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CULTURAL INTELLIGENCE IN AI-DRIVEN ONLINE LEARNING: EXAMINING BIAS AND INCLUSIVITY IN VIRTUAL CLASSROOMS

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A B S T R A C T

The integration of artificial intelligence (AI) into online education has transformed teaching and learning practices through personalization, automation, and adaptive learning support. However, the increasing use of AI-driven educational systems raises concerns regarding their ability to accommodate culturally diverse learners. While previous studies have primarily focused on the effectiveness of AI in improving engagement and learning outcomes, limited attention has been given to the role of cultural intelligence (CQ) in AI-mediated learning environments. This study examines how AI-integrated online learning platforms support or constrain cultural inclusivity among diverse student populations. The study employed an explanatory sequential mixed-methods design involving 230 participants, including students, instructors, and AI developers. Quantitative data were collected through surveys and analyzed using descriptive statistics, ANOVA, and regression analysis, while qualitative data from semi-structured interviews and focus groups were analyzed through thematic analysis. The findings indicate that although AI technologies improve accessibility and learning efficiency, many AI-driven systems still reflect dominant Western-oriented educational norms and communication styles. Non-Western learners and multilingual students reported lower engagement levels, particularly when AI-generated feedback and content recommendations lacked cultural representation and contextual sensitivity. The study also found that learners with higher levels of cultural intelligence demonstrated stronger adaptability to AI-mediated learning environments. This study contributes to the growing discussion on AI in education by positioning cultural intelligence as an important consideration in the design and implementation of AI-supported learning systems. The findings highlight the need for culturally responsive AI frameworks and emphasize the continuing importance of human–AI collaboration in creating equitable and inclusive online learning environments.

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INTRODUCTION

The rapid digital revolution of education has led to the widespread adoption of online learning environments, transforming pedagogy and student engagement worldwide (Makda, 2025; McCarthy et al., 2023; Mhlongo et al., 2023; Mohamed Hashim et al., 2022). Educational institutions have increasingly used AI-driven tools to customize learning experiences, automate evaluations, and improve instructional delivery. AI-powered adaptive learning systems, chatbots, automated feedback, and data-driven decision-making improve student outcomes in online education. As online learning globalizes, students from different cultures and learning styles join virtual classrooms.

Cultural diversity affects communication, cognitive processing, and involvement in schools (Atkinson et al., 2025; Dai & Wang, 2024; Zajda, 2021). Cultural intelligence (CQ), first described by Earley & Ang (2003), is essential for managing cross-cultural relationships (Kadam et al., 2021; Nazarian et al., 2024; Rajaram, 2023). Cultural intelligence (CQ) is the ability to function well in diverse cultural situations in four dimensions: metacognitive, cognitive, motivational, and behavioral. Cultural intelligence helps teachers bridge cultural gaps, foster inclusive learning environments, and foster meaningful cross-cultural interactions in traditional classrooms. AI in online education raises questions about cultural intelligence in digital learning contexts.

AI-driven educational systems analyze student behavior and performance metrics to improve learning (Bhardwaj et al., 2025; Ranjan, 2024; Srinivasa et al., 2022). Due to their training on datasets that may not adequately represent diverse cultural viewpoints, these systems often lack cultural sensitivity. Thus, AI-driven educational settings may exacerbate biases, making it difficult for marginalized students to participate in learning experiences that violate their cultural norms (Bhavana et al., 2025; Kunjumuhammed, 2024; Lin et al., 2024; Roshanaei, 2024).

Current AI and online education studies have focused on technological efficiency, student engagement, and learning analytics, ignoring the social impacts of AI in virtual classrooms. Research shows that culturally responsive pedagogy improves academic performance, student motivation, and involvement in traditional and hybrid schools. However, AI-integrated online learning settings that promote cultural diversity have received scant attention.

AI can customize learning experiences, but its use in online education often ignores cultural factors that affect student interactions, learning preferences, and communication styles. Thus, AI-integrated learning systems may fail culturally diverse students, worsening educational disparities (Takona, 2024; Yambal & Waykar, 2025). Cultural intelligence is critical for international communication and collaboration. Hence, it is important to examine how AI can improve culturally inclusive virtual classrooms. Previous studies have examined cultural intelligence in in-person educational settings, but less is known about CQ in AI-facilitated online learning environments. AI in education research emphasizes personalization, evaluation automation, and student involvement but not cultural inclusivity.

AI-driven educational technology often ignores student cultural diversity and uses Western-centric pedagogical frameworks that may not work for other learning traditions.

Due to the lack of culturally adaptive AI systems, non-dominant cultural students may face language barriers, culturally misaligned instructional materials, and insufficient representation in AI-generated feedback systems (Brown & Laihonen, 2025; Samuel et al., 2023). As AI becomes more prevalent, online education must address these concerns to avoid inequitable learning and decreased student engagement among culturally diverse learners. This gap highlights the need for study on cultural intelligence in AI-enhanced online learning to promote inclusiveness and equal access to quality education.

Although the integration of artificial intelligence in online education is increasing, current research predominantly emphasizes technological efficiency, personalization, and learning analytics, while insufficiently addressing the interaction of AI systems with cultural diversity. Cultural intelligence (CQ) has been extensively studied in face-to-face and intercultural learning situations, although its use in AI-driven learning environments is both under-theorized and practically insufficiently explored. This establishes a significant gap in comprehending how AI-mediated systems may either facilitate or hinder culturally diverse learners due to their inherent assumptions, feedback mechanisms, and content frameworks. This study seeks to investigate the influence of cultural intelligence on student engagement in AI-enhanced online learning settings. The study specifically examines how AI systems mirror, replicate, or adjust to various cultural learning preferences and communication methods. The study is directed by the subsequent inquiries:

1. How do students and instructors perceive the cultural inclusivity of AI-driven learning systems?
2. To what extent do AI-generated feedback and content recommendations reflect cultural bias?
3. How does cultural intelligence influence learner engagement in AI-mediated environments?

RESEARCH METHOD

Research Design

This study employed an explanatory sequential mixed-methods design to examine cultural intelligence in AI-driven online learning environments. The study began with a quantitative phase followed by a qualitative phase to provide a deeper understanding of the initial findings. This approach was considered appropriate because it enabled the researchers to explore both statistical trends and participants' experiences related to cultural inclusivity in AI-mediated learning.

In the first phase, quantitative data were collected through structured surveys to measure participants' perceptions of cultural inclusivity, learner engagement, and the adaptability of AI-based learning systems. The findings from the survey phase were then used to guide the development of the qualitative instruments. In the second phase, semi-structured interviews and focus group discussions were conducted to investigate participants' experiences and interpretations of AI-supported learning across different cultural contexts. This phase aimed to provide a more detailed explanation of the quantitative results, particularly regarding issues of cultural bias, communication challenges, and inclusivity in online learning environments.

To strengthen the validity of the findings, data integration was conducted through triangulation by comparing quantitative results with qualitative themes. The quantitative analysis identified general patterns of engagement and perceptions of inclusivity, while the qualitative findings provided deeper insights into culturally influenced learning experiences.

The mixed-methods design allowed for a more comprehensive understanding of the relationship between cultural intelligence and AI-driven online learning systems.

Participants

This study involved 230 participants consisting of 150 students, 50 instructors, and 30 AI developers who had direct experience with AI-integrated online learning environments. Participants were recruited from higher education institutions in Southeast Asia, particularly Indonesia and Malaysia, as well as South Asia, including India. Several participants were also affiliated with universities implementing global online learning platforms and AI-assisted instructional systems.

To support the analysis, participants were categorized into Western and non-Western cultural backgrounds based on their educational and sociocultural experiences rather than nationality alone. Participants classified within the Western background category generally experienced educational systems influenced by Anglo-European pedagogical traditions characterized by individualistic, analytical, and linear learning approaches. In contrast, participants categorized as non-Western backgrounds were associated with collectivist, contextual, and collaborative learning traditions commonly found in Asian and Global South educational settings. This classification was intended to facilitate a deeper understanding of how AI-driven learning systems interact with different cultural learning preferences and communication patterns. Demographic information, including background, educational level, and prior experience with AI-based learning systems, was collected to ensure diverse participant representation. The participant distribution is presented in Table 1.

Table 1
Participants' demographics

Category	Total Participants	Western Background (%)	Non-Western Background (%)	Undergraduate (%)	Graduate (%)	Doctoral (%)
Students	150	50	50	80	20	0
Instructors	50	60	40	0	100	0
AI Developers	30	70	30	0	60	40

Table 1 shows that students represented the largest participant group in this study, followed by instructors and AI developers. Students were equally distributed between Western and non-Western educational backgrounds, while instructors and AI developers were more dominantly associated with Western-oriented educational experiences. Most student participants were undergraduate students (80%), whereas all instructors had graduate-level educational qualifications. Among AI developers, 60% held graduate degrees and 40% held doctoral degrees. This demographic distribution provided diverse perspectives regarding the implementation of AI-enhanced learning systems and cultural inclusivity in online education.

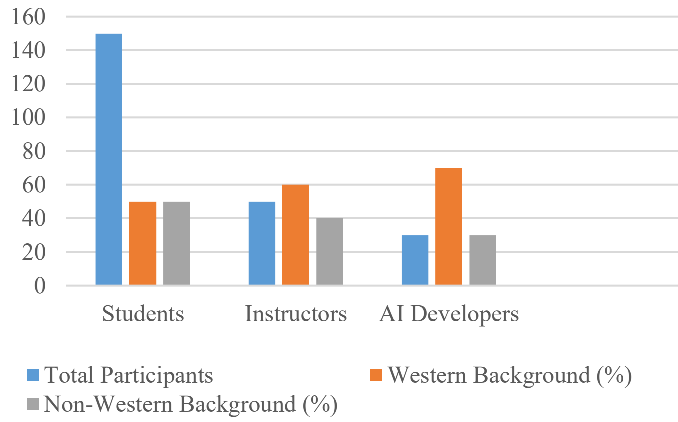

Figure 1. Distribution of participants by category

Figure 1 illustrates the distribution of participants involved in this study. Students constituted the majority of participants, reflecting their central role as primary users of AI-integrated online learning systems. Instructors represented participants who actively utilized AI-supported teaching methods in virtual classrooms, while AI developers contributed perspectives related to the design and development of AI-driven educational technologies. The inclusion of these three participant groups enabled the study to examine cultural intelligence and inclusivity in AI-mediated learning environments from multiple perspectives.

Instruments

This study utilized several instruments to ensure comprehensive quantitative and qualitative data collection. Quantitative data were collected using a structured questionnaire consisting of 32 items measured on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). The questionnaire was designed to measure three main constructs: Cultural Intelligence (CQ), AI Engagement, and Perceived Cultural Inclusivity. The Cultural Intelligence construct was adapted from the Cultural Intelligence Scale (CQS) developed by Ang & Van Dyne (2015), which includes four dimensions: metacognitive, cognitive, motivational, and behavioral CQ. Prior to the main study, the questionnaire was pilot-tested to ensure its reliability and clarity. The reliability analysis produced a Cronbach's alpha value of 0.87, indicating good internal consistency.

Qualitative data were collected through semi-structured interviews and focus group discussions to explore participants' experiences with AI-mediated learning environments. The interview protocol consisted of 8–10 open-ended questions focusing on AI bias, cultural representation, interpretation of AI-generated feedback, communication barriers, and learner engagement in culturally diverse online classrooms. Focus group discussions were conducted to encourage interaction among participants and to obtain broader perspectives on the inclusivity of AI-driven learning systems.

In addition to the questionnaire and interviews, this study employed an evaluation framework to assess AI-driven learning platforms based on three aspects: (1) cultural inclusivity of learning content, (2) linguistic diversity in AI-generated feedback, and (3) adaptability to different learning styles. Each aspect was evaluated using a four-point scale ranging from low responsiveness to high responsiveness. This framework enabled the researchers to examine how AI systems support or limit cultural diversity within online learning environments.

Data Analysis

This study employed both quantitative and qualitative data analysis techniques to examine the relationship between cultural intelligence (CQ), AI engagement, and learner satisfaction in AI-enhanced online learning environments. Quantitative data obtained from the survey were analyzed using descriptive statistics, one-way ANOVA, and multiple linear regression analysis. The regression model positioned AI engagement as the dependent variable, while cultural intelligence (CQ) served as the primary independent variable. Additional variables included perceived inclusivity and prior experience with AI-based learning tools, whereas demographic characteristics such as cultural background and educational level were treated as control variables. This analysis was conducted to identify patterns of engagement and differences among participants from diverse cultural backgrounds. Qualitative data collected through interviews and focus group discussions were analyzed using thematic analysis with the support of NVivo software. The coding process was conducted in two stages. The first stage involved open coding to identify emerging themes from participants' responses, while the second stage involved axial coding to organize the data into broader categories such as AI bias, cultural mismatch, feedback interpretation, communication barriers, and learner engagement.

In addition, the analysis of AI-generated feedback and content recommendations was conducted using a rubric-based evaluation framework focusing on cultural inclusivity, language diversity, and adaptability to different learning styles. To ensure reliability and consistency, two independent coders evaluated the qualitative data and AI assessment results, resulting in an inter-coder agreement coefficient of 0.82.

To strengthen the validity of the findings, data integration was conducted through triangulation by comparing quantitative findings, qualitative themes, and AI system evaluation results. This approach enabled the researchers to obtain a more comprehensive understanding of cultural intelligence and inclusivity in AI-mediated online learning environments.

RESEARCH FINDINGS AND DISCUSSION

Research Findings

Perceived Cultural Inclusivity in AI-Driven Learning Systems

The survey findings indicate that students and instructors hold varying perceptions regarding the cultural inclusivity of AI-driven online learning systems. As presented in Table 2, most students (62%) and instructors (74%) perceived AI-based learning platforms as moderately inclusive. However, 20% of students and 12% of instructors believed that current AI systems do not adequately accommodate cultural diversity. Only 18% of students and 14% of instructors considered AI systems fully adaptive to the needs of culturally diverse learners.

Table 2
Survey Results on AI Cultural Adaptability

Survey Aspect	Students (%)	Instructors (%)
AI perceived as moderately inclusive	62	74
AI perceived as failing to accommodate diversity	20	12
AI perceived as fully adaptive	18	14

The statistical analysis further demonstrated significant differences in AI engagement across cultural groups. As shown in Table 3, the ANOVA test revealed a significant relationship between cultural background and AI engagement ($p = 0.03$). In addition, regression analysis identified a strong positive relationship between cultural intelligence (CQ) and AI engagement (r = 0.68), indicating that participants with higher cultural intelligence were more capable of adapting to AI-mediated learning environments.

Table 3
Survey results on AI cultural adaptability

Analysis Type	Significance Level (p-value)	Correlation Coefficient (r)
ANOVA (Cultural Groups & AI Engagement)	0.03	
Regression (CQ & AI Engagement)		0.68

The findings suggest that AI systems currently support learning accessibility and engagement to some extent; however, cultural responsiveness remains limited. Non-Western students generally reported lower engagement levels and greater difficulties in adapting to AI-generated learning recommendations and feedback.

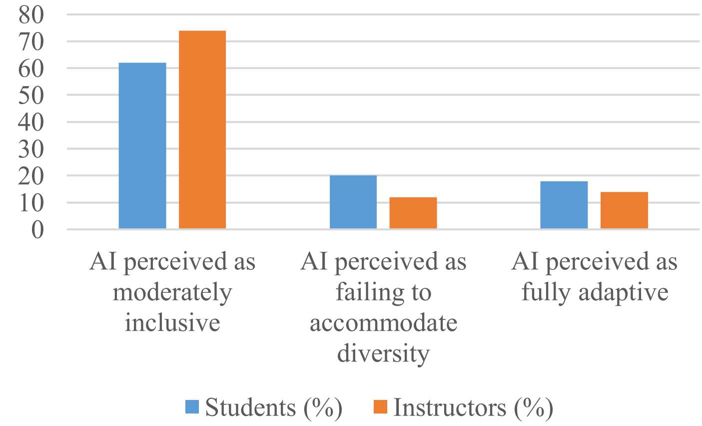

Figure 2. Survey results on AI cultural adaptability

Figure 2 illustrates students' and instructors' perceptions of cultural inclusivity in AI-based learning environments. The figure shows that although most participants considered AI moderately inclusive, a considerable proportion of students perceived AI systems as insufficiently responsive to cultural diversity. This indicates that students, as direct users of AI-enhanced learning platforms, experience more challenges related to cultural adaptation and representation.

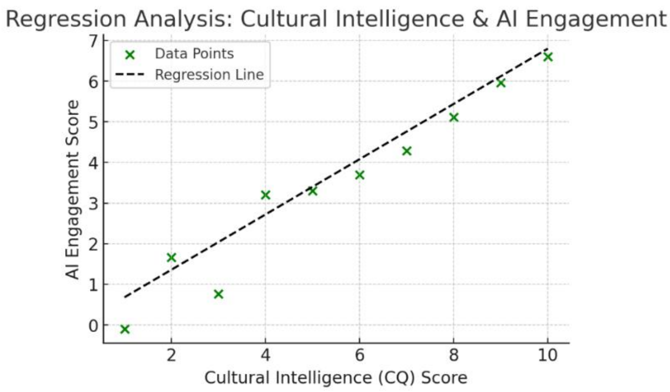

Figure 3. Regression analysis: cultural intelligence & AI engagement

The scatter plot in Figure 3 further demonstrates the positive relationship between cultural intelligence and AI engagement. Participants with higher CQ scores generally showed stronger engagement with AI-supported learning systems. Nevertheless, several participants with high CQ still reported challenges associated with cultural bias and contextual misunderstanding in AI-generated feedback.

AI Engagement Metrics Analysis

The analysis of AI engagement metrics examined participants' perceptions of fairness, inclusivity, and bias within AI-driven online learning systems. As shown in Table 4, 58% of students and 65% of instructors perceived AI systems as relatively fair. However, 23% of students and 18% of instructors believed that AI-generated feedback and content recommendations reflected cultural bias. Only a limited proportion of respondents perceived AI systems as highly inclusive.

Table 4
AI engagement metrics analysis

Engagement Aspect	Students (%)	Instructors (%)
AI perceived as somewhat fair	58	65
AI perceived as biased	23	18
AI perceived as highly inclusive	19	17

The comparative analysis presented in Table 5 reveals significant differences in AI engagement between Western and non-Western participants. Western students reported substantially higher engagement levels (75%) compared to non-Western students (40%). In contrast, low engagement levels were more commonly reported among non-Western participants.

Table 5
AI Engagement by Cultural Background

Cultural Background	High AI Engagement (%)	Low AI Engagement (%)
Western	75	25
Non-Western	40	60

These findings indicate that AI-driven educational systems are currently more aligned with Western-oriented educational frameworks and learning preferences. Participants from non-Western educational contexts frequently experienced difficulties related to language interpretation, culturally inappropriate recommendations, and limited contextual relevance in AI-generated content.

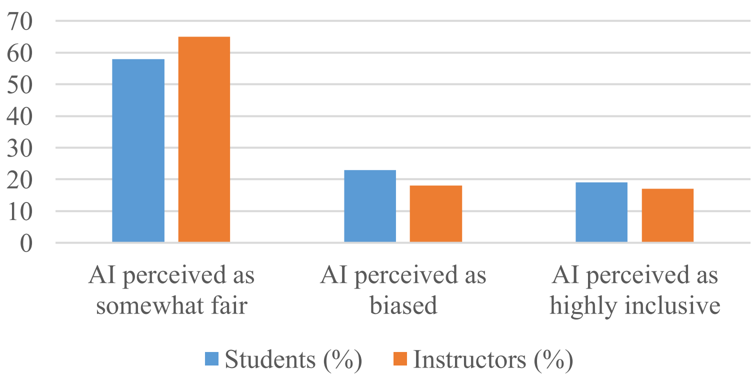

Figure 4. AI engagement metrics analysis

Figure 4 presents students' and instructors' perceptions of fairness, inclusivity, and bias in AI-supported learning systems. Instructors generally viewed AI systems more positively than students, although both groups acknowledged the existence of cultural limitations in AI-generated feedback and recommendations.

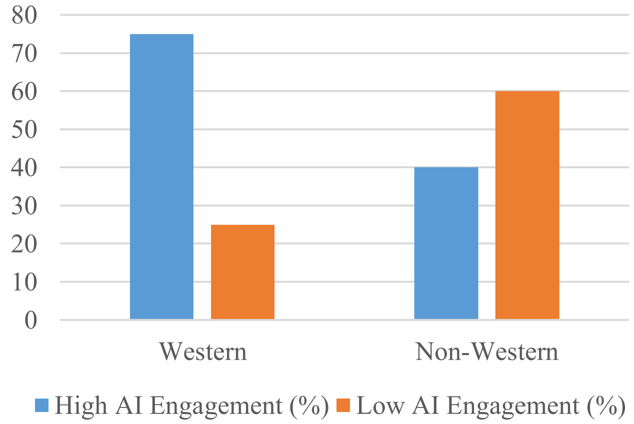

Figure 5. AI engagement differences across cultural backgrounds

Similarly, Figure 5 highlights the differences in AI engagement between Western and non-Western participants. The figure demonstrates that Western students showed significantly higher levels of engagement, while non-Western students experienced more barriers when interacting with AI-enhanced learning systems. The findings also indicate that cultural background alone does not fully explain variations in AI engagement. Other factors such as language proficiency, familiarity with digital technologies, and prior experience with AI-based learning systems may also influence participants' perceptions and engagement levels.

Cultural Bias in AI Feedback and Content Recommendations

The qualitative findings obtained from interviews and focus group discussions identified several issues related to cultural bias in AI-mediated online learning environments. Many participants acknowledged that AI systems were beneficial in supporting personalization and accessibility; however, participants also emphasized that AI-generated feedback and content recommendations frequently reflected Western-oriented educational norms and communication styles.

As shown in Table 6, 60% of participants perceived cultural bias in AI-generated content recommendations, while 55% reported that AI systems lacked contextual understanding in culturally sensitive communication. In addition, 52% of participants stated that AI systems failed to recognize culturally nuanced discourse patterns.

Table 6
Qualitative findings from interviews and focus groups

Theme	Percentage of Participants (%)
AI fosters inclusivity through personalization	45
AI exhibits cultural biases in content recommendations	60
Educators believe AI aids language translation	50
AI lacks contextual awareness in cultural communication	55
Students struggle with representation in AI materials	48
AI fails to recognize culturally nuanced discourse	52

Several participants from non-Western educational backgrounds explained that AI-generated feedback frequently misinterpreted indirect rhetorical approaches and narrative-based writing styles as unclear or ineffective. Participants also reported that AI-recommended learning materials predominantly reflected Western references and examples, resulting in limited cultural representation in online learning environments. Despite these concerns, some instructors acknowledged that AI-supported translation tools improved communication and accessibility for non-native English speakers. However, participants emphasized that AI-generated translations often failed to capture contextual and cultural nuances accurately.

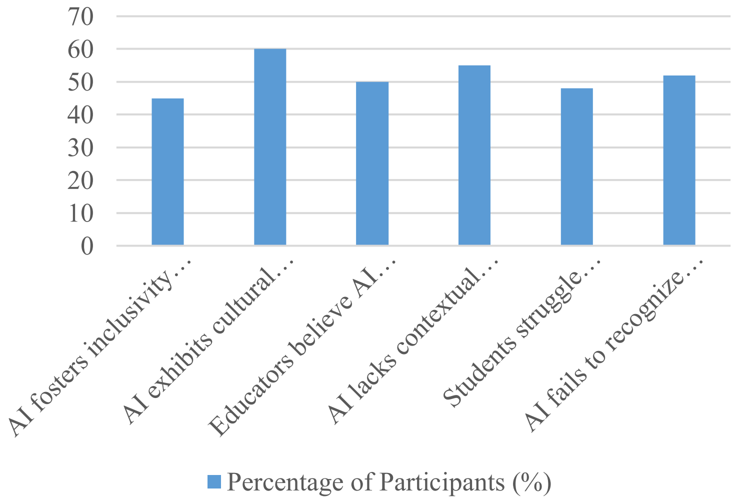

Figure 6. Qualitative findings from interviews and focus groups

Figure 6 presents participants' perceptions regarding major cultural inclusivity issues in AI-driven learning environments. The figure demonstrates that cultural bias in content recommendations and lack of contextual understanding were among the most frequently identified challenges.

Case Studies and Participant Experiences

Interviews and focus group discussions also revealed several notable participant experiences regarding AI-integrated learning systems. Some participants described positive experiences associated with AI-supported language assistance and accessibility, while others reported difficulties related to cultural representation and interpretation. One participant from Southeast Asia explained that AI-generated academic feedback favored direct and linear writing styles commonly associated with Western academic traditions. Narrative-based and indirect rhetorical approaches were often labeled as ineffective or unclear by the AI system. Another participant from the Middle East reported that AI systems rarely recommended culturally relevant references and predominantly suggested Western-oriented academic materials.

In contrast, an instructor from Latin America stated that AI-powered translation tools improved the participation of non-native English-speaking students in online discussions and collaborative learning activities. The findings from these experiences are summarized in Table 7.

Table 7
Case Studies on AI-Integrated Learning Experiences

Case Study	Challenge (%)	Success (%)
Cultural Misinterpretation in AI Feedback	70	30
AI-Enhanced Language Support	30	70
Bias in AI Content Recommendations	65	35

The findings demonstrate that AI technologies provide opportunities for improving accessibility and participation in online learning; however, cultural adaptation and contextual sensitivity remain important challenges in AI-enhanced educational environments.

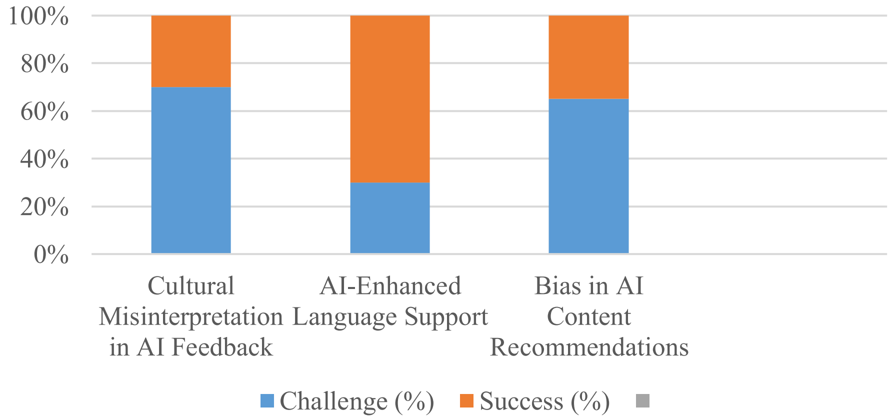

Figure 7. Challenges vs. successes in AI-integrated learning

Figure 7 illustrates the comparison between challenges and successful experiences reported in AI-integrated learning environments. The figure shows that cultural misinterpretation in AI-generated feedback and bias in content recommendations were identified as the most significant challenges. In contrast, AI-supported language assistance was perceived more positively, particularly in supporting communication and participation among non-native English-speaking students.

Table 8
Interview and focus group findings

Theme	Percentage of Participants Identifying Issue (%)	Positive Perception (%)	Negative Perception (%)
AI fosters inclusivity through personalization	45	45	55
AI exhibits cultural biases in content recommendations	60	20	80
Educators believe AI aids language translation	50	50	50
AI lacks contextual awareness in cultural communication	55	30	70
Students struggle with representation in AI materials	48	25	75
AI fails to recognize culturally nuanced discourse	52	22	78
AI-generated feedback misinterprets academic writing styles	57	20	80
AI content recommendations favor Western perspectives	62	18	82
Language translation AI lacks cultural sensitivity	50	30	70
AI-driven assessments do not consider diverse learning styles	58	28	72

Table 8 summarizes participants' perceptions of AI-supported learning environments. Although several participants acknowledged the benefits of AI personalization and language assistance, concerns regarding cultural bias remained prominent across most themes. The most frequently identified issues included bias in content recommendations, limited contextual understanding, and the misinterpretation of culturally diverse academic writing styles. These findings suggest that current AI-driven educational systems still have limited capacity to accommodate culturally diverse learners and communication patterns.

AI System Evaluation

The evaluation of AI systems focused on the analysis of AI-generated feedback, content recommendations, language diversity, and adaptability to different learning styles. The results indicate that many participants perceived AI-generated educational content as predominantly Western-oriented.

As shown in Table 9, 72% of participants reported that AI-recommended content primarily reflected Western perspectives, while 68% identified limited regional representation in AI-generated materials. In addition, 65% of participants stated that AI feedback favored Western academic conventions, and 60% believed that AI systems misinterpreted non-Western rhetorical styles.

Table 9
AI system evaluation findings

Evaluation Aspect	Percentage of Participants Reporting Issue (%)
AI feedback favors Western academic conventions	65
AI misinterprets non-Western rhetorical styles	60
AI-recommended content predominantly Western	72
Limited regional representation in AI materials	68
Translation tools lose cultural nuances	58
AI lacks linguistic diversity in recommendations	55

Participants also reported limitations in AI-supported translation systems. Approximately 58% of respondents believed that AI-generated translations frequently lost cultural nuances and contextual meaning in multilingual learning environments.

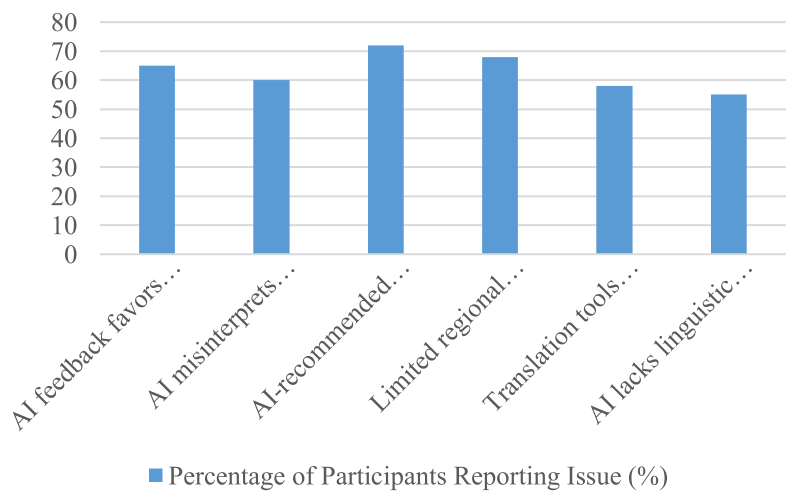

Figure 8. AI system evaluation: cultural and linguistic inclusivity

Figure 8 illustrates participants' perceptions regarding cultural and linguistic limitations in AI-integrated educational systems. The figure shows that Western-oriented content recommendations and limited regional representation were the most frequently identified concerns among participants.

Comparative Analysis of AI Responsiveness Across Cultural Groups

The comparative analysis revealed differences in how AI systems adapted to diverse learning styles and educational traditions. As shown in Table 10, 68% of Western students believed that AI systems effectively supported their learning preferences, while only 42% of non-Western students expressed similar perceptions.

Table 10
Comparative Analysis of AI Responsiveness Across Cultural Groups

Cultural Group	AI Effectively Adapts to Learning Styles (%)	AI Struggles with Learning Preferences (%)
Western Students	68	32
Non-Western Students	42	58
Non-Native English Speakers	44	56

Non-Western participants commonly described difficulties related to collaborative learning traditions, contextual communication styles, and culturally specific discourse patterns that were not adequately recognized by AI systems. Non-native English speakers also reported challenges in interpreting AI-generated feedback and recommendations in multilingual learning contexts.

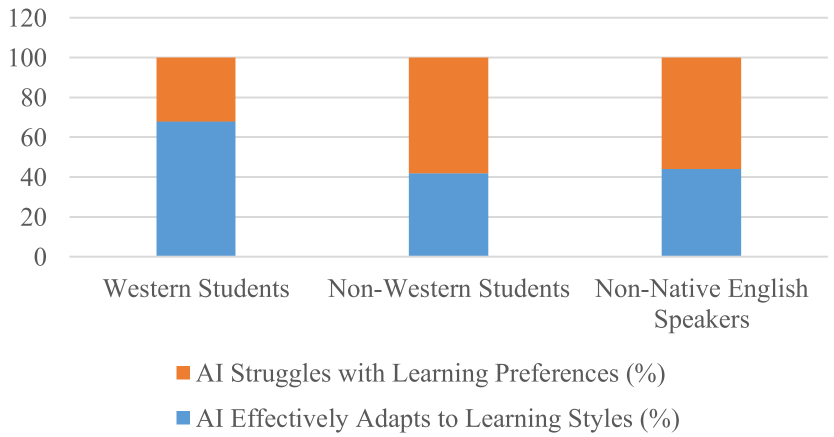

Figure 9. AI responsiveness across cultural groups

Figure 9 demonstrates the differences in AI responsiveness across cultural groups. Western students generally reported higher engagement and satisfaction levels, whereas non-Western students and non-native English speakers experienced greater challenges in adapting to AI-mediated learning systems. The findings indicate that current AI-driven learning platforms still require stronger cultural intelligence and greater adaptability to support equitable and inclusive online learning experiences for culturally diverse learners.

Discussion

The findings of this study demonstrate that cultural intelligence (CQ) plays an important role in shaping learner engagement in AI-enhanced online learning environments. Participants with higher levels of cultural intelligence showed greater adaptability to AI-mediated learning systems, particularly in interpreting AI-generated feedback and interacting within culturally diverse virtual classrooms. These findings are consistent with previous studies emphasizing that culturally responsive learning environments contribute to stronger student engagement and academic participation (Banwo et al., 2022; Eguchi et al., 2021; Kristianto & Gandajaya, 2023). The study extends previous discussions on cultural intelligence by demonstrating that CQ remains relevant not only in face-to-face learning environments but also in AI-supported educational contexts.

The study also reveals that current AI-driven educational systems still demonstrate limited cultural responsiveness. Although AI technologies improve accessibility through personalized learning pathways, automated feedback, and language support, many participants perceived AI-generated content and recommendations as predominantly aligned with Western educational norms and communication styles (Hadinezhad et al., 2024; Mouta et al., 2025; Ojha & Gupta, 2025). The quantitative findings showed that only 42% of non-Western students considered AI systems responsive to their learning preferences, compared to 68% of Western students. These findings suggest that AI systems remain more compatible with individualistic, linear, and analytical learning traditions commonly associated with Western educational environments.

The qualitative findings further support these results. Participants reported that AI-generated feedback often failed to recognize culturally specific rhetorical styles, indirect communication patterns, and collaborative learning approaches. Several non-native English speakers also indicated that AI-supported translation tools frequently overlooked contextual and cultural nuances in multilingual communication (Carlsson et al., 2024). Students and instructors similarly expressed dissatisfaction with AI-generated evaluations that misinterpreted culturally embedded writing styles and learning practices. These findings indicate that the limitations of AI systems are not necessarily caused by the technology itself, but rather by the datasets, pedagogical assumptions, and training conditions used during system development. In this context, AI bias should be understood as contextual and adaptable rather than fixed or unavoidable.

This study also highlights the risk of cultural bias and misrepresentation in AI-mediated learning environments. Many AI systems are trained using predominantly Western-oriented datasets, resulting in educational recommendations, assessments, and feedback mechanisms that may not adequately represent diverse cultural traditions and learning practices (Kassem et al., 2025; Mohebi, 2024; Williams, 2024). Consequently, students from non-Western educational backgrounds may experience lower engagement levels and reduced trust in AI-generated recommendations. Similar concerns have been reported in previous studies, which argue that AI-driven educational technologies may unintentionally reproduce existing educational inequalities if cultural diversity is not adequately considered in system design (Bucea-Manea-Țoniş et al., 2021; Bulathwela et al., 2024; Schiff, 2022; Tate & Warschauer, 2022). For example, AI systems frequently misinterpret indirect communication patterns and narrative-based reasoning commonly found in Asian, African, and Middle Eastern educational traditions, leading to feedback that may appear culturally insensitive or academically discouraging (Brokensha et al., 2023).

Another important issue identified in this study concerns algorithmic personalization and decision-making processes. AI systems primarily rely on predictive analytics and pattern recognition, which may not fully capture culturally diverse learning behaviors and communication patterns (Bhutoria, 2022; Halkiopoulos & Gkintoni, 2024). Participants from collaborative and high-context learning cultures reported that AI-generated assessments and recommendations often appeared rigid and insufficiently interactive. Similarly, non-native English speakers frequently perceived AI explanations as overly simplified and lacking contextual relevance. Students who preferred collaborative, oral-based, or context-oriented learning approaches also reported lower levels of engagement with AI-driven educational platforms (Ellikkal & Rajamohan, 2025; Vashishth et al., 2024). These findings suggest that AI-driven educational systems still require greater cultural adaptability to support diverse learners effectively.

From the perspective of educators and developers, one of the primary challenges lies in designing AI systems that integrate cultural intelligence into online learning processes. Educators frequently reported that AI-generated materials lacked contextual flexibility and were insufficiently adapted to specific classroom realities. At the same time, developers acknowledged that most current AI systems are designed primarily for efficiency and automation rather than cultural sensitivity (Eguchi et al., 2021; Salas-Pilco et al., 2022). Without the intentional integration of multilingual capabilities, culturally representative datasets, and context-sensitive pedagogical frameworks, AI systems may unintentionally reinforce educational inequalities rather than promote inclusivity in global online learning environments.

The findings highlight the importance of developing culturally adaptive AI systems for education. AI developers should incorporate more diverse datasets representing multilingual communication patterns, culturally specific rhetorical traditions, and different pedagogical approaches. AI-generated educational content should also include broader regional and cultural representation to improve inclusivity and contextual relevance. In addition, adaptive AI systems should be designed to recognize different learning preferences and communication styles rather than relying primarily on Western-oriented educational assumptions.

Despite the increasing capabilities of AI technologies, human educators remain essential in supporting culturally responsive learning environments. Educators play an important role in interpreting, contextualizing, and modifying AI-generated recommendations according to students' cultural and educational backgrounds. They also function as cultural mediators who help students navigate AI-supported learning processes in ways that remain pedagogically appropriate and culturally sensitive. Therefore, AI should function as a supportive educational tool rather than a replacement for human instruction.

The findings of this study also have implications for educational policy and ethical AI governance. Educational institutions and policymakers should establish guidelines for culturally inclusive AI implementation, including transparent algorithmic processes, regular audits of AI-generated educational content, and equitable representation across cultural groups. AI literacy programs for educators and students are also necessary to support the responsible and critical use of AI technologies in online learning environments.

This study demonstrates that AI technologies offer significant opportunities to improve accessibility and learning efficiency in online education. However, the effectiveness of AI-mediated learning environments depends largely on the extent to which cultural intelligence and cultural inclusivity are integrated into the design, implementation, and evaluation of AI systems.

CONCLUSION

This study demonstrates that cultural intelligence is a critical determinant of whether AI-enhanced online learning supports inclusion or instead reinforces existing cultural inequities. By combining survey data, qualitative insights, and AI system evaluation, the findings show that current AI-driven learning environments remain more compatible with Western academic norms, while non-Western and multilingual learners experience weaker alignment and lower engagement. These results indicate that AI personalization, when built on culturally narrow datasets and evaluative assumptions, risks standardizing learning practices rather than accommodating diversity.

This study advances research on AI in education by conceptualizing cultural intelligence as a functional design requirement for AI-integrated learning systems, not merely a contextual consideration. The findings provide a scientific basis for rethinking AI-supported pedagogy beyond efficiency and automation, emphasizing how feedback mechanisms, content recommendations, and discourse evaluation shape equitable learning opportunities across cultures.

Practically, the results highlight the need for culturally responsive AI implementation. AI developers should prioritize dataset diversification, culturally sensitive feedback rules, and regular audits of recommendation outputs to ensure balanced cultural representation. Educational institutions should adopt a human–AI collaboration model in which instructors act as cultural mediators, contextualizing and, when necessary, correcting AI-generated feedback to align with students' discourse traditions. At the policy level, guidelines for AI-assisted learning should incorporate explicit indicators of cultural and linguistic inclusivity.

Based on these conclusions, future research should experimentally test culturally adaptive AI features across diverse learning contexts, develop region-specific and multilingual training corpora, and examine ethical risks related to bias, transparency, and access. Addressing these directions will support the development of AI-enhanced online learning that is not only technologically advanced but also culturally responsive and educationally equitable.

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INFORMED CONSENT STATEMENT

Participation in this study was voluntary. Prior to participation, all participants were provided with clear information regarding the study's objectives, procedures, potential risks, and anticipated benefits. Participants were assured of the confidentiality of their personal information and informed that all data collected would be used solely for research purposes. They were also informed of their right to withdraw from the study at any time without penalty. Informed consent was obtained from all participants prior to data collection.

DATA AVAILABILITY STATEMENT

The data generated and analyzed in this study are not publicly available because they contain information that could compromise participant privacy and confidentiality. Restricting public access ensures compliance with ethical research principles and applicable data protection regulations. Nevertheless, the dataset may be made available to qualified researchers upon reasonable request for verification or further analysis. Any such request will be reviewed on a case-by-case basis and will require prior approval from the appropriate institutional ethics authority.

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