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Safeguarding Integrity in AI-Enhanced Education: Stakeholder Perspectives on Accuracy, Validity, and Ethics in ASEAN

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ABSTRACT

Artificial Intelligence (AI) is rapidly reshaping educational systems worldwide, raising critical debates about the reliability of AI-generated content, the validity of AI-driven assessments, and the ethical implications of its integration into diverse learning environments. This study examines the integrity of AI-enhanced education within the ASEAN region by focusing on three core dimensions: content accuracy, assessment validity, and ethical challenges. Data were collected from 661 respondents, including educators, policymakers, and technology providers, during the ASEAN Stakeholder Summit 2024 through a cross-sectional survey design. To interrogate the data, Chi-Square Tests of Independence were used to explore associations between categorical variables such as gender and ethical concerns, while ANOVA assessed differences in perceptions of AI-driven assessments across ASEAN member states. Correlation analysis further investigated relationships between respondent demographics and perceptions of AI accuracy, offering a nuanced view of stakeholder trust in AI-enabled practices. Findings indicate that while AI holds transformative potential for education, its deployment must be accompanied by region-specific guidelines, rigorous ethical safeguards, and multi-stakeholder collaboration. Such measures are essential to ensure that AI-driven education is both culturally relevant and socio-economically equitable, supporting responsible and sustainable implementation across the ASEAN context.

Keywords: Generative AI in Education, Assessment Validity, Ethical Challenges, ASEAN, Content Accuracy.

INTRODUCTION

Artificial intelligence (AI) is reshaping educational systems around the world by automating tasks in content creation and student assessment. In the Association of Southeast Asian Nations (ASEAN) region, the convergence of linguistic diversity, varied cultural norms, and uneven technological infrastructure intensifies both the potential benefits and the risks of AI's adoption. Educators, policymakers, and other stakeholders are hopeful that AI can streamline lesson planning, deliver personalized resources, and improve assessment accuracy. Yet concerns remain about misleading information in AI-generated materials, fairness in automated grading, and emerging ethical dilemmas tied to data privacy, algorithmic bias, and consent.

This paper examines these issues by gathering perspectives from 661 respondents, including educators, policymakers, and technology providers, across multiple ASEAN nations. We explore whether AI can enhance the integrity of education or inadvertently undermine it. Our investigation is guided by three research questions:

1. How do educators and policymakers perceive the accuracy of AI-generated content in their respective ASEAN contexts?
2. How do stakeholders evaluate the fairness and validity of AI-driven assessments, and do these perceptions vary by country or demographic factors?
3. Which ethical concerns, particularly regarding data privacy, bias, and consent, most influence attitudes toward AI integration, and do these concerns differ by gender or professional role?

LITERATURE REVIEW

The literature review examines three crucial areas. First, it explores how AI can generate and curate content, highlighting the potential for increased efficiency while acknowledging risks tied to misinformation or lack of context. Second, it looks at the validity of AI-based assessments, emphasizing both the speed and objectivity AI can provide and the challenges of bias or misalignment with diverse learning goals. Third, it addresses ethical considerations, focusing on privacy, data security, and fairness in AI-driven education. These sections underscore the need for careful implementation so AI's benefits can be realized without compromising integrity or inclusivity. A visual concept map can be found in **Figure 1**.

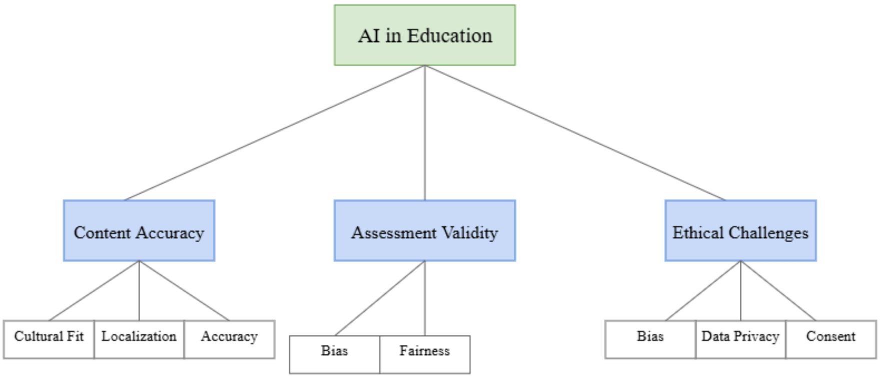

Figure 1. Concept Map

Theoretical Framework

This study is grounded in Stakeholder Theory and Cultural Contextualization Theory to understand AI integration in diverse educational contexts. Stakeholder Theory provides the foundation for examining how different groups (educators, policymakers, technology providers) have varying perspectives on AI implementation based on their roles, responsibilities, and potential impacts (Freeman, 1984). Cultural Contextualization Theory offers insight into how regional, linguistic, and cultural factors influence technology adoption and acceptance across ASEAN's diverse educational landscapes (Hofstede and Bond, 1988; Triandis, 1995). This dual theoretical approach recognizes that AI adoption in education is not merely a technical decision but involves complex negotiations between multiple stakeholders operating within distinct cultural and institutional contexts. The framework acknowledges that perceptions of AI accuracy, validity, and ethics are shaped by both professional roles (stakeholder positions) and cultural backgrounds (contextual factors). Stakeholder Theory explains why educators, policymakers, and technology providers may have different concerns about AI implementation - educators focus on pedagogical effectiveness and student outcomes, policymakers consider broader societal implications and regulatory needs, while technology providers emphasize technical capabilities and scalability. Cultural Contextualization Theory helps explain the significant regional variations observed across ASEAN countries, where different cultural values, educational traditions, and technological infrastructures influence AI acceptance and implementation approaches (Ong et al., 2024). This theoretical foundation guided our survey instrument development and analytical approach, focusing on the intersection of stakeholder perspectives and cultural contexts across the region's diverse educational landscapes.

Content Accuracy

In AI-Enhanced Education, content generation typically involves using AI tools to create or curate teaching materials, lesson plans, quizzes, and other resources (Kovilpillai et al., 2025; Rajaratnam et al., 2024). While AI can handle large datasets and produce content rapidly, it may overlook subtle cultural nuances and context-specific details, which can undermine the relevance and accuracy of what learners receive (Amanbekqyzy et al., 2024). In a region like ASEAN, where languages, cultural practices, and educational needs vary widely (Triana, 2025), a single AI model might miss important regional or cultural factors, resulting in generic or even misleading material (Trust et al., 2023). This underscores the need for thorough human oversight and localized training data to ensure AI-generated materials truly enhance education and remain culturally appropriate.

Raza and Singh (2024b) underscore that gender inclusivity in Malaysian STEM education hinges on incorporating diverse viewpoints into information systems so that generated materials remain accurate and relevant. Building on this principle, it becomes evident that AI tools must do more than simply produce or filter content, they should also adapt to the socio-cultural and educational contexts where learners engage with that content. (Chaparro-Banegas et al., 2024) illustrate how culturally responsive AI systems can help meet the differing needs of various learner groups, emphasizing the importance of adaptability in technology design (Chandramma et al., 2025; Stephanidis, 2023; Badmus et al., 2024). Drawing from these insights, this study posits that failing to consider cultural, gender, and contextual factors in AI-generated materials can perpetuate or even exacerbate existing biases, particularly in underrepresented STEM fields (Alsharif, 2025). Therefore, we argue that the design and implementation of AI in education calls for deliberate strategies, ones that blend technical innovation with social awareness, to ensure equitable access and relevance for all learners.

Assessment Validity

Validity gauges whether an assessment truly measures the knowledge or skills it aims to evaluate (Lee et al., 2024; Lim, 2024; Salleh et al., 2023). For instance, if an AI-driven system is assessing conceptual understanding, but its algorithm primarily checks rote memorization, the test isn't capturing what it should. Fairness, on the other hand, means that no group, such as those differing by gender, culture, or socio-economic status, is systemically disadvantaged by how the AI assigns scores (Chinta et al., 2024; Leslie et al., 2023). If the AI's training data lacks diversity, it can carry over biases that penalize students whose backgrounds or cultural contexts fall outside the "norm" reflected in that data (Daneshjou et al., 2021; Liang et al., 2022; Nivedhaa, 2024).

These issues become more pressing for underrepresented groups, particularly women in STEM-related roles and organizations, as algorithmic biases often compound existing systemic barriers (Raza and Singh, 2024a). When AI overlooks contextual factors or subtle differences in how learners approach tasks, valid assessment and fair treatment suffer. Bulut et al. (2024) argue that addressing these pitfalls begins with designing transparent AI frameworks, regularly testing them for bias, and ensuring that a wide range of voices shape their development (Frosio, 2025; Khazanchi and Khazanchi, 2024; Nixon et al., 2024; Sandhu et al., 2024). By doing so, educators and policymakers can make sure AI-driven assessments live up to their promise of scalability and efficiency without compromising the ethical and educational values at stake.

Ethical Challenges

Ethical challenges in AI-enhanced education extend beyond technical details and involve complex social, cultural, and legal dimensions. As Huang (2023) points out, AI systems require large volumes of student data, ranging from demographic information to learning analytics, raising serious questions about consent and the secure handling of personal information (Pechenkina, 2023; Shwedeh et al., 2024; Woolf, 2022). This is especially pressing in parts of ASEAN where data protection laws are either nascent or inconsistently enforced (Singh and Mahadevan, 2022). Without a strong regulatory backbone, AI-driven educational tools can overreach, gathering or using data in ways that learners and their families never intended. According to literature (Amoozadeh et al., 2024; Baek and Kim, 2023; Dunn et al., 2023; Kim et al., 2023), these vulnerabilities can undermine public trust and deter communities from fully embracing AI, undermining its educational potential.

Algorithmic bias compounds these data privacy concerns. Systems trained on homogenous or unrepresentative datasets risk embedding existing prejudices and stereotypes into educational processes (Chimbga, 2023; Golda et al., 2024; Uddagiri & Isunuri, 2024). For learners from marginalized backgrounds, especially women, rural populations, and low-income learners, this bias could manifest as anything from lower predictive scores to fewer personalized learning opportunities. Rather than benefiting from the efficiency and personalization AI promises, these groups may find themselves further sidelined. The DI-Girls Initiative (Hamdan et al., 2024) demonstrates that targeted interventions can empower students by boosting digital skills and confidence. Still, such initiatives address only one part of a broader ethical landscape. Technology developers, policymakers, and educators must all collaborate to eliminate harmful biases at the system level (Ferrara, 2024; Wei et al., 2025; Zhou et al., 2024).

From this study's perspective, an ethical approach to AI integration must account for the entire "data lifecycle", from collection and storage to algorithmic design to the interpretation of outputs. This approach is commonly denoted and is established in the literature (Adaga et al., 2024; Franzke et al., 2021; Liaw et al., 2021; Sriram et al., 2025; Zhang et al., 2022). This includes implementing robust consent protocols, ensuring the transparency of AI decision-making, and establishing recourse mechanisms for students who suspect inaccuracies or discrimination.

Also vital is the explicit recognition of cultural and gender nuances in system design (Duan et al., 2025; Globig et al., 2024). In ASEAN's multicultural environment, overlooking local norms or linguistic complexities can exacerbate inequities rather than alleviate them (Ghosh et al. 2024; Wang, 2023). In essence, the ethical challenges surrounding AI-enhanced education underscore a deeper need for inclusive development strategies that balance technological innovation with human rights, equity, and the diverse realities of learners.

METHODOLOGY

This study employed a cross-sectional quantitative survey to gather insights into how AI is perceived in education throughout the ASEAN region. A quantitative design was selected because it allows for systematic collection of numerical data from a broad range of respondents, enabling robust statistical comparisons across demographic groups and countries (Hossan et al., 2023; Rana et al., 2022; Vis & Stolwijk, 2021). The goal was to examine stakeholders' perspectives on content accuracy, assessment validity, and ethical issues linked to AI integration in education, all of which benefit from a measurable, comparative approach. This approach aligns with our theoretical framework, which recognizes that different stakeholder groups may have varying perspectives based on their professional roles and cultural contexts.

The flow diagram for the methodology can be found in **Figure 2**.

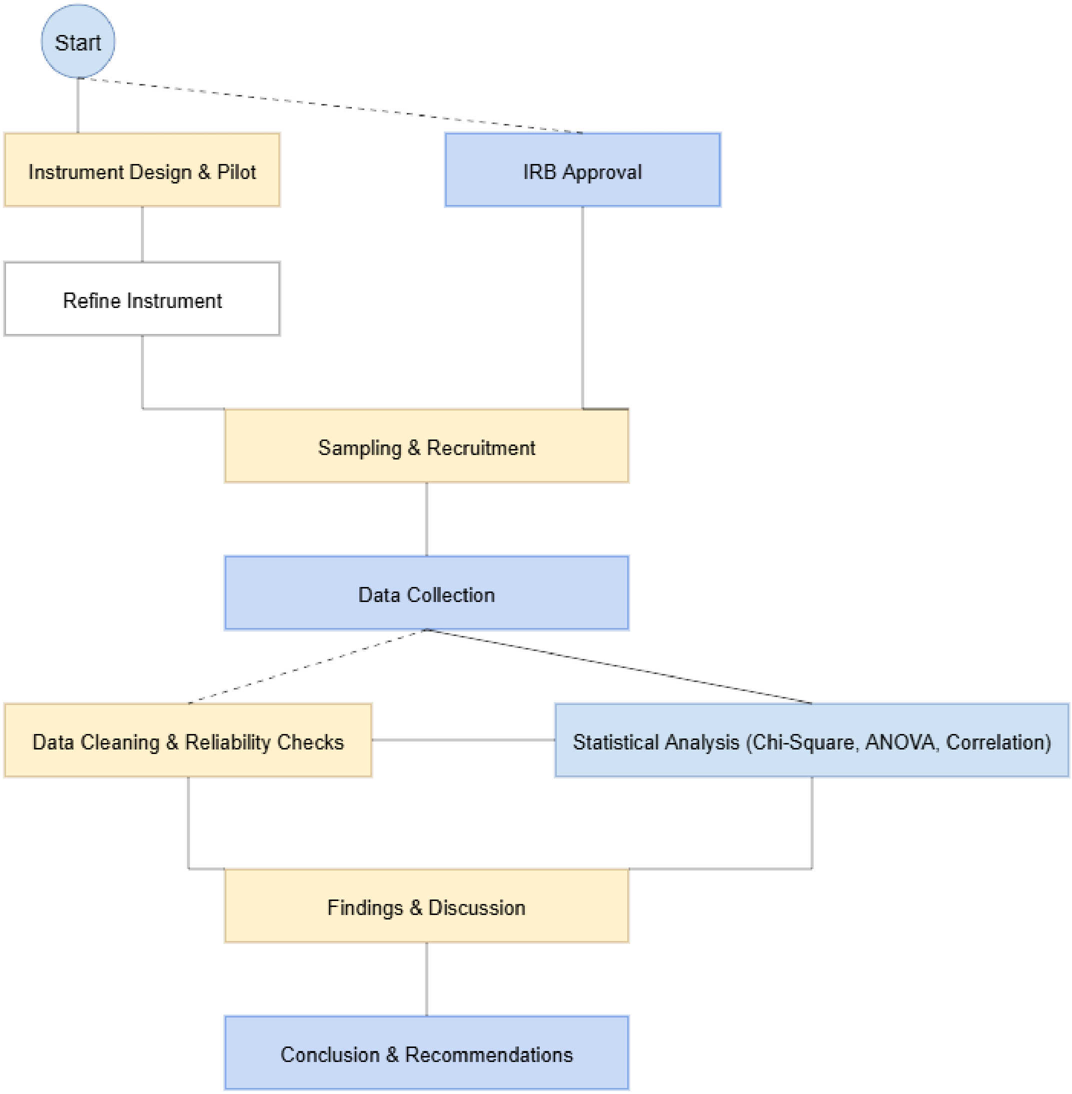

Figure 2. Flow diagram of the methodology

Research Design

A cross-sectional quantitative survey design was chosen for its ability to capture a "snapshot" of attitudes and experiences at a single point in time, which is especially useful in fast-evolving domains like AI in education (Cvetkovic-Vega et al., 2021; Ghanad, 2023; Maier et al., 2023). By employing a single-time data collection, potential biases related to repeated measures or attrition are minimized. This design also facilitates the comparison of different subgroups (e.g., gender, profession, country) without requiring complex longitudinal tracking, making it more feasible given the broad geographic scope of ASEAN and the diverse nature of the sample.

Sampling and Participants

A disproportionate stratified sampling method was used to ensure adequate representation of smaller ASEAN nations and underrepresented groups such as women in STEM. This approach was justified by the uneven population distributions across the region and the study's emphasis on examining intersectional aspects like gender and leadership roles (Iliyasu & Etikan, 2021; Makwana et al., 2023; Rahman et al., 2022). Participants (N = 661) included educators, policymakers, NGO representatives, and technology providers, reflecting a range of roles directly or indirectly involved in AI-enhanced educational initiatives. Restricting inclusion to individuals who have worked with or are impacted by AI-driven educational practices helped concentrate on informed perspectives, thereby strengthening the validity of the findings.

The rationale for the sampling strategy in this study was based on three key considerations. First, representation was a priority, as certain ASEAN countries have smaller populations that may be overlooked in standard proportional sampling. Ensuring adequate participation from these nations allowed for a more comprehensive understanding of AI's impact on education across the region. Second, the study aimed to capture diverse expertise by including respondents from various roles within the education sector, such as teachers, policymakers, and technology providers. This approach enabled a more nuanced analysis of AI's influence, incorporating perspectives from those directly involved in teaching and those shaping educational policies. Finally, the study deliberately oversampled underrepresented voices, particularly women in STEM and participants from lesser-known institutions. This decision was made to highlight potential biases and challenges these groups face, ensuring that the findings reflect a more inclusive and equitable perspective on AI's role in education.

Data Collection

Data were gathered through an online survey administered during the ASEAN Stakeholder Summit 2024 and further disseminated via professional networks, mailing lists, and social media channels specific to education and AI, with significant support from the Southeast Asian Ministers of Education Organization (SEAMEO). Online distribution ensured greater reach across geographically dispersed regions, recognizing the logistical challenges of physical data collection in diverse ASEAN contexts.

Survey Instrument

The survey instrument incorporated Likert-scale items to measure agreement levels on AI's efficacy in generating accurate educational content, the perceived validity of AI-based assessments, and concerns about ethical risks such as data privacy and bias. These scales were chosen for their ease of administration and their capacity to capture nuanced respondent attitudes (Kusmaryono et al., 2022; Tanujaya et al., 2022).

The survey instrument included three main constructs measured on 5-point Likert scales, with items adapted for different stakeholder groups:

Content Accuracy items included: "AI-generated educational content is factually accurate for my subject area", "AI tools can create culturally appropriate materials for students", "I trust AI-generated content without extensive human oversight", "AI content generation saves time while maintaining educational quality", "AI-generated materials meet pedagogical standards"

Assessment Validity items included: "AI-driven assessments fairly evaluate student understanding", "Automated grading systems are as reliable as human evaluation", "AI assessments accommodate diverse learning approaches", "AI-based feedback effectively helps students improve their learning"

Ethical Concerns items included: "I am concerned about student data privacy in AI systems", "AI tools may exhibit bias against certain student groups", "Students should provide explicit consent for AI use in their education", "AI algorithms should be transparent and explainable to educators", "Educational AI systems adequately protect student information", "I am concerned about AI replacing human judgment in educational decisions"

Additional stakeholder-specific items were included to capture role-based perspectives on AI integration challenges, benefits, and implementation concerns.

Demographic questions on age, gender, country of residence, and professional background facilitated subgroup comparisons and aligned with the study's focus on regional and demographic distinctions. A pilot group of 15 education, research, policy, governmental, and technology professionals evaluated the survey for clarity, length, and cultural appropriateness, prompting modifications to reduce ambiguity and ensure contextual relevance. Conducting a pilot study was deemed crucial for refining the instrument's clarity and reliability prior to large-scale distribution, particularly in a multinational setting where linguistic nuances can influence understanding (Aschbrenner et al., 2022; Teresi et al., 2022).

Data Analysis

Once data collection was complete, responses were systematically cleaned (removing incomplete entries, checking for duplicates) and coded for statistical analysis. Analyses were conducted using specialized software (SPSS) for accuracy and reproducibility.

Descriptive Statistics

Descriptive statistics played a crucial role in providing an initial understanding of the dataset by summarizing key characteristics of the respondents and their perceptions of AI in education. Measures such as means, standard deviations, and frequencies were used to present a general overview of the participants' backgrounds, including demographic factors such as age, gender, country of residence, and professional roles. Additionally, these statistics captured respondents' overall attitudes toward AI, with particular focus on variables like the perceived reliability of AI-generated content and the validity of AI-driven assessments. By analysing these summary measures, the study was able to offer a preliminary snapshot of trends and variations before moving into more complex statistical tests.

The justification for employing descriptive statistics lies in their ability to establish a baseline understanding of the data, which is essential for meaningful inferential analysis. Without this foundational step, it would be difficult to interpret the significance of relationships and differences identified through further statistical tests. By first assessing the distribution and central tendencies of key variables, researchers can ensure that subsequent analyses, such as Chi-Square tests, ANOVA, and correlation analyses, are built on a well-defined data structure. This approach enhances the reliability of findings and provides a clear starting point for deeper exploration into how AI is shaping educational practices across the ASEAN region.

Inferential Statistics

Inferential statistics were employed to examine relationships, differences, and patterns within the dataset, allowing for a deeper exploration of how various factors influence perceptions of AI in education. The Chi-Square Test of Independence was used to analyse relationships between categorical variables, such as gender and ethical concerns related to AI, including data privacy and bias (Shen et al., 2022). This test helped determine whether observed distributions significantly deviated from what would be expected if no association existed, aligning with the study's objective of identifying how demographic characteristics shape stakeholders' attitudes toward AI's ethical implications.

To assess variations in perceptions across different ASEAN countries, an Analysis of Variance (ANOVA) was conducted. This test compared mean differences in key variables, such as AI's assessment validity, across multiple national contexts (Chen et al., 2022; Dugard et al., 2022). When ANOVA identified statistically significant differences, post-hoc tests like Tukey's HSD were applied to pinpoint specific groups that differed (Nanda et al., 2021). This approach was particularly relevant given the study's focus on regional variations in AI acceptance and concerns, as educational infrastructure, policies, and AI integration levels vary significantly across ASEAN nations.

A correlation analysis was also performed to explore linear relationships between continuous variables, such as age and perceptions of AI-generated content accuracy (Janse et al., 2021). Correlation coefficients were used to assess both the strength and direction of these relationships, providing insights into whether generational differences played a role in shaping attitudes toward AI in education. This analysis was crucial in determining whether factors such as career stage or experience influenced respondents' views on AI's reliability and effectiveness.

The justification for these statistical tests was based on their alignment with the study's research questions, which sought to identify group differences and associations between key variables. Reporting effect sizes, such as Cohen's d (Carey et al., 2023; Dankel & Loenneke, 2021; Lovakov & Agadullina, 2021) and partial eta-squared (Adams and Conway, 2021; Correll et al., 2022; Iacobucci et al., 2023), further strengthened the analysis by highlighting the practical significance of the findings rather than relying solely on p-values. This comprehensive inferential approach ensured that the study provided robust, data-driven insights into the complexities of AI integration in education within the ASEAN region.

Reliability and Validity of the Survey

The reliability and validity of the survey were assessed to ensure the robustness of the measurement tools used in the study. Cronbach's Alpha was employed to evaluate the internal consistency of the multi-item scales that measured key constructs, including AI accuracy, assessment validity, and ethical concerns (Forero, 2023; Novak, 2025). This statistical measure ensured that the items within each scale were coherent and consistently captured the intended concepts, thereby enhancing the reliability of the findings. Cronbach's Alpha was employed to evaluate the internal consistency of the multi-item scales that measured key constructs, including AI accuracy, assessment validity, and ethical concerns (Forero, 2023; Novak, 2025). The survey demonstrated good internal consistency, with Cronbach's alpha coefficients ranging from 0.79 to 0.88 across different scales, indicating that the survey items were closely related and consistently measured their respective underlying constructs, reinforcing the dependability of the responses collected.

To further establish content validity, an expert review was conducted, involving eight senior academics and AI specialists (Elangovan & Sundaravel, 2021; Flake et al., 2022). These experts assessed whether the survey items accurately reflected the constructs of interest, ensuring that the questions were relevant, comprehensive, and aligned with the study's objectives. This process was particularly crucial given the rapidly evolving nature of AI in education, where emerging technologies and ethical considerations frequently shift. By incorporating expert feedback, the survey was refined to minimize ambiguity and enhance its applicability across diverse educational and policy contexts within the ASEAN region. These validation measures strengthened the credibility of the study, ensuring that the data collected accurately represented stakeholders' perspectives on AI-enhanced education.

Ethical Considerations

This study was conducted in accordance with established ethical standards and guidelines (Ali et al., 2025; Hamid, 2024; Hasan et al., 2021; Nag, 2025; Purvis & Crawford, 2024; Scior et al., 2024). Before starting the survey, participants were presented with a summary of the study's aims, procedures, and data usage, with their continuation indicating informed consent. To protect confidentiality, each respondent received a unique identification code, and all data were stored on secure servers accessible only to the research team.

Ethical clearance was received through the Asia Pacific University of Technology & Innovation's (APU) institutional review board (IRB Approval: tAPUFE/03/2024), ensuring alignment with international best practices in studies involving human participants. Such ethical safeguards are particularly crucial in AI-focused educational research, where concerns around data privacy and potential biases are heightened.

Methodological Limitations

This study faces several significant limitations that affect the interpretation of its findings. First, sampling bias is inherent in voluntary online surveys, potentially over-representing technology-forward respondents while under-representing those with limited digital access or AI scepticism. The disproportionate representation from the Philippines (54% of respondents) may skew findings toward perspectives from this country's educational context, limiting generalizability across the broader ASEAN region. Second, the cross-sectional design captures attitudes at a single point in time during rapid AI development, preventing analysis of how perceptions may evolve or causal relationships between variables. This temporal limitation is particularly relevant given the fast-paced nature of AI technological advancement and policy development. Third, all respondents attended the ASEAN Stakeholder Summit 2024, where AI presentations and objectives were established prior to survey completion. This shared exposure may have created response bias toward more favourable AI perceptions or influenced participants to align their responses with summit themes, potentially affecting the authenticity of reported attitudes. Fourth, self-report measures are susceptible to social desirability bias, particularly regarding ethical concerns where respondents may provide socially acceptable rather than genuine responses. The reliance on English-language surveys may have excluded non-English speaking educators, further limiting representativeness across ASEAN's linguistically diverse region. Finally, the study's focus on stakeholder perceptions does not capture actual AI implementation outcomes, student learning effects, or real-world performance data. This gap between perceived and actual AI effectiveness limits the practical implications for educational practice and policy development. Despite these constraints, the study's rigorous approach to survey design, sampling rationale, data collection procedures, and analytical methods ensures replicability and methodological transparency. The use of established statistical tools and ethical safeguards adds credibility to the results while acknowledging these inherent limitations.

FINDINGS

Content Accuracy

The survey results reveal that respondents from various ASEAN countries perceive generative AI as a powerful tool for enhancing content accuracy in education. A Chi-Square Test of Independence was conducted to examine whether attitudes towards AI's potential for content generation varied by country of residence. The test showed a statistically significant association between respondents' countries and their views on AI-generated content accuracy ($\chi^2 = 43.27$, $p = 0.001$), indicating that geographical differences play a role in how AI's capabilities are perceived in educational settings.

However, a Correlation Analysis between respondents' ages and their agreement levels on AI-generated content accuracy revealed no significant correlation ($r = 0.007$, $p = 0.88$). This suggests that age does not significantly influence perceptions of AI's ability to produce accurate educational material.

Assessment Validity

Concerns about assessment validity were addressed using several statistical tests. First, an ANOVA was conducted to compare the perceptions of assessment validity across countries, yielding significant differences ($F = 4.19$, $p = 0.0005$). Respondents from the Philippines and Malaysia were generally more positive about AI's ability to ensure valid assessments, while those from Indonesia and Myanmar expressed greater reservations. These regional variations highlight the importance of considering local educational contexts when deploying AI technologies for assessment.

Ethical Considerations

Ethical concerns, particularly regarding data privacy, bias, and consent, were critical points of discussion. A Chi-Square Test of Independence was used to evaluate the relationship between respondents' gender and their concerns about AI ethics. The test indicated a significant relationship between gender and concerns about ethical challenges ($\chi^2 = 30.70$, $p = 0.00033$). Female respondents were more likely to express concerns about AI-related ethical challenges compared to male respondents. This finding underscores the need for gender-sensitive policies that address unique concerns regarding data privacy, bias, and consent in the use of AI in educational environments.

Demographic Insights

A descriptive analysis of the respondents' demographics showed a diverse representation across ASEAN countries (**Table 1**). The majority of respondents were from the Philippines (359), followed by Malaysia (143) and Indonesia (67). The age distribution was concentrated in the 41-50 years (188) and 31-40 years (170) age groups, reflecting a mid-career professional demographic. Gender-wise, the survey was predominantly composed of female respondents (363), followed by male respondents (286), with a few identifying as non-binary (3) or preferring not to say (7).

Table 1. Summary of Regional Variations in AI Perceptions

Country	Sample Size	Key Findings from Statistical Analysis
Philippines	359	More positive perceptions of AI driven assessments
Malaysia	143	Similar positive assessment views to the Philippines
Indonesia	67	Greater reservations about AI assessments
Myanmar	25	Greater reservations about AI assessments
Others	67	Mixed perspectives across constructs

Based on ANOVA results, $F = 4.19$, $p = 0.0005$, and Chi Square analysis, $\chi^2 = 43.27$, $p = 0.001$.

Overall, these findings point to both optimism and caution in the integration of AI into education. While educators and other stakeholders largely agree on the potential benefits of AI for content accuracy and assessment validity, ethical considerations remain a critical area that demands attention. Significant variations across countries also suggest that local educational contexts and policies will need to be tailored to address both the opportunities and challenges presented by AI.

DISCUSSION

This study explored whether integrity can be maintained in AI-enhanced education, particularly in terms of content accuracy, assessment validity, and ethical challenges. The findings revealed significant regional and gender-based variations in perceptions of AI's role in education, consistent with our theoretical framework's emphasis on stakeholder diversity and cultural contextualization. These results underscore the need for adaptive, context-sensitive AI policies and ethical frameworks. These results align with and extend prior literature on AI in education, reinforcing both its potential benefits and the challenges that must be addressed to ensure fairness, accuracy, and inclusivity.

Content Accuracy

The results indicate that perceptions of AI-generated content accuracy vary significantly across ASEAN countries ($\chi^2 = 43.27$, $p = 0.001$). This aligns with previous research by Kovilpillai et al. (2025) and Rajaratnam et al. (2024), who highlight AI's ability to generate educational materials efficiently while noting the risks associated with cultural insensitivity and lack of contextual adaptation. Amanbekqyzy et al. (2024) and Trust et al. (2023) further emphasize that AI-generated content can sometimes be generic or misleading, particularly in linguistically and culturally diverse regions like ASEAN.

These findings both confirm and extend recent research in the ASEAN context. While our results align with Kovilpillai et al. (2025) regarding AI's efficiency in content generation, our study reveals significant country-level variations not previously documented in the region. The $\chi^2 = 43.27$ finding suggests that cultural and infrastructural differences create distinct AI adoption patterns across ASEAN nations, challenging assumptions of uniform AI implementation strategies. UNESCO discussion on AI in education (Valentini & Blancas, 2025) emphasize the importance of cultural contextualization, which our findings strongly support through empirical evidence.

The lack of correlation between age and AI content accuracy perceptions ($r = 0.007$, $p = 0.88$) contrasts with Western studies suggesting generational divides in AI acceptance. This finding may reflect the rapid technological adoption patterns common across age groups in ASEAN countries, where mobile-first digital transformation has created more uniform technology comfort levels across generations than observed in developed nations.

A key issue with AI-generated content is that many current models rely on predominantly Western-centric datasets, which do not adequately capture the educational needs and cultural nuances of ASEAN learners. This can lead to content that, while technically accurate, lacks relevance or fails to address region-specific educational challenges (Stephanidis, 2023). Moreover, AI's ability to incorporate context-specific pedagogical approaches remains limited, as it struggles to recognize the implicit teaching methodologies that vary across different countries and educational systems (Alsharif, 2025).

These findings reinforce concerns about AI's capacity to tailor educational content to specific cultural and linguistic needs, supporting the argument by Chaparro-Banegas et al. (2024) that AI-driven educational tools require significant human oversight to ensure cultural responsiveness. Additionally, research by Chandramma et al. (2025) underscores the importance of embedding culturally adaptive learning frameworks into AI models, ensuring that generated materials reflect the diverse educational philosophies of ASEAN nations. The study also supports Raza and Singh (2024b), who emphasize that gender inclusivity in STEM education is best achieved when AI-generated content integrates diverse perspectives. Failure to consider these variations may perpetuate biases and contribute to a learning environment where certain groups feel excluded or misrepresented.

The necessity of developing AI models trained on localized datasets and incorporating human review mechanisms is clear, ensuring that AI-generated educational content remains relevant and accurate across diverse learning contexts. Future research should focus on fine-tuning AI algorithms to incorporate not just linguistic adjustments but also pedagogical variations that align with regional educational goals. Policymakers and educators must work closely with AI developers to create tools that are not only efficient but also culturally and contextually appropriate for the diverse student populations in ASEAN.

Assessment Validity

The study found significant differences in how AI-based assessments are perceived across ASEAN countries ($F = 4.19$, $p = 0.0005$). Respondents from the Philippines and Malaysia generally viewed AI-driven assessments more favourably, whereas those from Indonesia and Myanmar expressed greater reservations. This variation aligns with findings by Lee et al. (2024), Lim (2024), and Salleh et al. (2023), who argue that AI's ability to enhance assessment efficiency must be weighed against its limitations in evaluating conceptual understanding and critical thinking skills.

These regional differences align with recent (Organisation for Economic Co-operation and Development [OECD], 2024) findings on AI readiness in education, which highlight the importance of technological infrastructure and regulatory frameworks in shaping AI acceptance (Taylor, 2024). Countries like the Philippines and Malaysia, with more developed EdTech ecosystems and clearer AI governance frameworks, demonstrate greater confidence in AI-driven assessment capabilities. Conversely, Indonesia and Myanmar's reservations may reflect concerns about digital equity and the potential for AI to exacerbate existing educational inequalities.

Recent advances in natural language processing and GPT-4 applications in STEM education (Zhang and Osman, 2025) have shown promise for more sophisticated assessment capabilities. However, our findings suggest that stakeholder acceptance remains contingent on local contexts, regulatory clarity, and demonstrated fairness across diverse student populations. This emphasizes the need for region-specific validation studies and culturally responsive AI assessment tools.

One major challenge with AI-driven assessments is their reliance on structured response formats, which may not effectively capture complex reasoning, problem-solving skills, or creativity (Daneshjou et al., 2021). While AI is proficient at grading multiple-choice and fill-in-the-blank assessments with high consistency, its ability to evaluate open-ended responses remains limited due to difficulties in contextual interpretation and the lack of nuanced judgment that human graders provide (Liang et al., 2022). This raises concerns about the over-reliance on AI in assessments that require deeper analytical thinking, particularly in subjects that demand qualitative analysis, such as the humanities and social sciences.

Additionally, the literature indicates that AI-driven assessments may inherit biases from the datasets on which they are trained (Chinta et al., 2024; Leslie et al., 2023). These biases can disproportionately affect marginalized student groups, a concern echoed by Raza et al. (2024), who emphasize the impact of algorithmic bias on women in STEM. AI-driven assessments, if not properly monitored, can reinforce existing disparities by favouring students whose responses align with the predominant data patterns used in AI training models, potentially disadvantaging those from diverse linguistic or educational backgrounds (Nivedhaa, 2024).

The present study's findings suggest that while AI assessments offer scalability and efficiency, their fairness remains a concern, particularly in countries with less developed AI infrastructure. This supports Bulut et al. (2024) assertion that AI-based assessments should be designed with transparency, regularly audited for bias, and adapted to diverse educational needs. To mitigate these issues, AI assessment models should integrate hybrid grading systems, combining AI's efficiency with human evaluators' contextual judgment to ensure that fairness, inclusivity, and accuracy are upheld in high-stakes evaluations. Furthermore, ongoing refinements in natural language processing (NLP) and machine learning should focus on reducing biases and enhancing AI's ability to interpret diverse student responses more equitably.

Ethical Challenges

Ethical concerns surrounding AI in education emerged as a critical issue, with female respondents significantly more likely to express concerns about data privacy, bias, and consent ($\chi^2 = 30.70$, $p = 0.00033$). This finding is consistent with research by Huang (2023), Pechenkina (2023), and Shwedeh et al. (2024), who argue that data privacy is a key barrier to AI adoption, especially in regions with weak regulatory protections. The risk of AI tools collecting and utilizing student data without clear consent frameworks raises serious ethical implications, particularly in countries where data governance laws are still evolving. As AI systems increasingly rely on vast datasets for personalization, the potential misuse of sensitive student information becomes a pressing concern (Baek & Kim, 2023).

The gender disparity in ethical concerns reflects broader patterns observed in recent meta-analyses on AI ethics perceptions (Wang et al., 2025), where women consistently express greater concern about algorithmic bias and privacy implications. This pattern may be particularly pronounced in educational contexts, where women comprise a majority of educators and may have heightened sensitivity to potential negative impacts on students. Recent research by Raza et. al. (2024) suggests that diverse stakeholder perspectives, particularly those highlighting potential risks, are crucial for developing robust AI governance frameworks.

UNESCO AI in Education guidelines (Miao et al., 2021) emphasize the importance of inclusive stakeholder consultation, particularly ensuring that voices raising ethical concerns are not marginalized in AI implementation processes. Our findings underscore that these gender-based differences in ethical perception represent valuable insights rather than obstacles, providing essential perspectives for comprehensive AI governance in education.

Moreover, the presence of algorithmic bias in AI-driven educational tools has been widely documented (Chimbga, 2023; Golda et al., 2024; Uddagiri & Isunuri, 2024). Women, rural learners, and low-income students often face systemic disadvantages due to unrepresentative training data. These biases can manifest in content recommendations, grading patterns, and predictive analytics, further marginalizing already disadvantaged groups (Ferrara, 2024). The DI-Girls Initiative (Hamdan et al., 2024) demonstrates that targeted interventions can empower female students by improving their digital skills and AI literacy, mitigating some of these ethical concerns. However, while such initiatives offer valuable solutions at the community level, they do not address the structural changes needed within AI development and policy frameworks.

This study's findings suggest that broader, systemic efforts are required to address these issues at the policy level. Technology developers, educators, and policymakers must collaborate to ensure AI tools prioritize transparency, fairness, and data security. Adopting ethical AI frameworks, such as requiring explainability in AI decision-making and implementing rigorous bias-testing protocols, can help safeguard learner rights (Wei et al., 2025). Furthermore, investment in regulatory mechanisms, such as independent AI ethics boards and continuous monitoring of AI-driven educational tools, is essential to mitigate unintended harms and build public trust in AI-powered education. Without such proactive measures, AI's potential benefits may be overshadowed by ethical risks that disproportionately impact vulnerable learner groups.

Implications for Policy and Practice

The findings of this study have several implications for the integration of AI in education. First, the significant regional and gender differences observed across content accuracy, assessment validity, and ethical challenges suggest that a one-size-fits-all approach to AI implementation will not be effective. Policies must be flexible, incorporating cultural, linguistic, and regulatory differences to ensure AI-driven educational tools align with local needs. This supports previous calls for context-sensitive AI frameworks that account for regional disparities in infrastructure, teacher preparedness, and AI literacy levels (Association of Southeast Asian Nations [ASEAN], 2024). Governments and institutions should prioritize localized AI training models and curriculum integration strategies that cater to the specific educational landscapes of each country.

Specifically, our findings align with UNESCO's AI in Education Recommendation (Miao et al., 2021), which calls for culturally responsive AI development and implementation. Policymakers should establish country-specific AI validation requirements that account for linguistic diversity, cultural norms, and pedagogical traditions. This includes developing localized training datasets, establishing culturally competent AI review processes, and creating region-appropriate ethical guidelines that reflect ASEAN values and priorities.

The OECD's AI Competency Framework for Education (OECD, 2024) provides a foundation for addressing the capacity-building needs identified in our study. However, our findings suggest that ASEAN countries require tailored approaches that acknowledge varying levels of technological infrastructure, regulatory maturity, and educator preparedness. Priority should be given to establishing regional AI education networks that facilitate knowledge sharing while respecting national sovereignty over educational policy.

Second, AI systems require stronger ethical frameworks that prioritize transparency, data privacy, and bias mitigation. The gender disparities in ethical concerns underscore the importance of inclusive AI policies that address diverse stakeholder perspectives. This aligns with Daneshjou et al. (2021), Liang et al. (2022), and Nivedhaa (2024), who advocate for regular AI bias audits and adaptive regulatory frameworks to protect underrepresented groups. Additionally, public-private partnerships should be encouraged to develop ethical AI governance models, ensuring that AI tools used in education are regularly monitored and updated to align with best practices in data security and fairness (Pechenkina, 2023).

Third, while AI holds great promise for improving educational efficiency and accessibility, maintaining integrity in AI-enhanced education requires a human-centred approach. AI should complement, not replace, educators' roles in ensuring fairness, accuracy, and ethical accountability. Aligning with Khazanchi and Khazanchi (2024) and Nixon et al. (2024), this study suggests that ASEAN policymakers and educators need to work collaboratively with AI developers to create equitable, transparent, and culturally relevant AI-driven educational tools. Capacity-building initiatives should be prioritized, equipping educators with the skills to critically assess AI-generated content and intervene where necessary to ensure alignment with pedagogical best practices.

Given the significant gender differences in ethical concerns identified in our study, policymakers must prioritize inclusive consultation processes that actively seek out and value diverse stakeholder perspectives. The higher ethical concerns expressed by female respondents should not be dismissed as resistance to innovation but rather embraced as essential input for developing comprehensive AI governance frameworks that protect all learners.

Furthermore, the regional variations in AI acceptance patterns suggest that ASEAN-wide AI education policies should incorporate flexibility mechanisms that allow member countries to adapt implementation timelines and approaches based on their specific contexts. Countries with more developed technological infrastructure, like the Philippines and Malaysia, could serve as regional pilot sites, while providing support and knowledge transfer to countries with emerging AI readiness.

Further, ongoing research should explore adaptive AI-driven assessment models, integrating human oversight to maintain assessment validity while leveraging AI's efficiency in grading and feedback mechanisms.

Finally, regulatory bodies must ensure that AI applications in education adhere to evolving international AI ethics guidelines, preventing misuse and fostering trust among educators and students. Policymakers should consider implementing standardized evaluation metrics for AI-driven educational tools, ensuring that their effectiveness is continuously assessed and refined. Without these safeguards, the risks of bias, ethical concerns, and cultural misalignment may outweigh the benefits, hindering the long-term success of AI-enhanced education in the ASEAN region.

CONCLUSION

This study examined the role of AI in education, focusing on content accuracy, assessment validity, and ethical challenges within the ASEAN region. The findings reveal significant regional and gender-based differences in perceptions of AI-generated content and assessments, supporting our theoretical framework's predictions about stakeholder and cultural variations, emphasizing the need for localized AI models and human oversight to ensure accuracy and cultural relevance. While AI offers promising advancements in educational efficiency, concerns over bias, privacy, and fairness highlight the necessity of ethical safeguards, transparency, and regulatory oversight. The results underscore that AI should serve as a complement to, rather than a replacement for, educators. Future research and policy efforts should prioritize inclusive AI frameworks, adaptive regulatory mechanisms, and capacity-building initiatives to maximize AI's benefits while mitigating its risks.

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