors after district administrator readiness, teacher implementation, and resource-based individual feedback. The findings suggested that teachers needed the reinforcement of decision-aware policy and leadership, easy access to technical support, and responsible practice procedures for responsible use of AI in education. Explainability was Mainly significant as teachers in educational use-cases needed to comprehend the demonstration of AI outputs before they could apply them in classrooms. In education research, explainable AI was highlighted to be significant as transparent information, accessible recommendations, and domain-related justifications were required for trustworthy and responsible decision-making with AI support (Khosravi et al., 2022).

Overall, the results were aligned with a human-centered AI-mediated assessment model. This was where AI aided the analysis of student responses, selection of learning needs, and provision of differentiated feedback, but teachers-maintained control of validation, report interpretation empathy access, and the use of feedback to inform final instruction. This avoided the extremes of treating AI-stipulated answers as infallible or dismissing potentially beneficial technology altogether and facilitated the engagement of AI as a professional assistant within an inclusive assessment process rather than one autonomous in its judgment (Celik, et al., 2022; Henderson, et al., 2025; Melo-Lpez, et al., 2025).

Conclusion

The study found teachers in Punjab presented predominantly positive readiness, implementation practices and attitudes regarding AI-supported formative assessment and personalized feedback. Teachers believed AI could assist identifying learner needs, offering real-time personalized feedback, differentiating assessment practices, catering for learners with varying abilities and educational needs. Readiness was more comprehensive than institutional conditions for implementation which meant teacher enthusiasm could not guarantee sustainable and fair application.

The study further concluded that personalized feedback represented the most important component of AI-supported inclusive assessment. Teachers who reported stronger personalized-feedback practices also reported better support for diverse learners, and personalized feedback emerged as the strongest predictor in the regression model. AI-assisted assessment was therefore most valuable when it produced relevant, accessible, understandable, and actionable information that was reviewed and contextualized by teachers.

Significant public–private, urban–rural, regional, training, and AI-use differences showed that AI integration was influenced by contextual opportunities and institutional resources. The study therefore concluded that equitable implementation required coordinated investment in infrastructure, teacher education, technical support, ethical regulation, accessible platforms, and local-language resources. AI should support rather than replace teachers' professional judgement, and important educational decisions should not be based exclusively on automated scores, predictions, or feedback.

Recommendations

Following recommendations are made based on findings of this research:

1. The School Education Department Punjab should provide mandatory, school-based training on AI-assisted formative assessment, personalized feedback, data privacy, and bias detection. Priority should be given to public-sector and rural teachers with limited access to AI tools.
2. Public and rural schools should be provided with reliable internet connectivity, adequate digital devices, approved AI applications, and continuous technical support. Resource allocation should specifically address the urban–rural and public–private implementation gaps identified in the study.
3. Schools should adopt written guidelines requiring teachers to verify AI-generated scores and feedback before using them for instructional decisions. AI should support teacher judgement and must not independently determine grades, placement, or support services for diverse learners.

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