SCIENTIFIC CULTURE
www.sci-cult.com

SCIENTIFIC CULTURE, Vol. 12, No. 4, (2026), pp. 11659-11673
Open Access. Online & Print

DOI: 10.5281/zenodo.124261106

HUMAN FACTORS IN AI-ASSISTED ACCREDITATION: EXPLORING TRUST, COGNITIVE IMPACT, AND USABILITY

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Received: 27/09/2025
Accepted: 05/02/2026

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ABSTRACT

As higher education accreditation grows more data-intensive and complex, Artificial Intelligence (AI) is increasingly viewed as a means to improve efficiency and consistency; however, successful implementation depends on human factors such as trust, cognitive impact, and usability. This study examines evaluators' perceptions of AI-assisted accreditation (Research Question 1) and investigates how trust, cognitive load, usability, perceived usefulness, and ethical use relate to acceptance and readiness for adoption (Research Questions 2–3) within Malaysian accreditation contexts. Using a cross-sectional, survey-based mixed-methods design, data were collected from 80 accreditation stakeholders, including Malaysian Qualifications Agency (MQA) panel assessors and higher education institution quality assurance administrators. Closed-ended survey items (five-point Likert scale) provided quantitative evidence for Research Questions 1–3, while open-ended questions were analysed thematically to contextualise and explain the quantitative findings for Research Question 1. Results show strong overall support for AI as a supportive (not substitutive) tool, particularly for repetitive and structured tasks such as report summarisation, mapping learning outcomes to the Malaysian Qualifications Framework, and identifying gaps against MQA standards (COPPA/COPIA). Trust in AI was generally positive but conditional on transparency, verifiability against human judgement, demonstrated reliability across cases, and the availability of training and guidelines; concerns centred on unreliable outputs (including hallucinations), over-reliance, and data confidentiality. Correlational analyses showed significant positive relationships among perceived usefulness, trust, usability, and ethical use. The findings highlight the need for human-centred, explainable, and context-specific AI designs, alongside governance and capacity-building initiatives, to enable responsible and effective AI integration in accreditation processes.

KEYWORDS: Artificial Intelligence; accreditation; higher education quality assurance; trust in automation; cognitive load; usability; MQA.

1. INTRODUCTION

Accreditation is a vital mechanism for ensuring quality and maintaining standards in higher education. It involves systematic evaluations to verify that institutions and programmes meet predefined benchmarks for quality and effectiveness (Sun & Yao, 2023). Accreditation plays a significant role in determining quality standards in higher education, which is particularly relevant in the 21st-century global education landscape (Yusuf & Basrowi, 2021). This statement aligns with the work of Hu and Cao, who argue that the process is crucial for affording both internal and external legitimacy to educational programmes, thereby underpinning quality assurance and improvement efforts (Hu & Cao, 2023). With the increasing complexity of accreditation processes and the growing demand for accountability, traditional methods often struggle to cope with the volume and intricacies of institutional data (Hussein et al., 2021). This challenge has prompted the exploration of Artificial Intelligence (AI) as a transformative tool in accreditation, offering innovative solutions to enhance efficiency and effectiveness (Sun & Yao, 2023). AI technologies can automate data analysis, streamline documentation processes, and provide advanced analytics that support informed decision-making (Wang et al., 2022).

For instance, AI tools can facilitate the analysis of large datasets, identifying patterns and trends that may not be readily apparent through manual evaluation (Bogren et al., 2020). Natural Language Processing (NLP) can summarise lengthy reports, flag inconsistencies, and ensure alignment with accreditation standards, thereby reducing the cognitive load on evaluators (Tejeda Lemus et al., 2023). Furthermore, Machine Learning (ML) algorithms can detect anomalies in institutional performance data and predict future trends, enabling proactive measures to address potential issues before they escalate (Hussein et al., 2021). Additionally, AI tools have the capacity to streamline and enhance the accreditation process by automating evaluation procedures, analysing vast amounts of data, and providing insights that might have been unattainable using traditional methods. Khlaif et al. (2024) highlight that the integration of generative AI tools can facilitate student assessment processes, enabling more efficient evaluation of educational outcomes and accreditation compliance. This can lead to more precise measurements of academic integrity, allowing institutions to align their standards with evolving educational needs.

Moreover, AI's analytical capabilities can help identify trends in educational quality and highlight areas requiring improvement, thereby providing educational leaders with actionable insights. Chan and Hu emphasise the importance of developing AI literacy for students and educators, noting that understanding the mechanics and implications of AI is essential for optimising its impact on learning outcomes (Chan & Hu, 2023). This capacity for data-driven decision-making can significantly enhance the accountability and effectiveness of accreditation processes. This integration of AI not only enhances the accreditation process but also fosters a culture of continuous improvement within educational institutions (Gloria Mtshali et al., 2019).

Despite its potential, the widespread use of AI in accreditation faces significant challenges. Evaluators frequently exhibit scepticism regarding AI's capacity to render equitable and precise decisions, thereby impeding its implementation (Tejeda Lemus et al., 2023). This distrust is exacerbated by concerns about the transparency of AI's decision-making processes, which creates additional challenges for integrating AI, especially in relation to ethical considerations. Hardie and colleagues argue that the adoption of AI tools in nursing education raises concerns about academic integrity and bias, which are equally significant in broader higher education contexts (Hardie et al., 2025). It is crucial to use AI tools ethically and ensure their implementation does not compromise educational values. Institutions must establish comprehensive guidelines for the ethical application of AI, which would involve continuous collaboration between educational leaders, faculty, and students to foster an understanding of the implications of these technologies (Azevedo, 2025). Moreover, the cognitive demands of understanding and using AI tools can overwhelm evaluators, particularly those without technical expertise, which reduces their overall effectiveness.

There is a need to bridge the gap between AI capabilities and the psychological needs of human evaluators. Addressing issues such as trust, cognitive load, ethics, and user-friendly design is essential to ensure that AI systems enhance, rather than hinder, the accreditation process. This study investigates these dimensions and contributes to the development of responsible and standardised guidelines for the ethical use of AI by MQA panel assessors and higher education institutions.

1.2 Objectives of the Study

The primary aim of this research is to explore how Artificial Intelligence (AI) can be effectively integrated into higher education accreditation processes while addressing the psychological and usability challenges faced by human evaluators. Specifically, the study investigates evaluators' perceptions of AI tools, examines the cognitive and emotional impacts of these tools on decision-making, and identifies factors influencing trust and usability. The study also aims to support the development of responsible and standardised guidelines for the ethical use of AI by MQA panel assessors and higher education institutions (HEIs). The findings will inform the design of AI systems that support human evaluators, enhance efficiency, and promote fair and transparent accreditation processes.

1.2.1 Research Objectives

1. To identify evaluators' perceptions of the use of AI in accreditation processes.
2. To examine the impact of AI tools on trust and cognitive load in accreditation processes.
3. To assess the relationships among perceived usefulness, trust, cognitive load, usability, and ethical use of AI among evaluators involved in AI-assisted accreditation.

1.2.2 Research Questions

1. What are the evaluators' perceptions of the use of AI in accreditation processes?
2. To what extent do psychological factors (e.g., trust, cognitive load) influence evaluators' acceptance of AI tools?
3. Is there a significant relationship among perceived usefulness, trust, cognitive load, usability, and ethical use of AI among evaluators involved in AI-assisted accreditation?

2. LITERATURE REVIEW

Incorporating Artificial Intelligence (AI) into higher education accreditation processes could make them more efficient, transparent, and better supported by evidence-based decision-making. AI technologies can automate various aspects of the accreditation process, thereby reducing the administrative burden on institutions and allowing evaluators to focus on more strategic tasks. For instance, AI can streamline data collection and analysis, enabling institutions to manage large volumes of information more effectively (Suhadi et al., 2024). This capability is particularly important given the increasing complexity of accreditation requirements and the demand for accountability in educational outcomes.

AI can also make the accreditation process more transparent by providing evaluators with clear, data-driven information that supports decision-making. By leveraging advanced analytics, AI can identify trends and patterns in institutional performance, facilitating a more objective assessment of compliance with accreditation standards (Hussain et al., 2020). This not only enhances evaluation quality but also fosters trust among stakeholders by ensuring that decisions are based on robust evidence rather than subjective judgments.

Furthermore, the use of AI in accreditation can lead to more timely and informed decision-making. Automated systems can provide real-time feedback and recommendations, allowing institutions to address potential deficiencies proactively (Rajput et al., 2023). This change to a more flexible accreditation process can help improve the quality of education and the effectiveness of institutions over time.

2.1 Psychological Factors – Trust & Cognitive Load

The factors contributing to trust in AI can be categorised based on user experience and ethical practices. Glos and Karwot's (2025) research show that people who have good experiences with AI-driven systems are more likely to trust them in the future. Conversely, concerns about data privacy and algorithmic bias undermine this trust, making it imperative for developers to adopt clear ethical standards and transparent practices in AI implementation (Akbar et al., 2024; Sarkar & Sarkar, 2024). In healthcare, the necessity for informed consent allows patients to feel more secure when interacting with AI, indicating that attention to ethical considerations directly correlates with trust levels (Freeman et al., 2024).

Understanding how users perceive and trust AI systems is crucial for effective implementation. Studies indicate that factors like transparency, explainability, and user familiarity influence trust in AI. For instance, Kumar and Bargavi (2024) articulate that the dynamics of trust significantly affect user interaction and decision-making regarding AI, emphasizing the multifaceted nature of trust in this technology. Additionally, it is significant to govern structures and stakeholder engagement in establishing trust in AI systems, particularly in complex fields like engineering and construction (Shehu et al., 2025). Trust not only influences user adoption but also the perceived usefulness of AI, as indicated by the varying acceptance levels across different demographics, including gender and academic discipline (Chavarria et al., 2025).

Trust is a critical factor influencing the acceptance and integration of AI technologies in various fields.

Yavorskyi (2025) identifies that AI is often perceived not merely as a tool but increasingly as a social actor, leading to complex trust dynamics that impact user interaction. Trust in AI is shaped by various factors, including perceived biases and transparency in decision-making processes. Studies, such as those by Bawack and Desveaud (2022), highlight that trust is one of the most studied antecedents of user adoption of AI technologies, emphasising the importance of fairness and accountability in establishing trust. Furthermore, research on the experiences of employees highlights the importance of transparent communication and ethical governance in fostering trust in AI applications within organisations (Mitchell, 2025).

Additionally, trust encompasses not only belief in AI's potential but also assurance of data privacy, security, and the ethical alignment of AI applications with user interests (Hegde et al., 2024). This sentiment is echoed by Ali and Shaban (2025), who illustrate that ethical concerns about algorithmic bias and privacy significantly undermine the trust necessary for effective AI deployment in academic peer review processes. The interplay of these factors suggests that establishing trust is crucial for the effective adoption of AI across various domains, including accreditation processes.

2.2 Usability of AI Systems

Usability is another critical component that influences user perceptions of AI. High usability facilitates a smoother interaction between users and AI, enhancing overall satisfaction and effectiveness. Cadelina (2025) suggests that advancements in AI methodologies significantly improve user experiences in human-computer interactions. The incorporation of user-centred design principles can lead to more intuitive AI applications, increasing usability while reducing user anxiety and resistance, as noted in the research of Kadenhe et al. (2025). Furthermore, studies have shown that iterative testing with users helps identify usability issues and ethical concerns before widespread application, reinforcing the significance of participatory design approaches in enhancing user trust and acceptance (Savveli et al., 2025).

Usability, within the context of AI applications intended for accreditation, refers to the efficacy and efficiency with which users can leverage AI tools to fulfil designated goals. Singleton emphasises that the implementation of AI in accreditation processes requires the mitigation of ethical considerations—specifically, bias, privacy, and transparency— to enhance human decision-making. Consequently, this implies the creation of user-friendly AI systems, thereby enabling seamless interaction with these systems for all involved parties, encompassing both accrediting bodies and educational institutions (Singleton, 2025).

However, the integration of AI into accreditation processes also faces challenges. One significant concern is ensuring that AI tools are adequately tailored to the unique demands of educational assessments. Kerboul et al. note that accreditation can boost the credibility of institutions while ensuring compliance with strict standards, but caution that practices must also be integrated with AI technologies to optimise accessibility and user experience (Kerboul et al., 2025). Furthermore, McMahon's research demonstrates the practical applications of artificial intelligence within the context of continuing professional development accreditation, revealing that although AI can enhance operational efficiency, the preservation of critical human oversight is paramount for ensuring both accountability and efficacy (McMahon, 2025). Users' perspectives on these considerations underscore the necessity of designing interfaces that accommodate human input and modification, thereby fostering an interactive environment in which AI serves as a supportive tool rather than a substitute for human discernment.

Additionally, challenges related to academic misconduct emphasise that reliance on AI tools could lead to unethical practices among students (Blomquist et al., 2025). Ensuring that these tools do not exacerbate existing inequalities or diminish critical thinking skills is crucial for their successful integration into accreditation practices (McGinty, 2025). Establishing ethical frameworks and continuous training for faculty is necessary to ensure that educators not only understand the technology but can effectively guide its ethical use within accreditation processes (Kim et al., 2025).

2.3 Ethical Considerations in AI

The ethical dimensions of AI deployment encompass a broad spectrum of issues, including privacy, accountability, and potential biases embedded within algorithms. Ethical concerns are prominent across almost all studies, as highlighted by Bearman and his colleagues, who stress that many discussions of AI in education fail to address its ethical implications adequately (Bearman et al., 2022). Moreover, the call for rigorous ethical standards in AI, as articulated by stakeholders from diverse fields, demands an integrated approach to governance and ethical frameworks (Gartner &

Krašna, 2023).

As AI technologies evolve, understanding different groups' perceptions and attitudes becomes crucial. Carvalho et al. (2025) highlight distinct patterns of trust, concern, and familiarity across various demographics, indicating a need for tailored strategies to ensure inclusive AI adoption. Social ethical perceptions play a mediating role in determining acceptance of AI technologies, demonstrating that ethical considerations must align with usability to foster positive perceptions (Lin & Chung, 2025). This interaction between usability and ethical frameworks shows how complicated people's feelings are about new technologies.

Governance structures for AI applications must evolve to address emerging ethical challenges. The integration of ethical codes into AI practices, as suggested by Gartner and Krašna (2023), can help mitigate risks associated with privacy violations and algorithmic bias. Studies conducted by Akbar et al. (2024) elucidate the dual role of AI in enhancing consumer trust while simultaneously raising ethical dilemmas related to data handling and algorithms. Thus, the development and implementation of these frameworks is not only a matter of compliance; it is vital for establishing a sustainable trust relationship between users and AI technologies.

2.4 AI in Accreditation and Its Usability

Recent studies show that AI has the power to change the way accreditation works by automating it and using advanced analytics. AI tools are increasingly being recognised for their ability to streamline document analyses, identify patterns in extensive datasets, and provide actionable insights that enhance decision-making capabilities. For example, Natural Language Processing (NLP) technologies can efficiently summarise lengthy accreditation reports, flag inconsistencies, and ensure that institutional practices align with established accreditation standards (Sun & Yao, 2023). This capability saves time and enhances the accuracy of the accreditation process by reducing human errors and oversight.

Moreover, Machine Learning (ML) algorithms can play a pivotal role in detecting anomalies and predicting trends in institutional performance, thereby facilitating proactive measures to address potential deficiencies before they escalate (Sun & Yao, 2023). The application of ML in accreditation contexts allows for the continuous monitoring of educational institutions, enabling evaluators to make informed decisions based on real-time data analytics. This dynamic approach to accreditation can lead to more responsive and adaptive quality assurance mechanisms, ultimately enhancing the overall educational landscape.

The integration of AI in accreditation processes also addresses the growing complexity of data management in higher education. AI can help make sense of the immense amounts of data that institutions collect about student performance, faculty qualifications, and institutional outcomes. For instance, AI-driven tools can assist in compiling and drafting accreditation documentation, conducting diagnostic reviews of compliance with accreditation criteria, and generating action plans to address identified gaps (Sun & Yao, 2023). This streamlines the accreditation process and enables institutions to engage in continuous improvement practices.

In conclusion, the potential of AI to enhance accreditation processes through automation and advanced analytics is significant. By leveraging NLP and ML technologies, institutions can improve the efficiency and effectiveness of accreditation while ensuring compliance with standards. However, the successful adoption of AI tools hinges on their usability and the preparedness of evaluators to engage with these technologies. As the landscape of higher education continues to evolve, embracing AI in accreditation will be key to preserving quality and fostering institutional accountability.

3. RESEARCH METHODOLOGY

3.1 Research Design

This study employed a cross-sectional, survey-based mixed-methods design to examine psychological and usability factors influencing AI adoption in higher education accreditation. Quantitative (closed-ended Likert-scale) items captured evaluators' perceptions and key human-factor constructs (supporting Research Questions 1–3). These were complemented by open-ended questions to provide contextualised explanations of participants' views, concerns, and system expectations, primarily enriching the interpretation of Research Question 1.

Data were collected via an online survey administered to accreditation stakeholders. The survey included (a) quantitative items measuring perceptions of AI use in accreditation, trust, cognitive load, usability, perceived usefulness, and ethical use, and (b) open-ended questions to elicit descriptions of tasks AI could support, concerns about AI use, and desired features for AI-assisted accreditation tools. The open-ended questions were designed to elaborate and contextualise Research Question 1, while Research Questions 2 and 3 were addressed using the quantitative dataset.

Accordingly, this paper reports quantitative findings to address Research Questions 1–3 and presents a thematic summary of open-ended responses to deepen and explain findings for Research Question 1.

3.2 Research Participants

3.2.1. Inclusion and Exclusion Criteria

Participants were selected using purposive sampling to ensure direct involvement in Malaysian higher education accreditation processes. Inclusion criteria required participants to (a) be MQA accreditation evaluators or institutional quality assurance administrators, (b) have a minimum of one year of active experience in accreditation activities, and (c) demonstrate familiarity with digital evaluation tools. Participants were also required to be actively involved in conducting or preparing for accreditation reviews. Individuals without accreditation experience or direct involvement in quality assurance processes were excluded from the study.

3.2.2. Participant Characteristics

The survey involved two primary stakeholder groups: MQA accreditation evaluators and institutional quality assurance administrators from public and private higher education institutions. A total of 80 usable responses were obtained. Demographic data collected included professional role, years of accreditation experience, institutional type, and prior experience with AI or machine learning tools. Participation was voluntary, and informed consent was obtained from all participants.

3.3 Sampling Procedures

The research utilised purposive sampling to select participants based on their direct involvement in higher education accreditation procedures. Participants were recruited from two primary stakeholder categories: (a) accreditation evaluators affiliated with Malaysian Qualifications Agency (MQA) review panels and (b) institutional administrators tasked with quality assurance and accreditation readiness. To qualify, participants needed to have a minimum of one year of active experience in accreditation activities, and to demonstrate proficiency with digital evaluation tools or data-driven assessment methodologies.

The sampling strategy was designed to include participants with sufficient practical expertise to provide relevant insights into integrating AI tools into accreditation workflows. The study aimed to obtain responses from a broad cross-section of the accreditation community, and the final sample comprised 80 survey respondents.

3.4 Data Collection and Data Analysis

3.4.1. Data Collection Procedures

Data were collected through an online survey consisting of both closed-ended (Likert-scale) items and open-ended questions.

3.4.1.1. Survey instrument. The study used an online survey to measure key constructs influencing AI adoption in accreditation and to capture open-ended feedback. All closed-ended items were measured on a five-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree) to ensure consistency for analysis and reporting. Items assessing *trust* were adapted from the 12-item *Trust in Automation Scale* (Jian et al., 2000) and contextualised to AI-assisted accreditation. Items reflecting perceived *cognitive load* were adapted from the *NASA Task Load Index* (NASA-TLX; Hart & Staveland, 1988) to capture perceived mental effort and task demands when interpreting AI-supported information in accreditation work. Perceived *usability* was measured using adapted items based on the *System Usability Scale* (SUS; Brooke, 1996), reworded to fit the accreditation context and the five-point response format. In addition, perceived *usefulness* and *ethical use* were measured using study-specific items aligned with prior technology acceptance and responsible AI literature, focusing on perceived performance benefits, appropriateness, transparency, and governance expectations for AI in accreditation. Open-ended items solicited respondents' views on (a) accreditation tasks where AI could add value, (b) perceived risks and concerns, and (c) desired features for an AI-assisted tool.

3.4.2. Data Analysis Procedures

Data analysis was conducted in two parts. First, quantitative survey data were analysed using descriptive and correlational statistics. Second, responses to the open-ended survey questions were analysed qualitatively to identify recurring themes related to evaluators' perceptions, concerns, and desired system features.

3.4.2.1. Quantitative analysis. Quantitative survey data were analysed using SPSS statistical software. Descriptive statistics were computed to summarise participant demographics and to describe central tendencies and variability for trust, cognitive load, perceived usability, perceived usefulness, and ethical use. Pearson product–moment correlation analyses were conducted to examine bivariate relationships among the key constructs. All statistical analyses were conducted using an alpha level of .05.

3.4.2.2. Qualitative analysis of open-ended survey responses. Open-ended responses from the survey were analysed using thematic analysis, following Braun and Clarke's (2006) six-phase approach. Responses were first read iteratively to support familiarisation, then coded to capture recurring ideas related to (a) accreditation tasks where AI could add value, (b) perceived risks and concerns (e.g., reliability, over-reliance, data protection), and (c) desired features for an AI-assisted tool. Codes were then reviewed and refined through repeated comparison across responses, and grouped into broader themes. To enhance analytical rigour, themes were checked for internal consistency and distinctiveness, and representative quotations were selected to illustrate each theme. The resulting themes are reported in the Results section under the qualitative findings for Research Objective 1 (Section 4.2.2) and are used to contextualise and explain the quantitative findings for Research Question 1.

3.5 Integration of Findings

Findings from the quantitative survey and the thematic analysis of open-ended responses were interpreted together to provide complementary insights for Research Question 1 (evaluators' perceptions of the use of AI in accreditation). Specifically, quantitative results (Section 4.2.1) describe overall patterns of perception, while qualitative themes (Section 4.2.2) provide contextual explanations and examples that help interpret those patterns. Quantitative results addressing trust, cognitive load, usability, perceived usefulness, ethical use, and their interrelationships were used to answer Research Questions 2 and 3.

4. RESULTS

4.1 Descriptive Statistics

Table 1. Demographic Profile and AI-Related Background of Respondents (N = 80).

Variable	Category	Frequency (n)	Percentage (%)
Role	Panel Assessor (Programme Accreditation)	75	93.8
	Panel Auditor (Institutional Audit/COPIA)	2	2.5
	Chairperson of Panel	1	1.3
	Field Expert / Subject Specialist	1	1.3
	Secretariat / Technical Committee Member	1	1.3
Years of Experience	Less than 1 year	37	46.3
	1–5 years	20	25.0
	5–10 years	17	21.3
	More than 10 years	6	7.5
Previous Experience with AI Tools in Quality Assurance	Yes	53	66.3
	No	27	33.8
Familiarity with AI Technologies	Not at all familiar	2	2.5
	Slightly familiar	5	6.3
	Moderately familiar	23	28.7
	Familiar	32	40.0
	Very familiar	18	22.5

4.1.1 Crosstabulation of Previous Experience with AI Tools and Familiarity with AI Technologies

The crosstabulation examines the relationship between respondents' previous experience with AI tools in quality assurance and their self-reported familiarity with AI technologies (N = 80).

Table 2. Crosstabulation of Previous Experience with AI Tools and Familiarity with AI Technologies (N = 80).

		Familiarity with AI technologies					Total
		Not at all	**Slightly familiar**	**Moderately familiar**	**Familiar**	**Very familiar**	
Previous experience with AI tools in Quality Assurance	Yes	2	4	20	19	8	53
	No	0	1	3	13	10	27
Total		2	5	23	32	18	80

Overall, respondents with prior experience using AI tools in quality assurance (n = 53) tended to report higher levels of familiarity with AI technologies compared to those without such experience (n = 27). Among experienced respondents, the majority fell within the *moderately familiar* (n = 20) and *familiar* (n = 19) categories, with a smaller proportion identifying as *very familiar* (n = 8). Only a minimal number reported being *not at all* or *slightly familiar* (n = 6 combined), suggesting that exposure to AI in professional QA contexts is associated with a baseline level of technological understanding.

In contrast, respondents without prior AI experience showed a different distribution. While some reported being *familiar* (n = 13) or *very familiar* (n = 10), a greater proportion clustered at lower familiarity levels (*slightly familiar* or *moderately familiar*, n = 4 combined), and none reported being *not at all familiar*. This indicates that familiarity with AI technologies may also be influenced by general exposure beyond formal QA use, although less consistently than for those with direct experience.

The association between previous AI experience and familiarity with AI technologies was statistically significant. The Pearson Chi-Square test indicated a significant relationship, $\chi^2(4) = 10.356$, $p = .035$. This suggests that familiarity with AI technologies varies systematically according to whether respondents have previously used AI tools in quality assurance contexts. The significant linear-by-linear association, $\chi^2(1) = 8.781$, $p = .003$, further indicates a positive trend whereby prior experience is associated with increasing levels of familiarity.

Table 3. Chi-Square Tests for the Association Between Previous Experience With AI Tools and Familiarity with AI Technologies (N = 80).

Chi-Square Tests			
	Value	**df**	**Asymptotic Significance (2-sided)**
Pearson Chi-Square	10.356[a]	4	.035
Likelihood Ratio	11.522	4	.021
Linear-by-Linear Association	8.781	1	.003
N of Valid Cases	80		
a. 4 cells (40.0%) have expected count less than 5. The minimum expected count is .68.			

However, this finding should be interpreted with some caution, as 40% of the cells had expected counts below five, which may affect the robustness of the chi-square test. Despite this limitation, the overall pattern supports the conclusion that prior hands-on experience with AI tools is meaningfully linked to higher familiarity with AI technologies, reinforcing the role of experiential exposure in shaping AI readiness among accreditation and quality assurance stakeholders.

4.2 Research Objective 1: To explore evaluators' perceptions of AI in accreditation processes.

4.2.1 Quantitative Survey

Responses were measured on a five-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree).

Table 4. Perceptions on the Use of AI in Accreditation and Quality Assurance Processes (N = 80).

Statement	**Strongly Disagree n (%)**	**Disagree n (%)**	**Neutral n (%)**	**Agree n (%)**	**Strongly Agree n (%)**
AI could help in improving the efficiency of accreditation reviews.	1 (1.3)	3 (3.8)	9 (11.3)	44 (55.0)	23 (28.7)
AI could provide useful summaries of institutional self-review reports.	–	–	13 (16.3)	43 (53.8)	24 (30.0)
AI may reduce repetitive administrative workload for assessors.	–	3 (3.8)	12 (15.0)	43 (53.8)	22 (27.5)
AI could help ensure consistency across different programme evaluations.	–	3 (3.8)	18 (22.5)	41 (51.2)	18 (22.5)
AI would complement, not replace, human judgement in accreditation.	1 (1.3)	–	6 (7.5)	30 (37.5)	43 (53.8)
It would be acceptable for AI to be used as a supportive tool in MQA audits.	1 (1.3)	1 (1.3)	5 (6.3)	47 (58.8)	26 (32.5)
AI could assist in mapping programme learning outcomes to the Malaysian Qualifications Framework (MQF).	–	2 (2.5)	14 (17.5)	40 (50.0)	24 (30.0)
AI could highlight gaps or misalignments with MQA standards (e.g., COPPA/COPIA).	–	2 (2.5)	14 (17.5)	42 (52.5)	22 (27.5)

Overall, respondents demonstrated consistently positive perceptions towards the use of Artificial Intelligence (AI) in accreditation and quality assurance processes. A substantial majority agreed or strongly agreed that AI could improve the efficiency of accreditation reviews (83.7%), reduce repetitive administrative workload for evaluators (81.3%), and provide useful summaries of institutional self-review reports (83.8%). Similarly, most respondents perceived AI as beneficial in promoting consistency across programme evaluations (73.7%) and assisting in mapping programme learning outcomes to the Malaysian Qualifications Framework (80.0%). Support was also evident for AI's role in identifying gaps or misalignments with MQA standards, including COPPA and COPIA criteria (80.0%). Importantly, respondents strongly endorsed a complementary role for AI rather than a replacement of human judgement, with 91.3% agreeing or strongly agreeing with this view. Consistent with this perspective, a large majority indicated that the use of AI as a supportive tool in MQA audits would be acceptable (91.3%). Overall, these findings suggest a high level of readiness and openness among evaluators towards integrating AI as an assistive, ethically bounded tool in accreditation practices.

Table 5. Overall Mean Score for Perceptions on the Use of AI in Accreditation and Quality Assurance Processes (N = 80).

	N	Minimum	Maximum	Mean	Std. Deviation
Perception	80	2.50	5.00	4.1156	0.57257
Valid N (listwise)	80				

The overall mean score for perceptions towards the use of AI in accreditation and quality assurance was high ($M = 4.12$, $SD = 0.57$), indicating a generally positive orientation among respondents. The mean value, which is well above the scale midpoint, suggests strong overall agreement with the proposed roles of AI as a supportive and efficiency-enhancing tool in accreditation processes. The relatively small standard deviation reflects a moderate level of consensus among respondents, indicating that perceptions were fairly consistent across the sample. Although responses ranged from moderate to very positive (minimum = 2.50; maximum = 5.00), the clustering of scores around the higher end of the scale reinforces the finding that evaluators largely view AI favourably when it is positioned as a complement to, rather than a replacement for, human judgement.

4.2.2. Qualitative Data

Q1: What tasks in the current accreditation process could AI help improve?

The findings indicate a strong consensus that AI could play a meaningful supportive and efficiency-enhancing role in technically demanding and repetitive components of the accreditation process. Participants consistently highlighted tasks related to mapping, alignment, and standardisation as areas where AI assistance would be most beneficial.

Specifically, respondents emphasised AI's potential to improve the mapping of Programme Learning Outcomes (PLOs) to Malaysian Qualifications Framework (MQF) domains, Course Learning Outcomes (CLOs), and assessment methods. These processes were perceived as time-consuming, cognitively demanding, and prone to inconsistency when conducted manually. AI was viewed as particularly useful in enhancing transparency, consistency, and traceability in programme evaluations and constructive alignment checks.

Several participants also noted that AI could reduce human variability and subjective bias, especially in areas where panel judgements may differ due to fatigue, workload, or interpretive differences. However, respondents were clear that AI should function as an augmentation tool rather than a replacement, supporting human judgement rather than substituting it. Overall, AI was perceived as most valuable when applied to structured, rule-based accreditation tasks rather than interpretive or value-laden decisions.

Q2: What are the main concerns about using AI in accreditation?

Despite recognising AI's potential benefits, participants expressed substantial concerns centred on trust, reliability, and ethical use. A dominant theme was the risk of hallucination and misinformation, with respondents worried that AI might generate outputs that appear authoritative but are factually incorrect or misaligned with accreditation standards.

Another major concern related to over-reliance on AI, particularly the possibility that panel members might accept AI recommendations uncritically, thereby diminishing professional judgement and reflective evaluation. This concern was closely linked to apprehensions about value erosion, where accreditation decisions might become overly procedural and lose their human, contextual, and ethical grounding.

Issues of data protection and confidentiality were also prominent. Participants highlighted the sensitive nature of accreditation documents and raised questions about data security, ownership, and compliance with governance requirements. Collectively, these concerns indicate that trust in AI within accreditation contexts is conditional, dependent on safeguards that ensure transparency, accountability, and human oversight.

Q3: What features are considered essential in an AI-assisted tool for MQA audits?

Participants articulated clear expectations regarding the design and functionality of any AI-assisted accreditation tool. The most frequently mentioned requirement was efficiency, particularly features that enhance speed and reduce administrative burden without compromising rigour.

Respondents emphasised the importance of a context-specific system, including automated MQF and COPPA mapping engines, OBE compliance checks, and structured flagging mechanisms to support Areas of Concern (AoC) identification. Rather than a fully autonomous system, participants strongly preferred tools that require assessor input, allowing panel members to validate, amend, or override AI outputs.

The findings also suggest a preference for modular or agent-based AI designs, where specific components of the accreditation workflow are supported by AI while final evaluative authority remains with human assessors. This reflects a broader expectation that AI tools should be transparent, explainable, and controllable, reinforcing professional trust rather than undermining it.

4.3 Research Objective 2: To examine the impact of AI tools on trust and cognitive load in accreditation processes.

This section presents the results on the impact of AI tools on trust and cognitive load in accreditation processes. Responses were measured on a five-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree).

Table 6. Perceptions of the Impact of AI Tools on Trust and Cognitive Load (N = 80).

Statement	Strongly Disagree n (%)	Disagree n (%)	Neutral n (%)	Agree n (%)	Strongly Agree n (%)
I would trust AI recommendations if explanations are clear and transparent.	–	3 (3.8)	27 (33.8)	38 (47.5)	12 (15.0)
I am concerned that AI might produce unpredictable or unreliable outputs.	–	8 (10.0)	21 (26.3)	37 (46.3)	14 (17.5)
AI assistance may help reduce my mental workload during accreditation.	–	5 (6.3)	12 (15.0)	43 (53.8)	20 (25.0)
AI could increase my workload if it requires too much interpretation.	2 (2.5)	22 (27.5)	24 (30.0)	23 (28.7)	9 (11.3)
I expect training and guidelines to build confidence in using AI in accreditation.	–	–	6 (7.5)	46 (57.5)	28 (35.0)
I would feel more secure if AI recommendations can be verified against human judgement.	–	3 (3.8)	12 (15.0)	35 (43.8)	30 (37.5)
I would be confident using AI if it demonstrated reliability across multiple accreditation cases.	–	3 (3.8)	11 (13.8)	37 (46.3)	29 (36.3)

The findings indicate that the impact of AI tools on trust and cognitive load in the accreditation process is largely conditional. In terms of trust, a majority of respondents reported that they would trust AI recommendations if explanations are clear and transparent, with 62.5% agreeing or strongly agreeing, while 33.8% remained neutral. Trust was further reinforced by verification mechanisms, as 81.3% of respondents indicated that they would feel more secure if AI recommendations could be verified against human judgement. Similarly, 82.6% reported confidence in using AI if it demonstrated reliability across multiple accreditation cases. At the same time, concerns regarding AI reliability were evident, with 63.8% agreeing or strongly agreeing that AI might produce unpredictable or unreliable outputs, indicating that trust in AI is accompanied by professional caution.

With respect to cognitive load, most respondents perceived AI as potentially reducing mental workload during accreditation activities, with 78.8% agreeing or strongly agreeing that AI assistance may help ease cognitive demands. However, perceptions were mixed regarding the possibility of increased workload. While 40.0% agreed or strongly agreed that AI could increase workload if it requires excessive interpretation, 30.0% reported neutral responses and 30.0% disagreed or strongly disagreed. This suggests that the cognitive impact of AI depends on how easily its outputs can be interpreted and integrated into existing decision-making processes. Overall, the results indicate that AI tools may reduce cognitive load and support decision-making when trust-related conditions such as transparency, reliability, training, and human verification are present, but may increase cognitive effort when these conditions are not met.

Table 7. Overall Mean Score for the Impact of AI Tools on Trust and Cognitive Load in Accreditation Processes (N = 80).

	N	Minimum	Maximum	Mean	Std. Deviation
Trust	80	2.86	5.00	3.8839	0.47413
Valid N (listwise)	80				

The descriptive statistics further support the findings on the impact of AI tools on trust and cognitive load in the accreditation process. The overall mean score for trust was moderately high (M = 3.88, SD = 0.47), indicating that respondents generally reported a favourable level of confidence in AI-assisted accreditation. From a cognitive load perspective, this level of trust suggests that AI tools are likely to reduce the mental effort required to process information and support evaluative judgement, as respondents do not appear to approach AI outputs with high scepticism. The relatively low standard deviation indicates a consistent pattern of responses across the sample, suggesting shared expectations regarding the role of AI in supporting decision-making. However, the observed range of responses (minimum = 2.86; maximum = 5.00) reflects variation in trust levels, implying that for some respondents, lower trust may necessitate additional cognitive monitoring and verification, potentially increasing cognitive load. Overall, the findings indicate that trust in AI functions as a key mechanism influencing whether AI tools alleviate or add to cognitive demands during accreditation decision-making.

4.4 Research Objective 3: To assess the relationships among perceived usefulness, trust, cognitive load, usability, and ethical use of AI among evaluators involved in AI-assisted accreditation.

Table 8. Descriptive Statistics for Perceived Usefulness, Trust, Usability, and Ethical Use (N = 80).

	Mean	Std. Deviation	N
Perceived usefulness	4.1156	0.57257	80
Trust	3.8839	0.47413	80
Usability	4.3264	0.53224	80
Ethical use	4.5821	0.47122	80

The descriptive statistics indicate generally positive perceptions across all constructs examined. Perceived usefulness of AI recorded a high mean score (M = 4.12, SD = 0.57), suggesting that evaluators largely viewed AI as beneficial in supporting accreditation tasks. Similarly, Usability was rated highly (M = 4.33, SD = 0.53), indicating that respondents generally found AI tools easy to use and practical. Ethical use of AI received the highest mean score (M = 4.58, SD = 0.47), reflecting strong agreement on the importance of ethical considerations in AI-supported accreditation. Trust in AI, while slightly lower than the other constructs, still demonstrated a moderately high mean (M = 3.88, SD = 0.47), suggesting cautious but generally positive confidence in AI tools.

Correlation analysis (Table 9) revealed statistically significant positive relationships among all variables ($p < .01$). Perceived usefulness was moderately correlated with trust (r = .571), usability (r = .671), and ethical use (r = .501), indicating that evaluators who perceived AI as more useful were also more likely to trust AI systems, perceive them as usable, and value their ethical application. Trust demonstrated a strong positive relationship with usability (r = .674), suggesting that higher usability is associated with greater trust in AI tools. Trust was also moderately correlated with ethical use (r = .492), indicating that ethical considerations may contribute to confidence in AI-assisted decision-making.

Usability showed the strongest association with ethical use (r = .713), highlighting a strong relationship between perceptions of ease of use and ethical implementation. This suggests that AI systems perceived as usable are also more likely to be viewed as ethically appropriate within the accreditation context. Overall, the findings demonstrate that perceived usefulness, trust, usability, and ethical considerations are closely interrelated factors in the use of AI for accreditation. These relationships suggest that evaluators' acceptance and use of AI tools are shaped by a combination of functional benefits, confidence in system outputs, manageable cognitive demands, and adherence to ethical standards.

Table 9. Correlations Between Perceived Usefulness, Trust, Usability, and Ethical Use of AI (N = 80).

	Perceived usefulness	Trust	Usability	Ethical use
Perceived usefulness	1	.571**	.671**	.501**
Trust	.571**	1	.674**	.492**
Usability	.671**	.674**	1	.713**
Ethical use	.501**	.492**	.713**	1
**. Correlation is significant at the 0.01 level (2-tailed).				

5. CONCLUSION, IMPLICATIONS, LIMITATIONS, AND RECOMMENDATIONS

5.1 Conclusion

This study explored the human factors influencing the adoption of Artificial Intelligence in higher education accreditation, with a particular focus on perceptions, trust, cognitive load, and related acceptance factors. The survey provides empirical evidence from quantitative scales and complementary insights from open-ended responses. Together, these findings indicate that evaluators' perceptions of AI are shaped by confidence in automated outputs, the mental effort required to interpret AI-supported information, and the perceived usability of these systems. The results reported in this paper address Research Questions 1–3 and provide an initial foundation for understanding readiness for AI-assisted accreditation.

At the same time, the findings should be interpreted in light of the study's scope and design. Because evidence is based on survey responses, conclusions about usability and cognitive impact reflect perceived experience rather than direct observation of evaluator performance with specific AI systems. Future studies can build on this work by incorporating hands-on evaluations and in-depth qualitative inquiry to better understand how trust, cognitive load, and ethical concerns develop during real accreditation tasks.

As Malaysia's higher education landscape continues to evolve, the responsible integration of AI into accreditation processes will be vital for enhancing efficiency, transparency, and institutional accountability. This study contributes to that effort by laying the empirical foundation for designing AI systems that support—rather than replace—human judgement, reduce cognitive burden, and uphold the integrity of accreditation processes.

5.2 Implications of the Study

The preliminary findings from this study highlight several critical implications for policy, practice, and system design in the context of AI adoption for accreditation. A primary takeaway is the necessity of a human-centred approach to AI. Trust, cognitive load, and usability are intricately linked, and this connection underscores the importance of designing AI tools that account for evaluators' psychological needs. Systems that genuinely support human judgement and reduce cognitive burden are more likely to be embraced and used effectively by stakeholders.

Transparency emerges as a key driver of trust. Evaluators express greater willingness to accept AI-generated recommendations when system outputs are explainable, traceable, and clearly aligned with established accreditation standards. The ability of AI to provide transparent reasoning not only fosters trust but also ensures that its role within accreditation processes remains accountable and supportive of institutional integrity.

Another significant implication is the value of AI literacy. Familiarity with AI tools, gained through exposure and targeted training programmes, enhances evaluators' confidence and substantially reduces cognitive strain. As AI technologies become more prevalent, structured training will be essential to ensure that evaluators can effectively interpret, utilise, and challenge AI-supported information during accreditation tasks.

Finally, the study's early results offer an empirical foundation for policy development. By grounding policy decisions in actual evidence, these findings can guide the Malaysian Qualifications Agency's digital transformation efforts and inform the creation of robust national guidelines for AI-assisted accreditation. Ultimately, this evidence-driven approach will support the responsible integration of AI, promoting efficiency and transparency while safeguarding the essential role of human judgement in the accreditation process.

5.3 Limitations of the Study

This study has several limitations that should be considered when interpreting the findings. First, the evidence is primarily survey-based and captures respondents' self-reported perceptions of AI-assisted accreditation rather than observed behaviour. Although open-ended items provided useful contextual comments, the study did not include in-depth interviews or focus groups that could probe how evaluators negotiate trust, interpretability, and ethical concerns in greater detail.

Second, no direct observation or hands-on evaluation was conducted with an actual AI tool in simulated or real accreditation tasks. As a result, conclusions regarding usability and cognitive impact reflect anticipated or perceived experience, and may differ from what occurs when evaluators interact with specific interfaces, outputs, explanations, and verification features under real time pressure and accountability requirements.

Third, the sample size (N = 80) is adequate for preliminary descriptive and correlational analysis, but the respondent profile was dominated by programme accreditation panel assessors. This may limit representation of the wider range of Malaysian accreditation stakeholders (e.g., institutional auditors, secretariat/technical roles, and administrators across diverse institution types), and therefore constrain the generalisability of the results to other stakeholder groups.

Finally, the cross-sectional design provides a snapshot of attitudes at one point in time and cannot capture how perceptions and trust may evolve with repeated exposure, training, policy changes, or improvements in AI reliability and governance.

Taken together, these limitations indicate that the findings should be viewed as an initial baseline. Future research would benefit from larger and more balanced samples, longitudinal designs, and task-based evaluations that assess performance, error detection, reliance, and decision quality when AI is embedded in authentic accreditation workflows.

5.4 Recommendations for Future Research

Building on the present findings, future studies should prioritise task-based, hands-on evaluations using prototype or real AI tools in simulated or live accreditation settings. Such designs would enable researchers to examine usability, workload, error detection, reliance, and decision quality under realistic time constraints and accountability conditions, providing stronger evidence than perceptions alone. Future research should also expand sampling to include a larger and more balanced representation of Malaysian accreditation stakeholders (e.g., institutional auditors, secretariat/technical roles, administrators, and diverse institution types) to improve generalisability and allow meaningful subgroup comparisons.

In addition, longitudinal approaches are recommended to track how trust, perceived usefulness, and cognitive load evolve over time with repeated exposure, training interventions, organisational policies, and improvements in AI governance and reliability. To deepen understanding of human factors in practice, researchers should strengthen qualitative inquiry through interviews, focus groups, and think-aloud protocols to explore how evaluators interpret AI explanations, resolve disagreements between AI outputs and professional judgement, and manage ethical and accountability concerns during accreditation work. Finally, comparative studies examining different AI design features (e.g., explanation formats, confidence indicators, citation or traceability mechanisms, and verification workflows) would help identify configurations that best support calibrated trust and effective decision-making in accreditation contexts.

ACKNOWLEDGEMENT

This study was supported by the Geran Penyelidikan Pendidikan Tinggi (GPPT) of the Malaysian Qualifications Agency (MQA) [SPG25-173-0173].

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